Forecasting Mix-Sensitive Semiconductor Fabrication Tool Set Requirements under Demand Uncertainty

by

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B.S. Mechanical Engineering, Stanford University, 1994

Submitted to the MIT Department of Mechanical Engineering and to the Sloan School of Management in partial fulfillment of the requirements for the Degrees of

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ABSTRACT

Due to tremendous fluctuation in the semiconductor market and rapid introduction of competitive products, demand forecasts and capacity requirements are difficult to predict. To meet rapidly fluctuating customer demand, manufacturers must have sufficient manufacturing capability and flexibility.

Planning for variable demand is complicated by the need to forecast tool requirements that are highly dependent on product mix. Lithography steppers (1-2 year lead-time, multi-million dollar capital assets) are the most mix sensitive tools in wafer fabrication. This work seeks to develop a model and improved business process to assess the impact of possible demand scenarios on lithography stepper requirements.

The model has two primary components: an optimizer and an uncertainty simulator. The optimization program calculates the minimum number of lithography steppers required to support a given mix scenario. Automating the current process reduces the amount of time required to assess various scenarios by over 70%, reduces the risk of errors, and provides consistent analysis and data sharing across several business teams.

The model also introduces an innovative approach to including uncertainty in the tool forecasting process. The model improves planning by taking into consideration uncertainty in demand volume, mix, and production parameters. Historical forecast error is evaluated to assess the uncertainty in forecasts and its impact on the mix sensitive tool sets. The work seeks to both enhance future forecasting and provide a tool for improved decision making in strategic long-range capacity planning.

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Gerald and Sharron Page,
who have given me so much.

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Chapter 1: Introduction and Overview

Over the past few years, shorter microprocessor product life cycles and fierce competition in the industry have increased the difficulty in forecasting demand for microprocessor chips. Semiconductor manufacturers typically maintain small or zero final goods inventories of wafers to minimize the number of wafers rendered obsolete when the demand pattern changes or a new product is introduced. Therefore, to meet the rapidly fluctuating customer demand, microprocessor manufacturers must have sufficient capacity and manufacturing flexibility. According to Bard et al [2], "for a given demand and planning horizon, the general facility design problem faced by semiconductor manufacturers is to decide how much capacity to build into their systems."

The difficulty in forecasting demand can also be attributed to the extensive semiconductor supply chain. As described by a forecasting firm for the semiconductor and related industries [1]:

> "economic factors change and start to influence the purchase behavior of End-Equipment customers. After some delay, the distribution channel, retailers and wholesalers, feel the change in demand. After another delay, they change their orders from OEMs. The latter revise their bookings of semiconductors and peripherals, impacting the backlog of" microprocessors.

Academic research has proven that when people are asked to predict the future, they tend to extrapolate the most recent past. Due to the long semiconductor supply chain, the semiconductor industry, and in particular microprocessor manufacturers, are particularly vulnerable. Forecasts of microprocessor demand are often based on extrapolations of extrapolations made both up and down the supply network. Due to the multiplicative effects, errors made in forecasts are compounded throughout the supply chain forecasts.

Correctly predicting and preparing for the market fluctuations have a significant effect on a semiconductor manufacturer's bottom line. According to recent business journals [22], one semiconductor manufacturer estimated the growth of the PC market to be 10% in the year 2000. Accordingly, they cut capital spending in 1999 from $5 billion to $3.4 billion. Instead, PC growth hit 18% and they had insufficient capacity to meet the increased demand for their microprocessor chips. "The bad forecast may have cost [the manufacturer] more than $800 million in lost sales [in 2000]. [A primary competitor, who] added capacity, grew its processor share to 18%, from 14% in 1999."

Semiconductor chip manufacturing is characterized by capital-intensive investments. The manufacture of microprocessors involves four main steps: fabrication, sort, assembly, and test. According to a 1999 industry trade journal, "Modern fabrication facilities (fabs) being built today by such companies as Motorola, Intel and Advanced Micro Devices run to more than 1 billion dollars, chiefly due to the high cost of machinery and the need for a cleanroom environment."[23] The Semiconductor Business News predicts that the costs of a new fabrication facility may reach $10 billion over the course of the next decade. Planning, construction, and ramp-up to full production can require a 3-4 year lead-time.

As Jordon and Graves [8] note in a 1995 article, increasing manufacturing flexibility is a key strategy for efficiently improving responsiveness to the market in the face of uncertain future product demand. Process flexibility is achieved by product assignment decisions including, which products are to be built at which plants and on which production lines. Since more than 60% of the total cost of a fabrication facility is attributed to the equipment alone, making efficient use of the machines is of great strategic importance.

1.1 Problem Description

Achieving a high degree of manufacturing flexibility and efficiency is very challenging in the manufacture of semiconductor chips. Several key process steps in fabrication, sort, assembly, and test are highly dependent on the product mix. The type of product being manufactured can significantly affect the number of lithography, epoxy, burn-in, and final test machines required to meet demand production. Swaminathan noted [25], tool requirements are often planned so "that the tools have a high utilization while meeting the demand projections." If the demand realized is less than projected in the coordinated demand projection, there is lower utilization of the tools. Alternatively, shortages occur if the actual demands are higher than forecasted or the product mix changes.

In fabrication, the lithography process is the most mix sensitive, and also the highest-cost, longest lead-time tool set. Lithography stepper technology also changes rapidly. Leading-edge manufacturers continue to adopt new technologies, further increasing the uncertainty in planning tool capacity. According to the semiconductor industry journals [23], the lithography exposure systems make up to 20% of the total cost of fabrication. If the total cost of a fab reaches the predicted $10 billion over the course of the next decade, a lithography bay could account for more than $2 billion of the cost. Today, industry averages for lithography steppers estimate tool costs between $8 and $9 million dollars, with an expected 20 to 30% increase in the cost of next generation 300 mm wafer exposure tools.

The number of exposure tools can vary greatly depending on the product mix. Given the intensive capital expenditure and the long-lead time, forecasting and assessing lithography tool requirements is a strategic step in the overall capacity planning process. The intent of this project is, therefore, defined as follows:

Develop and implement a model and accompanying business process to quickly and easily assess the impact of various demand scenarios on mix sensitive lithography steppers under demand uncertainty.

1.2 Introduction to Industry Partner

Intel Corporation is a semiconductor chipmaker that supplies the communication and networking industry with a wide range of microprocessor products. Intel serves numerous market segments including server, workstation, mobile, and flash.

In light of the tremendous fluctuations in the semiconductor market, Intel has a dedicated team responsible for developing a long-range capacity forecast. Each quarter, Intel's Strategic Capacity Planning (SCP) team publishes a 5-year forecast of manufacturing capacity requirements for all fabrication, sort, assembly, and test facilities.

The Strategic Capacity Planning team works with the product divisions to estimate demand for all market segments, including logic and flash products. They also evaluate current and predicted manufacturing capabilities. By assessing capabilities, market strategies, product revenues, and possible demand scenarios, SCP formulates a long-range plan (LRP) or capacity strategy. Once ratified by management, the new capacity statements and demand are published as the LRP Plan of Record.

Due to the complexity and variability in forecasting long-range demand, several 'what-if' demand scenarios are developed each cycle. Scenarios may include a delayed product launch, faster than anticipated growth of a market segment, or significant change in a production parameter such as die size. The effect on overall capacity requirements is assessed for those scenarios deemed to have highest likelihood of occurrence and the greatest impact.

For process steps like lithography, epoxy, burn-in, and final test, the type of product significantly affects the number of tools required. The most expensive, longest lead-time fabrication tool set, a lithography stepper, is the most sensitive to product mix. A comparison of two possible demand scenarios in the Q4 2000 cycle showed an increase of nine steppers required to meet an aggressive launch of a microprocessor to support mobile market demand. At an average tool cost of $8 million, this represents a potential $72 million additional capital investment to support the second demand scenario.

Each LRP cycle, the SCP team needs to further evaluate scenarios that significantly vary product mix, and hence mix sensitive lithography tool requirements. The team does not currently have a tool or business process within SCP to quickly and efficiently evaluate multiple scenarios. A subset of what-ifs, which they predict will have an impact on tool needs, is evaluated through a time-consuming, manual process with the industrial engineering team. Further, the current process does not take into consideration uncertainty in the forecast and the financial impact of tool requirements to support different scenarios.

1.3 Approach and Methodology

The thrust of this project is the development of a model and improved business process for analyzing the impact of various demand forecasts on mix sensitive lithography steppers. The optimization tool calculates the minimum number of additional lithography stepper tools required to support a given mix scenario, taking into consideration tool sharing, availability, and cost. Automating the current process reduces the amount of time required to assess various scenarios by over 70%, reduces the risk of errors, and provides consistent analysis and data sharing across several business teams. In addition, the tool improves the planning process by taking into consideration uncertainty in demand volume, mix, and production parameters across the planning horizon. The optimizer is integrated with Monte Carlo simulation software to assess the range of tool requirements given historical and anticipated variability. Assessing the financial impact of preparing for different scenarios enhances the decision-making capability in long-range capacity planning.

1.4 Project Goals and Measurements

The goals of the work included:

- Assessment of long-range planning processes in industry and commercial solutions for capacity planning
- Development of a linear program model to determine the number of lithography tools required to meet the demand for various possible demand scenarios
- Analysis of historical forecast error to assess uncertainty of future capacity forecasts
- Recommendation for an improved business process flow for assessing possible demand fluctuations

1.5 Thesis Structure

The remainder of the thesis is broken into four parts. The first part presents aspects of semiconductor manufacturing relevant to the remaining topics. The second part highlights current long-range capacity planning practices. The third section presents a methodology for improvement through utilization of a linear optimization model combined with a variability simulator using Crystal Ball®. The final section presents the model outputs and analysis of the methodology and model as enhancements to the current business practices.

Chapter 1 provides a background and overview. Chapter 2 includes an overview of the semiconductor manufacturing process, and more specifically the lithography process steps. The current process of long-range capacity planning is reviewed in Chapter 3.

The framework for forecasting capacity requirements is covered in Chapter 4. This chapter discusses both the process of assessing the impact of what-if demand scenarios and the method for calculating tool requirements. Chapter 4 further defines the need for improvements to the existing long-range planning practices and the methodology behind the model. Chapter 5 provides a detailed explanation of both components of the model, the optimization and variability simulator. Model validation and sample output results are reviewed in Chapter 6.

A review of literature regarding strategic capacity planning practices and commercial software solutions was also conducted as background to the methodology of the project. Results of the literature review and benchmarking activity are included in Chapter 7. The final chapter, Chapter 8, reviews and summarizes key findings.

Chapter 2: Manufacturing Process Overview

With the preceding outline of the problem domain, this work can now introduce microprocessor technology and an overview of the semiconductor manufacturing process. This chapter also discusses the lithography process and explains the sensitivity of lithography tool capacity to the product and mix of products.

2.1 Microprocessor Technology

Microprocessor devices are commonly referenced by the width of the transistor gates on the chip. In a 2001 article [15], Dr. Marcyk of Intel described the evolution of Intel's microprocessor devices. In 1993, Intel introduced a 0.50 micron[1] device, followed by a 0.25 micron device, and currently a 0.18 micron generation. In December 2000, Intel researchers demonstrated the future capability of 30-nanometer (0.03 micron) transistors. The demonstration of 0.03 micron capability indicates the possibility for continued scaling of future production processes.

The term process generation or process technology is often used to refer to a family of products with the same line width. Each new process technology generation results in increased capital expenditure for production, decreased cost per function, and increased complexity of processing and more process steps.

The transition between process generations typically occurs about every two years. Intel co-founder Gordon Moore postulated nearly 35 years ago that a doubling of the processing power would occur every 18 months. This became known as Moore's Law and has become one of the key forces behind the rapid, continuous development in the semiconductor industry. The pace of technological advancement continues to accelerate.

Typically, each process technology has followed a similar life cycle as the product transitions from ramp-up to full-production to ramp-down. Given the rapid pace of development, the life cycle of each process technology is becoming shorter.

Figure 1 shows actual production wafer starts per week data over an eight-year time horizon[2]. Early process generation (n) had a slow ramp of increasing WSPW requirements per quarter. Once the new process generation (n+1) is introduced, demand for the initial process (n) gradually ramps down. In the more competitive market place with increased competitive product offerings and faster speed of product introductions, the transition between processes is changing. Now technologies are experiencing a significantly faster

[1] One micron is about one-thousandth the width of a human hair.
[2] Note: WSPW data has been scaled from the actual data to demonstrate the trend, but disguise actual figures.

ramp up in demand. New products are introduced sooner, shortening the amount of time a product can recoup development and production investments. The accompanying ramp-down is significantly faster as demand transitions to the next generation processor.

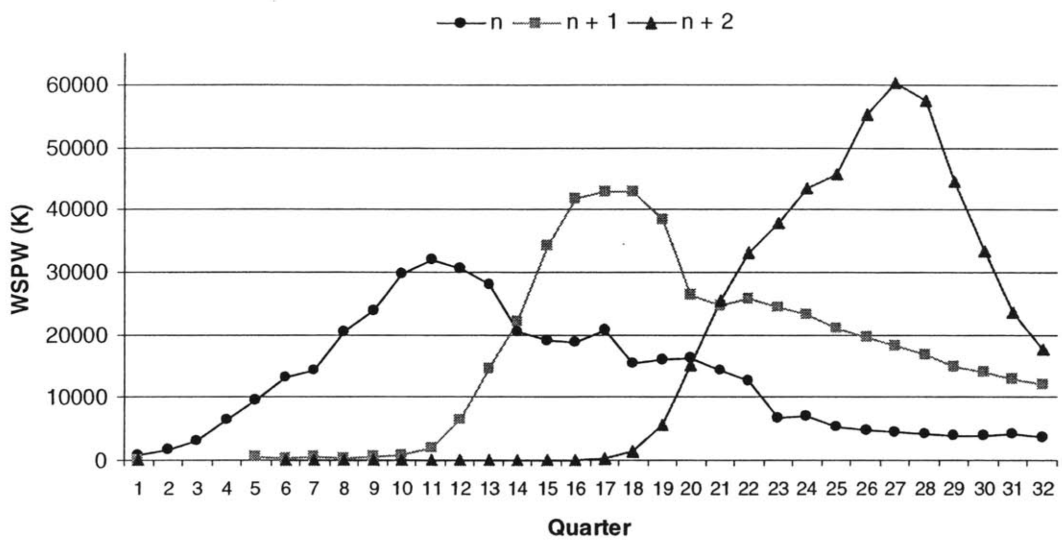

Figure 1. Microprocessor technology life cycles

2.2 Semiconductor Manufacturing Process

Semiconductor manufacturing begins with raw silicon wafers[3] and ends with packaged integrated circuits. Integrated circuits (IC) are essentially electronic devices consisting of many miniature transistors and other circuitry. Memory and logic products such as microprocessors are examples of integrated circuits.

The semiconductor manufacturing process includes two main phases: fabrication and assembly. During fabrication, multiple integrated circuits, often referred to as die[4] or chips, are produced on the wafer. In this phase, the wafers are sent through numerous processes, often multiple times, and often in re-entrant cycles.

As outlined in Van Zant's [26] reference guide to microprocessor manufacturing, the process of fabrication includes four basic operations in a seemingly infinite number of sequences and variations. "They are layering, patterning, doping, and heat treatments." In

[3] Wafer: a thin, usually round slice of a semiconductor material (silicon), from which chips are made.
[4] Die: a unit on a wafer separated by scribe lines; after all of the wafer fabrication steps are completed, die are separated; the separated units are often referred to as chips.

the layering process, thin layers of insulators, semiconductors, and conductors are added to the wafer. Numerous layers are added to each die to produce a functioning circuit.

In patterning, a series of steps result in the removal of selected portions of the surface layers to create a pattern on the wafer. Through the multiple processes of layering and patterning, the various physical parts of the transistors, resistors, capacitors, diodes, and metal conduction system are formed in and on the wafer. Patterning is the most critical part of the fabrication process and is done using a variety of photolithography steps. The most critical dimensions of the device are set by the patterning operation and errors can cause distortion or misplacement of patterns. Changes or defects in the electrical functionality of the device can result from errors in the pattern.

Doping, the process of adding an element that changes the conductivity of the semiconductor, and heating are the other primary processes. Heat treatments are used to anneal materials, deposit or grow layers, or otherwise change material properties. Through the process of fabrication, wafers repeat the layering, patterning, doping, and heating processes numerous times to produce a highly complex, multi-layer semiconductor device.

Following the water-fabrication process the wafer will have hundreds of die. Each die is electrically tested for electrical performance and circuit functionality. The testing process is referred to as sort, and is an important test of the wafer yield, which helps prevent costly packaging of non-functioning parts.

In the final step of the overall manufacturing process, good wafers are sent for packaging and test. Through the packaging process, wafers are separated into individual chips using high-precision diamond cutters and each working chip is placed in a protective package to allow for the attachment of external connectors. Each product is then tested to ensure operability and to determine performance characteristics. During the entire process, die on the same wafer may develop different characteristics, such as microprocessor speed. Classifying the various speeds from a given batch is known as "binning." After this stage, the packaged integrated circuits are ready for shipment.

2.3 Lithography Process Overview

As indicated in the Semiconductor Manufacturing Overview, the process of patterning is one of the most critical operations in semiconductor processing. The "wafers spend 60% of the process time in the lithography area."[26] Photolithography or lithography is most commonly used to identify this process of patterning. The following are definitions of terms frequently used in the photolithography process:

- Lithography: process of pattern transfer onto the wafer
- Photoresist: light-sensitive film spun onto wafers and "exposed" using high-intensity light through a mask. Depending on the type of resist, the exposed (or unexposed) photoresist is dissolved with developers. A pattern of photoresist remains, allowing etching to take place in certain areas while preventing it on other regions of the wafer.
- Stepper: a tool that aligns and exposes one (or a small number of) die at a time. The tool "steps" to each subsequent die on the wafer.

The lithography process is also the most mix sensitive step in fabrication. Depending on the die size for a given product or mix of products, the number of lithography tools required to meet a given demand forecast can vary significantly.

Photolithography is a multi-step process in which the required pattern is transferred from a mask or reticle onto the surface layer of the wafer, as shown in Figure 2. The wafer is moved or 'stepped' into position under the mask and the desired circuitry image is transferred to the wafer via ultraviolet light. Correct alignment of the image patterns and the precise dimensions of the image are essential to the functioning of the device.

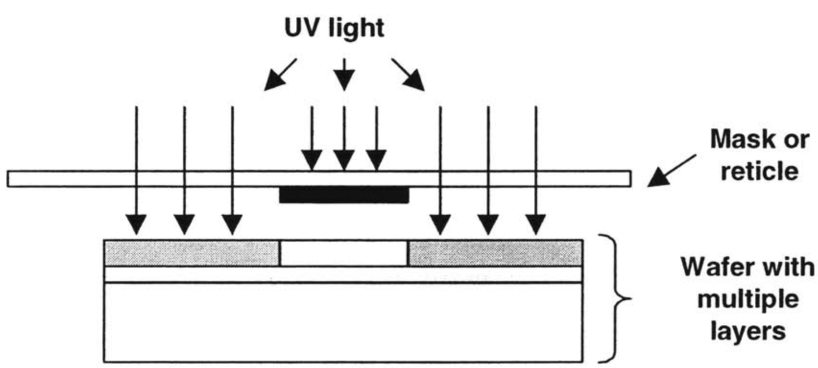

Figure 2. Exposure of the desired pattern onto the wafer

One of the most effective photolithography methods is a stepper. A reticle with the pattern of one or several chips is aligned, exposed, and then stepped to the next site on the wafer. A smaller reticle and smaller exposure area improves accuracy and reliability. For a given reticle, the number of die exposed depends on the size of the die. As shown in Figure 3, each time the lithography scanner steps to a new position, an area of the wafer is exposed. For larger die size products, only one die may be exposed per step, while multiple small die can be exposed each step of the scanner.

The number of lithography tools required to meet the demand for a given product depends on the number of good die out per tool. For larger die size products, fewer die are exposed and therefore more wafers must be run to meet a given die demand. To increase the number of die produced in a given time period, either the die size can be reduced or more machines can be added.

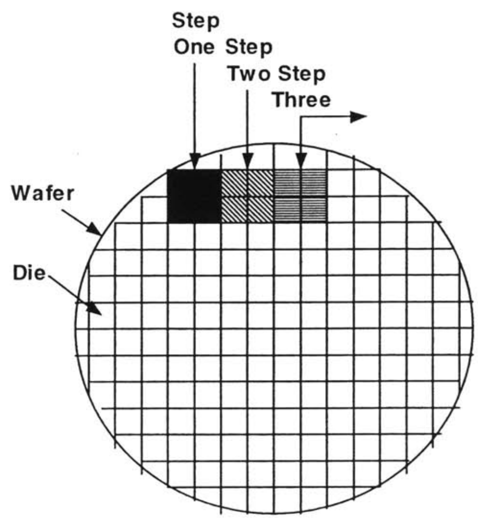

Figure 3. Number of die exposed each step depends on the die and reticle size

Each family of microprocessors, and often each product within that family, can have a distinctly different die size. Over the course of the product's life cycle, the size of the die may also shrink as engineering continues to make enhancements to the product. Shrinking the die size is a key strategic measure to increase the overall output production of core products. Changes can also occur in the reticle's size and exposure accuracy to increase the output of good die. For a large die size product, improving the stepper functionality such that two versus one die is exposed per step will double production output, assuming the same throughput efficiency.

Thus, we find that the number of lithography tools required to meet a given demand can vary significantly depending on the die size for a given product or mix of products. Given the sensitivity of tool capacity requirements, accurately forecasting demand levels and the corresponding capabilities is critical. The strategic capacity planning process and the issues addressed during the long-range planning process is discussed in the following chapter.

Chapter 3: Strategic Capacity Planning Overview

Intel's Strategic Capacity Planning team is responsible for the development of the long-range capacity plan for all Intel products and across all of fabrication, assembly, and test. The organization's vision is to align Intel's supply networks to customers' needs while maximizing shareholder value. Intel's production and capacity planning process, the Strategic Capacity Planning team, and the long-range planning process are discussed in Chapter 3. A more detailed discussion of calculating tool requirements and planning for possible demand scenarios follows in Chapter 4.

3.1 Production to Long-Range Planning

The period of time from actual production build plans to long-range forecast requirements can be broken into three segments as shown in Figure 4. Production build plan is the shortest time frame and represents the actual in-plant production plans zero to nine months into the future. The extended build plan is a longer-range production forecast, typically from nine months to 24 months into the future. Long-range capacity requirements, however, do not represent actual production schedules, but are overall forecasted capacity needs nine to 60 months out. The time periods are further described in the following section.

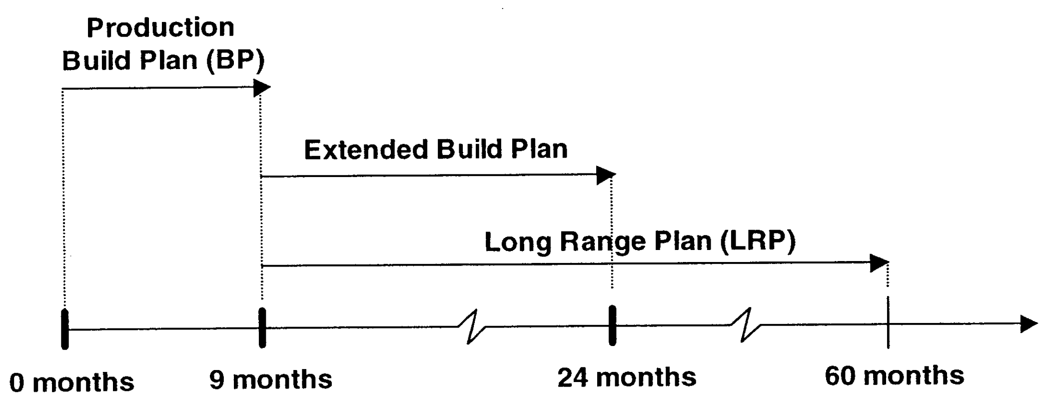

Figure 4. Short-term production planning to long-range capacity forecasting

The length of the horizon and how often the long-range forecasts are made varies across the industry. However, a typical long-range capacity requirements planning horizon begins approximately two quarters out and extends 15 quarters into the future. The long-range plan is based on predicted demand requirements and forecasted manufacturing capabilities. The long-range capacity plans are typically developed over a rolling threemonth time period, four times annually. The quarterly long-range plans may often reflect significant changes due to the large demand fluctuations in the semiconductor industry.

The long-range planning period is a critical component of the semiconductor manufacturer's strategy. Accurate forecasts of future demand requirements and the corresponding manufacturing capabilities are essential to ensure manufacturing flexibility. The semiconductor manufacturer has the most flexibility during the long-range planning period to assess various market segments and prepare manufacturing capacity accordingly. The long-range plan drives capital investment decisions including the development of new fabrication facilities, assembly/test sites, and subcontracting arrangements.

An extended build plan reflects the planned production over the two-to-six quarter horizon. During this period, there is less flexibility to react to changes in demand. Long-lead time production equipment, such as lithography steppers, limits some manufacturing flexibility within the extended build-plan. During the extended-build plan timeframe, decisions about which products are produced at which plant and external sub-contracting manufacturing can be made to react to changes in the forecasted product demand. Since the build plan is close to the actual production timeframe, the plan is updated monthly, in contrast to the quarterly long-range planning cycle.

The production planning cycle (referred to as the build plan horizon) typically extends 9 months into the future. During this planning horizon, the actual wafer start per week production schedules, allocation of product production per fabrication facility, and assembly/test routing decisions are made. As with the extended build plan, the build plan is conducted on a monthly basis.

3.2 Strategic Capacity Planning Team Structure

The Strategic Capacity Planning (SCP) team is responsible for Intel's long-range strategic capacity roadmap and production facility investment decisions. Each quarter, the team assesses the 5-year forecasted product demand, requirements, product parameters, factory parameters and capacity. The output is a roadmap ratified by management, which includes the plan for all capital and building by factory and technology across all fabrication, assembly, and test facilities.

As shown in Figure 5, the SCP team is divided into three primary teams and four support teams. The Demand Information Team works with the product divisions to forecast demand requirements. The Factory Capability Team (FCT) is responsible for assessing current and predicted future factory capabilities. The Roadmap Analysis Team is responsible for incorporating the demand and factory capability forecasts to develop a 5-year plan for wafer start capacity requirements across the entire Intel manufacturing network. Four additional teams support these efforts, including systems, organizational development, modeling, and finance.

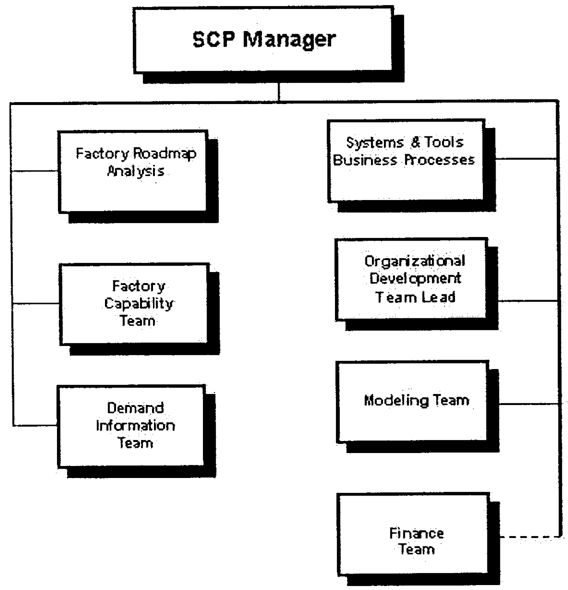

Figure 5. Strategic Capacity Planning organizational structure

3.3 Long-Range Planning Process

Through the long-range planning process, the forecasted demand is compared to the current factory capability. As depicted in Figure 6, the gap between forecasted requirements and anticipated capabilities is assessed. In the event of a shortfall in capacity between demand requirements and current capability, decisions must be made as to which markets will be supported and how much additional capacity can be added. A capacity roadmap is developed that allocates the forecasted capacity to demand and determines committed capacity levels.

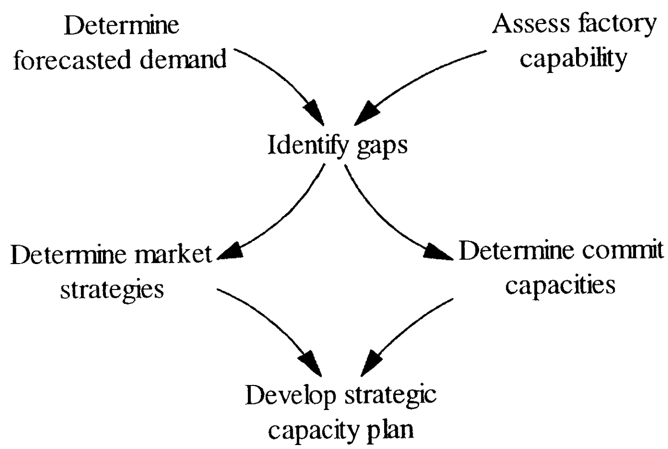

Figure 6. Long-range planning procedure

Through the long-range planning process, both a committed capacity and a possible upside scenario capacity plan are developed. The commit capacity is the published long-range plan and includes production routings; it is a combination of current and forecasted production capabilities. The demand fulfillment and production plans are made based on the commit capacity roadmap. There is high confidence that the forecasted commit capacity requirements will be met. In addition, a plan that reflects a possible upside potential is developed for resource planning, space assessments, equipment requirements, headcount, and material planning. This plan includes incremental opportunities such as converted capacity availability and possible demand variations. It represents the target capacity to which the supply side plans, but it contains some significant risks.

For example, for a new product with uncertain demand, the commit plan represents the planned capacity capabilities and hence the committed delivery levels for that processor. However, the commit capacity plan may be insufficient to meet potential upside demand. The potential upside plan, therefore, represents the target capacity. The supply side, such as raw material, subcontracting, and tool procurement, targets the higher capacity requirements in preparation for the potential upside demand.

As shown in Table 1, several key strategic questions are addressed through the long-range planning process. In the area of demand assessment, decisions must be made regarding market strategies, possible demand forecasts, and predicted product parameters. Factory capability assessments focus on current capacity, sub-contracting opportunities, factory production parameters, equipment requirements, and product routing between fabrication facilities. The final strategic capacity plan is determined by assessing the demand versus current factory capacity. Several possible capacity plans are evaluated to determine the equipment and capital impacts of different demand forecasts. In the process of selecting and ratifying a long-range plan, needed for long-horizon procurement decisions, strategic questions about target markets, process technologies, and financial planning are made.

Demand Assessment
Which products should be added and deleted from the long-range forecast?
What is the base case (most likely) demand forecast?
Which 'what if' demand scenarios are possible?
What are the predicted product parameters (such as die size, yields, and run rates)?
Factory capability assessment:
What capacity is and will be available?
Are there possible space constraints in the fab?
Is there sufficient sub-contracting capability?
What fungibility (tool sharing, reuse, and allocation) issues exist?
What are the forecasted factory production parameters?
Is there an impact on equipment requirements?
What is the most efficient product routing strategy?
Strategic capacity plan determination:
What gaps exist between the forecasted demand and factory capabilities?
Which demand scenario is the most likely?
What are our strategic market positions?
Which process technologies and products will be allocated capacity?
What are the financial impacts of the possible capacity roadmaps?

Table 1. Key strategic decisions in the long-range planning process

Through the quarterly long-range planning process, the Strategic Capacity Team develops a capacity roadmap for all of Intel's products and across the fabrication, sort, assembly, and test processes. Based on the capacity plan, strategic investment decisions are made, including plant expansions, new plant construction, sub-contracting agreements, and tool procurement. As discussed in Chapter 2, the steps in the process that are sensitive to the die size of the product further complicate tool procurement. Lithography stepper capacity is highly dependent on the product or mix of products. The current process of assessing tool requirements and the impact of possible demand scenarios on tool requirements is discussed in Chapter 4.

Chapter 4: Framework for Forecasting Capacity Requirements

Through the long-range planning process, a WSPW capacity roadmap is developed to meet forecasted demand projections. During the planning process, several strategic questions are addressed such as, which products should be supported and how much capacity must be added or reallocated.

In making such strategic decisions, numerous factors are considered, including the impact to high-cost, long-lead tools like lithography steppers. The process of calculating stepper tool requirements is described in the following chapter.

As previously discussed, the number of steppers required to meet a given demand can vary greatly depending on the product. As a result, a comparison of the impact to mix sensitive tool requirements for various possible demand scenarios must be assessed when making strategic capacity decisions. The current process of forecasting demand scenarios and the opportunities for improvement are outlined in Sections 4.1 and 4.2. A new model and revised process flow are defined which address several shortcomings to the existing procedures. The two-part model includes an optimizer to calculate the number of tools required and a Monte Carlo simulation to assess the impact of demand uncertainty. The details of the new model are covered in Chapter 5.

4.1 Calculating Tool Requirements

Numerous variables and levels of complexity must be considered when calculating lithography tool set requirements. Within each process technology, there are several product families comprised of hundreds of individual products. Each product family may include a number of variations of a product, due to specific feature sets required per market segment like workstation, server, or desktop.

Each of the individual products has a different run rate per lithography stepper tool type. Further, for a given stepper tool, each product will require a different number of layers on the wafer. Therefore, for the purposes of this model, the numerous individual products are grouped into product 'buckets'. Product buckets are defined as those products within a product family that have the same die size. Since each product within the 'bucket' has the same die size, a run rate and number of layers for the product bucket is determined.

As shown in Figure 7, each process technology has individual product buckets, which have a distinct number of manufacturing layers per wafer. In addition, each process technology has an associated tool set, a subset of tools per bucket, and a specific run rate per tool type.

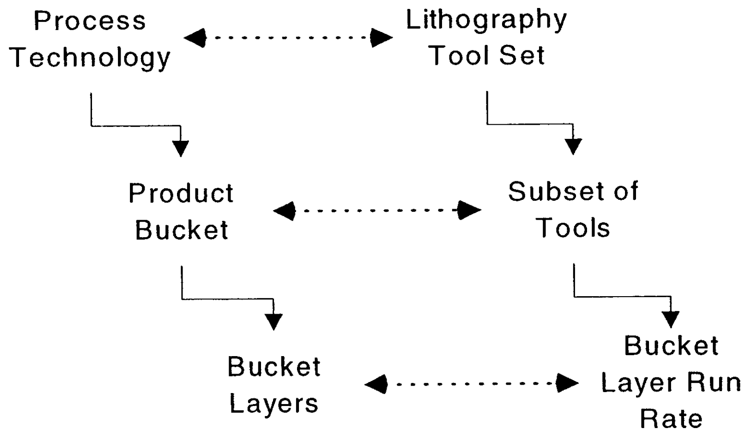

Figure 7. Hierarchy of technologies and lithography stepper tools

An example of the process, product bucket, and tool relationships is highlighted in Figure 8. For a given process technology, A, assume there are 4 product buckets (1-4). For two tool types, X and Y, each product bucket has a different run rate and number of layers that must be applied at that tool type.

Process Technology A		Tool Type X		Tool Type Y		...
		Run Rate	# of Layers	Run Rate	# of Layers	
Product Buckets	1	33	3	53	8	...
	2	43	4	54	2	...
	3	40	8	23	1	...
	4	35	1	19	5	...
	⋮	⋮	⋮	⋮	⋮	

Figure 8. Example of tool type product specific parameters

Within each process technology, there may be upwards of 30 individual product buckets. To further scale the model, only a subset of buckets is used and all other products are grouped in a 'Various' bucket with an assumed average run rate and number of layers. The subset of buckets is selected based on a weighting algorithm that gives more weight to near term WSPW requirements. For each process technology, four to five major product buckets with higher near-term production requirements are used.

Each process technology is manufactured on a given set of lithography tools. More specifically, a layer on a product is applied in a specific lithography stepper. With each new generation of microprocessor, an accompanying set of new-and-improved lithography steppers is introduced. In general, older process generations run on older tools and at the time of each new process generation, a new lithography stepper tool platform is introduced. The allocation of each new manufacturing technology to a new process technology is often referred to as a 'waterfall strategy.' Due to the high cost of the lithography steppers, tool reuse and continued enhancement of tool capability is a priority.

Stepper tools may be used on a variety of process generations, but have different production parameters for each process. Further, each product bucket within a given technology has a different run rate on a tool. And at the most detailed level, each product bucket layer has a run rate specific to a lithography stepper type. In summary, a given lithography stepper can produce different product bucket layers within a product family at different run rates.

When planning lithography stepper tool requirements, the peak demand is of the greatest concern. At the peak, the most tools will be required. Both the timing and the quantity of units demanded at the peak are the most difficult to forecast.

During the ramp-up of a process technology, new tools are installed to support the peak production levels. When lithography tools are installed, several months of initial qualification and testing are required before they attain the anticipated full-production level. Tools in the final stages of qualification may have lower yields, lower utilization, higher rework, or slower run rates. During tool start-up, yields are often lower, therefore; more wafers must be started through the process to make up for the lower output. The result is an increase in the capacity and corresponding tools required to meet demand. These tools are often called 'spike' tools because the tool is not required once all equipment has reached full-production capability. Planning for the potential spike in tool requirements further increases the complexity of forecasting tool needs.

And finally, determining tool set requirements is complicated by the long-lead time required to procure the equipment. Receipt of a tool often takes 12-24 months (4-8 quarters) depending on the tool type. Forecasts of projected tool set needs often extend 8 to 16 quarters into the future. Given the long lead-time, extensive cost, and mix-sensitivity of the tool, forecasting lithography tool set requirements is a key component of the strategic capacity planning process.

4.2 *Forecasting Demand Scenarios*

As Section 4.1 describes, each process technology includes numerous product families, each comprised of hundreds of individual products. The product manager forecasts demand for the complete range of products in a given technology.

The product manager's forecast is typically expressed as the thousands of units required per quarter per product per process technology (Ku/qtr). The Strategic Capacity Planning Demand team converts the forecasted product demand from Ku/qtr to wafer starts per week (WSPW) required to meet the unit demand. The number of wafer starts required to meet the desired demand varies based on each product's estimated die yield per wafer and wafer yield.

A 'base case' forecast of wafer start per week requirements per quarter is developed. The base case represents what planners feel is the most likely forecast for demand. In addition to the base case, multiple scenarios are developed to assess the impact of possible demand changes on capacity requirements.

During each quarterly cycle, several possible scenarios are developed and their likelihood of occurrence assessed. The scenarios represent a possible 'what if' case for aggregate process level volume fluctuations, product mix changes within and between technologies, and the tradeoffs between flash and logic market segments. The scenarios may also address the possible changes in production parameters. Further enhancements to the product, such as a decreased die size, can significantly affect the products run rates and yield, and hence the number of wafer starts per week required to meet the same level of demand. For those scenarios with an anticipated higher likelihood of occurrence, further study is conducted to determine the exact impact on capital equipment and the total wafer start per week capacity required.

Creating the demand scenarios is a substantial task. A possible scenario may include a faster ramp of one process technology. The associated impact on the other technologies is also considered, and their demand forecasts adjusted accordingly. In addition, when the demand for a logic processor changes, adjustments must be made in the demand for the associated chip set.

Common demand scenarios include:

- A cumulative growth rate in microprocessor demand.
- Delays in a product family launch, which in turn increases demand for the current product and a mirrored effect on the associated chip sets.
- Increased demand in a specific market segment, which drives increased wafer start requirement capacity for the product family.
- A change in a production parameter such as die size. A 5% decrease in the die size of a product can significantly reduce the number of production tools required and wafer start per week capacity required for the same number of wafer outs.
- A faster market penetration of a new product.
- Transition of a product from one process technology to another, which affects both the current and new process technology platforms.

4.2.1 Challenges with current process

Each quarterly cycle, typically 25-30 'what-if' demand scenarios are identified. The likelihood of occurrence and the level of impact are then assessed. As shown in Figure 9, those scenarios with an assumed higher probability of occurrence and higher impact are given priority for further evaluation.

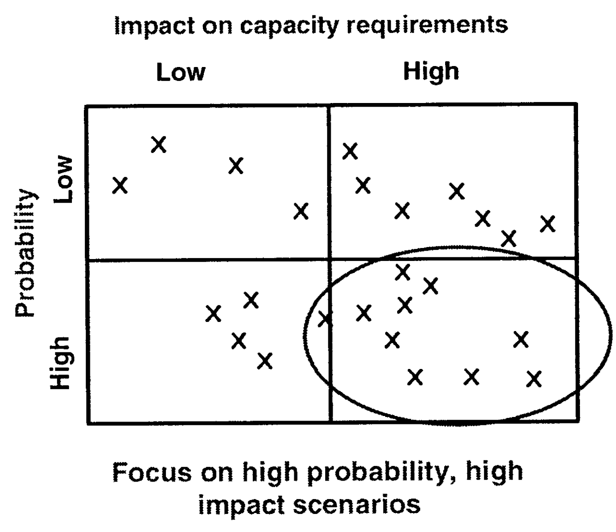

Figure 9. Selection of critical scenarios for further evaluation

A primary area for further assessment includes the impact that each possible scenario has on the mix-sensitive lithography tool set. As shown in Figure 10 below, the scenarios are then reviewed with several industrial engineers responsible for the lithography manufacturing process. Given the scenario description, the team determines whether they anticipate a significant impact on tool requirements. Five or six scenarios that are deemed to have the greatest impact are further assessed.

The current process uses a spreadsheet model. Each cycle, all updated product die sizes, run rates, product categories, and current tool inventory must be manually input to the spreadsheet model. The number of tools for each scenario is calculated and comparisons between the scenario and base case projections are evaluated. The result of the analysis is a critical component to assessing which scenario should be considered for the long-range strategic capacity plan. There are several opportunities for improvement of the current process for assessing the impact on mix sensitive tool sets.

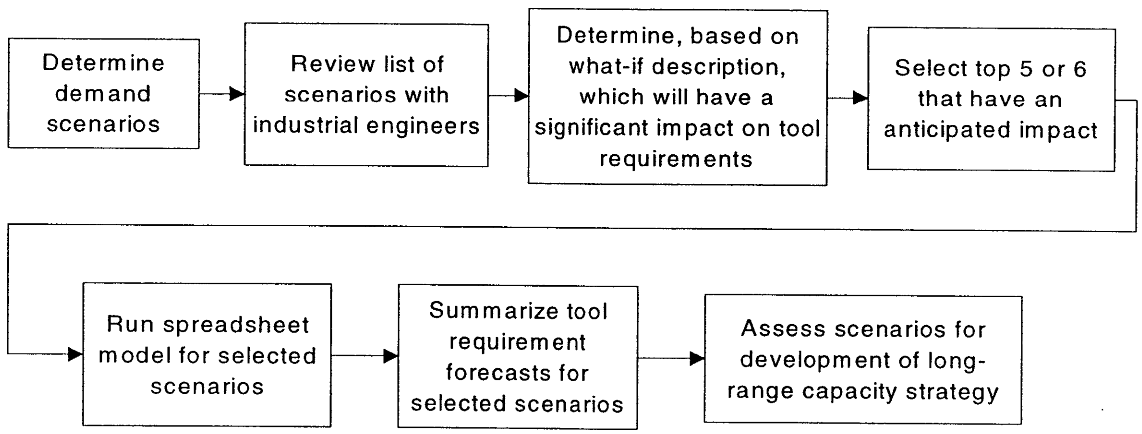

Figure 10. Current process flow for assessment of what-if scenarios

The current calculation process is as follows:

For each scenario:

Per process technology (each stored as an individual spreadsheet model):

- Calculate mix and WSPW requirements per product category
- Update production parameters including run rate, utilization, and rework per tool type
- Calculate the production outs per week per tool type

For all technologies:

- Copy-paste calculated number of die out per week per tool type per process technology into the virtual factory model
- Update tool inventories per tool type
- Update layers required per tool type per technology
- Calculate the number of tools required to support demand

Numerous cut-and-paste steps are required to calculate the number of tools required to support a given 'what-if' demand scenario. Due to the time intensive effort required, only a subset of the possible scenarios is evaluated each cycle, possibly overlooking a scenario that has significant implications.

Each quarter, updated manufacturing and product parameter assumptions and parameters must be entered into the spreadsheet model for each technology. Run rates, utilization, and rework assumptions per product bucket per process technology per tool are determined. These values are entered into the multiple spreadsheet models for each process generation. A common data warehouse would significantly reduce data entry time. The production parameters are used across multiple organizations. Therefore, it is essential that common assumptions are made for the parameter levels. To ensure consistency, a tool that draws upon a common database of quarterly production assumptions is essential.

Further, the industrial engineers complete the calculations, but the output is an essential component of the long-range planning process. To increase the efficiency of the analysis, the Strategic Capacity Planning team would benefit from having a tool within their organization to quickly and effectively assess the impact.

However, the most significant improvement to the current what-if analysis procedure is incorporation of an assessment of uncertainty in the forecasts. The current method relies on a point estimate of WSPW per quarter over time. Figure 11 demonstrates that in reality, the demand may fall within a given range of estimates.

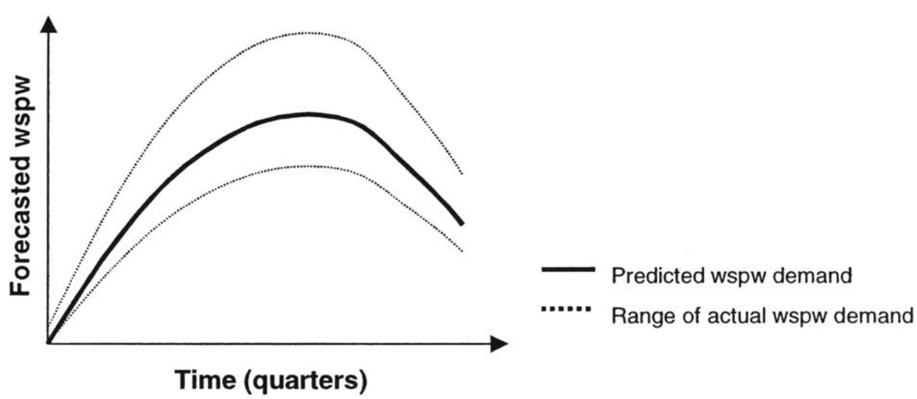

Figure 11. Actual WSPW demand forecasts vary within a range of the forecast

A comparison of past forecasts to the actual production indicates there is significant error in the demand forecasting. Figure 12 compares the actual wafer starts in the fab versus the quarterly forecasts for that same production quarter for one process generation.

Each of the 20 plots is the long-range forecast created that quarter for the time period over Q1'95 to Q1'02. For example, in Q2'96, a forecast was made for WSPW requirements for the period Q4'96 to Q3'00. That forecast varied significantly from subsequent forecasts and the actual production in that same time period. Note that all data is based on the actual production WSPW data and the forecasts; however, the data has been disguised. The volume of demand, the timing of peak demand, and the product mix within a process technology are variable. The significant variation in the forecasts versus the actual production should be included in the assessment of the impact of possible demand scenarios. Further discussion of the forecast error and percentages is included in Section 5.3.

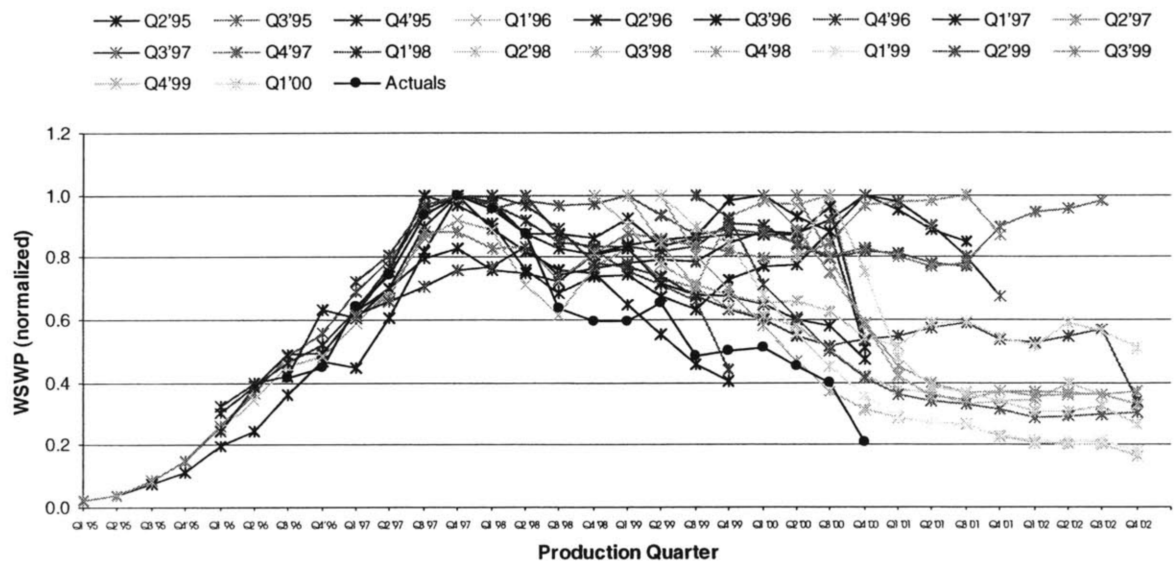

Figure 12. Variability in quarterly WSPW forecasts for a given technology platform

The current method of forecasting also assumes a specific estimate of mix between products A and B. As depicted in Figure 13, the actual mix of products falls within a range of likely estimates and not at the exact forecast. For example, the current what-if for a slow ramp of Product B is a point estimate of the percentage of Product A and Product B in the overall mix. However, similar to the volume forecast, there is a range of possible demand mixes, represented by the dotted line around the point estimate.

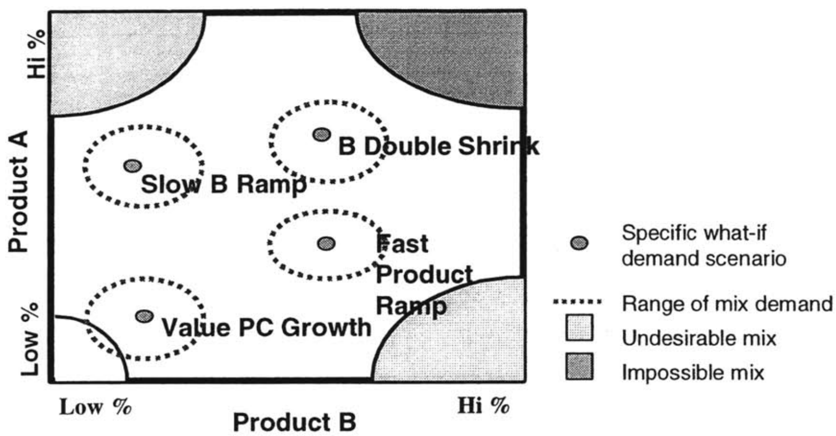

Figure 13. Actual product mixes vary within a range of the forecast

A recent study by Swaminathan documents the importance of scenario planning that takes into consideration demand uncertainty.[25] The researcher developed a model for procuring semiconductor fabrication equipment using two heuristics, one based on the data related to the cost of the tools and another based on the approach to procuring tools. A comparison was made between the performance of the heuristic to the solution of a single, point demand projection. The results "indicate that the heuristics provide effective solutions even for large problems and their performance is superior to the solutions of the coordinated planning approach."

Further, the study includes an optimization model with the objective of minimizing the stock-out costs incurred. The model calculates the expected costs when a single demand forecast is used versus scenario planning. The result demonstrates lower costs for scenario planning than single demand procurement strategies. "It implies that planning for a set of demand scenarios is always far more efficient than planning for a coordinated demand forecast based on the most optimistic estimate of product demands."

A final area for improvement to the current process is the addition of an economic options analysis for those scenarios with a high probability of occurrence and a high impact on tool requirements. The decision matrix (Figure 14) shows that, when prepared for a possible scenario, the return on being prepared must be compared to the cost of unnecessary preparation if the scenario does not happen. Likewise, the tradeoff between the cost of preparation versus the loss of not being prepared (having insufficient capacity to meet demand) must also be weighed. A complete options analysis is an extensive, yet valuable last step. Currently, complete financial assessments are conducted for a small subset of possible scenarios. As described in Section 6.3, an options analysis based on the output of the model is an area for further study.

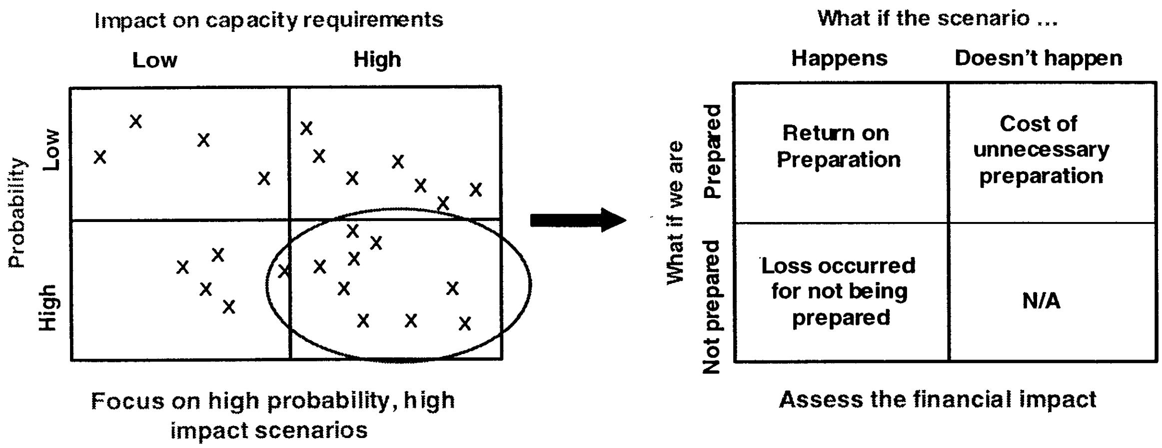

Figure 14: Options analysis decision matrix for what-if demand scenarios

4.3 Model Overview

As discussed in section 4.2, there are significant opportunities for improvement to the current method of calculating tool requirements and the associated business process. The intent of the project is defined as follows:

Develop and implement a model and accompanying business process to quickly and easily assess the impact of various demand scenarios on mix sensitive lithography steppers under demand uncertainty.

The improved tool is comprised of two primary components:

- Optimization routine to calculate tool requirements
- Monte Carlo simulation to assess the impact of forecast errors

The high-level model architecture is shown in Figure 15. Wafer start per week demand forecasts and the measure of forecast errors are entered into the model. The Monte Carlo simulator selects a value for each variable within the defined probability distribution. The optimizer calculates the number of tools required to meet those demand requirements. The simulator selects another value for each variable and the optimizer recalculates. After multiple trials, a distribution of the minimum number of tools required to meet a given demand scenario is generated.

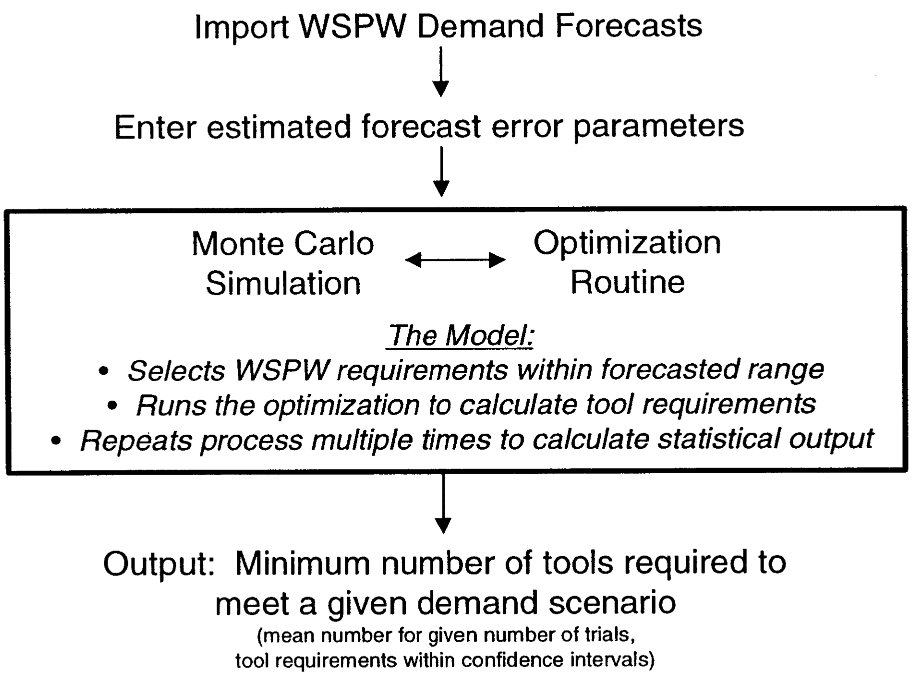

Figure 15. High-level model architecture

4.3.1 Revised process flow

The proposed process flow shown in Figure 16 leverages the new model to quickly calculate and efficiently assess multiple what-if demand scenarios. Parameters such as die size, utilization, rework, and run rates are updated in the common database. The user then selects the desired scenario from the Strategic Capacity Planning database, runs a macro to generate the individual product WSPW quarterly estimates, loads the forecast in the model, and runs the model. The model is constructed such that the user can run either the optimizer independently or include the variability assessment.

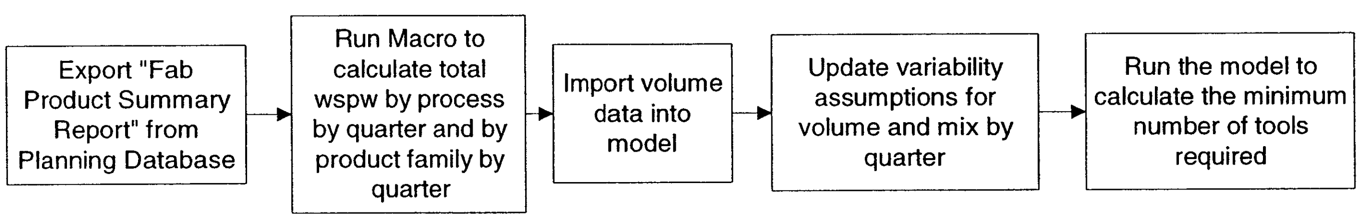

Figure 16. Revised process flow for assessment of scenario impact on tool requirements

As can be seen, the current process is tedious, even for the analysis of one possible demand scenario. Complexity grows very quickly as the number of possible demand scenarios, products, processes, and lithography stepper tools increases. The problem is further complicated as the demand forecasts are point estimates of the WSPW required for a given product in a future production quarter.

By using a common database of parameters needed to calculate tool requirements, the amount of cut-and-paste data entry is significantly reduced. A linear program quickly and efficiency calculates an optimum solution within the given constraints. Finally, the solution is further improved by including an assessment of the impact of the inevitable demand uncertainty.

Chapter 5: Forecasting Tool Requirements Model

Lithography steppers are the most capital-intensive tool-set in fabrication. Therefore, assessing the impact on the number of tools required is an important step in making the strategic decisions of which product mixes will be supported in the long-range capacity plan.

As outlined in Chapter 4, the model developed is used to compare the number of lithography steppers required to meet various demand scenarios. The model has two primary components, the optimizer to calculate the minimum number of tools necessary and the simulator to assess the impact of demand uncertainty. Comparisons are typically made between the base case demand projection and multiple what-if demand scenarios. The model architecture, the structure of the optimization and simulation model, and key assumptions are detailed in the following Chapter.

5.1 Model Architecture

The mix model includes both an optimizer and a Monte Carlo simulator. The optimization is achieved with a linear program that determines the minimum number of lithography steppers required to meet a given demand scenario.

What is linear programming?

'Linear programming is a mathematical technique for solving a broad class of optimization problems that require maximizing or minimizing a linear function' [14] of decision variables. An optimal solution to the problem requires that the values of the decision variables satisfy a set of constraints.

The model described over the next several pages and pictured in Figure 17 is a linear program using the ILOG OLP Studio™, a programming environment that provides access to a suite of optimization algorithms. The operator interface is in Microsoft® Excel with a Microsoft® Visual Basic® macro written to call the optimization function. When the optimization executable is called, the linear program retrieves data from the Microsoft® Access database required for the optimization calculations. In addition, the optimization routine checks to ensure that the user has the necessary ILOG licenses. The optimization routine runs and the results are written to the database. The Visual Basic macro then retrieves the stored results and displays the output in the Excel user interface.

When the optimizer is used with the variability forecasting module in Crystal Ball®, the above process is repeated for each trial of the simulator. The optimization model can be run individually, however, with the forecasted WSPW demand imported directly by the user.

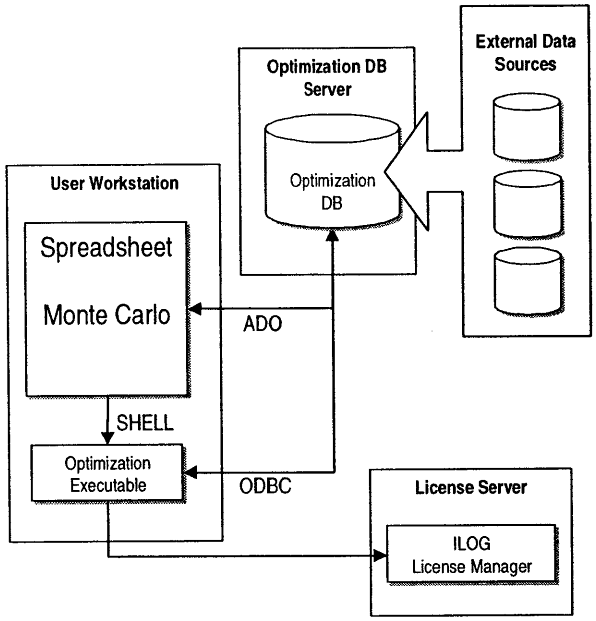

Figure 17. Model architecture

5.2 Linear Optimization Model

5.2.1 General model assumptions

The model calculates the number of additional tools required at a virtual factory level. The term 'virtual factory' refers to multiple distinct manufacturing facilities utilizing the same process technology to fabricate a variety of different products. The multiple facilities operate at many levels as a single combined facility. This model aggregates tool inventory across all facilities. The solution does not take into consideration that the capacity of a tool at one facility cannot, in application, be combined with the capacity of a tool at another location.

In addition, the model assumes an eight-quarter critical planning horizon. The model output is, per each tool type, the number of additional tools needed per quarter over an eight-quarter time horizon.

5.2.2 Model inputs

The model incorporates tool type, product, layer, and process level detail for each tool. The following indices are used throughout the model:

- i indicates stepper type

- j indicates product type
- k denotes a particular layer of a product

The program relies on extensive data inputs, but relatively few operator inputs.

Data Inputs

There are several inputs that are required for the optimization function. The data is stored in an Access database linked to the optimization routine:

- *Product buckets per process.* As explained in Section 4.1, multiple product buckets (type j) are defined per process. The product buckets are assumed to remain the same for the 8 quarter planning cycle.
- *Manufacturing layers for each product bucket.* Each product (type j) requires a specific number of layers (k), which are applied in different tool sets (stepper type i) for each technology. The number and type of each layer in a given product bucket is also assumed to remain the same for each quarter.

Per quarter, for each of the first 8 quarters in the long-range planning cycle:

- *Utilization and rework per tool per process.* Every tool has a different level of utilization and rework. For new tools, the utilization will increase over time and the rework will decrease as the capability of the tool improves.
- *Stepper run rates per layer per product bucket.* Run rates for each product may vary over time. For example, die size changes in the product can significantly change the run rate for that product on a given tool. In addition, as a product's manufacturing process improves, the run rate may decrease.
- *Forecasted tool inventory in the virtual factory for each stepper* type. The model takes into consideration tool inventory currently in the virtual factory and tools that are on order, but not yet in production. Therefore, for each quarter, the number of available tools may change as new tools are put into production.
- *Tool costs.* The actual purchase cost of each tool is included. As new technologies are introduced, several older machine types are no longer purchased. For tools that will no longer be procured, the costs have been set at one billion dollars; since the model seeks to minimize the number of new tools at the lowest cost, it will not select those tools with the excessively high costs. The

tool cost data is required per quarter as some tools may be phased out during the 8-month planning period of the model and new tools introduced.

Operator Inputs

The primary operator input is the estimated wafer start per week (WSPW) demand per product per process. For each scenario that the user wishes to analyze, the forecasted WSPW data must be imported to the model. The user exports a report from the planning database that includes the process technology, product name, die size, and forecasted WSPW by quarter. A macro was written to assign each individual product to the associated product bucket. The macro then calculates the total WSPW requirements by bucket by process by quarter. The WSPW data for each product bucket is imported into the optimization model.

5.2.3 Optimization model operation

The goal of the model is to compare the impact of possible demand scenarios on mix-sensitive lithography steppers. Given the cost versus the potential revenue of each product mix, decisions will be made on target market segments and capital budgeting decisions. As discussed in Section 4.1, determining tool requirements is a complex task, which depends on numerous factors. Therefore, due to the level of complexity, several assumptions have been made in the model. The model assumes a virtual factory and does not take into consideration specific factory-level capabilities and requirements. The model is a helpful planning tool, but is not intended for making factory and tool type and quantity specific procurement decisions.

Decision Variables

Using the notation defined in the *Model inputs* section, the decision variables are:

- x_{ijk}: the number of wafers running layer k of product j on stepper type i
- y_i: the number of additional tools of type i required

Objective Equation

As the model is formulated, the objective is to minimize the number of additional tools per tool type per quarter. Thus the objective equation minimizes the sum of the costs of additional tools needed to support a given demand scenario. As Equation

(1) shows, the objective function is based on a weighting factor, the cost of utilizing a given stepper. The linear program takes into consideration the current tool inventory, capacity required, and the run rate by layer by product by tool type. The weighting factor, therefore, not only considers the cost of the tool, but also the efficiency of running each product per tool type.

$$\text{Objective Equation} = \min\left(\sum_{i} w_i y_i\right) \tag{1}$$

Once the optimization routine has been called, an executable extracts the necessary data for calculations from the Access data warehouse. Data includes current tool inventories, tool capacities, product run rates, etc. A capacity consumption factor of running one wafer on stepper type i of product j of layer k is calculated (c_{ijk}). The capacity consumption factor is determined as a function of utilization, rework, and run rate metrics.

The wafer starts achievable (WSA) are also calculated for each layer k for products j for each qualified stepper of type i, assuming that the indicated stepper type runs only layer k. The capacity costs for each stepper for product j on layer k is determined. The cost is normalized to generate a simple ratio of capacity costs per layer, with a base of 1.

Model Constraints

The optimization results are based on three primary constraints:

- The capacity used per tool can not exceed the capability of the tool. This relationship is written as Equation (2):

$$\sum_{i} c_{ijk} x_{ijk} \leq \sum_{i} s_{ijk}(r_i + y_i) \ \forall (j,k) \tag{2}$$

Where:

c_{ijk} is the capacity consumption factor of running 1 wafer on stepper type i of product j on layer k. This is a unit-less factor, based on a normalized value of the costs of running multiple layers on a given stepper type.

r_i is the inventory of stepper type i

s_{ijk} is the available capacity of stepper type i on layer k of product j

- The sum of capable capacity on all layers over all tools must equal total demand as shown in Equation (3):

$$\sum_{i} x_{ijk} = p_j \quad \forall(j,k) \tag{3}$$

Where p_j is the virtual factory requested starts (demand) of product j

- The number of wafers running specific layers of a product on a stepper type and the number of additional tools required to meet the demand can not be negative. Equation (4) represents the non-negativity constraint.

$$x_{ijk}, y_i \geq 0 \quad \forall(i,j,k) \tag{4}$$

For each tool type, the minimum number of additional tools is calculated on a quarterly basis. The minimum number of tools is above and beyond the number of tools assumed to be in production for that quarter plus tools on order assumed to be in production for that quarter.

Each quarter in the model is assumed independent. Therefore, for a given quarter, the model uses the routine as formulated above to determine the optimum result. Then, the optimization is repeated for each of the next seven quarters, over an eight-quarter time horizon. For example, the output of the model may indicate a need for two additional tools of Type X in Q2'02 and five additional tools of Type X in Q3'02. The five additional tools in Q3'02 are independent of the Q2'02 forecast. In other words, if the 2 tools required in Q2'02 are purchased and installed in anticipation of the demand increase, then the number of tools needed in Q3'02 is five less the two purchased the prior quarter, for a total of 3 additional tools. The model was structured such that each quarter is treated independently so that demand, production, and parameter variations can be made on a quarterly basis and the output per quarter is actual number of additional tools needed, independent of tool changes in prior quarters.

5.3 *Variability Model*

5.3.1 Historical Analysis

Section 4.2.1 demonstrates the inherent inaccuracy of long-range forecasts. To determine the magnitude of the forecast error, an analysis of the historical forecasts versus the actual production was conducted. For the purposes of the analysis, the various technology processes were divided into three categories: new processes (recently or soon to be released technology platforms), ramping (technology platforms not yet at full-production, but increasing in demand), and established (mature technologies at their peak or ramp-down phase).

For each 'established' and 'ramping' process, the following were assessed:

- Evolution of the forecasts based on the life cycle of the product.
- Mean, median, and standard deviation in the forecasts.
- Average and normalized forecast error per quarter, calculated by comparing forecasts over the past six years versus actual wafer starts per week.
- Forecast error in predictions 1, 2, et cetera, quarters in the future.
- Forecast error relative to the production volume.

The analysis of the forecast variation indicates that the level of variability is significant. The variability is also highly dependent on the life cycle stage of the technology platform. Historically, there is little direct correlation of demand from one quarter to the next. For example, if there is a 5% increase per quarter for the past three, it does not necessarily imply a 5% increase in the fourth quarter. Rather, semiconductor demand typically follows the life cycle profile. Correlation does exist however, between the product mix and volume. Increased demand for certain products will drive an increase in the overall demand versus a tradeoff in demand between product lines. Actual production data was unavailable at a product family level to assess actual versus forecasted error.

The following summarizes the variation between the process technology forecasts and actual wafer starts per week.

Forecasting error increases dramatically as forecasts are made further in the future. As shown in Figure 18, correctly predicting further into the future is more challenging due to unanticipated demand fluctuations and new product introductions. The calculations are based on the total error in all forecasts made from Q1'95 to Q1'98 one to eight quarters into the future. An average of 8 forecasts were used to determine this forecast error. Further analysis of the error indicates that there is a slight positive bias. For this given process technology, there is a tendency to overestimate the demand than under-estimated the capacity requirements.

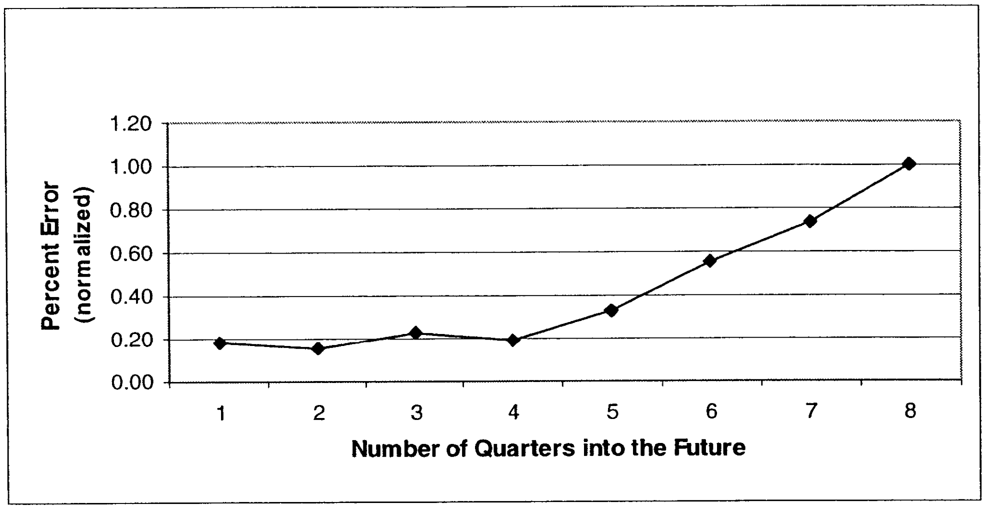

Figure 18. Average forecast versus number of quarters in the future

Further analysis of the error showed that the error in predicting both the timing and the actual WSPW at peak was larger than the error in forecasts for the ramp-up and ramp-down of the process technology. Also of interest is the amount of error in forecasts of the peak that are made one to eight quarters into the future. Figure 19 shows the normalized percent error when forecasting the peak of the technology 1-8 quarters in the future based on actual vs forecasted WSPW requirements for the peak of the technology. To generate this analysis, forecasts made one-to-eight quarters into the future for the time period assumed to be the peak of the technology were averaged. As the figure indicates, the amount of error in the forecast of the peak increases as you forecast further into the future. And, compared to the overall average of the error in the forecasts, shown in Figure 18, the error forecasting the peak is larger.

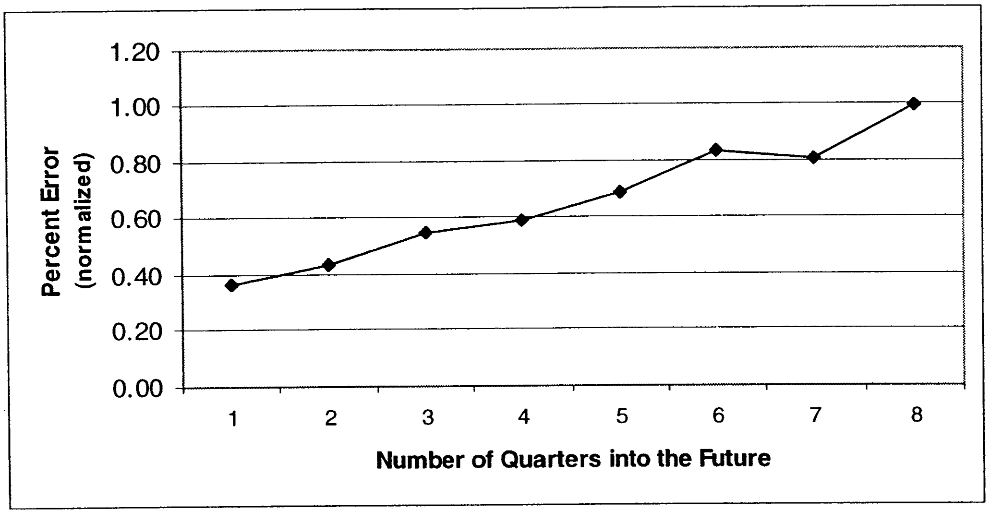

Figure 19. Average forecast error of the process technology's peak demand

The length of time of the technology's plateau is also highly variable. How long a technology sustains peak production level varied between platforms. In some instances, the technology began ramp down quickly as a new replacement platform was introduced.

Forecasts for the technology ramp-down have much less variation and seem to more closely follow the standard technology life cycle. However, later technology platforms have experienced a secondary hump, less than the peak technology volume. As demand for microprocessors transitions from process generation (n) to (n+1), the associated chip sets for the later technology (n+1) are often transitioned to the older platform (n). As a result, a slight increase in demand or secondary hump is often noted late in the life cycle of process generation (n+1).

The variation in the forecast appears proportional to the predicted volume. As the volume of predicted wafer starts per week increased, the amount of error in the forecasts increased proportionally.

5.3.2 Variability Model Architecture

The current forecasting process uses point estimates for the anticipated quarterly demand. The most likely WSPW requirements, by quarter, by product family, by technology are estimated. Given the difficulty in correctly predicting the actual amount, several what-if scenarios are generated, based on a variety of possible alternative outcomes. However, as discussed, the process can be further improved by defining each of the forecasts as a range or set of values. Rather than predicting demand for Product A to be 5120 units in Q2 of

2003, the anticipated volume can range from 4000 to 6000 units within a given profile or probability distribution.

A software package called Crystal Ball was used to generate forecast variation due to the demand uncertainty. Crystal Ball extends the capability of the Excel spreadsheet model by allowing the forecasts to vary within a given range of possible outcomes. The output is a more meaningful statistical picture of the range of possible tool requirements given the uncertain demand forecasts.

A Monte Carlo spreadsheet simulation was created to imitate the anticipated real-life outcomes. The Monte Carlo simulator generates random values for uncertain variables over and over to measure the effect of uncertainty. The term Monte Carlo simulation was named for Monte Carlo, Monaco, where games of chance such as roulette and slot machines are played in the numerous casinos. Similar to the random behavior of chance, the Monte Carlo simulation picks variable values within a defined probability distribution at random to simulate a model.

The output of the model includes the number of tools required and associated statistics: mean number of tools, number required for given levels of certainty, the range of tools needed, and the standard deviation. Because Monte Carlo simulation uses random sampling to estimate the model results, these statistics will always contain some level of error. Crystal Ball allows one to define a confidence interval around the outputs; a bound that attempts to measure the error within a given level of probability. Confidence intervals are used to determine the accuracy of the statistics, and hence, the accuracy of the simulation. As more trials of the simulation are calculated, the confidence interval narrows and the statistics become more accurate.

5.3.3 Variability Model Formulation

Three primary areas of forecast variability exist that directly influence the number of tools required to meet a given demand scenario: WSPW volume, product mix, and production parameters. Parameters include decreases in die size and increased machine capability, which affect run rates, tool utilization and rework and hence tool output capability. Scenarios are often generated each cycle to address such parameter fluctuations as improvements in die sizes. Given that the scenarios specifically address such changes, die sizes were assumed constant over the planning horizon of the model. However, the effect of both volume and mix variation have been included in the model simulation.

The input to the optimizer is the by quarter forecast for each product bucket within each process technology. As shown in Figure 20 below[1], the WSPW forecast per technology and the individual product family estimates are variable. All actual WSPW forecasts have been disguised. In this example, there are two process technologies, A and B. Product buckets within each process technology are represented as Product Bucket 1, 2, 3 et cetera.

		WSPW Forecast Per Quarter							
		Q1 Y1	Q2 Y1	Q3 Y1	Q4 Y1	Q1 Y2	Q2 Y2	Q3 Y2	Q4 Y2
Process Technology	A	28629	29392	30026	29534	29443	29384	29014	28142
Product Buckets	1	4036	4107	4221	4294	4025	3832	3518	3020
	2	3090	3236	3343	3345	3484	3525	3559	3431
	3	7454	7706	7748	7568	7457	7455	7381	7254
	4	14049	14343	14714	14327	14477	14572	14556	14437
Product Mix %	1	14.10%	13.97%	14.06%	14.54%	13.67%	13.04%	12.13%	10.73%
	2	10.79%	11.01%	11.13%	11.33%	11.83%	12.00%	12.27%	12.19%
	3	26.04%	26.22%	25.80%	25.62%	25.33%	25.37%	25.44%	25.78%
	4	49.07%	48.80%	49.00%	48.51%	49.17%	49.59%	50.17%	51.30%
Process Technology	B	26006	26873	27064	28523	29019	29840	29835	29724
Product Buckets	1	8509	8667	8782	8847	8934	9273	9358	9211
	2	46	649	770	2170	2626	3094	3140	3223
	3	17451	17557	17512	17506	17459	17473	17337	17290
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Uncertain Process Technology WSPW per Quarter Demand

Uncertain Product Family Mix per Quarter

Figure 20. Uncertain input variables to the optimization model

The estimated WSPW for each product bucket can be calculated by multiplying the percent of that product in the overall process technology mix times the process technology volume as shown in Figure 21. Therefore, for a given per quarter forecast of the technology, the mix of product buckets can be used to calculate the WSPW per bucket.

Process Technology

	WSPW Forecast Per Quarter			
	Q1 Y1	Q2 Y1	Q3 Y1	Q4 Y1
A	28629	29392	30025.7	....

*

Product Buckets in Process A

	Q1 Y1	Q2 Y1	Q3 Y1	Q4 Y1
1	14.10%	13.97%	14.06%	....
2	10.79%	11.01%	11.13%	....
3	26.04%	26.22%	25.80%	....
4	49.07%	48.80%	49.00%	....

=

WSPW per Bucket per Process A

	Q1 Y1	Q2 Y1	Q3 Y1	Q4 Y1
1	4036	4107	4221	....
2	3090	3236	3343	....
3	7454	7706	7748	....
4	14049	14343	14714	....

Figure 21. Calculation of WSPW/product bucket/technology input to the optimization model

[1] Note: All actual WSPW forecasts have been disguised. Forecasts shown were randomly generated in Microsoft Excel.

As previously discussed, both the volume and mix are assumed variable. For each uncertain variable, Crystal Ball is used to set a range of possible values within a probability distribution. The distribution type is selected based on the conditions of the variable. Common probability distribution types include normal, uniform, triangular, and lognormal.

The process technology volume was modeled with a lognormal probability distribution. Lognormal distributions are used in situations where values are positively skewed, for example in financial analysis for security valuations. For example, stock prices exhibit this trend because they cannot fall below the lower limit of zero but may increase to any price without limit. The process technology estimates meet the conditions for the lognormal distribution:

- The uncertain variable (WSPW/quarter/technology) can increase without limit but cannot fall below zero.
- The uncertain variable is positively skewed with most of the values near the lower limit. The lognormal distribution ensures that all WSPW forecasts are non-negative and do not typically approach infinity.
- The natural logarithm of the uncertain variable has a normal distribution

Figure 22 is an example of how the uncertain process technology demand profile was generated. For each scenario under evaluation, the Strategic Capacity Demand team's forecast was loaded into the model. The mean of the distribution was assumed to be the point estimate generated by the scenario.

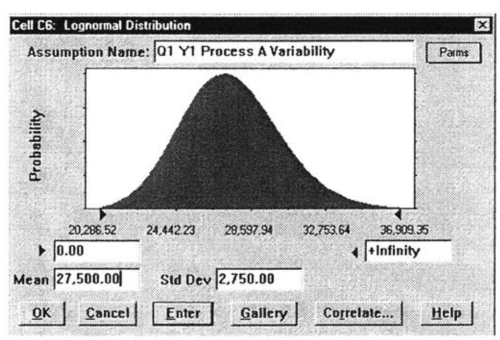

Figure 22. Definition of the probability distribution for WSPW demand forecasts

The standard deviation of the forecast estimate was based on the assessment of historical error. As described in Section 5.3.1, there is significant error between the actual production and forecasts. The model assumes that each process technology follows the same life cycle profile. It also assumes that variability in future WSPW forecasts will be the same as the variability of forecasts made in the past. If this assumption is true, then errors in an (n+1) technology will follow the errors made in the forecasts of its predecessor, (n). Each logic process is assumed similar to a previous technology platform and a similar correlation between platform generations is assumed for flash. For example, for a given technology platform, C, the error is similar to a predecessor technology, A. In Excel the percent error of the forecast was calculated and Crystal Ball was referenced to that value as the expected standard deviation. This model architecture allows one to easily adjust the level of estimated error in the forecast to assess the impact on tool requirements. Error estimates can be quickly updated and can be different for each quarter. This allows the user to set the error estimates per quarter to reflect that the error in the forecast changes based on the life cycle of the process technology.

There are risks associated with the assumption that the error made in current forecasts emulates errors in the past. For example, the current constrained or unconstrained manufacturing environment at the time of forecasting may affect predictions of future demand. Further, in a constrained environment, actual production is limited to available capacity. The forecast may have far exceeded the constrained environment, resulting in a large error term. However, for the purposes of the comparative analysis of the effect of various scenarios, the assumptions are acceptable provided consistent assumptions are made for each scenario analysis.

As the model is constructed, the standard deviation assumptions in the uncertain variable probability distributions reflect that both the volume and timing of peak production is highly variable. For example, assume the scenario predicts that the peak demand is 12,000 WSPW in Q3. If the standard deviation assumptions for the Q3 and Q2 estimates are 1,000 WSPW and 800 WSPW respectively, then the peak could occur in Q2 versus Q3. As shown in Figure 23, if the simulator selects a value plus one standard deviation from the mean in Q2 and minus one standard deviation in Q3, the assumption for peak demand shifts from Q3 to Q2. This further reflects the value of the statistical analysis versus point estimates given the uncertainty of the demand forecasts.

Q2 Std Dev	Q2 Lower Bound	Q2 Mean	Q2 Upper Bound
800	10,200	11,000	11,800
Q3 Std Dev	Q3 Lower Bound	Q3 Mean	Q3 Upper Bound
1,000	11,000	12,000	13,000

Figure 23. Uncertainty of peak demand reflected in variability model

The forecasts for the product mix are also uncertain. Mix assumptions were modeled as normal probability distributions as shown in Figure 24.

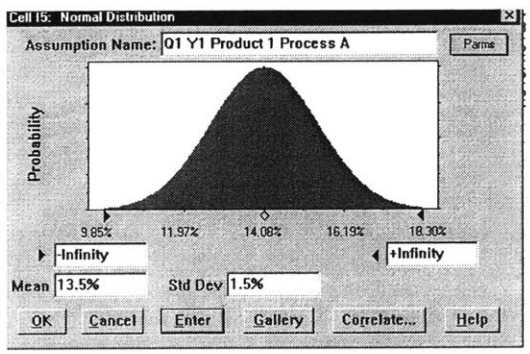

Figure 24. Definition of the probability distribution for product mix forecasts

The normal distribution is used to describe uncertain variables, quite often, natural phenomena such as I.Q.s or height. In this case, the mix variation matches several normal distribution characteristics:

- Some value of the uncertain variable is the most likely. The point estimate made in the forecast is assumed to be the most probable.
- The uncertain variable could as likely be above the mean as below. The mix could be just as likely plus or minus one standard deviation from the mean.
- The uncertain variable is more likely to be in the vicinity of the mean than far away.

As with the volume forecasts, the mean is the point estimate forecasted by the Strategic Capacity Demand team's scenario forecast. However, in this case, the user enters the assumptions on how much error there is in the mix forecasts by adjusting the standard deviation. For uncertain scenarios, the variation of the mix between products can be quite large. The user can take this uncertainty into consideration by increasing the standard deviation of the forecasts. Since each mix percentage is set as an independent variable cell, the simulator may select mix values within each probability distribution profile that don't total 100%. To compensate for this, the percentages selected by the simulator were normalized to 100% and then input into the model. Testing of this assumption to correct for greater than 100% mix indicated there was no significant change in the statistical output of the model.

The model architecture also allows the user to set a high level of uncertainty around a particular product. For example, if demand for Product 1 in Process Technology A is highly unpredictable, the user can increase the error in the mix forecast for Product 1 to assess the level of impact on tool requirements and determine what level of capital expenditure will be necessary to ensure demand is met.

A simplified version of the Monte Carlo simulation was also constructed as shown in Figure 25. In this model, the WSPW forecast for each product bucket/process technology/quarter was defined as an uncertain variable. This form of the model is in contrast to the method discussed earlier, which varied both the product mix and overall process technology totals.

WSPW Forecast Per Quarter

		Q1 Y1	Q2 Y1	Q3 Y1	Q4 Y1	Q1 Y2	Q2 Y2	Q3 Y2	Q4 Y2
Process Technology	A	28520	28927	29350	29459	29358	29421	28970	28182
	1	4036	4107	4221	4207	4028	3825	3540	3065
Product Buckets	2	3090	3236	3343	3363	3494	3582	3557	3418
	3	7454	7706	7748	7586	7408	7472	7346	7290
	4	14049	14343	14714	14303	14428	14542	14527	14409
Process Technology	B	26064	26368	27182	28455	29186	29804	29913	29809
	1	8599	8624	8759	8845	8995	9235	9397	9290
Product Buckets	2	9	167	857	2066	2730	3086	3160	3271
	3	17456	17577	17566	17544	17461	17483	17356	17248
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Uncertain Product Bucket Demand Per Quarter

Figure 25. Uncertain WSPW input variables to the optimization model for the revised model

In this architecture, the WSPW forecast per product bucket per technology was directly modeled as a lognormal distribution. Again, the mean is equal to the forecasted point estimate of the selected scenario. The standard deviation of the estimate is set as the process technology level error. The percent error for each product bucket is, therefore, the same. The user can manually adjust the standard deviation estimate to assess the impact of a more uncertain WSPW forecast for a given product.

The revised model architecture decreases the number of uncertain variables as only the per-bucket uncertainty is considered, versus the process level and mix uncertainty shown previously. The number of assumptions and estimates of forecast error is also reduced using the simplified model structure.

5.3.4 Variability Model Output

In the variability model, the number of tools required is set as the output being simulated and analyzed. After the desired number of trials, the statistics of the output and the certainty of any one single output can be viewed. As shown in Figure 26, the output of interest is the mean forecasted number of tools required to meet a given demand scenario. In addition, the minimum number of tools required given the range of possible demand inputs can be determined. Also of interest is the number of tools required to be 95% confident you will have sufficient tool capacity to meet demand. Various percentiles can be assessed; they represent the confidence of achieving a value below a particular threshold.

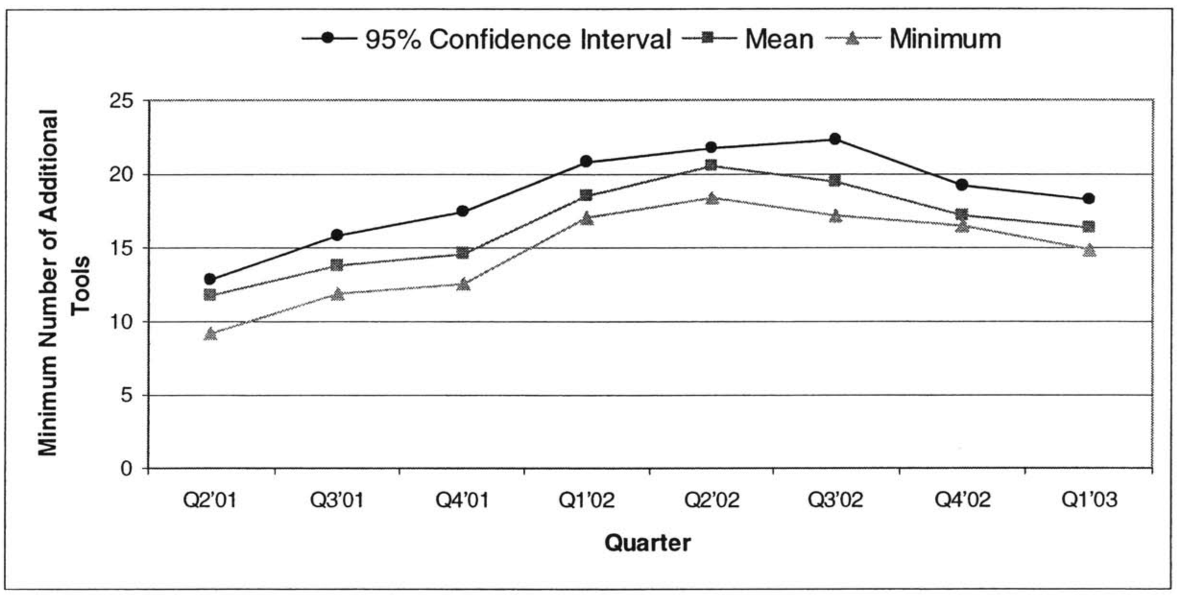

Figure 26. Output of the variability model for a given tool type

As shown in Chapter 5, the model is a complex integration of multiple software tools to create a user-friendly, powerful analysis tool. To demonstrate the capability and use of the model, a case example has been created and is described in Chapter 6.

Chapter 6: Model Validation and Results

This chapter presents a case study of the model using a simplified situation consisting of three technology processes and eight product families. The simplified case study demonstrates the use and output of the optimization model.

6.1 Application of the Model

Consider a semiconductor manufacturer who produces one flash technology process, with two primary product categories, Alpha and Beta. In addition to flash products, the manufacturer has two generations of logic process technologies. Process technology A includes three product families. Delta is the flagship product; it offers significantly faster processing speeds than its closest competitors on the market. However, Delta is a very large die size product that often drives increased tool requirements. Chi is a smaller die size product and is an older version of Delta. The remaining products in this technology platform are part of the Epsilon family. Epsilon includes a variety of smaller volume Process A products, primarily chip sets for Kappa (a Process B technology product).

The final technology process, Process B, is a new technology platform. Products included in this category are Gamma, Kappa, and Lambda. Kappa is a new product with an intended Q2'01 launch data. Lambda is an assortment of smaller volume product families. Gamma is an established product with a small die size and lower demand.

Technology Process	Product Family	Die Size	Comments
Flash Process 1	Alpha	S	Ramping product
	Beta	L	Established product
Logic Process A	Chi	S	Established product
	Delta	M	New flagship product
	Epsilon	L	Kappa chip sets
Logic Process B	Gamma	S	Established product
	Kappa	M	New product launch
	Lambda	L	Various small vol. products

Table 2: Products included in the example case study

For this case study, there are five stepper types, A-E. For each process technology, the various steppers are used to apply different layers on the wafer. Critical layers, for instance, may be applied on a newer generation lithography stepper tool. Each product family Alpha – Lambda will run on different steppers at different run rates with a different number of layers applied per tool as shown in Figure 27.

		Stepper Type Run Rate					Stepper Type Number of Layers				
Technology Process	**Product**	**A**	**B**	**C**	**D**	**E**	**A**	**B**	**C**	**D**	**E**
Flash Process 1	Alpha	23	2	10	9	n/a	8	11	1	8	0
	Beta	14	5	14	16	n/a	8	11	1	8	0
Logic Process A	Chi	10	8	14	n/a	n/a	6	9	6	0	0
	Delta	n/a	11	23	n/a	n/a	0	9	6	0	0
	Epsilon	n/a	9	32	n/a	n/a	0	9	6	0	0
Logic Process B	Gamma	3	n/a	9	14	23	6	0	3	9	2
	Kappa	6	n/a	11	17	25	6	0	4	9	1
	Lambda	4	n/a	15	21	14	2	0	2	9	1

Figure 27. Per product, per tool type data included in the example case study

In this study, the user of the model would like to evaluate the impact on mix sensitive lithography steppers. The tool requirements to meet the base case demand forecast is compared to three possible demand scenarios:

a) The total annual market (TAM) demand increases for all logic and flash technologies by 20%. In this scenario, the per quarter demand for each product increases by 20% over the base case predictions.

b) The new flagship Delta product achieves faster market penetration than anticipated, driving a significant increase in demand. In this scenario, the flash products have the same quarterly demand as in the base case. While the Delta demand increases, demand for the older product, Chi, drops. The increased Delta demand also impacts Process Technology B products, which all experience a decreased volume demand given this scenario.

c) Kappa's product launch is delayed from the intended Q1 date to Q4. As a result, there is zero demand for Kappa until Q4. Demand increases for Chi, an older product, which is an acceptable substitute in the market until the new product is launched.

Table 3 includes the WSPW quarter forecasts for each of the products in the case example, both for the base case as well as for each of the three possible demand scenarios. The data is entered as point estimates into the optimization; variability in the forecasts is not included in this example. Note that all WSPW demand has been disguised.

Base Case

		WSPW Requirement							
Technology Process	**Product**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**	**Q7**	**Q8**
Flash Process 1	Alpha	1611	2902	3061	3138	3628	3593	2990	2443
	Beta	1386	2009	2388	1228	72	0	0	0
Logic Process A	Chi	14501	12131	9626	6907	4556	2296	1941	1958
	Delta	10962	15415	16855	16840	11424	4909	625	0
	Epsilon	618	1212	1020	477	196	92	13	0
Logic Process B	Gamma	1337	2625	3493	4235	5544	7113	6159	5663
	Kappa	31	521	1979	6852	12277	15151	14615	14557
	Lambda	203	669	937	1656	2183	3286	4423	5122

20% TAM Increase

		WSPW Requirement							
Technology Process	**Product**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**	**Q7**	**Q8**
Flash Process 1	Alpha	1933	3482	3673	3766	4354	4312	3588	2932
	Beta	1663	2411	2866	1474	86	0	0	0
Logic Process A	Chi	17401	14557	11551	8288	5467	2755	2329	2350
	Delta	13154	18498	20226	20208	13709	5891	750	0
	Epsilon	742	1454	1224	572	235	110	16	0
Logic Process B	Gamma	1604	3150	4192	5082	6653	8536	7391	6796
	Kappa	37	625	2375	8222	14732	18181	17538	17468
	Lambda	244	803	1124	1987	2620	3943	5308	6146

Rapid market penetration of Delta Product

		WSPW Requirement							
Technology Process	**Product**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**	**Q7**	**Q8**
Flash Process 1	Alpha	1611	2902	3061	3138	3628	3593	2990	2443
	Beta	1386	2009	2388	1228	72	0	0	0
Logic Process A	Chi	10151	8492	6738	4835	3189	1607	1359	1371
	Delta	17539	24664	26968	26944	18278	7854	1000	0
	Epsilon	433	848	714	334	137	64	9	0
Logic Process B	Gamma	1203	2363	3144	3812	4990	6402	5543	5097
	Kappa	28	469	1781	6167	11049	13636	13154	13101
	Lambda	183	602	843	1490	1965	2957	3981	4610

Delayed launch of Kappa Product

		WSPW Requirement							
Technology Process	**Product**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**	**Q7**	**Q8**
Flash Process 1	Alpha	1611	2902	3061	3138	3628	3593	2990	2443
	Beta	1386	2009	2388	1228	72	0	0	0
Logic Process A	Chi	21752	18197	14439	10361	6834	3444	2912	2937
	Delta	10962	15415	16855	16840	11424	4909	625	0
	Epsilon	494	970	816	382	157	74	10	0
Logic Process B	Gamma	1123	2205	2934	3557	4657	5975	5174	4757
	Kappa	0	0	0	1337	2625	3493	4235	5544
	Lambda	264	870	1218	2153	2838	4272	5750	6659

Table 3. WSPW demand for the base case and three scenarios

The output of the model, the additional number of tools required per tool type per quarter is included in Table 4. The model output will include fractional numbers of tools. As previously discussed, the cost of a lithography stepper is significant, therefore, rounding to the higher number of tools can imply a significant cost. However, the model's intent is to be used to compare the relative impact between possible demand scenarios and not for the procurement of equipment. The rounding errors are considered negligible when comparing the relative impact between the possible demand scenarios.

		Q2'01	Q3'01	Q4'01	Q1'02	Q2'02	Q3'02	Q4'02	Q1'03
Base Case	Stepper A	26.86	20.55	19.46	14.39	7.99	0.00	0.00	0.00
Base Case	Stepper B	26.77	12.34	9.14	0.39	0.00	0.00	0.00	0.00
Base Case	Stepper C	0.00	0.00	0.00	2.24	17.98	24.97	16.71	11.61
Base Case	Stepper D	0.00	0.00	2.07	11.09	21.71	26.42	20.85	17.41
Base Case	Stepper E	21.86	16.55	16.46	12.39	6.99	0.00	0.00	0.00
20% TAM Increase	Stepper A	30.59	25.03	23.92	18.34	10.73	1.03	0.00	0.00
20% TAM Increase	Stepper B	38.42	26.60	23.05	7.51	0.00	0.00	0.00	0.00
20% TAM Increase	Stepper C	0.00	0.00	0.00	9.08	27.97	36.36	26.45	20.33
20% TAM Increase	Stepper D	0.00	0.00	4.88	15.71	28.45	34.11	27.42	23.30
20% TAM Increase	Stepper E	24.59	20.03	18.92	13.34	5.73	0.00	0.00	0.00
Rapid Delta Penetration	Stepper A	28.90	20.55	19.46	14.39	7.99	0.00	0.00	0.00
Rapid Delta Penetration	Stepper B	34.32	12.34	9.14	0.39	0.00	0.00	0.00	0.00
Rapid Delta Penetration	Stepper C	0.00	0.00	0.00	0.93	16.42	23.15	15.26	10.39
Rapid Delta Penetration	Stepper D	0.00	0.00	1.17	10.21	20.66	25.20	19.88	16.59
Rapid Delta Penetration	Stepper E	26.90	19.55	19.46	8.39	2.99	0.00	0.00	0.00
Delayed Launch of Kappa	Stepper A	31.13	20.55	19.46	14.39	7.99	0.00	0.00	0.00
Delayed Launch of Kappa	Stepper B	40.31	12.34	9.14	0.39	0.00	0.00	0.00	0.00
Delayed Launch of Kappa	Stepper C	0.00	0.00	0.00	0.93	16.42	23.15	15.26	10.39
Delayed Launch of Kappa	Stepper D	0.00	0.00	1.17	10.21	20.66	25.20	19.88	16.59
Delayed Launch of Kappa	Stepper E	31.13	10.55	9.46	8.39	0.00	0.00	0.00	0.00

Table 4. Optimization model output for a multiple scenario analysis

Figure 28 summarizes the impact of the three possible demand scenarios versus the base case. The graph shows a comparison of the total number of additional tools required to meet the demand in each of the three scenarios and the base case. The number of additional tools per quarter is the total number required in addition to those assumed to be in production or on order and in production for that quarter. Each quarterly total is independent of the prior quarter. No assumptions are made regarding tool purchases in prior quarters based on the output of the model.

As expected, tool capacity for the 20% TAM increase in demand is significantly larger than the base case for all quarters in the planning horizon. The rapid market penetration of the Delta products requires more machines in Q2'01 through Q4'01 due to the significant increase in demand for the larger die size product. Due to the Kappa delay, tool requirements will increase in immediate timeframe. The increase is driven by the demand switching from the new product to an older, larger die size product, until the Kappa is at full production.

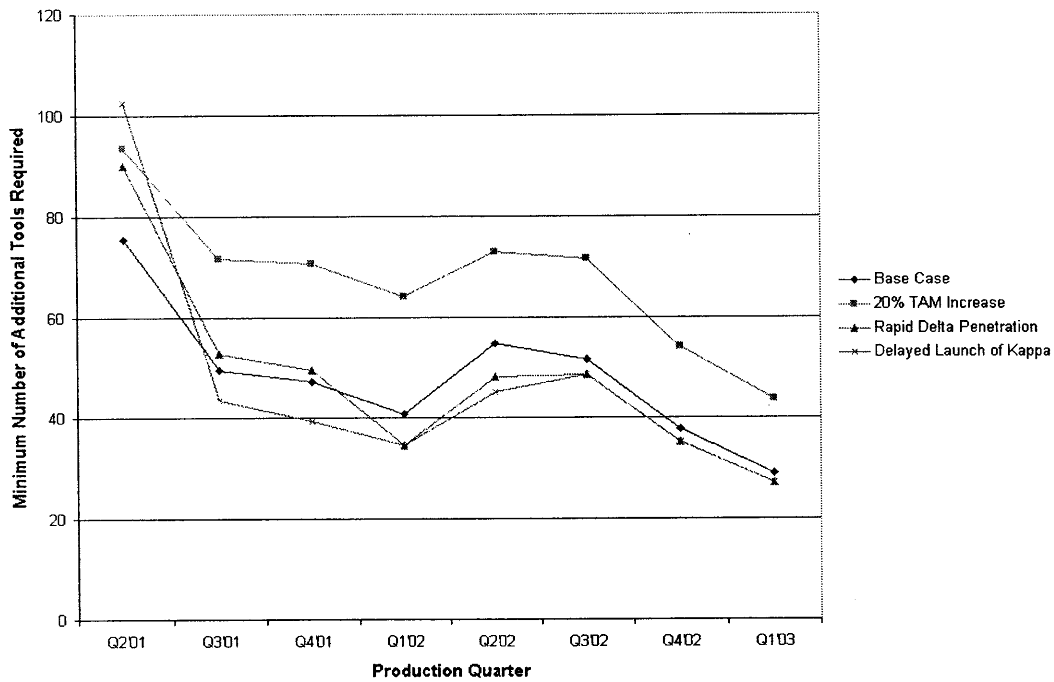

Figure 28. Number of tools required for base case versus three demand scenarios

Figure 29 demonstrates the capability of looking at per tool type requirements. As new tool technologies are introduced and as product manufacturing specs per tool change over time, tool requirements fluctuate. In this case, the base demand projection requires a decrease in tool types A, B, and E over time and an increase in types C and D. Such analysis is extremely valuable for developing tool transition, tool reuse, and procurement strategies.

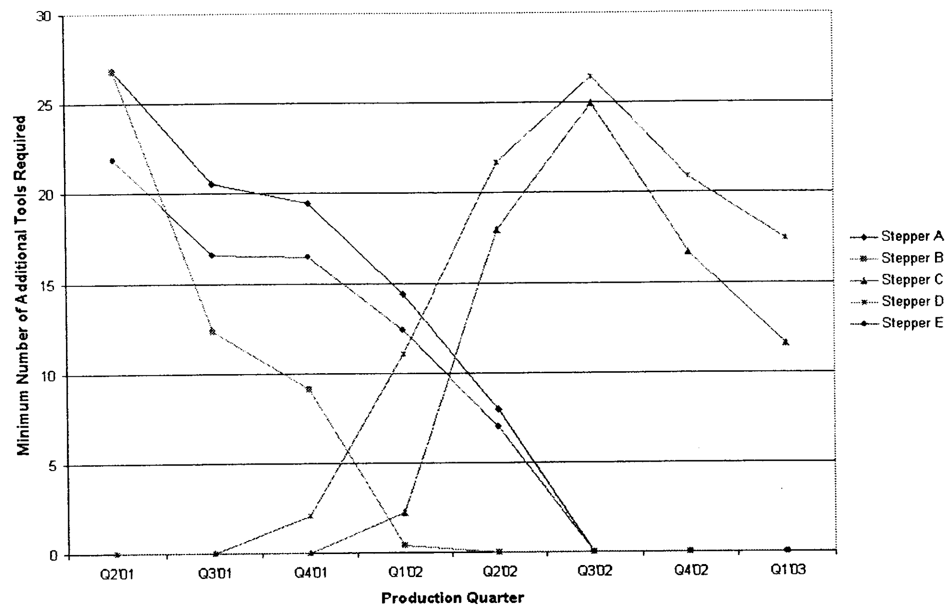

Figure 29. Per stepper type tool requirements to meet the base demand case

Given the level of detailed output from the model, several alternate cuts on the data can be made such as a comparison of tool requirements for a specific tool type given different possible demand scenarios. Such a comparison is done for Stepper Type D and is shown in Figure 30. Note that the same number of Stepper Type D tools is required for both the rapid delta penetration and the delayed launch of Kappa.

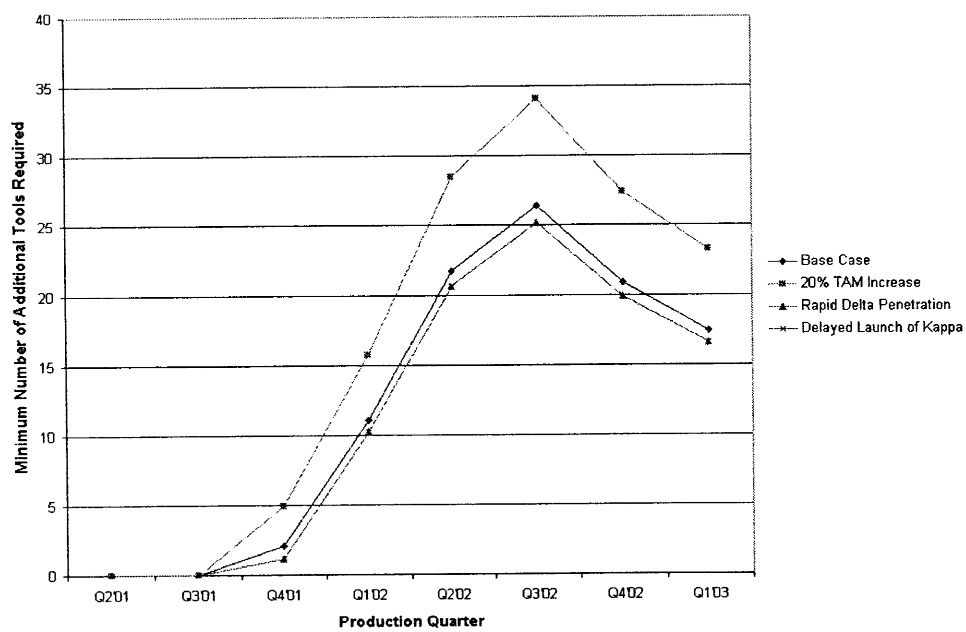

Figure 30. Stepper type D requirements for base versus three demand scenarios

Running the model for each possible demand scenario takes only a few minutes per run. The ability to quickly and efficiently operate the model increases the ability to assess the impact of multiple scenarios. Given the high capital costs and long-lead times of the stepper tools, planning for required tool capacity is a critical step in the long-range capacity planning process. The model is a valuable tool to provide more accurate and more efficient data analysis essential in the planning process.

6.2 Benefits of the New Model and Business Process

The new model significantly reduces the time required to compare multiple scenarios. Once the database has been updated with the correct quarterly production parameters, demand forecasts can be entered and an optimized solution achieved in less than four minutes for a single scenario. If additional variability analysis is desired, the optimizer can be run with the front-end simulator. The run time then depends on the number of trials run. Clearly, the more trials run, the more accurate and meaningful the output of the Monte Carlo simulation. There is a tradeoff, however; the model processing time increases as more runs of the simulation are made.

A common database stores all tool, parameter, and performance data such as die sizes, utilization, and rework. The data warehouse structure eliminates the time consuming task of updating parameters in the multiple Excel models. The model architecture not only saves time inputting data, but also decreases the risk of errors and improves data sharing between multiple users of the model.

An optimization function is used to calculate tool requirements. The minimization is based on tool costs and run rates. The model inherently looks for the most efficient tool on which to run each product. With the former method, assumptions had to be made regarding which tools would be allocated which products.

The optimization also includes a more detailed assessment of the number of tools required. The previous process assumed that all layers of a particular product had the same run rate on a given tool. In reality, the run rate per layer per product per technology can vary for each individual tool type. This level of detail is included in the optimization model, providing a more exact solution.

The revised model takes into consideration the variability inherent in the demand forecasts. With the current process, the demand forecast is assumed to be exact. In reality, there is variation around the WSPW requirements for a given product and there is variability in the mix of products. The Monte Carlo simulator includes the potential for inaccurate forecasts and allows one to assess the impact of the variation on the number of tools required to meet a given demand 'what-if.' The challenge with implementation of the variability model is the increased learning curve and acceptance within the users. Agreement must be reached on the estimates of forecast error to ensure consistent usage and assumptions.

Changing parameter settings in the model can easily generate slight revisions to scenarios. For example, increasing the number of die exposed per step can be achieved by either decreasing the die size or by improving the precision of the reticle. Specific what-if scenarios are often generated to determine the impact of die size changes. However, enhancements to the reticle performance are not. The model allows one to easily address such a possible analysis by simply adjusting the run rates for the affected process in the database and rerunning the optimization.

Given the architecture of the model, future enhancements can be easily made to further increase the precision of the output, user friendliness, and expanded capabilities.

6.3 Ongoing Improvements and Future Enhancements to the Model

To further enhance the model's capability and effectiveness, multiple improvements and ongoing enhancements are possible. As the optimization model and the new variability assessment methodology gain buy-in and user support, momentum for improvements and acceptance as a tool of record will increase. Specific improvements could include, but are not limited to, the following:

Minor model changes can be made to make the tool more efficient and user friendly. For example, enhanced output graphs or charts, a longer forecast range for 16 vs 8 quarters, and variations to the objective function are possible. Alternate objective functions could be written to answer such questions as: how many total tools are required or how many excess tools will be in production?

Larger-scale enhancements include linking the Access data warehouse to a common database of shared parameters across several business units. The current data warehouse is an offline population of multiple data sources. An extensive data warehouse eliminates multiple data storage centers and reduces the risk of potential inadequacies of the data.

The estimated probability of occurrence of each scenario could be explicitly included in the model. Making procurement decisions for the tools must also take into consideration the likelihood of occurrence of that scenario.

As discussed in Section 4.2.1, the financial impact of each scenario must be assessed. For every scenario, there is the option of investing in the capital equipment to be prepared for a possible fluctuation in demand. The cost of preparation must be compared to the possible revenue potential if the demand scenario occurs. Alternatively, the cost of excess capacity must also be weighed. Non-financial aspects further complicate the options analysis. For example, decisions to invest in capacity to support a new market segment or strategic product launch may be necessary regardless of the risk of excess capacity.

The process of forecasting and planning for long-range capacity requirements is extremely challenging in the semiconductor industry. As demonstrated in the case study, the output of the model provides a valuable assessment of the impact of possible product mix scenarios. There are several advantages to the model and opportunities for continued enhancement and ongoing development have been identified. The following chapter describes a benchmarking study of external software products and methods used by others in the industry to forecast long-range capacity requirements.

Chapter 7: Literature Review and Benchmarking Study

Due to the complexity in the semiconductor manufacturing process and the fluctuations in the industry, forecasting demand and planning capacity to meet customer requirements is difficult. Considerable research has been conducted and documented in the area of semiconductor planning. An assessment of texts, current periodicals, and academic research was conducted as background to this work and was used in the formulation of the model criteria and architecture. Section 7.1 highlights some of the documented practices in the semiconductor industry. In addition, examples were considered from other industries faced with similar cost-intensive manufacturing overhead and highly variable demand.

Several companies have developed complex software solutions that attempt to integrate all or part of the semiconductor supply chain. To better understand the issues and questions addressed by the software solutions, several commercial packages were reviewed and are discussed in Section 7.2.

Benchmarking common industry practices and commercial solutions contributed to the definition of the project deliverable and the framework of the model. Key contributing factors are summarized in Section 7.3.

7.1 Review of Literature on Capacity Planning

The literature related to the problem of capacity planning is diverse and covers a wide range of topics. The process of planning can be divided into two primary categories: strategic and operational planning. Strategic planning includes the determination of what products to market, which equipment sets to use in the factories, and the planning of the introduction and retirement of process technologies. The operational aspect of enterprise-wide planning includes the quotation of delivery dates to customers and the determination of output schedules across the fabrication, sort, assembly, and test process steps. According to Leachman of the Engineering Systems Research Center [12], "There are practically no formal systems for strategic enterprise-wide planning in the semiconductor industry, although there are a number of formal systems for operational enterprise-wide planning."

As described in the Engineering Systems semiconductor industry analysis, strategic planning is generally performed ad hoc using spreadsheet tools. Alternatively, the operational planning system is used in an off-line simulation or "what-if" mode. The research indicates that operational planning calculations are made iteratively under different assumptions of products, equipment, and processes to determine more strategic long-range plans. "The particular form of the analysis tends to follow the tastes and preferences of the particular analyst, and it is thus difficult to ascribe a specific technique or methodology for strategic planning to a given particular semiconductor firm."

Although there are few formal, consistent processes used in the semiconductor industry, strategic planning, in particular capacity planning is a critical component of the manufacturer's success. As noted by Jordon and Graves [8] "Increasing manufacturing flexibility is a key strategy for efficiently improving market responsiveness in the face of uncertain future product demand." Planning for manufacturing flexibility and sufficient capacity requires assessing the impact on high-cost, long-lead time tools whose capacity levels are significantly influenced by the type of product or groups of products being manufactured. The problem defined in this work is how to model and calculate long-range capacity requirements for one such tool set. The strategic capacity planning process for mix-sensitive tool sets includes two research questions. How are tool capacity requirements calculated quickly and efficiently for a variety of possible demand forecasts? And second, how are tool requirements forecasted in the face of significant demand uncertainty?

A common tool used to address the first question is mathematical optimizations. Leachman [11] indicates that although the semiconductor manufacturing process is extremely complex, the planning is significantly improved by using optimization techniques. "Planning in the industry is performed both incrementally and in a regenerative fashion. Incremental planning involves adding production to an existing plan in order to meet new demand. . . regenerative planning involves a complete reassessment of the plan in light of revised demands or other changes in the input data. . . [R]egenerative planning offers the ability to more fully optimize production." Optimization has been used predominantly to date for the purpose of incremental, production planning purposes. However, optimization has been more recently applied to the problem of capacity planning (e.g. Stray et al [24]). A specific example of the use of optimization for the purposes of capacity planning is Peters and McGinnis' [20] work in the electronic assembly industry.

Peters et al present and discuss a model for assigning products to various plants when changing product production routings can significantly alter capacity requirements and availability. Although the Peters study focuses on electronic assembly systems, there are numerous similarities to the semiconductor industry that make their model relevant to this work. Similar to the semiconductor industry, the electronics market is faced with short product life cycles, high-cost production facilities, and fluctuating demand. Production facilities are either focused (dedicated to one product line) or nonfocused. The Peters work seeks “a better understanding of the nature and impact of capacity constraints on the strategic configuration decision when a pure focused strategy is used.”

Peters demonstrates the use of an optimization model to calculate the minimum capacity required to satisfy production requirements. In the course of calculating the minimum requirements, an initial set of product assignments/reassignments is developed as well as “a network flow based procedure for determining the optimal assignment/reassignment process.”

The intended output of the Peters model is similar to the questions addressed in this work. This thesis is focused on the development of a tool to assess the impact of possible demand forecasts on tool set requirements. The optimization approach discussed by Peters addresses the same desired result. The model and solution determines the minimum capacity solution for a given scenario.

> “The decision maker can compare this solution to the company’s current or planned configuration. In addition, due to the speed of the solution procedure, the decision-maker can perform sensitivity analysis on the input information to determine how the solution changes with differing estimates of future parameter values (e.g., product introduction times, demand forecasts, etc.). This information about the best solutions based on capacity and reassignment costs under different scenarios may provide valuable insight to the decision maker.”

The Peter’s model is focused on the electronics industry, but the methodology and optimization approach is applicable to the problems addressed by this work.

Papageorgiou, Rotstein, and Shah [19] document a supply chain optimization model used for the pharmaceutical industry. Like Peters’ work in the electronic assembly market, the pharmaceutical industry has several similarities to semiconductors. The typical life cycles of new drugs are becoming shorter, making strategic decisions about capacity plans, product development schedules ever more critical. Papageorgiou “describes an optimization-based approach to selecting both a product development and introduction strategy and a capacity planning and investment strategy.” A mixed-integer linear programming model is used to select “the optimal product development and introduction strategy together with long-term capacity planning and investment strategy at multiple sites.” Although the authors acknowledge that the scope of the model is prohibitively large, it demonstrates the possible use of an optimization approach to assessing capacity requirements. Papageorgiou also identifies the need for an extension to the work that takes into consideration demand uncertainty. “For example, the uncertainty on the outcome of the clinical trials of all candidate products could be incorporated within our existing framework.”

A similar optimization approach to determine capacity expansion requirements in the semiconductor market is documented by Bard [2]. "For a given demand and planning horizon, the general facility design problem faced by semiconductor manufacturers is to decide how much capacity to build into their systems." He models the capacity expansion problem "as a nonlinear integer program in which the decision variables correspond to the number of tools at a workstation." Bard addresses a similar problem as the intent of this thesis. "Semiconductor facilities are designed to run certain technologies or product families at a predetermined rate of output." When changes occur in the intended product or product mix, the capacity of the system is impacted. Bard uses his optimization model to calculate tool-set configurations for different budget values and corresponding optimal cycle times to generate a frontier curve for the trade-off between capital and cycle time and capital and WIP. "These relationships can also be used to evaluate the impact of changes in throughput, product mix and technology on WIP and cycle time. Such trade-off curves provide management with a range of options as well as a means of conducting a margin analysis."

In addition to such external literature, a review of planning procedures and tools internal to Intel was conducted. The internal assessment highlighted best practices within other organizations and existing tools that could be leveraged. Wuerfel [28] documents the use of a linear program to solve the problem of allocating wafer start production to various factories to maximize the total wafer output of all factories combined. Wuerfel's study is used in the operational planning (build plan) stage in which the actual production routings for product are determined. The product routing is complicated by the lithography process step. "The lithography area complicates the problem since its process steps are extremely sensitive to factory product-mix. This sensitivity is because stepper run-rates are greatly determined by a product's die size and the number of die per exposure field." Wuerfel's Lithography Loadings Optimizer determines the optimum production routing within the lithography capacity constraints for that given product mix. Wuerfel's work is intended for short-term planning, but is very relevant to the intent of this thesis. The linear program developed by Wuerfel addresses the lithography capacity constraints driven by the product or mix of products being manufactured.

Many of the optimization solutions cited do not take into consideration the uncertainty in the product demand or production process. As Leachman [11] discusses, planning in the semiconductor industry is daunting due to the inherent complexities in the manufacturing process, the product structure, and demand. "There may be significant uncertainties in market demands; and there may be a great variety of demand types for each finished good, ranging from firm orders to flexible customer contracts to reliable forecasts to risky forecasts." Due to the uncertainty, treating demand uniformly is an oversimplification of the problem.

This work seeks to address both the question of how are capacity requirements calculated and, second, how are tool forecasts made in the face of demand uncertainty? As Petkov and Maranas [21] note, "Deterministic models for process planning and scheduling assume that product demands are known with certainty. However, in medium and long-term planning, product demands fluctuate. Failure to properly account for product demand fluctuations may lead to either unsatisfied customer demands and loss of market share or excessive inventory costs."

One common approach to addressing the possible fluctuations in forecasts is to run several optimization routines that calculate capacity requirements for each of the possible demand scenarios. Leachman [11] proposes an iterative optimization calculation to address the possible changes in the optimization variables. Although the iterative, scenario based approach is a very straightforward way to implicitly account for uncertainty, Petkov points out that the scenarios "typically rely on either the *a priori* forecasting of all possible outcomes or the discretization of a continuous multivariate probability distribution." Petkov notes that Monte Carlo sampling is often used to address multivariate probability sampling. "The basic idea of Monte Carlo methods is to generate a large enough number of random variates distributed according to the evaluated multivariate probability function." Petkov also notes, however, the disadvantage of Monte Carlo sampling with the optimization routine. "Monte Carlo sampling based approaches require multiple function evaluations to estimate the objective function, constraints, and their gradients at every iteration of the optimization algorithm." The Petkov solution is a stochastic model, which maximizes expected profits "subject to the satisfaction of single or multiple product demands with prespecified probability levels (chance-constraints)." The Petkov approach is applied to medium- and long-term planning for chemical batch plants, but the philosophy is applicable to the planning of tool capacities in the face of demand uncertainty.

As previously discussed, strategic planning in the pharmaceutical market faces many of the same challenges as the semiconductor industry. Examples of how uncertainty is addressed in strategic planning are relevant to this work. Gupta and Maranas [9] point out:

> "One of the key sources of uncertainty in any production-distribution system is the product demand. . . . Deterministic planning and scheduling models may thus yield unrealistic results by failing to capture the effect of demand variability on the

> tradeoff between lost sales and inventory holding costs. Failure to incorporate a stochastic description of the product demand could lead to either unsatisfied customer demand and loss of market share or excessively high inventory holding costs. . ."

Gupta and Maranas describe a two-state stochastic program in which uncertain product demands and other uncertain variables are "modeled as normally distributed random variables. This approach has been widely invoked in the literature as it captures the essential features of demand uncertainty and is convenient to use." Similar to Gupta, Blau et al recognize the impact of demand uncertainty and describe a model that uses a Monte Carlo simulation in Crystal Ball. Blau's model is used in the strategic product development planning process to assess possible product portfolios and the trade-offs between the portfolio's risk and rate of return.

In the semiconductor industry specifically, Swaminathan [25] addresses the challenge of wafer fabrication tool procurement in the face of demand uncertainty. Changes in the technology and products, lead-time for procurement, the cost of the tools, and unpredictable demands are all factors that make tool procurement planning difficult. Swaminathan describes an "analytical model for tool procurement that incorporates the uncertainty in demand forecasts and provides methods to operationally hedge against it. Our model enables a manufacturer to plan for a set of possible demand scenarios (as opposed to a single coordinated plan) and procure an efficient set of tools." The model uses a mixed integer program and two heuristics to explicitly capture uncertainty in demand. Swaminathan's work demonstrates that, "planning for a set of demand scenarios is more efficient than planning for a coordinated demand forecast."

As evidenced by the literature review above, taking the impact of demand uncertainty into capacity planning is critical. Various models and techniques have been used to address the uncertainty in the tool capacity requirement calculation. In addition to literature, the solutions provided by several commercial software solutions were analyzed.

7.2 Analysis of Commercial Software Solutions for Capacity Planning

There are numerous commercially available software packages that are used by manufacturing firms to improve strategic enterprise-wide planning. i2 Technologies, SAP, PeopleSoft, and Manugistics are some of the many commercial solutions. Some of the software vendors, such as i2's High Tech Electronics and Electronics Industry segment, have package solutions intended specifically for the semiconductor industry. Semiconductor manufacturers such as Motorola and Philips Semiconductor are users of such commercial planning solutions.

Commercial solutions provide the benefit of structured, previously tested, generally user-friendly packages. The software package often integrates multiple aspects of the overall supply chain, including customer management, supplier relationship management, inventory management and strategic alliances. In addition to providing strategic planning capabilities, many of the software solutions integrate with the operational packages that are responsible for planning day-to-day production.

Specific questions addressed by supply chain software packages, such as i2 Technologies' RHYTHM Profit Optimization include [7]:

- What is the most profitable mix of products to manufacture given current resources?
- Is outsourcing the correct strategy and at what level?
- What is the financial impact of adding capacity, decreasing inventory levels, increasing demand for a product, or lowering minimum requirements for demand fulfillment?
- How much would additional capacity on a given resource improve the bottom line?

The software solutions have a general framework, which is not always flexible for very application-specific requirements. Extensive specialization and customization of the software package may be required to meet the needs of each customer. In addition, there are significant start-up costs. Commercial packages require not only purchase of the software, but often multiple user licenses, integration services, application consulting, and long-term service and support.

Three packages frequently used in the semiconductor industry were assessed. A brief summary of the analysis of each vendor's solution can be found in Appendices 1-3.

7.3 Summary of Key Findings and Influence on the Design of this Work

Benchmarking capacity planning practices across the semiconductor and related industries provides valuable insights into ways to improve and expand current planning practices. The literature and commercial software solutions reviewed influenced the problem definition and model architecture described in this thesis.

Optimization models by Bard, Leachman, and Peters and McGinnis demonstrate the applicability of optimization models in the capacity planning process. In this work, the model uses a linear program to address the question of how to quickly and efficiently calculate tool capacity requirements. The optimization approach allows one to easily determine capacity requirements and to assess the impact of changing product and manufacturing parameters. As demonstrated by Bard [2], the optimization model allows one to change product mix, product run rates, and tool parameters to assess the associated impact on capacity.

As demonstrated in the literature, taking into consideration demand uncertainty is a critical component of the planning process. The current process used by the Strategic Capacity Planning team does not address the demand uncertainty. Numerous model architectures have been developed to address the variability. This work introduces an innovative approach to combining an optimization model and Monte Carlo simulation to address the uncertainty. The model is a straightforward solution, which addresses each uncertain variable as a probability distribution.

The literature and commercial software solutions reviewed contributed to the problem definition and architecture of the model. Summary comment and possible follow-on work are discussed in Chapter 8.

Chapter 8: Conclusions

Due to the rapid fluctuations in market demand and the ever increasing pace of technological development, planning for manufacturing flexibility is ever more critical. As the timing of capacity roadmaps accelerate, the time to develop new products is shorter as is the production window to recover investments. Assessing the impact of demand fluctuations on mix sensitive, critical tools becomes ever more essential.

This thesis describes an improved modeling approach and an improved model and business process for determining the impact of possible demand scenarios. The work first discussed the challenges inherent in forecasting integrated circuit demand and the complexity inherent in the manufacturing process. The thesis then introduced an innovative solution to the current methods of assessing the impact of mix-changes on lithography steppers. An optimization model was built to determine an optimum solution, the minimum number of tools required to meet a given WSPW demand forecast. The model was then expanded through integration with a Monte Carlo simulation. The simulation incorporates an assessment of variability due to the uncertainty in forecasting, both demand volume and product mix. A case scenario was created to demonstrate the model's functionality and output. The thesis also reviews current literature on the practices of capacity planning as well as commercial software tools commonly used for long-range strategic planning.

While the model developed provides improved analysis and increased efficiency in the planning process, there are areas for continued study. As discussed in Section 4.2.1, a complete analysis of the most likely, highest impact scenario should include an integrated analysis of the value created by preparing for a possible demand scenario. Belnap, [3] in his 1995 Massachusetts Institute of Technology thesis, discusses options analysis as an innovative tool for manufacturing decision-making:

> "As manufacturers become more cross-functionally integrated and globally competitive, manufacturing decisions are becoming increasingly complex. Among the tools available to manufacturing decision-makers, NPV and similar financial tools have traditionally been the backbone for operational decision analysis. However, because these financial tools capture only operational value and not strategic value, decision-makers are often misguided in their decisions and/or the management of those decisions."

Belnap introduces "the theory of financial options (stock options) and develops the analogy of stock options to options on real assets (real options)." The theory of real options can be used for quantifying the strategic value of a manufacturing decision as a complement to operational, net present value. The options analysis described by Belnap could be integrated with the model developed in this thesis.

For each demand scenario, there are tradeoffs between the revenue potential generated by the demand for that mix and volume of products and the costs of preparing manufacturing capacity to meet that demand. The concept of assessing real options analysis as a follow-on to this work was presented and accepted. Implementation and integration, however, will meet with several of the same challenges faced during the implementation of the optimizer and Monte Carlo simulation.

Linear programs that take into consideration several constraints to find an optimum solution are not uncommon in the planning process. As a result, the concept of using a linear program based on a common database of inputs was well received and accepted. The initial concept tool included only a few processes, products, and a limited time frame. The demonstrated capability and value of the model increased acceptance. The momentum generated from the initial wins contributed to the successful development of the full-scale model, which incorporated a larger range of process technology generations and a longer time frame.

Using a simulator to assess the impact of forecast uncertainty was however, not a common practice. The current planning process relies on the generation of several independent demand scenarios as point estimates of future demand. As the research demonstrated, there is error in the forecasts due to the demand uncertainty. The approach of applying historical error to future forecasts in a Monte Carlo simulation was an innovative approach. A key element of the project was, therefore, experiencing the process of pitching a new concept, demonstrating the potential, gaining credibility, and obtaining buy-in from key stakeholders for the development of the integrated model.

Appendix 1. Commercial Software Overview: SAP

Package Overview:

SAP's Advanced Planning Optimizer has three sub-components:

Demand Planning
Production Planning
Supply Network Planning

Specifics:

The SAP solution has a basic package that the user changes to address his or her needs. SAP does not view each application as a customized solution; rather the user manages the package to meet requirements.

The SAP solution is intended for planning within the short-term, 9-month window. However, the package could also be used for longer-term planning, but at a different level of aggregation. For example, instead of assessing the machine-specific requirements, the aggregate capacity, space, and machine needs would be determined.

APO's Demand Planning package includes a toolbox of statistical forecasting techniques to create the most accurate forecast. Demand plans are based on historical patterns as well as statistical methods, which include average models, exponential smoothing, causal factors, and trend dampening.

The Supply Network Planning (SNP) module is defined as a midterm planning tool to match supply and demand throughout the entire chain. The package integrates purchasing, manufacturing, distribution, and transportation. It models the entire supply network and related constraints and provides cost/profit based optimization capability.

Within SNP, the Capable to Match (CTM) solver takes prioritized demand and tries to match it to categorized supply. CTM is responsible for making sourcing decisions within the supply chain and ensures that multiple locations meet a single requirement. CTM uses priorities to determine how a requirement can be supported, which product should be supported first, which transportation lane should be sourced first, and what recipe should be run at a specific location. The Interactive Planning Table (IPT) can be used to quickly assess the capacity plan for a specific product over time.

Various modules are available within SNP. One such module is the model mix planner. This module enables production planners determine the optimum order sequence and scheduling for manufacturing products with a large number of variants.

Industries and Customers Served:

SAP has several customers who currently use the SAP ERP systems and have expanded their applications to include the Supply Network Planner. SAP does not have a dominant presence in the semiconductor market. Users are from varied industries including food and beverage, chemicals, transportation, and consumer products. Companies such as Mott's, Dow Corning, Colgate, Goodyear, and Lufthansa have implemented the Supply Network Planning packages.

Appendix 2. Commercial Software Overview: i2 Technologies

Package Overview:

The RHYTHM Supply Chain Management Software (SCM) has three sub-processes:

- Demand Planner: Helps the manufacturer understand the customer's buying patterns and develop accurate forecasts. Long, intermediate, and short-term horizons are included.
- Demand Fulfillment: Assigns delivery dates to customer orders and provides reliable delivery date commitments.
- Supply Planner (SCP): Optimally positions resources to meet demand. Strategic planning, inventory planning, distribution and transportation planning are included.

Planning within the SCP package can be done at a strategic, high-level with Master Planner or factory production level with Factory Planner. Long-term planning is more mathematical, often using optimization techniques, while short term planning is based on heuristics.

i2 modules can be incorporated into other business process systems such as SAP, Oracle, or others. In fact, 40-50% of their applications are integrated with 3rd party software packages.

Specifics:

Master Planner: The Master Planner allows for high-level, strategic analysis of demand forecasts versus overall facility capacity to determine if additional capacity is required. Most users apply Master Planner for planning in the one-year time horizon; however, the product could be easily applied for the two-five year time horizon required for long-range planning. The system is flexible enough to allow one to look at demand from two lenses: given the current demand, capacity, and business rules, what criteria are violated or what capacity is required given the projected demand.

The Master Planner package integrates planning across the entire supply line, from fab, sort, assembly, test, to final transportation and logistics. The effect of a demand change can be easily assessed throughout the entire supply line.

Master Planner is typically used to plan requirements at a high level. However, both the factory and Master Planner can be used at the machine level. The package can determine the number of burn-in chambers or steppers required as well as the percentage utilization and production loading. For longer-term planning, the machines are often grouped categorically. For example, the number of steppers is determined versus the specific requirements for each machine type.

With Master Planner, one can run several what-if demand scenarios to determine the capacity required for each. One can also change the product mix and assess the impact on capacity requirements. For example, one can run a 90/10% mix of two different products and then change the mix to 70/30% to determine the new capacity required. The software will also report the customer service levels and assess the business rules violated with the different combinations.

Rhythm Profit Optimization: This module, included within RHYTHM SCP Master Planner, calculates the financial impact of a plan by modeling cash inflows for sale of product and outflows for procurement of material, performance of manufacturing and distribution operations, and for carrying inventory. With the profit optimizer, planning organizations can answer such questions as what is the most profitable mix of products to make, where should the products be made, and how much additional capacity on a given resource would improve the bottom line. In a capacity constrained environment, the profit optimizer is used to determine what is the optimum product mix that maximizes profit. The model optimizes on revenue and costs given the resource requirements for operations, resource availability, and material requirements. A Product Intrinsics" report can be generated which shows both dimensions critical to determine the attractiveness of a product in the mix. The margin information as well, as the different usages of critical resources or materials are evaluated to determine which products are the most attractive.

Factory Planner: At the Factory Planner level, exact production schedules are determined. The i2 Factory Planner is closely integrated with AutoSimulation's APF package for production execution. Factory Planner is based on the Theory of Constraints. Given the business criteria defined, Factory Planner looks for the 'most critical' bottleneck in the system. The optimizer then level loads that bottleneck, assesses the impact on the overall system, and then looks for the next most critical bottleneck and repeats the process.

One can also set hard and soft limits on various constraints. The system will then report which of the constraints have been violated and to what extent. Similarly, one can set tolerances for the system. For example, within what range one will allow the system to plan over capacity, what is the maximum overdue order, or what lead-time window is acceptable. One can then optimize based on different objectives such as ship all orders before the promised date.

Factory Planner is used for planning in the short-term, when one is working with a finite capacity available. The Factory Planner can help prioritize orders based on the capacity available.

Industries and Customers Served:

The primary industries served by i2 include semiconductor, automotive, general consumer, energy & chemicals, metals, pharmaceuticals, and transportation.

Motorola currently uses Master and Factory Planner solutions for long and short term planning. Dell is one current user of the i2 solution. They use the Factory Planner and run continual 'what if' demand scenarios to determine the effect of product demand variations. They run the what if analyzer off-line to determine the most critical effects and identify avoidance game plans before they happen. Other customers of the i2 solutions include Apple, Digital, HP, Seagate, AMD, Fujitsu, IBM, National Semiconductor, NEC, Phillips Semiconductor and others.

Appendix 3. Commercial Software Overview: Manugistics

Package Overview:

Manugistic's Business Process package is called NetWORKS. Within the NetWORKS solution set, there are numerous modules including NetWORKS Demand™, NetWORKS Strategy™, NetWORKS Commit™, NetWORKS Fulfillment™, NetWORKS Supply™, NetWORKS Master Planning™, NetWORKS Transport™, NetWORKS Scheduling™, NetWORKS Procurement™, among others.

Specifics:

The NetWORKS Master Planning and Strategy modules would have the closest applicability for long-range strategic planning.

<u>NetWORKS Master Planning</u> is typically intended for planning in the short term given existing material and capacity availability. The optimizer produces an optimized plan to allocate and coordinate limited resources based upon different business strategies. The planning package optimizes based on the use of constrained resources to improve customer service and profit while reducing asset investment.

<u>NetWORKS Strategy</u> models a company's global trading network to help a company determine optimal inventory levels, the appropriate product mix across a network, optimal production, storage, and distribution locations, and appropriate seasonal pre-builds. The optimizer balances the global supply chain network over time by product, customer, product life cycle, and location for maximum profits.

Industries and Customers Served:

The primary industries served by Manugistics include apparel, automotive, consumer packaged goods, electronics, food, and government. Manugistics does not have a specific focus on the semiconductor industry. Customers within the electronics industry include Analog Devices, Bose, Compaq, Ericsson, Harris Semiconductor, IBM, Lucent, Nokia, and others.

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