The Development of a Decision Support Software Application to Improve Capital Equipment Management

by

Eric C. Selvik

B.S. in Mechanical Engineering
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Submitted to the Sloan School of Management and the Department of Mechanical Engineering
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Abstract

A shift from a factory-constrained to a market-constrained business environment has driven Intel to modify its operational focus to emphasize reduced costs, higher equipment utilization, and increased return on capital investment. Current methods of planning and managing factory capacity have not been able to eliminate WIP bubbles and other operating inefficiencies that result in elevated costs and reduced predictable capacity.

A new Intel technique called the 80% Confidence methodology provides novel ways of considering equipment availability by measuring and tracking the A80 Indicator, which is the 20th percentile of the daily average tool set availabilities. By focusing on the worst days of equipment availability, the A80 indicator represents a minimum availability that can routinely be expected, and therefore makes capacity planning more predictable.

This thesis describes the development of a Web-based software application, called the Equipment Management Improvement Tool (EMIT), that improves equipment management decisions by predicting equipment A80 availability given preventative maintenance schedules and basic reliability parameters. It discusses the background, motivation, development methods, and results of the development, and illustrates one of many practical applications through a case study of the effects of a PM schedule change on A80 availability. The thesis offers suggestions for improvements, and forwards future areas for extension of the application functionality.

Thesis Supervisor: Arnold Barnett, Professor of Management Science
Thesis Supervisor: Duane Boning, Associate Professor of Electrical Engineering

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I raise a toast to Arthur Guinness for his lovely pints of creamy stout that helped make the gray go away....Slainte!

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1. Introduction and Background

1.1 Thesis Overview

The shift from a factory-constrained to a market-constrained business environment and the drop in prices for PC microprocessors has eroded the incredible profitability that Intel has achieved for many years. In its effort to maintain its high profit margins on products while ensuring quality and delivery, Intel has endeavored to find areas for cost reduction and increase in return on assets. Given that Machinery and Equipment account for 37% of Intel's total assets (1997 Intel Annual Report), it is no surprise that equipment management has become a prime focus area for streamlining and improvement projects. For semiconductor manufacturers like Intel, equipment management decisions such as how much capacity to keep, how often to perform preventative maintenance, how much inventory buffer to maintain, and what trade-offs to make between technology and manufacturability have become critical to maintaining competitiveness.

A recent technique for improving operations in equipment-intensive, high-volume manufacturing is Intel's A80 Equipment Availability indicator and Methodology. Developed in 1994 at Intel's Fab10 in Ireland, this methodology builds on the recognition that for high-volume manufacturing over long periods of time, predictable manufacturing performance is as important as high mean performance. The A80 indicator (or 80% Confidence) seeks to focus Intel's operations and capital equipment management on predictable equipment capacity by creating a new tool availability metric by which equipment performance is measured. Now, instead of looking at average availability as a measure of the performance of a tool set, Intel looks at the A80 Indicator, a statistic which reports the 20th percentile of the daily tool group availability over a 28-day rolling period. The A80 statistic captures an indication of both the mean and the variation of the availability of equipment. Therefore, striving to maximize A80 forces equipment management policies to consider both the elevation of the mean and reduction of the variation. By concentrating on the A80 statistic, Intel ensures that 80% of the time a required level of equipment is available for processing, and therefore has greater predictable capacity to efficiently manufacture product and meet customer demand.

This changed focus in measuring equipment availability and utilization has brought into question the methods used in planning and executing scheduled preventative maintenance (PM). It was realized that how you schedule the PMs for your tool set will have performance effects on A80 (your predictable capacity), while not necessarily affecting the average availability. It is possible, therefore, that bottlenecks are designed into the manufacturing system simply in how the preventative maintenance is managed, resulting in WIP bubbles, lost throughput, and other operating inefficiencies. It is clear that new methods must be discovered to maximize A80 when managing the interplay of downtime events for capital equipment.

To address the complexities of equipment management decisions, a software application was developed that computes the expected A80 availability performance of capital equipment given basic inputs about the scheduled and unscheduled events that characterize the machine. The development project took place in Intel's Fab 10 in County Kildare, Ireland, from June through December 1998, and resulted in the introduction of the software application called the Equipment Management Improvement Tool (EMIT) to the Intel intranet.

This thesis describes the background, motivation, developmental process, and results of the development of the EMIT software application. The thesis also discusses recommended improvements to the application, and suggests future functionality to extend the usefulness of the model.

1.2 Thesis Organization

The thesis is divided into seven chapters, followed by a case study described in an appendix.

- Chapter 1 provides an overview of the thesis, a brief history of Intel, and the motivation for the project out of the current business environment.
- Chapter 2 discusses the problems surrounding machine unavailability and the methods of measuring and rating machine performance. A more in-depth introduction of A80 is offered, as well as examples of the potential benefits from this metric
- Chapter 3 describes the problem statement, objective, purpose, scope, and general motivation for the project.
- Chapter 4 discusses the approach used to solve the problem, decision points in the development process, and the assumptions imbedded in the resulting application.
- Chapter 5 provides a full description of the resulting software application, with discussion on the inputs, outputs, and how the application works.
- Chapter 6 discusses the interpretation of the output, addresses some of the potential weaknesses in the model, and offers some larger take-aways and visions for future consideration.
- Chapter 7 recommends improvements that can readily be achieved with the EMIT application, and future extensions of the model into capacity and WIP analysis.

- The Appendix A describes the set up and results of a sample use of the application in analyzing the potential effects on A80 availability that a change in PM policy will have.

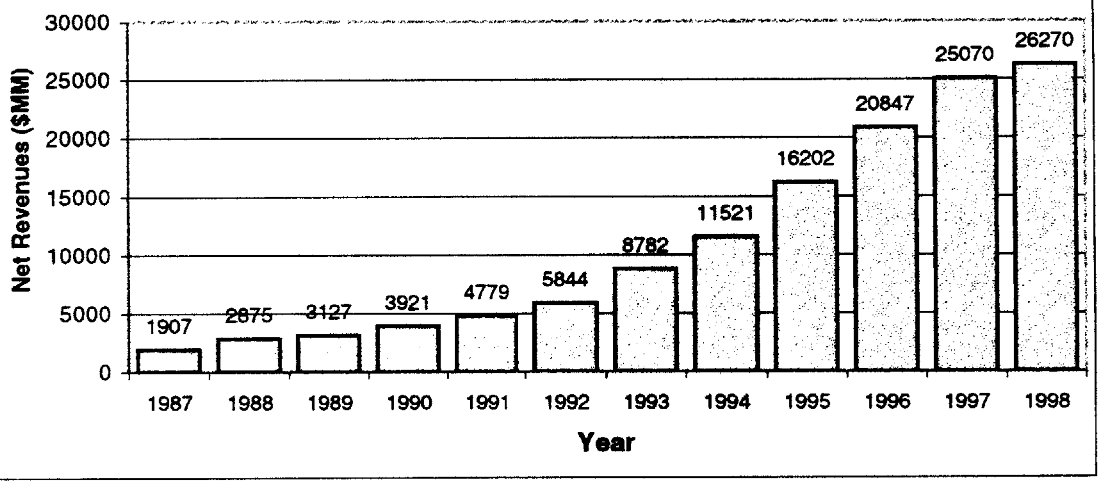
1.3 History of Intel

Intel Corporation was founded in 1968 by Robert Noyce and Gordon Moore in Mountain View, CA. Through well-known products such as the Pentium, Pentium Pro, Pentium II, and now Pentium III, Intel has grown to become the world's largest semiconductor manufacturer. With nearly 80% of the world market, Intel is the undisputed leader in the production of microprocessors.

Intel's first products were primarily memory chips and microcontrollers. In 1971, Intel produced the first microprocessor (named the ***4004***) and by the late 1980's the company was focused on the production of the microprocessor and other logic chips which provide the 'brains' inside of computers. As the personal computer market blossomed, so did the demand for faster, more powerful microprocessors. This increased demand for processing capability drove Intel to introduce new, more powerful and complicated processors through the accelerated development of circuit designs and fabrication processing technologies. For many years, Intel has maintained the dominant position in this market through carefully planned and controlled releases of new technology that has kept them constantly ahead of their competition. Their technological superiority also allowed them to maintain high profit margins on their products (58% gross margins), capitalizing on the premium that consumers where willing to pay for increased processing capability. Intel had long operated in a factory constrained business environment, meaning that the demand for their products outweighed their capacity to produce, and that they could sell every chip they produced at a premium. Consequently, Intel was incredibly profitable.

For the years 1987 – 1997, Intel's closing stock price achieved a compound annual growth rate of 42% (from Intel website, www.intc.com). As depicted in **Figure 1.1**, 1998 marked the 12th consecutive year of record revenues for Intel.

Figure 1.1: Intel Net Revenues



1.4 Current Business Environment

A recent change in the personal computer market has driven Intel to refocus its business strategies. The emergence of a new market segment – the sub $1000 PC market – has left Intel vulnerable. This market uses lower performance processors than the high-end that Intel has traditionally led the development in. Intel underestimated the significance and size of this market, and largely ignored it, choosing to move ahead with higher performance, more expensive microprocessors for higher-end computers.

The emergence of this new market segment and a simultaneous downturn in the overall demand in the PC industry placed Intel in a market-constrained business environment, characterized by oversupply of their high margin chips. This substantial change in the business environment requires a significant modification in the way Intel runs its business. Instead of excessive demand, Intel faces overcapacity. Instead of competing on technology, they are forced to compete on cost. Gone are the days when the marginal revenue far exceeded the cost to produce a chip and nearly any expense could be justified for technological advances and increased output. Intel now faces steadily falling prices for personal computers that result in lower prices for microprocessors. In order to compete in the new sub-1000 PC market and avoid losing a large percent of its market share to its competitors, Intel must significantly reduce the cost to manufacture its chips. Specific implications of this objective are a reduced investment in capital equipment and more efficient and cost effective use of existing capital equipment. Furthermore, costs can be reduced through improved WIP and inventory management and an increased focus on total cost of ownership and return on investment for all decisions, including equipment purchase, staffing, and factory loading.

This new frame of mind is a difficult cultural change for such a large company that for so long maintained a very different mental model of what it took to compete and succeed in the semiconductor manufacturing industry. In the past, issues of manufacturability were routinely subverted to technological increases because the marginal cost to produce was always far below marginal revenue on each chip. This technological focus had strong influences on many operational areas within Intel. Equipment purchase decisions, staffing decisions, and improvement project selection were driven by technology issues, many times "to the exclusion of availability" and other manufacturability aspects.

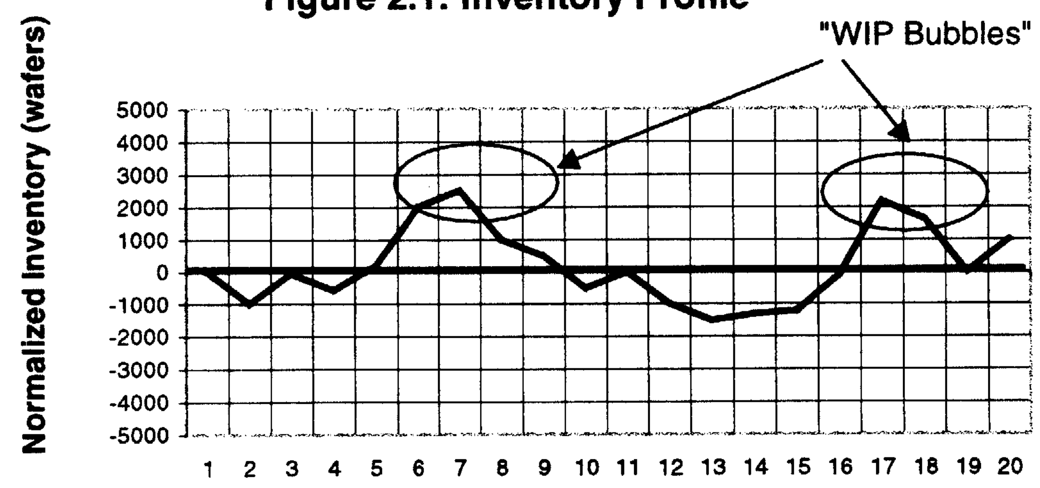
This paradigm shift represents the high-level motivation for this thesis project – helping Intel make better decisions about how they manage their equipment in order to increase efficient use, decrease total cost of ownership, increase the return on investments, and better manage WIP and inventory.

2. The Problem

2.1 Variable Output and WIP Bubbles

One of the major problems in manufacturing systems that increases costs and reduces efficiency is variable or unpredictable process output. At Intel's wafer fabrication facilities, one of the most visible results of unpredictable output is the formation of "WIP bubbles", large WIP build-ups that propagate through the manufacturing system. **Figure 2.1** depicts a sample WIP profile snapshot from Fab 10, where the WIP level at each process step is shown normalized to the planned, or balanced level.

Figure 2.1: Inventory Profile



As depicted in the graph, the WIP bubbles cause the WIP profile to deviate considerably from the balanced condition. These WIP bubbles have many negative effects on the manufacturing system, including increased throughput time for a lot that severely limits responsiveness to rapidly changing demand, slower detection of quality problems [Wein], and the need to keep excess capacity which amounts to higher capital equipment expenditures.

In addition, there are the less quantifiable but significant negative consequences of general chaos in the factory from over-stressed equipment and workers, and scheduling problems for both human and capital resources.

2.2 Theory of Constraints

At Intel, it is felt that predictability is a key to manufacturing success. Statistical process control is used throughout to track processes and reduce process variability. Factories are designed and managed using elements of the Theory of Constraints, whereby the system is balanced with respect to the output of the bottleneck process.

The Theory of Constraints (TOC), developed by Eli Goldratt, forwards that within any system there is always at least one weak link that constrains the overall output of the system. The system can produce no more than the constraint (known as the bottleneck) can deliver, no matter how productive or efficient the other links in system operate. Therefore, in order to maximize the output of the system, it is imperative to identify the constraint and maximize its output.

In order to increase the throughput of a manufacturing system, Goldratt offers the following steps for Constraint Management:

1. Identify the system constraints
2. Exploit the constraint
3. Subordinate all other processes to the constraint.
4. Elevate the constraint
5. If Constraint is "broken," return to step 1 to find the new system constraint.

According to this theory, the proper amount of capacity at each process step can be determined to balance the manufacturing system by the constraint, thereby increasing throughput and minimizing WIP. Despite using the Theory of Constraints to balance the factory throughput, Intel finds that WIP bubbles continue to propagate through their fabs, and in addition, the bottleneck seems to move among different processing steps.

The WIP bubble problem can, in general, be traced to an incomplete understanding of the capacity of the fabrication system, and specifically the capacity at each of the process steps. One could argue that these WIP fluctuations would not occur if sufficient capacity were maintained at each step to deal with upstream variability in process output. However, semiconductor manufacturing equipment is very expensive, with typical single tool prices of $500,000 to $3 million, and entire fab costs in the neighborhood of $5 billion. Given these hefty equipment costs and the current business environment of cost cutting, one must look carefully at the financial and operational trade-offs on carrying "burst capacity," or extra machinery to deal with WIP fluctuations.

A more cost-effective approach is to try to optimize the capacity of the equipment already in place and understand what the key variables are that affect the throughput performance of the system.

2.3 Capacity Calculations

When trying to understand the mismatch in predicted and actual capacity, an obvious place to start is to look at the method used to calculate capacity of a tool set or system. According to the Theory of Constraints, the identification of the system constraint and near constraints is accomplished by finding the process steps that have the lowest capacity. Intel often designs factories so that the process step with the lowest capacity is that which has the highest cost or most technology intensive equipment. By setting the capacity of the factory by the capacity of the intended or designed constraint, Intel can determine the theoretical capacity needed at each of the other process stations in order to maintain a smooth WIP flow through the system.

Intel uses the following equation to calculate tool set capacity:

$$\mathit{Capacity} = (RR * U/A * \mathit{Avail} * 168 * \#\mathit{tools})/(\#\,\mathit{step} * LY)$$

Where

RR = run rate in wafers per hour
U/A = utilization to availability ratio: time the machine is processing WIP/ time machine is ready to process WIP
Avail = tool set availability (%)
168 = hours per week of theoretical process time
# tools = number of machines in the tool set
# step = number of times a wafer is processed by tool set in mfg. process
LY = line yield (% of good wafers passed on to next process step)

In accordance with TOC, the U/A of the constraint tool set is set to 1.0 (100% utilization) in order to achieve the goal of maximizing constraint output (TOC Step 2: Exploit the Constraint). For non-bottleneck tool sets, a design U/A of 0.85 is used. This provides “protective capacity” to ensure that the processes upstream of the constraint will keep the bottleneck fed, and the downstream tools can easily handle the WIP processed by the bottleneck and move it quickly away from the constraint. (TOC Step 3: Subordinate non-constraints to the constraint)

Assuming for now that the U/A is fixed, the other variables in the capacity equation are availability and line yield (***Run rate*** is fixed by the equipment capability, and ***# steps*** is fixed by the process) Line yields are generally very high, with little variability, and there are many processes in place to continue to improve this indicator. The most impact in the capacity variation, then, comes from the availability.

The long-term average availability will vary depending on the downtime events that occur with the machine, which can be generally classified as scheduled, unscheduled, and non-scheduled events. Scheduled events are periods when the machine is not available for a planned reason, and would include time the machine is down for preventative maintenance, performance monitors, engineering testing, and scheduled qualifications. Unscheduled events are times of unplanned machine downtime, and include activities when the machine is in repair, is waiting for product, or is waiting for a technician. The non-scheduled downtime includes events like factory shutdowns and automation work. The non-scheduled downtime accounts for a very small percentage of the total machine downtime and for practical purposes can be treated like unscheduled downtime.

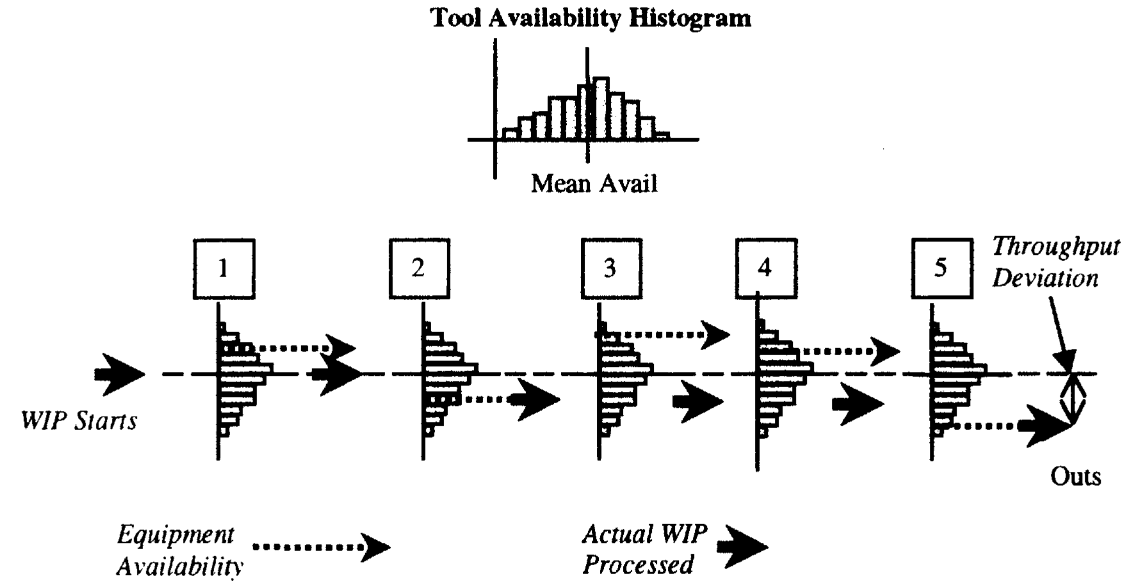
The availability statistic that is generally used to determine capacity is the long-term average availability:

$$\textit{Availability} = \textit{Total tool uptime/ total time}$$

where uptime is the time that a tool is able to process WIP, whether or not it does so. The average availability is a good general indicator to determine total system output capabilities and long-term throughput expectations for equipment sets, systems, and factories. However, using the average availability implies that 50% of the time the equipment availability is below the expected level, which implies that half the time the tool set or system will not have the capacity level that was calculated. This "time insensitivity" of availability leads to problems with unpredictable throughput, since one will inevitably have machine availability when there is no WIP to process, and one will not have machine availability when there is WIP. When one of these conditions occurs, WIP backs up at process stations and causes WIP bubbles to propagate through the manufacturing system.

Figure 2.2 below illustrates this effect. A tool set might have an availability distribution like that shown in the top of the figure. Consider a system of five tool sets with a variable availability that are balanced so that their average availability gives them sufficient capacity to maintain the desired throughput. A given amount of material is started based on the balanced factory capacity which is determined by the factory constraint. Even though the first machine has higher than average availability, only the WIP that was started is available to process, and so only that amount is passed to the next tool set for processing. The second tool set experiences below average availability, and therefore only part of the WIP can be processed. The rest waits in a buffer in front of the process step. The third tool set is performing very well, but it is being fed only a fraction of the WIP it is capable of processing, and it can only process that which is passed to it from the upstream process. A similar circumstance occurs at tools set 4 and 5 where a below average availability day again reduces system output. We can see at the last station that the actual system output is well below the expected amount, and the throughput deviation can be traced to the machine availability mismatch with the WIP availability. In general, the downside variation reduces factory output, and upside variation is often lost elsewhere in the manufacturing system.

Figure 2.2: Deviation from Expected System Throughput



2.4 The A80 Metric

Realization that the mean statistic was not robust in determining system capacity led Intel to begin investigating new techniques to help mitigate the unpredictability problem. One such technique is Intel's A80 Equipment Availability Indicator and 80% Confidence Methodology. Developed in 1994 in Intel's Fab10 in Ireland, this methodology seeks to focus Intel's operations and capital equipment management techniques on predictable equipment capacity by creating a new tool availability metric by which equipment performance is measured. This metric, known as the A80, calls attention to the days of low equipment availability, and seeks to improve equipment performance on the worst days over elevating the average availability over all days.

2.5 What is A80 or 80% Confidence?

A80 is essentially a statistic representing the 20th percentile of the daily average availability data of a tool set over a rolling 28-day period. The daily average availability is found by summing the total uptime for all individual machines in a tool set and dividing by the total machine hours, which is the number of machines times 24 hours.

$$\textit{Daily Average Availability} = \frac{\Sigma \text{ Ai}}{\text{n} * 24} \quad \text{where Ai is the daily availability for the } i^{th} \text{ tool in a set of } n \text{ tools}$$

For instance, a set of 5 tools might have a daily total of 100 hours of uptime, so the daily tool set availability would be

$$A = 100/5*24 = 86.6\%$$

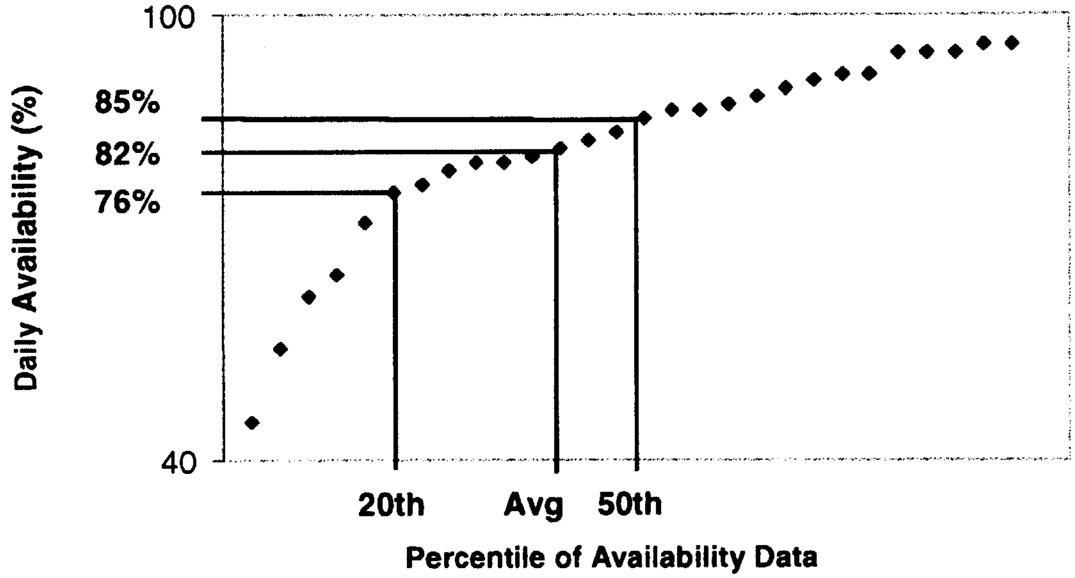
To find the A80 of a tool set, the daily tool set availabilities are listed in ascending order, and the 20th percentile of the data set is calculated (the sixth lowest availability). This is the availability at which one has 80% confidence that the tool set has performed.

For example, consider a 28-day period with the following daily tool set availabilities listed in ascending order, :

45,66,62,65,72,76,77,79,80,80,81,82,83,84,86,87,87,88,89,90,91,92,92,95,95,95,96,96

The A80, calculated as the 20th percentile of the data set is 76%, as shown in **Figure 2.3**. Also shown are the 50th percentile (85%) and mean availability (82%) of the data set for comparison.

Figure 2.3: Cumulative Percentile of Availability Data

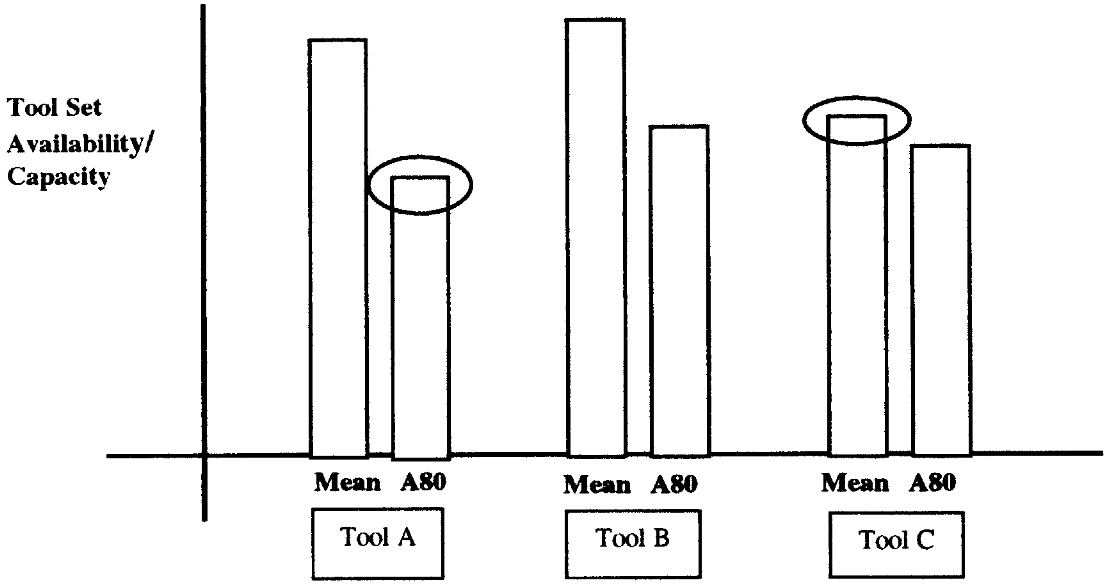


2.6 Benefits of A80 and 80% Confidence Methods

By focusing on the A80 and achieving the 80% Confidence availability goals, Intel has found that their tool performance is more predictable, and that WIP levels and system throughput vary less. Furthermore, the effort to increase A80 has led to a set of 80% Confidence Methodologies which have helped better utilize equipment and avoid some capital investment in increased capacity.

An example of an immediate benefit of the A80 analysis is the improved diagnosis of the constraint tool set in a manufacturing system. Consider the three tool sets illustrated in **Figure 2.4.** When comparing the mean availabilities, Tool C appears to be the bottleneck, and therefore one would subordinate the system to its throughput. One would also focus projects on improving the availability of this tool in order to increase system throughput (elevate the constraint). However, if the A80 statistic is compared, Tool A emerges as the constraint tool set, perhaps because Tool A has a high mean but highly variable availability and output. Using Tool A instead of the more predictable Tool C as the system constraint would have major changes in the factory loading and system improvement strategies.

Figure 2.4: A80 vs Mean Statistic



3. The Project

The equipment management challenges that erratic WIP levels invite, along with the general trend to cut costs and increase return on investment, necessitate the discovery and testing of new equipment management methods to maximize A80 and improve equipment performance. However, difficulties arise when trying to predict A80 availability. Percentile statistics are much less tractable than mean-based indicators, and require a more complicated approach to modeling and prediction.

In response to this need for a tool for analyzing A80 performance, the following project definition was established:

3.1 Problem Statement

There exists no tool for accurately planning and optimizing the interplay of downtime events for processing equipment when considering A80 availability. Current equipment availability applications provide summary data on past equipment performance, but are not geared to forward-looking equipment issues such as preventative maintenance (PM) design improvement testing, PM optimization, or equipment purchase decision inputs.

3.2 Project Objective

The objective of the project is to develop a software application that accurately models and predicts A80 equipment availability given basic reliability parameters. This tool will help to improve A80 equipment availability by assisting in the simultaneous management of machine maintenance activities and random machine failures.

3.3 Purpose

The purpose of the application is to deliver expected A80 equipment availability statistics based on equipment performance characteristics and PM schedules, and to predict the effects of equipment management policy changes on availability performance and WIP levels for systems of tool sets.

The information gathered using the application would be used in many ways. One important use is to discover and test new WIP and PM management methods to improve equipment availability. Another very practical use is to compare expected outcomes of candidate improvement projects to prioritize the highest-leverage activities, resulting in better use of engineering time. Also, the application output will enable analysis of factory capacity and inventory profiles to better understand interactions among systems of tools. Additionally, the application can be used analyze and compare expected equipment A80 performance when considering the purchase of new tools.

3.4 Project Scope and Design Criteria

To bound the project and provide some criteria to guide and motivate the development, the project scope was set by a few general guidelines. It was decided that the application should be Windows compatible and/or a Web based platform for compatibility with current Intel IT norms. The target customer for the application was set initially as Intel internal, with possible extension to external customers. These target users for the application include Equipment Engineers, Manufacturing Engineers, Production Supervisors, the WIP Management Team, and the Capital Equipment Development Group. One last high-level criteria was that the application should be general enough to model any type of semiconductor processing or other capital equipment. This would enable use by any equipment group within Intel, as well as the potential to develop the application into a new product for sale to other companies and industries.

4. The Approach

4.1 Product Definition

At the outset of the project, many key attributes for the product were undefined. Very little was understood about what exactly the software program should do, how it would work, what inputs and outputs were required, who the users would be, what their needs were, and how this product would fit with Intel's current suite of tools.

In order to understand what the needs were for such a product and put some definition on functionality and scope, extensive interviews were conducted with a wide variety of key constituents and potential users. The people interviewed included

- Equipment Engineers for Metal Etch, Planar, and CVD equipment groups
- Technicians for Planar equipment (on shop floor)
- Manufacturing engineer, Industrial Engineer
- Members of WIP management team
- Equipment Manager of Stepper supplier
- Equipment Engineer of supplier
- Functional Area Manager (Lithography)
- Manufacturing Engineering Manager
- Automation group engineer
- Process engineer, planar equipment

The interviews served the purposes of identifying the target user group and understanding the users' needs for a software tool, what inputs they would have available, and what outputs they would expect and find useful. Furthermore, it ensured that the development would produce a product that people would use, that did not duplicate existing applications, and that fit well with existing systems.

From the interviews conducted, a list of general customer needs was determined. Some of the desired attributes were that the application must be easy to use, with easy access to input information, and easy processes for entering information into the model. Another important need was fast output, with no more than 10 minutes necessary to run a simulation. Of course, the model must be technically sound in order to be convincing enough to motivate changes. Finally, it was preferred that, as much as possible, the output be displayed in charts and graphs.

4.2 Product Placement

Another important consideration was how this particular software product would relate to existing tools used by Intel employees to model and analyze equipment availability information. There already existed the Improvement Engineering Applications (IEN Apps) that allowed engineers to analyze past data on equipment performance. These applications queried Intel databases and calculated availability statistics for any tool set in Intel's virtual factory, reporting the results in tabular and graphical format. Using these applications, employees could track equipment performance (average availability, A80, line yield) and monitor indicator trends.

There is another application at Intel that is used to model factory performance. It is a very complicated discrete event simulator that models all facets of and transactions in the factory. This model uses as an input very specific information about the tool characteristic, equipment failures, PM schedules, run rates, as well as staffing schedules, technician ability level, and other detailed information about process variables. The output contains specific directions on optimal factory loading and staffing plans. However, this application is quite complicated, requires heavy computing capability, is difficult to learn, and takes significant amounts of time to set up and run.

The proposed application seemed to comfortably fill the open space for a tool that provided A80 modeling capability, but that was quick, accessible, and easy to use.

4.3 Data Collection and Interpretation

Intel has a very well developed process control and data collection system called Workstream that controls and tracks activities that occur to every entity (wafer or tool) on the factory floor. Furthermore, there are query systems that allow users to pull data and track tools over time. These provide a rich source of data for performing process and equipment analysis.

When analyzing data for the development of this product, one of the challenges was to interpret the data into actual events. If a query is run to look at all events for a tool when it is logged "down" (i.e. not available), the Workstream database will show many entries for one event. For instance, if a tool fails and must be repaired, it must first be logged 'down to production', then logged in a repair state. The repair state might have several different repair entries and some nested testing states, and the tool might be logged in a waiting state for a part. When the tool is repaired, it might be logged into a different state in order to enter the information about the repair that was just completed. In this way, many entries describe one repair event, and this series of data entries varies significantly from event to event and tool to tool. Time was spent on the factory floor understanding some of the nuances of how the tools are actually logged on the floor. For instance, some technicians might follow a preventative maintenance routine exactly as is directed by the procedure. This might require performing an activity, returning to the Workstream workstation to enter that the activity had been completed, and then reading the next activity, going back to the tool to complete that activity, and returning to the workstation to enter information about the completion of that particular instruction. Although this is the standard procedure, the reality is that having to go back and forth between the tool and the workstation so frequently is time consuming and frustrating for technicians. Therefore, some technicians will perform several of the PM routines in succession, and then return to the workstation to enter in the completion information at the same time. These and other variable data input procedures create some challenges in trying to parse the data into descriptions of discrete events that are meaningful to estimating availabilities.

4.4 Development Software Selection

A key decision point was what type of software to use for development. As shown in **Figure 4.1**, different software packages offered a range of pro's and con's. In the end, the customer requirements and resource and time constraints dictated that a more simple software environment be used giving the advantages in ease of use and implementation. Another key benefit of using the simpler software was the ability to use previously written code which would save time and resources and allow easy integration into the current Improvement Engineering software application suite.

Figure 4.1: Software Environment Selection Matrix

Software	Pros	Cons	Comments
Excel	• easy to use • easily supported • runs on any laptop or desktop	• too simple, not robust enough to handle simulations	• Probably won't cut it
Visual Basic	• easy to program and support • runs easily on systems • allows for time simulations • allows for slick user interfaces, and is compatible with host of other software products • can perform real time feedback and output	• perhaps not robust enough • not as respected in scientific and engineering communities	
AutoMod	• software licensed by Intel • contains simulation capability • robust and respected • compatible with other Intel models (JPC, etc.) • Good for detailed tool level intra-actions	• is its own language, requires programming skills • more complicated than Excel, VB	
AutoSched	• software licensed by Intel • contains simulation capability • robust and respected • compatible with other Intel models (JPC, etc.) • Good for higher level tool group models • coding not necessarily required	• more complicated than Excel, VB	• coded in AutoMod
ASAP	• software licensed by Intel • contains simulation capability • robust and respected • compatible with other Intel models (JPC, etc.) • Good for detailed tool level intra-actions	• more complicated than Excel, VB	• coded using C++
Mathematica	• Quite robust and mathematically solid • respected by scientific and engineering worlds	• Not easily supported • Not real time simulator • Requires special programming skills • Can't be run on all systems	
C++	• well-known. widely used • integrates well with other apps • versatile	• codes slowly	• probably used in conjunction with VB, other app

4.5 Model Assumptions

In order to simplify some of the complex variables that determine availability and throughput, the model starts with some basic assumptions. One is that the machines are independent, so that the availability of one is not affected by the availability of any other. It was assumed that there is uniform loading across the tool set, so that each machine in the group processes the same number of wafers per unit time. It was assumed that there is no correlation between Time Between Failure (TBF) and Time To Repair (TTR): the time it takes to repair a piece of equipment is unrelated to the amount of time since it was last repaired. Similarly, it was assumed that there is no correlation between scheduled and unscheduled events, so that the occurrence of a scheduled event has no impact on the chances of an unscheduled event occurring, and vice-versa. Other assumptions include that the factory is in stead state, with constant wafer loading (e.g. 7000 WSPW), and that there is no prioritization of lots at any tool set.

Assumption 3, no correlation between TBF and TTR, is a key assumption for the basic operation of the application. Initial analysis of the data established that, for the Westech Planar equipment over the six month time frame, values of Time Between Failure and Time To Repair were uncorrelated. The data was analyzed using sample correlation coefficient analysis to determine the coefficient of correlation, $\rho_{x,y}$:

$$\rho_{x,y} = \frac{\mathrm{cov}(x,y)}{\sigma_x * \sigma_y}$$

where:

$$\mathrm{cov}(x,y) = 1/\mathrm{n}\ \Sigma(x_i - \mu_x)(y_i - \mu_y)$$
$$\sigma_x^2 = 1/n\ \Sigma\ (x_i - \mu_x)^2$$
$$\sigma_y^2 = 1/n\ \Sigma\ (y_i - \mu_y)^2$$

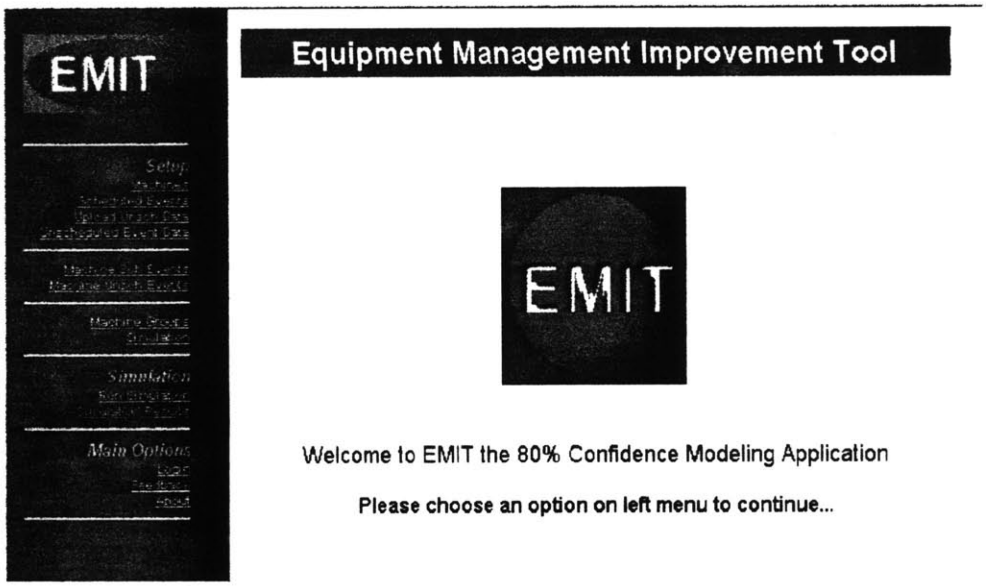
For the Westech Planar equipment data, a correlation coefficient of $\rho_{x,y} = -.019$ was found between the TBF and TTR. This is sufficiently close to 0 to assume no correlation.

5. The Result: Equipment Management Improvement Tool

5.1 Summary of Key Functionality

A software application was developed according to the project scope and customer input that addresses the problem statement. The resulting application is called the Equipment Management Improvement Tool, or EMIT. This application predicts the A80 availability of a tool set given the preventative maintenance schedule and the statistical pattern of unscheduled downtime events of the equipment. **Figure 5.1** shows the main screen for the application.

Figure 5.1: Main Screen for EMIT



Welcome to EMIT the 80% Confidence Modeling Application

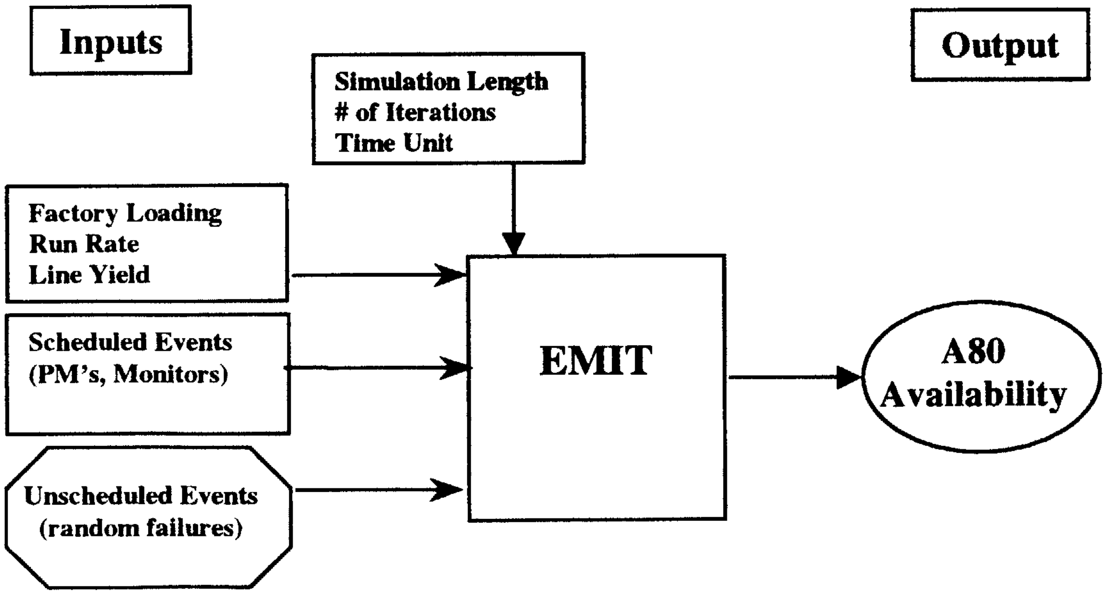
Please choose an option on left menu to continue...

Using this application, an engineer can determine how changes in equipment maintenance routines and reliability parameters will affect the A80 availability of a set of tools. Furthermore, the user can compare these expected outcomes among several projects, and thereby choose to work on the project that provides potential for the largest performance increase.

5.2 Using EMIT

The EMIT A80 module predicts the A80 performance for a defined machine group based on input about the machines' scheduled and unscheduled downtime events. **Figure 5.2** depicts the Input/Output structure of the application.

Figure 5.2: I/O Diagram



5.3 Inputs

The inputs to the model are the following:

- Run Rate: the wafers per hour that a machine is capable of processing.
- Wafers visits per hour: the number of wafers expected to pass through the machine. This is a function of factory loading, yield, and the number of process steps the wafer sees at each machine.
- Machine PM schedules (scheduled events): input as a frequency, duration, and offset, where the offset is the number of hours from the beginning of the simulation that the first PM of this type occurs. A unique PM schedule can be entered for each machine, allowing for PM phasing across tool sets.
- Unscheduled Event Data: Time Between Failures (TBF), and Time To Repair (TTR), uploaded from an Excel worksheet as strings of comma separated integers that are actual values of TBF and TTR from historical data on the machine. (Alternatively, the user can input a made-up distribution for each of these parameters). Both TBF and TTR values are found through querying Intel's database of operations data and separating out these variables using an Excel worksheet (called the Downtime Event Sorting Tool, described below in **Section 5.4**)
- Simulation length: the number of hours over which the simulation should run (suggested between 672 and 2016 hours = 1 to 3 months)
- Number of Iterations: number of runs of the simulation desired. Generally, the more iterations run, the better characterization of the machine performance, but the longer it takes to complete the simulation.

A number of links in the Set Up menu on the left-hand side of the screen allow the user to input the required information to run the simulation. In general, the user would use the following links to create and run a simulation of a tool set:

1. Machines: enter information about a machine (name, run rate, wafer outs, yield, etc.)
2. Scheduled Events links: enter frequency, duration, offset
3. Upload Unsch Data / Unscheduled Event Data: create unscheduled event profiles by either uploading data or manually entering TBF and TTR distributions
4. Machine Sch Events / Machine Unsch Events: associate downtime events with specific machines
5. Machine Groups: group individual machines into tool sets
6. Simulation: enter simulation parameters, including Machine Group, length, and number of iterations
7. Run Simulation: select and run a simulation
8. Simulation Results: view results of any previously run simulation

5.4 Data Retrieval: Downtime Event Sorting Tool

To pull data for the unscheduled events input, a complementary tool called the Downtime Event Sorting Tool was developed to support EMIT. It is a query application that allows the user to extract the necessary data about unscheduled downtime events needed to run the EMIT application. The query is run and it collects data on the specified machines over a specified time period. This information is then entered into an Excel worksheet equipped with macros to help sort the data for entry into the EMIT application. The worksheet is essentially a set of "if/then/else" and logic algorithms that characterize the events according to certain parameters reported from the data query. The application classifies each event listing as Scheduled, Unscheduled, or Other event type by looking at the description of the event and labeling it as S, U, or O accordingly. Some examples of event classification types is shown below:

Unscheduled	Scheduled	Other
WAITING PART	IN PM	DEVELOPMENT
WAITING TECH	SCHED QUAL	AUTOMATION
WAITING PROD	PERF MONITOR	
IN REPAIR	ENGINEERING	

Based on the classification of Scheduled (S), Unscheduled (U), or Other (O), the amount of time spent in the logged event, and the start and finish times of each logged event, similar "if/then/else" and logic functions group the individual logged events into discrete downtime events (DTEs). This is necessary since one discrete DTE can include many separate logged events, as described in **Section 4.3**. If a logged event marks the last entry for one discrete DTE, then it is designated as such. Knowing these designations allows the application to easily determine the actual start and finish times of the discrete DTE. The application then adds up the time in event for each logged event to determine a total time in event for the discrete DTE, which is actually the Time to Repair (TTR) for that event.

Because the model characterizes events as either scheduled or unscheduled, it is necessary to remove time spent in a scheduled event (preventative maintenance) from the time in between unscheduled events in order to arrive at an actual TTR. The model already accounts for the time in between failures spent in scheduled downtime, so this time should be removed from input data for the unscheduled downtime. An accompanying worksheet "purifies" the data by removing any "scheduled" or "other" downtime that might have been included in the TBF for the unscheduled events. After that, the TBF and pure TTR are saved in .CSV file, which is the appropriate file type for the EMIT application to upload.

5.5 How EMIT Works

When all the inputs are entered and the simulation is run, the application models equipment behavior by creating a virtual calendar for each tool in the set, and placing downtime events into this calendar based on the event profiles defined by the user. The virtual calendar for a machine can be thought of as a time array where each element of the array represents the machine state for one time unit of the simulation. Each element has three possible values: *A*, *S*, or U. A value of *A* in the array denotes a time unit that the machine is available to process WIP. A value of *S* or *U* indicates time when the machine is not available, but is instead down for a scheduled or unscheduled event, respectively. Based on the user input for number of tools in the set, a corresponding number of such time array calendars would be created in the database.

When a simulation is run, the model goes through and populates the time array for each machine in the group modeled. The application first initializes the array so that all machine-hours are marked available (all integers in time array = *A*). Then, it places all of the scheduled events in the time-array calendar for each machine. This is accomplished by changing the array elements from *A* to *S* that correspond to the hours of scheduled downtime, as denoted by the frequency, duration, and offset by the user.

Unscheduled downtime events are treated as random occurrences according to the distributions input for the Time Between Failures and the Time To Repair. A Monte Carlo simulator was developed that randomly selects among the unscheduled failure data that is extracted from the Intel database and uploaded into the application in the form of TBF and TTR values (in hours). This approach was chosen for a couple of important reasons. One is that using actual data preserves the mean and distribution of actual equipment performance. Also, the data can be extracted without much trouble, and takes no extra distribution modeling (i.e. trying to fit the data to a normal or other distribution).

In order to place the unscheduled events into the time array, the application goes to the unscheduled events data and selects randomly from the TBF values. It then divides this number in half to get the number of available hours from the beginning of the simulation that the first unscheduled event occurs. A TTR value is then randomly selected, and the two numbers together define one unscheduled downtime event. For each unscheduled downtime event established through the random selection of the TBF and TTR values (g,h), the application counts g number of A's in the array corresponding to the TBF values, and changes the next h array values that equal A to U. Any array values that are already S or U are skipped over. This process is repeated until the length of the simulation is exceeded, for each machine, for each simulation run. Note: only the TBF for the first event in each simulation run is divided by 2; the rest use the actual TBF value randomly selected.

5.6 Example

As an example, let us assume that a machine has one preventative maintenance activity, a daily activity lasting two hours that is performed at 10 AM each day. The scheduled event therefore has the following parameters:

Frequency = 24
Duration = 2
Offset = 3 (the model is assumed to begin with the first shift at 7 AM)

Also, the machine has input data describing the unscheduled events that consists of the following two sets of 14 variables:

TBF: 1, 77, 21, 4, 30, 9, 12, 2, 23, 8, 29, 45, 84, 2
TTR: 1, 22, 2, 13, 4, 5, 36, 53, 8, 1, 13, 41, 10, 9

Figure 5.3, below, shows how the application would construct and fill a time array to model equipment with these input parameters.

The application will first place the scheduled event, changing the fourth and fifth, 28th and 29th, 52nd and 53rd elements, etc. from *A* to *S*, until the full length of the simulation (as input by the user) is filled. Then, in order to define the first unscheduled downtime event, the application would randomly choose a number between 1 and 14, say 7, corresponding to a TBF of 12 hours. Dividing this value by 2 for the first event gives a TBF of 6. Then, it chooses another random variable, say 11, which picks a TTR of 13. Given the unscheduled event (6,13), the model counts out the first six available hours (skipping hours already marked 'down' for scheduled events) and blocks out the next 13 available hours, again skipping those already declared down for scheduled activity. For this example, the 9th to 21st elements would be changed from *A* to *U*, as depicted in **Figure 5.3**. The application then selects two more random numbers, say 4 and 6, corresponding to a TBF of 4 and TTR of 5 from the input data sets. Since this is not the first unscheduled event placed in the time array, the event (4,5) is placed by changing hours 26, 27, 30, 31, and 32 from *A* to *U*.

Figure 5.3: Example Simulation Time Array

Hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Array Value	*A*	*A*	*A*	*S*	*S*	*A*	*A*	*A*	*U*	*U*	*U*	*U*	*U*	*U*	*U*	*U*	*U*	*U*	*U*	*U*	*U*

Hour	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	...	...
Array Value	*A*	*A*	*A*	*A*	*U*	*U*	*S*	*S*	*U*	*U*	*U*	*A*	*A*	*A*	*A*	*A*	*A*	*A*	*A*	*A*	*A*

Array Value:
A = available
S, *U* = unavailable for scheduled or unscheduled event

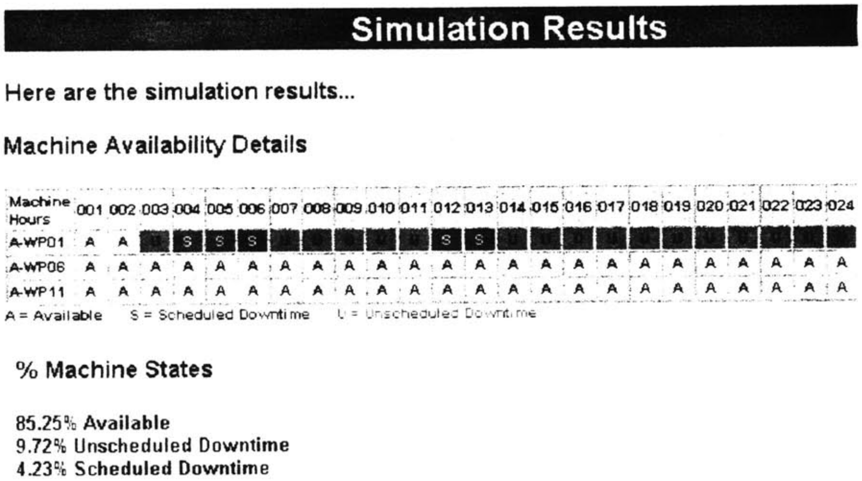
This process is repeated until the end of the time array for the machine is reached, and it starts for the next machine, which may or may not use the same TBF and TTR data.

5.7 Model Output

When all of the iterations of a simulation have been completed, the application calculates a daily average availability across the tool set. It counts the number of A's in all of the machine arrays for each 24 hour time block and divides by the daily number of tool-hours, which is equal to the number of machines in the tool set times 24 hours in the day. (So if we had chosen a length of 2400 hrs for the simulation, we would have 100 daily availability percentages stored for the tool set at the conclusion of the simulation). From this set of daily tool group availabilities, EMIT calculates the 20th percentile, rounds to the nearest integer, and stores the number as the A80 statistic for that iteration. All arrays are then reset, and this sequence is repeated for the number of iterations that the user directed the simulation to run. Therefore, the output of the simulation is a list of ***k*** A80 values, where ***k*** is the input number of simulations

The application reports the simulation output in a number of ways: tables, graphs, and lists of summary statistics of the simulated data. The simulation results are shown in **Figures 5.4, 5.5 and 5.6**.

Figure 5.4: Simulation Output – Avail Table



Simulation Results

Here are the simulation results...

Machine Availability Details

Machine Hours	001	002	003	004	005	006	007	008	009	010	011	012	013	014	015	016	017	018	019	020	021	022	023	024
A-WP01	A	A	U	S	S	S	U	U	U	U	U	S	S	U	U	U	U	U	U	U	U	U	U	U
A-WP06	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A
A-WP11	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A

A = Available S = Scheduled Downtime U = Unscheduled Downtime

% Machine States

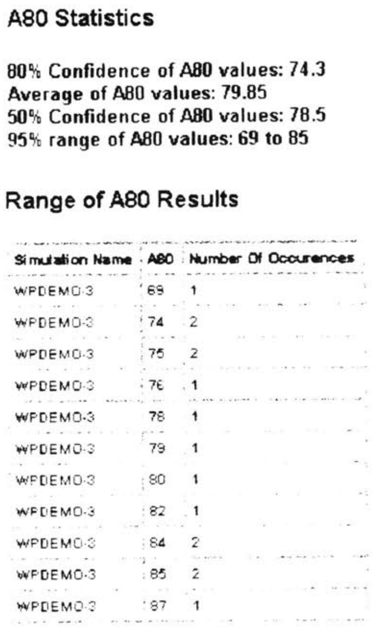
85.25% Available
9.72% Unscheduled Downtime
4.23% Scheduled Downtime

The Avail Table is a graphical display of the state of each machine in the group for each hour of the last iteration of the simulation. It is shown as a row of boxes containing an A, S, or U corresponding to that machine being Available, down for a Scheduled event, or down for an Unscheduled event, respectively. Some corresponding machine state statistics are shown describing the average availability, unscheduled downtime, and scheduled downtime for the iteration depicted in the table.

Figure 5.5 and 5.6 below show the rest of the output. A list of summary statistics is presented that characterizes the output of the simulation in terms of the 80% Confidence (20th percentile) of the A80, the average A80, the mean A80, and a 95% confidence interval of the A80 availabilities.

A table displays the actual A80 availabilities output from the entire simulation as an A80 value and frequency of occurrence, while the Graph is a histogram that displays this distribution of values from this table.

Figure 5.5: A80 Availability Results Output



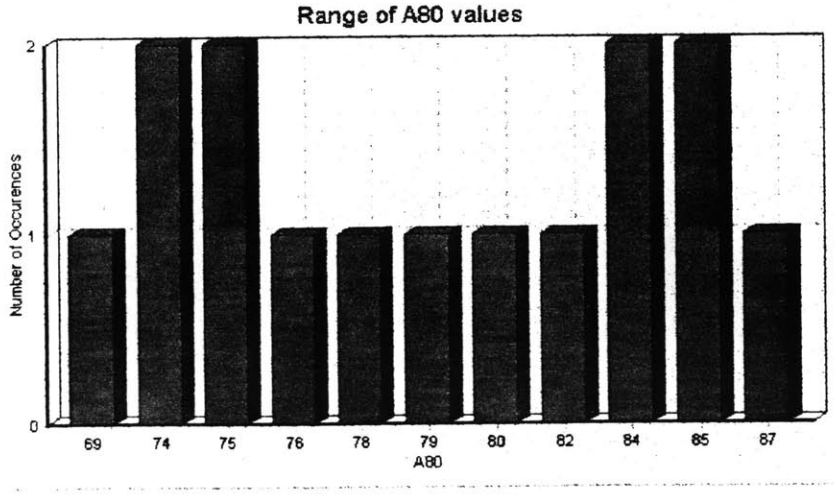
A80 Statistics

80% Confidence of A80 values: 74.3
Average of A80 values: 79.85
50% Confidence of A80 values: 78.5
95% range of A80 values: 69 to 85

Range of A80 Results

Simulation Name	A80	Number Of Occurences
WPDEMO-3	69	1
WPDEMO-3	74	2
WPDEMO-3	75	2
WPDEMO-3	76	1
WPDEMO-3	78	1
WPDEMO-3	79	1
WPDEMO-3	80	1
WPDEMO-3	82	1
WPDEMO-3	84	2
WPDEMO-3	85	2
WPDEMO-3	87	1

Figure 5.6: Availability Graph



When running a simulation in EMIT, the user can select before hand the type of output he or she would like to see by answering YES or NO to the Include Avail Table and Include Graph prompt boxes. By limiting the graphical output, time is saved in running and presenting simulation results.

6. Discussion

6.1 Interpretation of the Output

Since the output of the model is a distribution of A80 values, the interpretation thereof proves less than straightforward. Given the different ways to interpret the output from the simulation, several statistics are calculated and presented. These are:

1. 80% Confidence of A80
2. Average A80
3. Median A80
4. 95% Confidence Interval

Certainly it is helpful to know what A80 availability on average one could expect from the tool set. Therefore, one might look to the mean and/or median. Additionally, it is useful to discover to what degree we know that the average value represents the average of the population, so a 95% Confidence Interval of outcomes is presented. Furthermore, it is important to capture a measure of the dispersion of the output, and/or some measure of the predictability of the A80 output. A strong argument can be made that given an acceptance of the A80 statistic as a strong indicator of predictable and repeatable performance, the 20th percentile of the output A80 availabilities is a valuable representation of your tool group's predictable A80 performance - in essence, an A80(A80).

Overall, it is important to realize that given the same system of equipment with the same PM schedules and same patterns of machine failures, a range of A80 performance can be expected, as demonstrated by the range of the model output. This information could be used to drive tool set improvement projects that focus first on reducing variation in the A80 availability, and then raising the mean A80 of the machine group. The realization that A80 can vary will also color the interpretation of what it means to have a bad A80 week or month. Instead of viewing this unusually low availability performance as having a special cause, you might realize that the system as designed is capable of producing such a low availability outcome, due to the random nature of the failure modes. This will have impacts on reactions and corrective actions to these types of situations.

6.2 Why 80% Confidence

The reasons that the 80% Confidence level (20th percentile) is used are the following *(adapted from the 80% Confidence Student Guide, Babikian et al)*:

1. Tool availability distributions vary from normal to non-normal distributions, and generally for normal distributions one might look at standard deviations as a measure of predictability. In particular, one could choose 1 sigma on each side of the mean, giving us a lower confidence level of 16%. For non-normal distributions, one might choose the inner quartile range, or the 25th – 75th percentiles, leaving the lower confidence level of 75%. For practical purposes, the generally used confidence level is chosen in between the two at 80%.
2. The Pareto Principle, which forwards that 80% of results are achieved by solving 20% of the problems, implies that the 80% confidence level is a good indicator for focusing tool availability improvement.
3. Plotting Average Daily Availability of a tool set on a cumulative percentile graph shows that in general the lowest performing days are outliers, and indicate days when special cause problems, or serious process excursions, have occurred. Since these are not common cause problems, and there is a mechanism already established to deal with these types of problems,

Intel should focus on the common cause problems. Data suggests that the 20th percentile is a good cut-off point for the outlier data.

4. Choosing a number smaller than 80% gives you less confidence in the predictability of equipment availability, where choosing higher numbers causes you to skew the data with very non-routine excursions. 80% gives you baseline, but allows you to remain insensitive to outliers. (from the 80% Confidence Student Guide):

The selection of 80% as the appropriate confidence level is occasionally questioned, particularly since the reasons given are by no means mathematically rigorous. Indeed, there is no theoretical reasoning why the 20th percentile of the availability is the correct indicator of how well a tool set is performing. Taken in the context of system throughput and WIP level management, it is likely that the 20th percentile is not the absolute correct measure of tool set availability that corresponds to maximum factory throughput.

However, other organizational issues become very important when considering implementing a new metric by which people will be judged. The A80 Indicator and 80% Confidence concept represent substantial changes for Intel employees in the way that their performance is measured. Any organizational change will encounter resistance, and particularly if the change involves a method of performance evaluation and reward. This makes it important to design a metric that is accessible enough to establish and maintain the support of all constituents.

A new statistical method cannot on its own improve the performance of a system. The workforce must understand, internalize, and utilize the method if the gains are to be realized. Such a concept needs to be understandable at every level of the organization, irrespective of each individual's knowledge of statistics. Therefore, it is important that such an initiative is easily communicated and understood by individuals with a varying background in statistical methods. In cases like this, rule-of-thumb indicators can be more effective than mathematically precise ones. In simplifying the concept, Intel might focus on a slightly sub-optimal indicator some or most of the time, but the fact that people can understand and use the A80 indicator is a huge improvement over looking strictly at mean availability. A marginally sub-optimal indicator that is used by everyone is better than the optimal indicator used by no one.

In this light, A80 represents a "beach head" for operational improvement through statistical indicators. Whether or not the 20th percentile is the absolute correct measure would require lengthier analysis. However, one must consider all of the trade-offs involved with changing performance indicators. It is apparent that the A80 availability metric provides significant operational improvement over the average statistic. When judging whether A80 is accurate enough, one must consider that the effort in discovering and implementing a new, more accurate statistic might outweigh the incremental improvement that this new metric might offer.

6.3 TBF and TTR: Moving Away from Mean Statistics

In the semiconductor manufacturing industry, downtime events are typically characterized in terms of their Mean Time Between Failure (MTBF) and Mean Time To Repair (MTTR). SEMI/Sematech, the semiconductor industry standards associations, define MTBF as the average number of hours producing until a failure is encountered, and MTTR as the average time required to correct a failure and return the equipment to a condition in which it can perform its intended function.

As we have seen, the A80 Methodology is based on the observation that mean statistics are insufficient to indicate the predictable availability of capital equipment. Given that the largest contributor to machine unavailability is random failure, it would follow that one would question the robustness of mean statistics for modeling the time sensitive effects of random failures on machine availability, and in fact, find them as insufficient as the mean availability indicator.

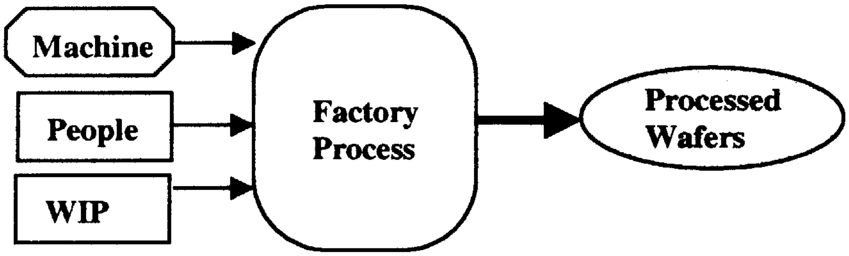
A better method of representing the unscheduled failures is one which indicates the variation in the frequency and duration of these events. By treating the unscheduled downtime as a probabilistic distribution rather than simply relying on averages like MTBF and MTTR, EMIT more accurately captures the random nature of and the negative effects of variability on tool availability. Just as A80 has been shown to be a more robust indicator of predictable machine availability, EMIT provides a more robust treatment of the interplay of scheduled and unscheduled downtime events.

6.4 Future Considerations: U80 and T80

Machine availability is a critical factor in the success of any manufacturing firm that relies on capital equipment to manufacture products. Obviously, one cannot make product unless the process machine is running. However, the goal of an Intel fab is not to have machines with high availability. Rather, it is to produce as many chips as possible as cost-effectively as possible with the same equipment set. This focus difference is subtle but important, particularly when considering metrics by which you measure the performance of workers and machines. As is the case in any organization, you get what you measure, and if you focus metrics and compensation entirely on machine availability, you will likely achieve high availability, but potentially at the cost of sub-optimal factory performance.

As depicted in **Figure 6.1**, in order to process a wafer, three inputs must be available at the same time: a worker, a wafer, and a machine.

Figure 6.1: Wafer Process Inputs



The A80 indicator focuses on increasing the predictable availability of the machines, but the two other inputs should also be considered when looking at improving factory performance. In particular, one might consider the predictable availability of these other inputs when modeling the process to determine the overall wafer processing capability of the system. A convenient way of tracking the WIP and People inputs is the Utilization statistic, or U/A (utilization divided by availability). This statistics reflects the amount of time that a tool set was processing wafers given that it was available:

$$U/A = \frac{\textit{time spent processing wafers}}{\textit{total available machine time}}$$

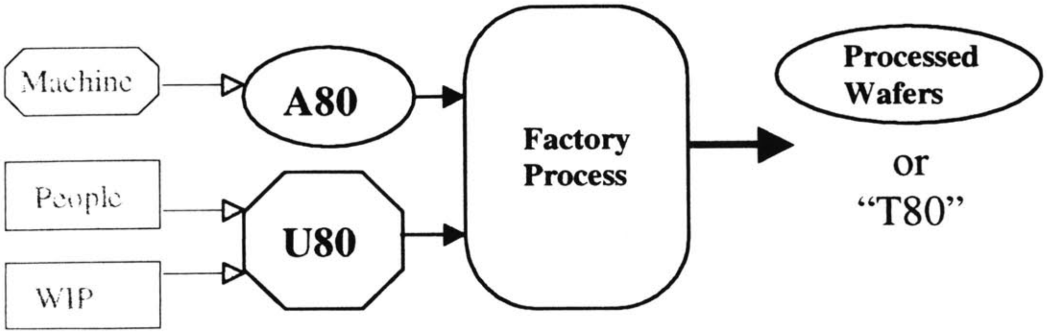
An analysis of the U/A ratio for a set of 12 Planar tools for a period of 19 weeks showed the following results for tool utilization:

80% Confidence Utilization (U80):	68%
Average Utilization:	83%
Median Utilization:	90%
95% Confidence Interval:	44%-99%

The U/A is shown to vary significantly, perhaps as much as the machine group availability might. It seems reasonable, therefore, that if you track A80 availability, you might also track "U80", or the 20th percentile of the U/A data, as a measure of your predictable utilization.

By tracking and modeling U80 in addition to A80, you move towards a more accurate portrayal of predictable capacity or throughput. This type of analysis gives a much more robust characterization of the capacity, showing the daily variation of capacity over the length of the simulation. From this information one could calculate a "T80" or 80% confidence of daily throughput capability by looking at the 20th percentile of the daily throughput values, or some other more robust statistic. **Figure 6.2** shows this concept framework. This line of analysis would more closely follow the big picture goals of Intel, and help to guide equipment management decisions so that the global optimum of increased throughput is preserved.

Figure 6.2: Metrics for Modeling Wafer Processing



7. Recommendations

7.1 Application Improvements

Although EMIT was successful in modeling equipment availability, it was a Beta version, and there exist many opportunities to improve the accuracy, functionality, and usability of the application.

There are a few recommendations to upgrade the application that would be fairly straightforward, and would have significant impact of the performance of the tool. One is to upgrade the application to an SQL environment from the current MS Access, which will make the application faster and more flexible. It will also make it possible to refine granularity of simulation from 1hr to 0.5 hr or less, which will provide more accurate models of machine behavior. Finally, there is much room for an improved user interface, adding more GUI features, and faster feedback.

7.2 Database and Accuracy Improvements

The MS Access database software is satisfactory, and provides an easy development environment for the application. However, upgrading to a more powerful database will allow for faster and more flexible use. It will also allow for future functionality improvements. Therefore, it is recommended that EMIT be transferred to a more robust SQL environment.

Due to the limitations of the current database, the application does not store the individual daily availability values that are produced in each run of the simulation. Instead, for each simulation run the application finds the 20th percentile of the daily values, stores it, and then rewrites over the array with the next set of values from the next iteration. It might be helpful to instead retain all of the raw daily availability values so that other analyses could be performed on the data. For instance, one might want to look at the other percentiles other than the 20th to test other possible indicators. Also, the daily availability values are important when trying to determine daily throughput amounts.

7.3 Model Granularity

The current time step for the application is one hour. It is recommended that this is changed to a smaller increment, like 0.5 hours. This will add accuracy to the simulation, since it will then more closely follow the actual performance of the tools. The TTR for many downtime events is less than an hour, or in between 1 and 2 hrs. These events are largely grouped into the 1 and 2 hour TTR brackets, and the lack of distinction between these two categories makes the model less accurate.

7.4 User Interface Improvements

An important feature for the application is an automated data querying system that allows quick and easy entering of information about machines. Having the data acquisition routines for the unscheduled downtimes embedded in the application will make the tool much more user friendly, and consequently more widely used.

Other upgrades to the interface would help engineers to fully exploit the benefits of the system. One in particular is to upgrade the GUI. For instance, having the ability to drag and drop events onto actual calendars days would make establishing the PM schedules much easier and with a greater degree of visibility of how the events might stack up. For instance, the current method of entering in the scheduled downtime events is not very user friendly. As it stands, the user must phase PM events by entering an Offset when defining the event. This is cumbersome, and makes it difficult to schedule the PMs with vision as to how they stack up with respect to the other tools in the machine group. Some recommendations for development are

1. Allow the user to enter a frequency for the scheduled event that includes a window time over which that event can be initiated. For instance, for a weekly PM one might specify 168 hrs +/- 4 hrs. The application might then either allow the event to be moved within this window, or automatically place the event within the window to maximize the availability.
2. Show a calendar for each machine where the user can click-and-drag scheduled events to different times. Perhaps if this feature were combined with the one just described, the application could show the window on the calendar, and if the user drags the event outside of the acceptable window, could send a warning that the PM time rule has been violated.

7.5 Data Acquisition Improvements

The Downtime Event Sorting Tool is admittedly one of the rougher pieces of EMIT, and there exist many ways it can be improved to more quickly and efficiently process the data for input into the EMIT unscheduled event data records. The most ideal solution is to have the data acquisition process automated so that it is invisible to the user and can be accomplished from within the EMIT application without having to jump out to Excel and upload a file. The actual logical algorithms uses to classify and sort the data can likely be simplified to run more efficiently and elegantly.

7.6 Relaxing the Assumptions to Extend the Model

The first cut analysis of data from the Westech Polishers in Fab 10 has implied that there is no correlation between TBF and TTR. However, such a relationship may be found to exist for other tool sets over different time periods. Therefore, it may be necessary to relax the assumption that these variables are independent. This would be accomplished by modifying the input data and the application functionality so that for a given TBF a unique set of TTR values is input and randomly chosen from.

7.7 Other Potential Features

In addition to the availability module, the tool might include a WIP analysis module and a cost component that considers total cost of ownership - the consumables, technician time, and overhead tied to PM activities, and the impact of variability thereon.

These are just a few of the obvious ways the model might be improved, and it is hoped that the EMIT application will evolve to include new functionality that makes it easy for users to find accurate solutions to their equipment management challenges.

8.0 Summary

The project was successful in meeting the objectives set at the start, and in providing a valuable learning experience for the thesis. The major points can be summarized as follows:

Issues surrounding capital equipment utilization are crucial to the viability of manufacturing firms, particularly when the capital equipment costs are as high as those in the semiconductor industry. Therefore, it is becoming increasingly important for Intel to make the most informed equipment management decisions to best utilize their capital investments.

The 80% Confidence methodology provides new ways of considering equipment availability by combining an indication of the average and the variation in one measurement, and focusing efforts on making the days of worst performance due to common causes better.

Although it is not mathematically rigorous, the A80 indicator is a large improvement over using the mean availability to assess predictable equipment availability. It is a powerful metric that is easily communicated and understood, and therefore can be internalized by employees across an organization.

A Web-based software application was developed to predict the A80 availability of a set of machines given basic information about the scheduled and unscheduled downtime events.
At the core of the application is a Monte Carlo simulator that chooses randomly from TBF and TTR data of the tool set to model the random failures suffered by equipment. This is a more robust treatment of unscheduled downtime events than the semiconductor industry standard

MTBF and MTTR, and provides a better sense of the true, time sensitive effects of the random failures. The tool is general enough to be used by many types of employees, and has many practical applications in providing support to equipment management decisions.

Recommendations suggest improvements that focus on upgrading the database, refining the model granularity, and adding additional graphical user interfaces. Future extensions might tie tool set and system throughput to the PM scheduling and other equipment management decisions by adding WIP analysis capability to EMIT. Also, Intel might consider tracking equipment utilization (U/A80) to get a sense of the predictable availability of workers and WIP, which, along with equipment availability, are necessary inputs to process a wafer.

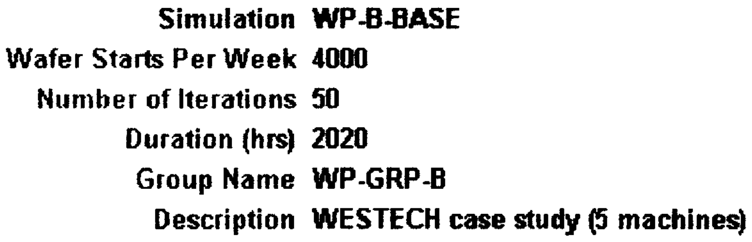
Appendix A: Case Study of PM Policy Change

A set of five Westech Planar tools was modeled to demonstrate one of the many uses of EMIT. The simulation consisted of two cases, each with the same machines run under different PM policies. One run, the *Base Case*, used actual PM schedules and Unscheduled Event Data for the Westech Planar tool set studied. The second run, *Test Case*, used a modified PM Schedule that substituted a new Semi-Annual PM of 11 hours duration for the Quarterly PM (5 hours duration) and Semi-Annual PM (8 hours duration) PMs of the *Base Case*. All other parameters remained the same.

A.1 Simulation Set Up

The following Simulation Inputs were used for the case:

- Number of Tools: 5
- Run Rate: 8 wafers/hour
- Wafer Outs per Hour: 4 wafers/hour
- Unscheduled Event Data: from Westech Planar tool set data, loaded using Upload Data link



Simulation	WP-B-BASE
Wafer Starts Per Week	4000
Number of Iterations	50
Duration (hrs)	2020
Group Name	WP-GRP-B
Description	WESTECH case study (5 machines)

Machine PM Schedules for *Base Case*:

PM Type	**Frequency (hrs)**	**Duration (hrs)**
Weekly	168	2
Pad Change	200	3
Monthly	672	2
Quarterly	***2016***	***8***
Semi Annual	***4032***	***5***
Annual	8064	5

Machine PM Schedules for *Test Case*:

PM Type	Frequency (hrs)	Duration (hrs)
Weekly	168	2
Pad Change	200	3
Monthly	672	2
Semi Annual	***4032***	***11***
Annual	8064	5

A.2 Simulation Results

The results of the simulations are depicted below in **Figures A.1** and **A.2**. Although the *Base* and *Test* cases showed similar results, the *Base Case* demonstrated higher A80 availability measured in 20th Percentile, Average, and Median A80.

Figure A.1: Case Study Simulation Results

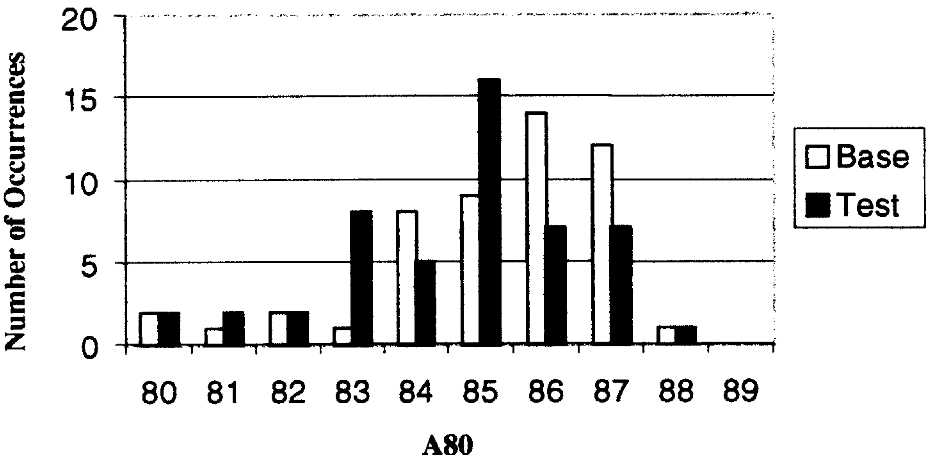


Figure A.2: Case Study Results

Measurement	Base Case	Test Case
80% Confidence of A80 values:	84	83
Average of A80 values:	85.2	84.6
50% Confidence of A80 values:	86	85
95% range of A80 values:	81.5-87	82-87

A.3 Discussion

The simulation demonstrates an intended use for the tool, where an Equipment Engineer might be considering a change to a PM activity (in this case, the Semi-Annual and Quarterly PMs). The EMIT application allows the Engineer to understand the consequences on the A80 Availability statistic of changing the PM content and time requirement. Furthermore, it allows Engineers to design and test new PM schedules that incorporate existing PM content to discover ways of improving overall A80 Availability.

Consider the differences in the two cases modeled above. In looking at machine time spent down for PM, we see that the proposed change in PM policy in the *Test* Case reduced the total amount of downtime for each machine. Focusing on the activities that changed between the cases, the *Base Case* specifies a Quarterly PM of 8 hours and a Semi-Annual PM of 5 hrs. On an annual basis, these activities would account for 4(8)+ 2(5) = 42 hours of downtime per machine, and therefore over the course of the simulation (2020 hours), roughly 10 hours of downtime per machine. Similarly, the *Test Case* specifies only a Semi-Annual PM of 11 hours duration, and would therefore contribute 22 hours annually and roughly 5 hours per machine over the duration of the simulation.

Given this decrease in total PM time, one might expect that the A80 availability would <u>increase</u> by changing the PM schedule from the *Base Case* to the *Test Case*. However, as seen in the results, the *Test Case* demonstrates <u>lower</u> A80 availability, despite less total time spent in PM.

This result points out the importance of what Intel calls "PM Modularization." or. Intel has found that modularizing PMs, or breaking long, infrequent PM activities into shorter, more frequent activities, increases A80 availability. Because tools are not tied up in long PM activities, the tool set is more flexible to absorb the downtime due to random failures, providing a more predictable level of equipment capacity.

PM Modularization is one of many techniques that can be used to increase predictable availability, and the EMIT application provides a useful tool for discovering and testing new methods of increasing machine availability and, in general, improving equipment management decision making.

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