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Supply Network Capacity Planning for Semiconductor Manufacturing With Uncertain Demand and Correlation in Demand Considerations

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Abstract

A semiconductor supply network involves many expensive steps, which have to be executed to serve global markets. The complexity of global capacity planning combined with the large capital expenditures to increase factory capacity makes it important to incorporate optimization methodologies for cost reduction and long-term planning. The typical view of a semiconductor supply network consists of layers for wafer fab, sort, assembly, test and demand centers. We present a two-stage stochastic integer-programming formulation to model a semiconductor supply network. The model makes strategic capacity decisions, (i.e., build factories or outsource) while accounting for the uncertainties in demand for multiple products. We use the model not only to analyze how variability in demand affects the make/buy decisions but also to investigate how the correlation between demands of different products affects these strategic decisions. Finally, we demonstrate the value of incorporating demand uncertainty into a decision-making scheme.

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ABSTRACT

A semiconductor supply network involves many expensive steps, which have to be executed to serve global markets. The complexity of global capacity planning combined with the large capital expenditures to increase factory capacity makes it important to incorporate optimization methodologies for cost reduction and long-term planning. The typical view of a semiconductor supply network consists of layers for wafer fab, sort, assembly, test and demand centers. We present a two-stage stochastic integer-programming formulation to model a semiconductor supply network. The model makes strategic capacity decisions, (i.e., build factories or outsource) while accounting for the uncertainties in demand for multiple products. We use the model not only to analyze how variability in demand affects the make/buy decisions but also to investigate how the correlation between demands of different products affects these strategic decisions. Finally, we demonstrate the value of incorporating demand uncertainty into a decision-making scheme.

Key Words: Supply Network Capacity; Stochastic Programming; Production Planning; Semiconductor Manufacturing

1. Introduction

The supply network of the semiconductor industry, illustrated in Figure 1, requires many expensive steps. With the increasing globalization of company operations, it is important to benefit from advanced optimization techniques for cost reduction in long-term operational and strategic planning. Stray et al. (2006) developed a Mixed Integer Program (MIP) to aid allocation and routing decisions in the semiconductor industry. The model determines effective allocation of products to wafer fabrication facilities and routes the wafers in process to the initial testing area of wafers and integrated circuits (sort). These tested wafers are then sent to a facility where they are cut into individual chips, and placed in a package (assembly). Next, they are routed to final test facilities for testing and classification (test), and later shipped to distribution centers (demand) or customers.

Semiconductor manufacturing is a cyclical and dynamic business; thus there have been major swings in demand since the industry was founded. The complex process of matching final demand with projected and available capacity clearly merits the use of formal decision support techniques. However, model in Stray et al. (2006) does not consider the uncertainty of future demand which is usually the case in semiconductor industry. On the other hand, with the recent improvements in computer computation there have been several papers published in the literature which considers demand uncertainty in planning for semiconductor industry (Barahona et al. 2005, Hood et al. 2003, Huh et al. 2006, Swaminathan 2000). Huang and Ahmed (2009) give a multi-stage formulation of tool planning in semiconductor industry under uncertainty and present analytical bounds on the value of the multi-stage stochastic programming. In this paper, we present a two-stage stochastic integer programming model that can handle demand uncertainty and is capable of making dynamic decisions based on later realization of the demand to optimize and analyze a semiconductor supply network. For this purpose, we use Stochastic Integer Programming (SIP) to improve system flexibility and solution robustness under demand uncertainty. A two-stage model with complete recourse is formulated, wherein the production, planning, transportation and outsourcing decisions are taken as the first stage decisions without the full knowledge of future demand. After realization of the demand for multiple products (i.e. specifying uncertain parameters), the second stage (recourse) actions are taken to adjust the production and planning decisions to maximize total expected profit. Different than the previous studies in the literature, we use our model to analyze the effects of the correlation between products into the strategic decision making process. We consider positive correlation of demand among the product families which can be caused by the industrial life cycle of the leading indicator product, e.g. a chip set, affecting the demand for other products (Meixell and Wu 2001). We also consider negative correlation case on the demand of product families. This can occur in the semiconductor industry for succeeding technologies in the market (Cakanyildirim and Roundy 2002) where an increase/decrease in demand for the newer technology may lead to an increase/decrease in the demand for the older technology. In addition, the case of no correlation among the demand of product families is also analyzed.

We use our SIP model to analyze the trade-off between building a new fab and outsourcing production. We also carry out extensive numerical studies to understand the conditions when it is profitable to build a new fab. Our numerical results indicate that for each problem, there is a certain variance interval that makes investing in a new fab reasonable, i.e., there is a lower bound and an upper bound for the variance levels where it is profitable to invest. Contrary to our intuition that says it is better to invest when there is low risk, our results show that the lower bound may be different than zero depending on the correlation between products. We demonstrate that the lower bound for this variance interval increases as the positive correlation between demand for different products increases. We also investigate the benefits of incorporating demand uncertainty into the decision-making framework.

<<Figure 1>>

2. Literature Review

Semiconductor manufacturing is a global process and involves a complex network consisting of wafer fabrication facilities, sort facilities, assembly facilities, warehouses and distribution centers as shown in Figure 1. The majority of chips cross at least one international border during processing. Customs, transportation, and storage issues all add uncertainty to the supply process. To save labor costs and take advantage of tax breaks, manufacturers have globally dispersed the stages of the manufacturing process. For many years, semiconductor companies have had the option to do the assembly and test operations in-house or to subcontract this work. This complex network structure makes production and capacity planning activities very difficult tasks for industry practitioners and provides the motivation to use mathematical tools in decision support.

The use of optimization models for routing and planning in the semiconductor industry has been discussed using linear programming and mixed integer programming as well as stochastic programs (Chouinard et al. 2008, Azaron et al. 2008, Thanh et al. 2008, Huh et al. 2006, Barahona et al. 2005, Hood et al. 2003, Swaminathan 2000,). For example, Thanh et al. (2008) recently presented a deterministic mixed integer linear program for designing a production distribution system. On the other hand, Chouinard et al. (2008) evaluates the impacts of uncertainty related to recovery, processing and demand volumes at the same time in logistics network design with the integration of reverse logistics into supply chains. Azaron et al. (2008) present a multi-objective stochastic program with multiple uncertain parameters in a way to not only minimize total expected cost, but also to minimize financial risk.

Stochastic linear programs are linear programs where some of the problem data (parameters, or coefficients) are treated as random variables (Kall et al., 1994). Recourse programs are those where some decisions (recourse actions) are taken after uncertainty is realized, to adjust the plans that were made when data was unknown. Wallace (2000) discusses the issues in decision making under uncertainty. He comments on the use of sensitivity analysis to facilitate decision making under uncertainty by means of a deterministic tool, namely parametric linear programming and demonstrates that stability and optimality are unrelated where parameters are uncertain. He suggests stochastic programming as a useful tool in minimizing expected costs. Walsh (2000) has a similar approach, developing a flexible workforce in a semiconductor environment using two-stage stochastic programming with recourse to handle uncertain parameters.

For semiconductor capacity planning with uncertain information, Huh et al. (2006) present a capacity planning model that addresses tool procurement and retirement decisions to minimize expected lost sale costs and capital costs. They assume product demands to be uncertain and time is modeled as a continuous variable. In a supply network planning problem, the complexity of the model increases very fast due to the increment in the problem size when introducing uncertainty to the model. With this fact, it is obvious that the computational tractability will dramatically decrease with continuous time consideration as in Huh et al. (2006).

In an earlier study, Swaminathan (2000) models the tool capacity planning problem with uncertainty related to demand profiles. Heuristic methods are presented to find robust procurement plans in a single time period because of the computational difficulty that stochastic integer programs have. Beside the shortfall of considering only a single period, the planning activity includes only tool procurement decisions which are only one option in production planning.

Barahona et al. (2005) formulate a stochastic mixed integer program for capacity planning under demand uncertainty for semiconductor manufacturing. The objective is defined as minimizing the expected unmet demand due to capacity and budget constraints. Again, demand is modeled with a discrete set of scenarios and they present a heuristic to solve the large scale planning problem which is based on a branch and bound procedure with cutting planes. They consider a planning time frame that makes the problem more tractable. However, most of the supply chain planning decisions are made for longer time frames. In addition, the correlation on multiple products is not considered as a factor affecting strategic decisions. For a similar problem in semiconductor manufacturing, Hood et al. (2003) use stochastic integer programming for capacity planning. They consider a small number of scenarios for demand profiles on multiple products. However, the paper is mainly focused on how robust decisions can be made via stochastic programs in business planning integration. They conclude that their model is robust to demand uncertainties and product mix changes.

In the literature, several other studies tackle uncertainty in different industries with stochastic programming. Santoso et al. (2005) consider several factors other than demand including processing costs, supplies and capacities as uncertain. They also present a sampling strategy with an accelerated Benders Decomposition algorithm to quickly compute high quality solutions for large scale supply chain design problems. In addition, a robust optimization model is presented by Leung et al. (2007) to address a multi-site production planning problem for a lingerie company. A medium-term planning horizon with an objective of minimizing the total production, inventory, labor, and workforce changing costs are considered. The difference between the solution robustness and model robustness is addressed in the paper. However, they do not compare the stochastic linear programming solution with the robust solution to address the advantages and disadvantages of robust and stochastic programming models.

Goh et al. (2007) present a new method for minimizing the supply chain risks which are defined with uncertain parameters in the planning horizon with a multi-stage stochastic program. They provide the theoretical background for solving multi-stage stochastic programs which is computationally hard but they do not provide any computational results for different cases and problem instances.

In this paper, the model of Stray et al. (2006) is extended, to include uncertainty in product demand and the correlation between demands of multiple products. Allowing for uncertainty to be represented in the mathematical model for demand, leads to more robust decisions in strategic planning which is demonstrated using the value of the stochastic solution and the efficiency of stochastic solution metrics. In addition, considering the correlation between the demands on multiple products gives additional insights on make/buy decisions by identifying upper and lower bounds for the level of correlation between multiple products. The model also provides the recourse actions in each scenario that further help in minimizing the total expected costs.

In this work, we present a two-stage stochastic programming model with mixed integer recourse to address the semiconductor manufacturing capacity planning problem with demand uncertainty. Two-stage stochastic programs with integer recourse are computationally hard to solve as the second stage integrality constraints cause the recourse function to be non-convex. However, there exist solution methodologies to address this problem. Lucas et al. (2001) present a solution method for two-stage stochastic integer programs based on Lagrangian relaxation and column generation. This method can also be applied in the semiconductor manufacturing setting. Ahmed and Shapiro (2002) present a branch-and-bound based algorithm to solve problems with integer second-stage variables and a finite number of scenarios.

For the rest of the paper, we formulate the supply network of a semiconductor manufacturer under demand uncertainty with a two-stage, multi-period stochastic mixed integer program (SMIP) with complete recourse. In contrast to the work cited above, we do not present a new solution methodology in this work but rather concentrating on a thorough analysis of optimal make/buy decisions under demand uncertainty with various demand correlation structures between products. We also demonstrate the value of using stochastic programming in our decision-making framework. Finally, we conclude by suggesting some future research directions.

3. The Stochastic Mixed Integer Programming Model

In our model we model the semiconductor supply network under uncertain demand using a two-stage, multi-period Stochastic Mixed Integer Program (SMIP) with recourse. The first stage decisions include purchasing of tools at various production facilities, outsourcing production or even construction of a new production facility depending upon the demand. The second stage (recourse) actions include increasing the internal capacity (purchasing tools) as well as external capacity (subcontracting) and cancellation of contracts for outsourcing made in the first stage, as shown in Figure 2.

<< Figure 2>>

The model provides information regarding the tradeoffs between risk and expected short and long-term returns. It is coded in AMPL (A Modeling Language for Mathematical Programming, Fourer, Gay and Kernighan 1993) and solved using CPLEX 6.5.2 (CPLEX 1997). The model is formulated in the Appendix and below we present the notation of the formulation.

The Sets and Indices

Sets are the group of items that relate to each other in a particular way or that are treated in a similar fashion. For modeling purposes, various sets are used and are listed below with their indices.

$\omega \in \Omega$	Set of all scenarios
$f \in FAM$	Set of all product families
$p \in PKG_f$	Set of packages for each product family f
$b \in BIN_{fp}$	Set of bins for each product of package p and family f
$l \in L$	Set of all location sets. Includes wafer fab set L_F, sort location set L_S, assembly set L_M, test set L_T and demand center set L_D
$i \in TG_l$	Set of constraining tool groups at location l

The Parameters

Parameters, indexed over sets, are the costs associated with the variables. Because of the two stage nature of the problem, the parameters that describe the costs associated with the second stage and are indexed over ω in addition to other indices. Superscript 1 and 2 differentiates the parameters appearing in stage one and stage two, respectively. Note that the products are indexed over *f* for wafer fab and wafer sorts, *fp* for assembly, *fpb* for test and *fpbq* for the demand locations. Table 1 shows the parameters in the first stage.

<<Table 1>>

Second Stage Parameters

The parameters shown in Table 2 are second stage related parameters which have different values depending on the scenarios, thus they are indexed over the set of scenarios Ω. These parameters include the costs for unmet demand, contract cancelations, last minute machine purchases, and sales revenues depending on uncertain product demand.

<<Table 2>>

Decision Variables

We assign a production variable to quantify the load of the factory for each of the wafer fabs (F), wafer sorts (S), assemblies (M) and test (T) facilities in each time-period. We allow for inventory both before and after each of the locations and these inventories are superscripted as *B* and *A* respectively. Superscript 1 and 2 differentiates the first and second stage variables as shown in Table 3. The second stage variables are indexed over the scenarios ω ($\omega \in \Omega$).

<<Table 3>>

Integer And Binary Book Keeping Variables

The bookkeeping variables, displayed in Table 4, keep track of the available resources.

<<Table 4>>

The Objective Function

The objective function, to maximize the total profit, is represented in two parts. The first part (see 1-1 in Appendix) consists of all the costs incurred and the revenue generated in the first stage. Included are the production, storage, and transportation costs at each facility. Costs for capacity increments (such as plant building and removal costs) and for equipment purchase and removal costs are also considered. The demands that are not met are penalized for underproduction. These costs are subtracted from the revenue generated by sales. The second part (see 1-2 in Appendix) of the objective function represents the costs incurred and the revenue generated for each scenario in the second stage; these are similar to those in the first part of the objective function and include sales revenues, penalty of not meeting demand and last minute machine purchasing over different scenarios. It also includes additional costs that are consequences of rectifying actions taken to recover from the first stage decisions (the recourse costs) such as amounts to be refunded due to contract cancellations. The second stage costs are further discounted by the probability of occurrence associated with each scenario. The production costs are at wafer fabs, wafer sorts, assembly and test locations; the transportation costs incurred are from wafer fab to sort, wafer sort to assembly, assembly to test and from test to demand locations and in between storage cost at all locations.

Model Constraints

The model incorporates network flow constraints, capacity constraints and logical constraints. These constraints are listed separately for the first and second stages. All the constraints are numbered and can be identified as first stage or second by their suffix.

Network Flow Constraints

The constraints 2-1, 2-2, 3-1 and 3-2 in Appendix are the basic network flow model where material flow conservation is enforced, i.e. total inflow is equal to total outflow. We describe the network flow constraints in two parts. Part A (2-1 and 2-2) deals with balance of flow between outflow of products from a facility and the shipment of products to the next facility. Part B (3-1 and 3-2) deals with balance of flow between the inflow of materials into a facility and the amount of products started for production. Part A and Part B together enforce the material flow conservation.

Capacity Constraints

These constraints (4-1 and 4-2) ensure that the amount of work for a given tool group is less than the time available for production for each Fab, Sort, Assembly and Test facility. The total time needed to produce the fraction of lots started at the current time-period and the fraction of lots carried from previous time-periods (including the backup jobs) should be less than the total available time on machines. The time needed for production in the second stage includes the time required by the addition of new tool groups in this stage.

Tool Counting Constraints

This set of constraints (5-1 and 5-2) defines the total number of machines in a tool group after the addition or removal of machines.

Facility Counting Constraints

These constraints (6-1) guarantee that the status of the facility indicator variables is correct. The variable for plant addition indicator is turned on if there is a facility to be built.

Number of tools limiting constraints

To restrict the size of such a large-scale model, we include only the constraining tool groups for capacity modeling. Thus, limits are posed on the addition of the tool group to avoid the non-bottleneck tool groups appearing as a constraining tool group. This set of constraints (7-1 and 7-2) limits the total number of tools that can be bought and the number of tools that can be bought within each tool group.

Production Suppressing Constraints

These constraints (8-1 and 8-2) ensure that production ceases in a facility that is removed. A large number M is multiplied by the existence indicator variable, and this has to be greater than or equal to the production variable X. This constraint extends over all the production variables.

Bin Allocation Constraints

These constraints (9-1 and 9-2) take into account all products sold from a given group of inter-classified sellable chips. The amount sold should be less than the number available in stock. These constraints also account for the inventory stored due to excess production.

Contract Cancellation Constraint

The number of lots for which money can be refunded upon a contract cancellation should be less than the lots planned for outsourcing. These equations (10-1 and 10-2) are for fabrication and assembly locations. The model can easily be scaled to incorporate outsourcing of Test, but it is generally not practiced because of intellectual property concerns.

Demand Constraint

This set of constraints (11-1 and 11-2) ensures that the amount sold is less than or equal to the demand and determines the under production.

4. Case Study

Various scenarios are run based on the changing demand of two products that we consider. In all the cases discussed below the planning horizon is five years, divided into 11 periods. The first eight periods are one fiscal quarter (three months) in length and the last three periods are one year each. Making the time-periods of different lengths serves two purposes (Fleten, Wallace and Ziemba 2002). First, it provides a long planning horizon, which mitigates the end effects without increasing the number of time-periods. Second, mixing short and long periods allows the model to address both short-term as well as long-term decisions.

The supply network has two wafer fabs, two assembly facilities, one foundry unit (contract fab), and one outsourced assembly unit (Figure 1). One wafer fab and one assembly facility already exist and another of each can be built depending on the scenario. There is one sort and one test facility that already exist in the supply network. For the foundry and assembly-outsourcing unit, two contract types are possible: planned contracts and emergency contracts. Planned contracts constrain first stage decisions and emergency contracts are associated with second stage decisions. The decisions on the planned contracts can be cancelled in the second stage, but with some penalty. There are five demand centers where finished products are stored and sold to customers. The decisions to construct the wafer fab or the assembly facility are made only in the first stage, which lasts for 2 years, and production in new facilities can be started after a lag of a few time-periods (five time-periods for fab and four time-periods for assembly) that takes care of the time to build and equip the facility. Developing the leading edge technology takes even longer, so the necessary equipment may not be available to equip the new facilities. These lags were deemed reasonable by industry participants. Similarly, the decision to remove a facility is also made in the first stage.

The two product families considered in the model are put into two package types and they are divided into two bins. Each bin represents a different speed of chips. The demands for chips are clustered together by product family. The model includes only the bottleneck tool groups. Implanters and steppers are considered in the wafer fabs, testers in wafer sort facilities, wire bonders in assembly facilities and testers in test facilities. Purchasing these tool groups can increase the capacity of the facility, either in the first or in the second stage. It is assumed that other tools needed to keep these key tools the bottleneck would also be purchased.

Table 5 shows the data for the parameters used in the stochastic programming model. All the data are approximate figures gathered by Stray (2006). Prices for specific chips can easily drop 50% in a year, and microprocessors are upgraded significantly every 18 months. Figure 3 shows the predicted demand pattern for 20 quarters, i.e., 60 months (5 years). Note that we assume the demand for a product increases initially until it reaches its peak demand. Once a new product is introduced into the market, demand for the current product typically declines. The new product launched has a life cycle trend similar to the first one. Although semiconductor products have shrinking lifecycles and our model is capable of handling it, we use the same life cycle for both of the products for simplicity.

<<Table 5>>

The model is run for various cases to determine the changes in the decisions made by the model for different levels of demand. The uncertain demand is parameterized (Meixell and Wu 2001) by its deviation from the mean and the correlation between the demands of the two product families. Demands for various scenarios are generated by choosing different levels of deviation from the mean and the correlation between demands of the two product families.

We start our analysis with a four-scenario case, which is further extended to a nine-scenario case. Some analyses are also done with sixteen and twenty-five scenario cases. The four-scenario case deals with two levels of demand for the two product families under consideration, thus providing the four (2^2) scenarios. Similarly, the nine-scenario case deals with three levels of demand for the two product families, thus providing the nine (3^2) scenarios. We get the sixteen-scenario (4^2) and twenty five-scenario (5^2) cases in the same manner with four and five levels of demands for two products.

<<Figure 3>>

<<Figure 4>>

Case I –Threshold Analysis

The objective of this analysis is to determine the threshold where the key decisions change (e.g. building of a new Fab). For this purpose, we use a four-scenario case where the demand for two product families changes over the time-periods. The four scenarios generated here are with the two levels of demand of each product family. The two levels are ten percent deviation on the positive and negative side of the mean. Five such four-scenario cases are generated, where the deviation of demand from the mean is increased in steps of 10%. These scenarios are a discrete approximation of the uncertainty in the demand. The correlation in the demand, discussed in later sections, is fixed at negative forty percent. We run these five cases for the four-scenario model over its planning horizon of five years which provides a widespread variation in demand.

Figure 4 shows the results and the decisions made from the runs mentioned above. The different levels of deviation in demand are shown on the x-axis. The shortages, outsourcing and cancellation of planned outsourcing are weighted over the four scenarios. Note that a new fab is built to meet the expected demand only in cases where the deviation in demand from forecast is twenty percent or less. In rest of the cases, the uncertainty in the demand precludes a long-term investment in a fab. The model suggests the alternative of outsourcing the production of wafers to a foundry even though the unit cost of production is higher. On the graph, this manifests as a sudden rise in the outsourcing level after the twenty percent deviation. The unmet demand (shortages) also increases with the uncertainty in demand as the model is risk averse and suggests producing less. Since unit costs are higher on contract wafers, there is a decrease in expected profit as demand deviation increases.

CASE II - Correlation in Demand

As stated above, there is a positive probability of occurrence for each of the four scenarios. The assignment of the probabilities determines the correlation coefficient *r*.

The most common approach would be to assign equal probability to each scenario. In this case, r would be zero, i.e., the demands of the products are independent of each other. We also consider the case where the demand for all products is positively correlated (increasing overall market) and the case of negative correlation where an existing product is phased out while a new product is phased in. A correlation of negative forty percent implies that the scenarios with high values of demand for product one and low value of demand for product two are weighted more heavily than the scenarios where the demand for both products is high or low and vice-versa when r is positive forty percent. We note that the choice of the probability for a specific value of r is not unique leading to different performance for the same r.

In the section above, we ran the four-scenario model with r = -0.4, now we do the similar analysis when r = 0 and r = 0.4, to determine the effect of correlation between the products on the decisions and the results of the model. Figure 5 shows the probability distribution for the four scenarios, which determines the correlation coefficient r. For each r, the four-scenario model is run with five levels of deviation from the mean.

<<Figure 5>>

The results and decision from the model when r = 0, i.e., when the demand of each product is independent of each other, is shown in Figure 6a. It is of interest to note that a new fab is built in the case when the demand deviation is at twenty percent and not in the case of ten percent deviation, which is counter-intuitive. In the ten percent deviation case, there is simply not enough demand to justify the fab even in the high demand scenario. At twenty percent deviation in demand, the production in the owned fab is more economical than contract production for the scenarios of high demand. As the deviation in demand increases, there is a need to increase the capacity, but the risk associated with the low demand scenarios is so high that losing sales is more cost effective than overproducing. The other results of shortages and the expected profit is the same as seen in the previous case where r = -0.4, i.e., the shortages increase and the expected profit decreases as the variability in demand increases.

<<Figure 6>>

At r = 0.4, the demand for the products are positively correlated. Figure 6b shows a similar trend in shortages and the expected profits as seen earlier in case of $r=-0.4$ and $r=0$. The new fab is built in the cases where deviation in demand was twenty and thirty percent from the mean, which explains the sudden drop in outsourcing for these levels.

The expected production starts in each of the supply network nodes, namely wafer fabs, sorts, assembly and tests are shown in Table 6 for all the cases discussed above ($r=-0.4$, $r=0$, $r=0.4$). The table also shows the sales in each of the demand centers. It can be seen here that the sales are lower for the positive correlation case, which is consistent with our discussion above. The positively correlated case guarantees a higher risk and it is more sensitive to deviation in demand because there is a need to prepare for additional capacity when the demand for both the products are high and conversely lower capacity is needed when the demand for both the products are low. In these cases of higher risk, the model acts conservatively and decisions are made to under-produce rather than over-produce.

<<Table 6>>

CASE III - Value of Stochastic Solution

When dealing with a stochastic programming model, it is essential to determine the usefulness of the model (Birge and Louveaux 1997). This can be determined by comparing it with the Perfect Information model solution and the Expected Value model solution. For the perfect information case, the model is run with individual scenarios and the solution is weighted with the probabilities assigned to the scenarios. For the expected value model the demand for each scenario is weighted by its probability and the model is run with the expected value of the demand to determine the first stage decisions. These first stage decisions are then put into the stochastic integer programming model to determine the expected value solution (EEV).

Figure 7 shows the Value of Stochastic Solution (VSS) and the Efficiency of the Stochastic Solution (ESS) over deviation in demand. VSS is defined as the distance of the stochastic solution (RP) from the expected value solution. ESS is defined as a ratio between VSS and the difference between Perfect information (PI) solution and expected value solution.

$$ESS = \frac{VSS}{PI - EEV} = \frac{RP - EEV}{PI - EEV}$$

<<Figure 7>>

Although VSS has a small percentage increase as uncertainty increases, it results in huge (millions of dollars) savings since a new fab currently costs about $3.5 B. On the other hand, ESS does not increase with the variability in demand. From ten to twenty percent deviation in demand, the ESS increases, and this illustrates that the stochastic solution becomes useful when the variability is increased, but as we go forward, four scenarios are not sufficient to approximate all the uncertainty in demand. This illustrates the need to use more scenarios to map the uncertainty. Thus, we run nine-scenario, sixteen-scenario and twenty-five-scenario cases at twenty percent deviation in demand to determine the ESS trend.

We use three levels of demand to generate the nine scenarios for two products. The three levels are twenty percent deviation from the mean on both sides and the mean level. For the sixteen-scenario case, we use four levels, of which two are at ten percent deviation from mean and the other two are at twenty percent deviation. Similarly, for the twenty-five-scenario case we use the four levels from sixteen-scenario case and add a mean level to it. Figure 8 shows the increment in the efficiency of the stochastic solution when the number of scenarios used to approximate the uncertainty is increased. Although increasing the number of scenarios to map the uncertainty brings the stochastic solution nearer to the perfect information solution, there is still an upper bound on the efficiency of the stochastic solution and the cost associated in terms of solution time is high.

<<Figure 8>>

5. Conclusions and Future Research

We provide a supply network model for semiconductor manufacturing where the total expected profit is maximized when product demand is uncertain. A stochastic mixed integer program with recourse was developed to provide solutions that reduce the overall risk in planning. The recourse actions include adding internal as well as external capacity with cancellation of contracts that were made in anticipation of high demand. When the uncertainty in demand increases, a more conservative approach is adopted, and the model displays an inherent tendency of no commitment, i.e., the capacity increment is negligible. In addition to the uncertainty in demand, we study the effect of correlation between the demands of two products. It is evident from the analysis, and also as stated by Simchi-Levi (2000) that positive correlation between the products (e.g. increasing market size) involves higher risk compared to negative (e.g. introduction of new products) or no correlation. We also evaluate the usefulness of our model compared to the alternatives available. The model was compared to the expected value model (Stray 2006) and to the perfect information case, which revealed that as the uncertainty in demand increases, our model improves its performance over the expected value model. However, the gap between the stochastic solution and perfect information solution also increases with the increment in variability of demand. By increasing the number of scenarios to map the uncertainty of demand our results show that, the Efficiency of Stochastic Solution increases. Thus, adding uncertainty to the deterministic version of the model with multiple scenarios has yielded more realistic and robust results and analysis on correlation between multiple product demands resulted with unintuitive decisions for strategic make/buy problems.

We have chosen reasonable parameters for system characteristics such as production times, plant construction lags, etc. However, there are other sources of variability in the semiconductor supply chain. The specific geography of both the facilities and the customers can affect system responsiveness. In particular, some countries have less efficient distribution systems and more cumbersome border crossing procedures. Five days was the maximum time quoted to any major customer (Maltz et al., 2000). Lead times tightened as the “Dell model” became more common, and low margin ECM’s (e.g. Solectron, Flextronics) have taken over core manufacturing processes for a number of OEM’s. Customers in these countries require higher inventory levels, and facilities in these countries are subject to more variability in demand. It might be useful to disaggregate demand into customer classes of varying profitability, and ask what kind of demand merits building a new facility. Considering the issues of equipment availability brought up by Myersdorf and Peleg (2002), not to mention the very high cost of semiconductor manufacturing equipment, understanding the drivers of each new facility could be a significant contribution to overall supply network performance.

Variability of service supplier performance is also a concern. It would be useful to include performance levels of contract manufacturers and transportation providers as a risk factor in looking at make/buy decisions in the supply network (of course, performance levels can vary at internal facilities as well). We have assumed constant pricing throughout the product lifecycle. This is clearly not the case for semiconductors. Although varying revenue and profit margins makes the problem more complicated, it should be addressed. Pricing policy is one of the major levers a manufacturer has to deal with flattening or declining demand, and obsolescence can also be accounted for through multiple pricing scenarios.

Logical constraints could be included in this model. Logical constraints are sets of constraints that become active only if a particular decision is made. These logical constraints can be used to make outsourcing more realistic. Another embellishment could be to consider new product launch strategy, i.e., when the new product should be launched in the market. Based on the demand trends in the model and the uncertainty associated with it, the model could be enlarged such that it could decide the optimal time-period the new product should be released in the market. In this research, we pre-determined the timing of release of the new product.

We believe that the work here is an excellent start toward improving the decision process for network strategies in the globally dispersed semiconductor industry. As we noted in the introduction to this paper, the sheer extent of these networks increases the risks associated with make/buy decisions. The need to add capacity in large, expensive increments adds to the stakes in these decisions. Overall, refining models such as the one explored in this paper has huge potential payoffs for semiconductor manufacturers and other cyclical industries with high capital costs and multi-stage supply networks.

6. Appendix: Stochastic programming model

Objective Function:

$$
\begin{aligned}
&Max \\
&\sum_{t\in 1..r,f,p,b,l\in L_D}\left(PV^{1}_{fpblt}Z^{1}{}_{fpblt}-PEN^{1}{}_{fpblt}\xi^{1}{}_{fpblt}\right) \\
&-\sum_{t\in 1..r,f,l\in L_F}\left(PC_{flt}X^{1,F}_{flt}+IC_{flt}W^{1AF}_{flt}\right)-\sum_{t\in 1..r,f,l\in L_F,d\in L_S}TC_{ldt}Y^{1FS}_{fldt}-\sum_{t\in 1..r,p,s\in L_F,l\in L_S}IC_{flt}W^{1BS}_{sflt} \\
&-\sum_{t\in 1..r,f,s\in L_F,l\in L_S}\left(PC_{flt}X^{1S}_{sflt}+IC_{flt}W^{1AS}_{sflt}\right)-\sum_{t\in 1..r,f,s\in L_F,l\in L_S,d\in L_M}TC_{ldt}Y^{1SM}_{sfldt}-\sum_{t\in 1..r,f,s\in L_F,l\in L_M}IC_{flt}W^{1BM}_{sflt} \\
&-\sum_{t\in 1..r,f,p,s\in L_F,l\in L_M}\left(PC_{flt}X^{1M}_{sfplt}+IC_{flt}W^{1AM}_{sfplt}\right)-\sum_{t\in 1..r,f,p,s\in L_F,l\in L_M;d\in L_T}TC_{ldt}Y^{1MT}_{spldt}-\sum_{t\in 1..r,p,q,f\in L_F,l\in L_T}IC_{flt}W^{1BT}_{sfplt} \\
&-\sum_{t\in 1..r,f,p,s\in L_F,l\in L_T}PC_{flt}X^{1T}_{sfplt}-\sum_{t\in 1..r,f,p,b,s\in L_F,l\in L_T}IC_{flt}W^{1AT}_{sfpblt}-\sum_{t\in 1..r,f,p,b,s\in L_F,l\in L_T;d\in L_D}TC_{ldt}Y^{1TD}_{fpbldt} \\
&-\sum_{t\in 1..r,f,p,b,s\in L_F,l\in L_D}IC_{flt}W^{1BD}_{sfpblt} \\
&-\sum_{t\in 1..r,l\in L}\Psi^{A}_{lt}PBC_{lt}-\sum_{t\in 1..r,l\in L}\Psi_{lt}POC_{lt}-\sum_{t\in 1..r,l\in L}\Psi^{R}_{lt}PRC_{lt} \\
&-\sum_{t\in 1..r,l\in L,i\in MT}M^{1A}_{ilt}MPC_{ilt}-\sum_{t\in 1..r,l\in L,i\in MT}M^{1}{}_{ilt}MOC_{ilt}
\end{aligned}
\tag{1-1}
$$

$$
+P_{\omega}\left(
\begin{array}{l}
\displaystyle\sum_{\omega,t\in r+1..N,f,p,d\in L_D}(PV^{2}{}_{\omega fpbdt}Z^{2}{}_{\omega fpbdt}-PEN^{2}{}_{\omega fpbt}\xi^{2}{}_{\omega fpbdt}) \\
\displaystyle-\sum_{\omega,t\in r+1..T,f,l\in L_F}\left(PC_{flt}X^{2,F}_{\omega flt}+IC_{flt}W^{2AF}_{\omega flt}\right)-\sum_{\omega,t\in r+1..T,f,l\in L_F,d\in L_S}TC_{ldt}Y^{2FS}_{\omega fldt}-\sum_{\omega,t\in r+1..T,p,s\in L_F,l\in L_S}IC_{flt}W^{2BS}_{\omega sflt} \\
\displaystyle-\sum_{\omega,t\in r+1..T,f,s\in L_F,l\in L_S}\left(PC_{flt}X^{2S}_{\omega sflt}+IC_{flt}W^{2AS}_{\omega sflt}\right)-\sum_{\omega,t\in r+1..T,f,s\in L_F,l\in L_S,d\in L_M}TC_{ldt}Y^{2SM}_{\omega sfldt}-\sum_{\omega,t\in 1..r,f,s\in L_F,l\in L_M}IC_{flt}W^{2BM}_{\omega sflt} \\
\displaystyle-\sum_{\omega,t\in r+1..T,f,p,s\in L_F,l\in L_M}\left(PC_{flt}X^{2M}_{\omega sfplt}+IC_{flt}W^{2AM}_{\omega sfplt}\right)-\sum_{\omega,t\in r+1..T,f,p,s\in L_F,l\in L_M;d\in L_T}TC_{ldt}Y^{2MT}_{\omega sfpldt}-\sum_{\omega,t\in r+1..T,p,q,f\in L_F,l\in L_T}IC_{flt}W^{2BT}_{\omega sfplt} \\
\displaystyle-\sum_{\omega,t\in r+1..T,f,p,s\in L_F,l\in L_T}PC_{flt}X^{2T}_{\omega sfplt}-\sum_{\omega,t\in r+1..T,f,p,b,s\in L_F,l\in L_T}IC_{flt}W^{2AT}_{\omega sfpblt}-\sum_{\omega,t\in r+1..T,f,p,b,s\in L_F,l\in L_T;d\in L_D}TC_{ldt}Y^{2TD}_{\omega fpbldt} \\
\displaystyle-\sum_{\omega,t\in r+1..T,f,p,b,s\in L_F,l\in L_D}IC_{flt}W^{2BD}_{\omega sfpblt} \\
\displaystyle-\sum_{\omega,t\in r+1..N,l\in L,i\in MT}M^{2A}{}_{\omega ilt}MPC^{2}{}_{\omega ilt}-\sum_{\omega,t\in r+1..N,l\in L,i\in MT}M^{2}{}_{\omega ilt}MOC_{ilt} \\
\displaystyle+\sum_{t\in r+1..N,f,l\in L_F}OUTC_{\omega flt}OC^{F}_{\omega flt}+\sum_{t,f,p,l\in L_M}OUTC^{2}{}_{\omega flt}OC^{M}_{\omega fplt}
\end{array}
\right)
\tag{1-2}
$$

Network Flow Constraints:

$$X_{flt}^{1F}[1-C_{plt}]Q_{flt} + X_{flt-1}^{1F}C_{flt-1}Q_{flt-1} + W_{flt-1}^{1AF} - W_{flt}^{1AF} - \sum_{d \in L_S} Y_{fldt}^{FS} = 0 \quad \text{2-1}$$

$$: \forall \ f \in FAM \ , l \in L_F, t \in 1,\ldots, r$$

A

$$X_{flt}^{1F}[1-C_{flt}]Q_{flt} + X_{flt-1}^{1F}C_{flt-1}Q_{flt-1} + X_{\omega flt}^{2F}(1-C_{flt})Q_{flt}$$
$$+ X_{\omega flt-1}^{2F}C_{flt-1}Q_{flt-1} + W_{\omega flt-1}^{2AF} - W_{\omega flt}^{2AF} - OC_{\omega flt}^{F} - \sum_{d \in L_S} Y_{fldt}^{FS} = 0 \quad \text{2-2}$$

$$: \forall \ f \in FAM \ , l \in L_F, \omega \in \Omega, t \in r+1 \ldots T$$

$$Y_{fldt}^{1FS} + W_{flt-1}^{1BS} - X_{fldt}^{1S} - W_{flt}^{1BS} = 0 \quad \text{3-1}$$

$$: \forall \ l \in L_F, f \in FAM \ , d \in L_S, t \in 1,\ldots, r$$

B

$$Y_{\omega fldt}^{2FS} + W_{\omega flt-1}^{2BS} - X_{\omega fldt}^{2S} - X_{fldt}^{1S} - W_{\omega flt}^{2BS} = 0 \quad \text{3-2}$$

$$: \forall \ l \in L_F, f \in FAM \ , \omega \in \Omega, d \in L_S, t \in r+1,\ldots, T$$

Capacity Constraints:

$$\sum_{f \in FAM} \left(T_{ifl}\left(X_{fl,t-1}^{1F}C_{jl,t-1} + X_{flt}^{1F}(1-C_{jlt})\right)\right) \le \alpha_{il} M^{1}{}_{ilt}\left(TPL_t - S_i\right) \quad \text{4-1}$$

$$: \forall \ i \in MT_l, l \in L_F, t \in 1 \ldots r$$

$$\sum_{f \in FAM} \left(T_{ifl} \left(\begin{matrix} \left(X_{flt-1}^{1F}C_{jlt-1} + X_{flt}^{1F}(1-C_{jlt})\right) + \\ \left(X_{\omega flt-1}^{2F}C_{jlt-1} + X_{\omega flt}^{2F}(1-C_{jlt})\right) - OC^{F}{}_{\omega flt} \end{matrix} \right) \right) \le \alpha_{il} M^{2}{}_{\omega ilt}\left(TPL_t - S_i\right) \quad \text{4-2}$$

$$: \forall \ i \in MT_l, l \in L_F, t \in r+1 \ldots T, \omega \in \Omega$$

Tool Counting Constraints:

$$M^{1}{}_{ilt} = \sum_{n=1}^{r}\left(M_{il\,n}^{1A} - M_{il\,n}^{1R}\right) + m_{il} \quad : \forall i \in MT_l, l \in L, t \in 1 \ldots r \quad \text{5-1}$$

$$M^{2}{}_{\omega ilt} = \sum_{n=r+1}^{t}\left(M^{2A}_{\omega iln} - M^{2R}_{\omega iln}\right) + M^{1}{}_{ilt} \quad : \forall i \in MT_l, \omega \in \Omega, l \in L, t \in r+1 \ldots T \qquad \text{5-2}$$

Facility Counting Constraints:

$$\Psi_{lt} = \sum_{r=1}^{t}\left(\Psi^{A}_{lr} - \Psi^{R}_{lr}\right) \quad : \Psi_{lt}, \Psi^{A}_{lr}, \Psi^{R}_{lr} \in \{0,1\}, t \in 1 \ldots T, l \in L \qquad \text{6-1}$$

Number of Tools Limiting Constraints:

$$M^{1}{}_{ilt} \le MAX^{S}_{il} \quad : \forall i \in MT_l, l \in L, t \in 1 \ldots r$$
$$\sum_{i \in MT} M^{1A}{}_{ilt} \le MAX^{T}_{l} \quad : \forall t \in 1 \ldots r, l \in L \qquad \text{7-1}$$

$$M^{2}{}_{\omega ilt} \le MAX^{S}_{il} \quad : \forall i \in MT_l, l \in L, t \in 1 \ldots T, \omega \in \Omega$$
$$\sum_{i \in MT} M^{2A}{}_{\omega ilt} \le MAX^{T}_{l} \quad : \forall t \in r+1 \ldots T, l \in L, \omega \in \Omega \qquad \text{7-2}$$

Production Suppressing Constraints:

$$\Psi_{lt} M \ge X^{1,S1}_{flt} \quad : \forall f \in FAM, l \in L, t \in 1 \ldots r, S1 \in (F, S, M, T) \qquad \text{8-1}$$

$$\Psi_{lt} M \ge X^{1,S1}_{flt} + X^{2,S1}_{\omega flt} \quad : \forall f \in FAM, l \in L, t \in r+1 \ldots T, S1 \in (F, S, M, T) \qquad \text{8-2}$$

Bin Allocation Constraints

$$\sum_{q \in BET_b} \zeta^{1}{}_{fpqdt} - \sum_{q \in BET_b} Z^{1}{}_{fpqdt} \ge 0 \quad :$$
$$\forall f \in FAM, p \in PKG_p, b \in BIN_p, d \in L_D, t \in 1 \ldots r \qquad \text{9-1}$$

$$\sum_{q \in BET_b} \zeta^{2}_{\omega fpqdt} - \sum_{q \in BET_b} Z^{2}_{\omega fpqdt} \ge 0 \quad :$$
$$\forall f \in FAM, p \in PKG_p, b \in BIN_p, d \in L_D, t \in r+1 \ldots T, \omega \in \Omega \qquad \text{9-2}$$

Contract Cancellation Constraint

$$OC^{F}_{\omega ft} \leq O^{F}_{\omega ft} : \forall t \in r+1\ldots T, f \in FAM, \omega \in \Omega \qquad 10\text{-}1$$

$$OC^{M}_{\omega fpt} \leq O^{M}_{\omega fpt} : \forall t \in r+1\ldots T, f \in FAM, p \in PKG_{p}, \omega \in \Omega \qquad 10\text{-}2$$

Demand Constraint

$$\mathrm{D}^{1}_{fpbdt} - \mathrm{Z}^{1}_{fpbdt} \leq \xi^{1}_{\omega fpbdt}$$
$$: \forall\ f \in FAM\ , p \in PKG_{f}, b \in BIN_{q}, d \in L_{D}, t \in 1,\ldots, r \qquad 11\text{-}1$$

$$\mathrm{D}^{2}_{\omega fpbdt} - \mathrm{Z}^{2}_{\omega fpbdt} \leq \xi^{2}_{\omega fpbdt}$$
$$: \forall\ f \in FAM\ , p \in PKG_{f}, \omega \in \Omega, b \in BIN_{p}, d \in L_{D}, t \in r+1,\ldots, T \qquad 11\text{-}2$$

6. References

Ahmed, S., Shapiro, A., 2002. The Sample Average Approximation Method for Stochastic Programs with Integer Recourse, Preprint available at www.optimization-online.org,

Azaron, A., Brown, K.N., Tarim, S.A., Modarres, M., 2008. A multi-objective stochastic programming approach for supply chain design considering risk. International Journal of Production Economics 116, 129-138.

Barahona, F., Bermon, S., Gunluk, O., Hood, S., 2005. Robust capacity planning in semiconductor manufacturing. Naval Research Logistics 52, 459-468.

Birge, J.R., Louveaux, F., 1997. Introduction to Stochastic Programming, Springer Series in Operations Research.

Cakanyildirim, M., Roundy, R.O., 2002. SeDFAM: semiconductor demand forecast accuracy model. IIE Transactions 34, 449-465.

CPLEX, 1997. Using the CPLEX Callable Library, Incline Village, NV.

Chouinard, M., D'Amours, S., Ait-Kadi, D., 2008. A stochastic programming approach for designing supply loops. International Journal of Production Economics 113, 657-677.

Fleten, S., Wallace, S.W., Ziemba, W.T., 2002. Hedging Electricity Portfolios via Stochastic Programming. In: J. L. Higle, W. Römisch (Eds.), The IMA volumes in mathematics and its applications. Springer, Berlin.

Fourer, R.D., Gay, D.M., Kernighan, B.W., 1993. AMPL: A Modeling Language for Mathematical Programming. Boyd & Fraser publishing company.

Goh, M., Lim, J.Y.S., Meng, F., 2007. A stochastic model for risk management in global supply chain networks. European Journal of Operational Research 182, 164-173.

Hood, S.J., Bermon, S., Barahona, F., 2003. Capacity planning under demand uncertainty for semiconductor manufacturing. IEEE Transactions on Semiconductor Manufacturing 16 (2), 273-280.

Huang, K., Ahmed, S., 2009. The value of multi-stage stochastic programming in capacity planning under uncertainty. To appear in *Operations Research*.

Huh, W.T., Roundy, R.O., Cakanyildirim M., 2006. A general strategic capacity planning model under demand uncertainty. Naval Research Logistics 53, 137-150.

Kall, P., Wallace, S.W., 1994. Stochastic Programming, Wiley- Interscience Series in Systems and Optimization.

Leung, S.C.H., Tsang, S.O.S., Ng, W.L., Wu, Y., 2007. A robust optimization model for multi-site production planning problem in an uncertain environment. European Journal of Operational Research 181, 224-238.

Lucas, C., Mirhassani, S., Mitra, G., Poojari, C.A., 2001. An application of lagrangian relatxation to a capacity planning problem under uncertainty. Journal of the Operational Research Society 52, 1256-1266.

Maltz, A.B., William, L.G., Dale, S., Rogers, R. B., Grey, W., Katircioglu, K., 2000. Lessons from the Semiconductor Industry. Supply Chain Management Review 4 (5), 42-52.

Meixell, M.J., Wu, S.D., 2001. Scenario Analysis of Demand in a Technology Market Using Leading Indicators. IEEE Transactions on Semiconductor Manufacturing 14 (1), 65-75.

Myersdorf, D., Peleg, B., 2002. Semiconductor Capital Equipment Delivery-Can the Risk Be Shared. The Supply Chain Connection (Stanford Supply Chain Forum) January, pp. 5-6.

Santoso, T., Ahmed, S., Goetschalckx, M., Shapiro, A., 2005. A stochastic programming approach for supply chain network design under uncertainty. European Journal of Operational Research 167 (1), 96-115.

Simchi-Levi, D., Kaminsky, P., Simchi-Levi, E., 2000. Designing and Managing the Supply Chain. McGraw-Hill, Boston, MA.

Stray, J., Fowler, J.W., Caryle, W.M., Rastogi, A.P., 2006. Enterprise-Wide semiconductor manufacturing resource planning. IEEE Transactions on Semiconductor Manufacturing 19 (2), 259-268.

Swaminathan, J.M., 2000. Tool capacity planning for semiconductor fabrication facilities under demand uncertainty. European Journal of Operational Research 120, 545-558.

Thanh, P.N., Bostel, N., Peton, O., 2008. A dynamics model for facility location in the desing of complex supply chains. International Journal of Production Economics 113, 678-693.

Wallace, S.W., 2000. Decision Making Under Uncertainty: Is Sensitivity Analysis of Any Use? Operations Research 48 (1), 20-25.

Walsh, M., 2000. Operator cross-training in wafer fabrication under uncertainty: a stochastic programming approach. Thesis, Arizona State University, Department of Industrial Engineering, USA.

FIGURES

Figure 1: A Semiconductor Supply Network

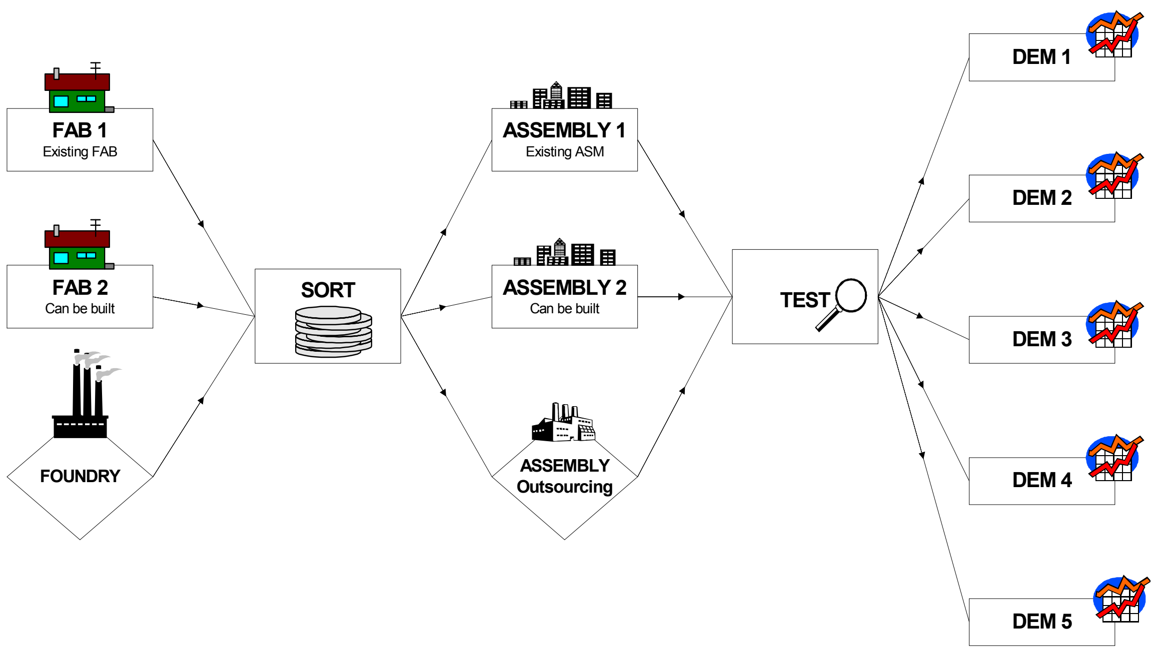


Figure 2: The decisions taken at stage one and two

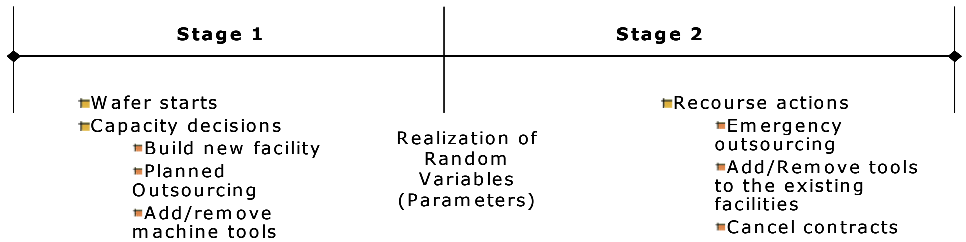


Figure 3: Demand Trend of Semiconductors

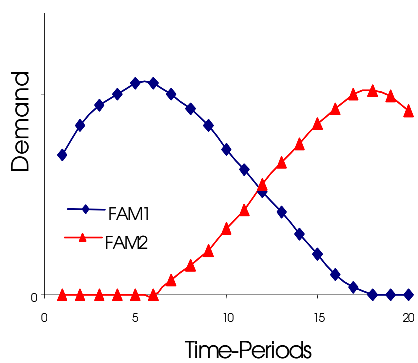


Figure 4: Four scenario model *r* = -0.4

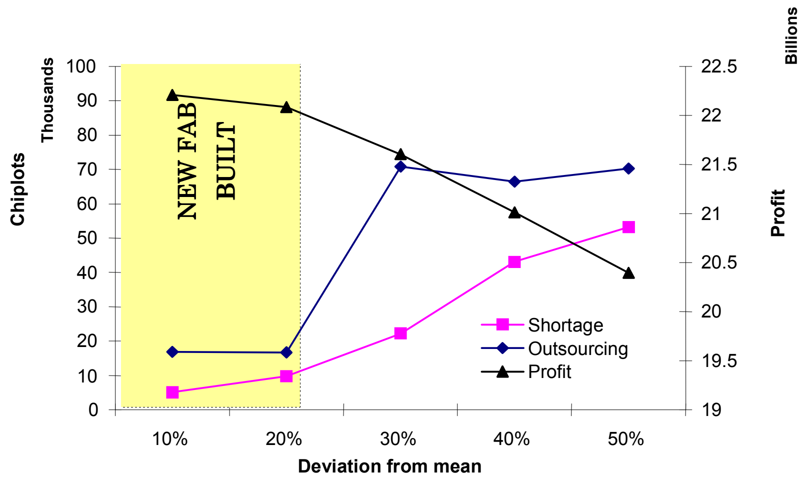
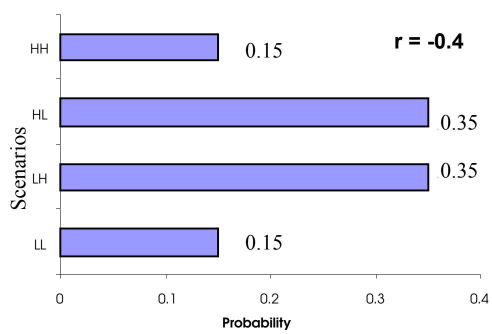


Figure 5: Probability Distribution for the Four Scenarios r=-0.4 and r=0.4



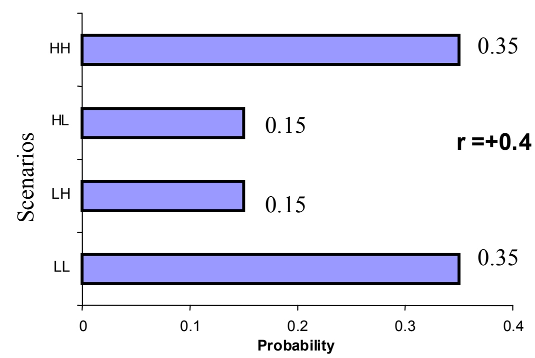
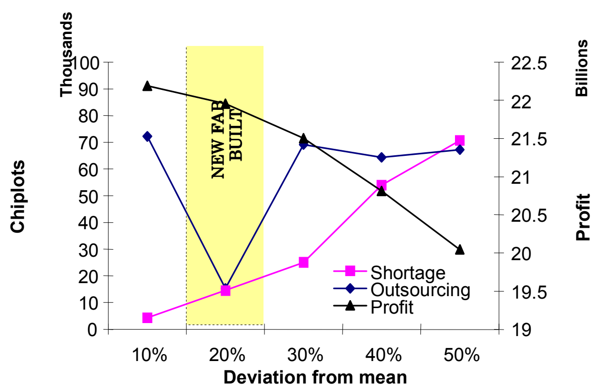


Figure 6: a) Correlation r = 0 **b) Correlation r = 0.4**



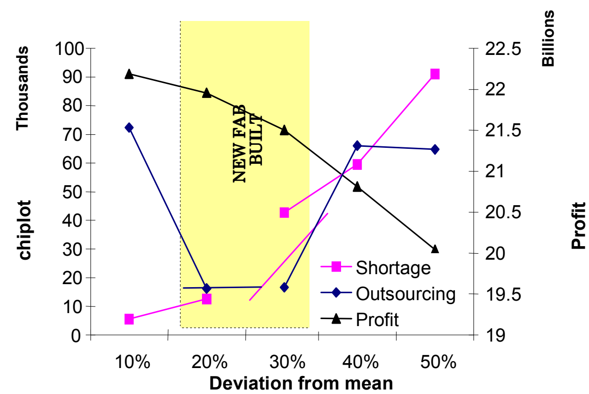


Figure 7: Efficiency and Value of Stochastic Solution

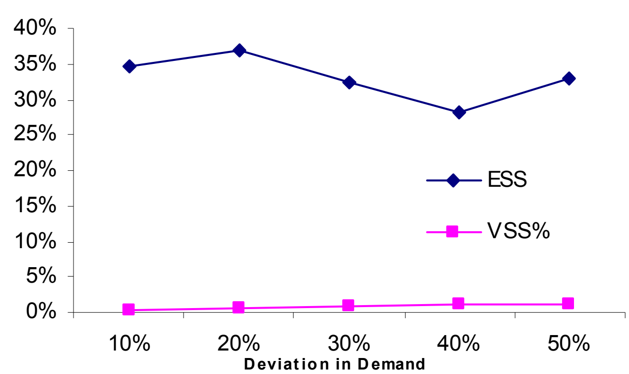
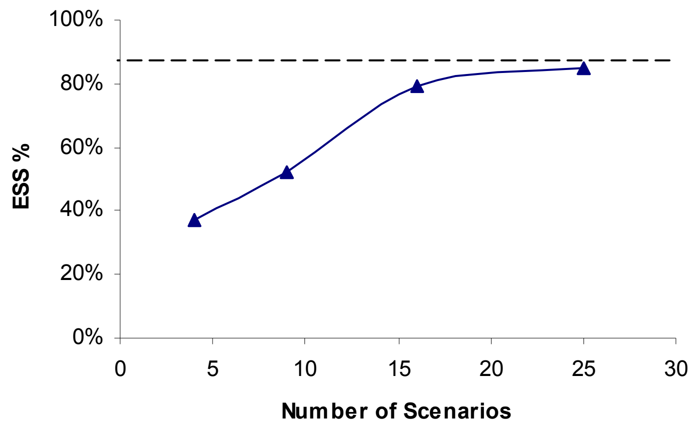


Figure 8: Efficiency of Stochastic Solution (ESS) for Four, Nine, Sixteen And Twenty-Five Scenario Case



TABLES

Table 1: Description of the Parameters Used in First Stage

Parameters	Description
N	The number of time-periods in the model indexed over t. Time-periods 1 to r represent the first stage and $r+1$ to N represent the second stage
TPL_t	The length of time-period t expressed in hours
C_{flt}	Cycle fractions of products of family f that start in time-period t and complete in the next time-period $t+1$ at location l
Q_{flt}, Q_{sfplt}	Yield fractions for product f at wafer fab and sort, for product fp at assembly. The yield at assembly is also indexed over s, the wafer fab in which the original wafer was manufactured at location l in time-period t
Q_{sfpblt}	Yield of products at testing operations. Resulting bins b of a product, depending on origin fab s, family f, package p, location l and time-period t
T_{ifl}	The processing time of product for family f on tool group i in location l
α_{il}	Maximum utilization of a tool i at location l
S_{ilt}	The average setup or the downtime for tool group i at location l in time-period t
m_{il}	The number of initial tools in tool group i at location l
MAX^S_{il}	The maximum number of machines in tool group i at location l

Parameters	Description
MAX^T_l	The maximum number of machines total in all tool groups at location *l*
PC_{flt}	The cost of starting a product lot of family *f* at location *l* in period *t*
TC_{ldt}	The transportation cost per lot from location *l* to *d* in period *t*
IC_{flt}	The inventory for product of family *f* in location *l* in period *t*
G_{fp}	The number of chips on a wafer for family *f* and package *p*
WLS_l	The number of wafers in a lot at location *l* (wafer fab and wafer sorts)
CLS_l	The number of chips in a lot at location *l* (at assembly, test and demand centers)
PBC_{lt}	The building cost for a facility at location *l* in period *t*
POC_{lt}	The operating cost for a facility at location *l* in period *t*
PRC_{lt}	The cost of removing a facility at location *l* in period *t*
MPC_{ilt}	The purchasing cost for a single machine *i* in the facility at location *l* in period *t*
MOC_{ilt}	The costs for operating machine *i* in the facility at location *l* in period *t*
D^1_{fpblt}	Demand for product of family *f* in package *p* and bin *b* at location *l* in period *t*
PV^1_{fpblt}	The sales revenue per chip of family *f* package *p* and bin *b* at demand location *l* in period *t*
PEN^1_{fpblt}	Penalty for not meeting demand per chip of family *f* package *p* and bin *b* at location *l* in period *t*

Table 2: Description of the Parameters Used in Second Stage

Parameters	Description
P_{ω}	The probability of each scenario
$PV^2_{\omega fpblt}$	The sales revenue per chip for scenario ω, of family *f* package *p* and bin *b* at demand location *l* in period *t*
$D^2_{\omega fpblt}$	Demand for scenario ω, product of family *f* in package *p* and bin *b* at location *l* in period *t*
$PEN^2_{\omega fpblt}$	Penalty for not meeting demand per chip for scenario ω, of family *f* package *p* and bin *b* for period *t*
$MPC^2_{\omega i l t}$	The purchase cost of a single machine *i* for scenario ω, in facility at location *l* in period *t*
$OUTC_{\omega fplt}$	The amount to be refunded when an outsourcing contract is cancelled for scenario ω product of family *f* in package *q* at location *l* (wafer fab and assembly) in period *t*

Table 3: Description of Stage One and Stage Two Decision Variables

Variables	Description
$X^{1,S1}_{flt}$, $X^{2,S1}_{\omega flt}$ S1 $\in$(F, S, M, or T)	Number of lots for product of family *f* to start at location *l* in period *t*
$W^{1,S1,S2}_{flt}$, $W^{2,S1,S2}_{\omega flt}$ S1 $\in$(A or B);S2 $\in$L	Number of lots for product of family *f* to put in inventory before and after location *l* in period *t*
$Y^{1,S1,S2}_{fldt}$, $Y^{2,S1,S2}_{\omega fldt}$ S1, S2 $\in$(F, S, M, or T)	Number of lots for product of family *f* shipped between locations *l* and *d* in period *t*
Z^{1}_{fpblt} , $Z^{2}_{\omega fpblt}$	Number of lots for product of family *f*, package *p*, and bin *b* sold at location *l* in period *t*
ξ^{1}_{fpblt} , $\xi^{2}_{\omega fpblt}$	Number of lots for product of family *f*, package *p*, and bin *b* short of demand at location *l* in period *t*
ζ^{1}_{fpblt} , $\zeta^{2}_{\omega fpblt}$	Number of lots for product of family *f*, package *p*, and bin *b* available at demand center *l* in period *t*
$OC^{S1}_{\omega fpblt}$ S1 $\in$(F,A)	Amount of money refunded when a planned contract is cancelled for product of family *f*, package *p*, and bin *b* at location *l* in period *t*
$M^{1A}{}_{ilt}$, $M^{2A}{}_{\omega ilt}$	The number of machines added to tool group *i*, in location *l* in period *t*
$M^{1R}{}_{ilt}$, $M^{2R}{}_{\omega ilt}$	The number of machines removed from tool group *i*, in location *l* in period *t*
$\Psi^{A}{}_{lt}$, $\Psi^{R}{}_{lt}$	Facility addition or removal indicator for location *l* in period *t*

Table 4: Integer and Binary Bookkeeping Variables

Variables	Description
$M^{1}{}_{ilt}$, $M^{2}{}_{\omega ilt}$	The number of machines available for tool group *i*, at location *l* in period *t*
Ψ_{lt}	The plant existence indicator (0,1) variable for location *l* in period *t*

Table 5: Data Set for the Parameters

PLANT BUILDING COSTS	Fab ~ $1B	
	Sort $100M	
	Assembly and Test ~ $200M	
PLANT OPERATING COSTS	Fab ~ $50M/year	
	Sort ~ $10M/year	
	Assembly and test ~ $20M/year	
TOOL PURCHASE COSTS	FAB	Steppers ~ $7M
		Implanters ~ $3M
	Assembly	Wire Bonders ~ $1M
	Test	Testers ~ $4M
TOOL OPERATING COSTS	10 % of purchase costs/year	
PLANT BUILDING LAG (Time lag between building decision and full capacity operability)	Fab ~ 15 months	
	Assembly and Test ~ 12 months	
TOOL EFFICIENCY	70 % of total available time	
TOOL DOWNTIME	60 hrs / per quarter	
PROCESSING TIME (Total time for a product needed on a bottleneck tool)	Fab	Steppers ~ 1.2 hours per lot of 25 wafers
		Implanters ~ 1.3 hours per lot of 25 wafers
	Assembly ~ 0.3 hrs per chip	
	Test ~ 0.3 hrs per chip	
CYCLE TIMES (at high load of facilities)	Fab ~ 45 days	
	Sort ~ 2 days	
	Assembly ~ 5 days	
	Test ~ 5 days	
PRODUCT YIELD OF PLANTS	Fab ~ 96 %	
	Test ~ 96 %	
	All others 100%	
PRODUCTION COSTS (VARIES WITH PRODUCT)	1 % of operating costs of the tools (Higher or lower depending on product)	
	Foundry	Contracts ~ $ 25K-$28K per lot
		Recourse ~ $ 26K-$29K per lot
	Assembly	Contracts ~ $ 3.5K- $ 4K per die lot
		Recourse ~ $ 3.6K- $ 4.1K per die lot
CONTRACT CANCELLATION PENALTY	Foundry ~ $ 2000 per lot	
	Assembly ~ $300 per die lot	
INVENTORY COSTS	1-15 % of the revenue of the product /year (Lower at Fab and higher at Demand center)	
WAFER LOT SIZE	25 wafers with 200 die each	
DIE LOT SIZE (FOR ASSEMBLY AND TEST)	1000 die	
REVENUE FOR SOLD PRODUCTS (VARIES)	$10K ±2.5K to $100K ±25K per wafer	

Table 6: Production Starts and Sales: At wafer fabrication and sort facilities, the production starts are by wafer lots (25 wafers). At assembly and test centers, the production starts are by chiplots (1000 chips). The sales at demand centers are also shown in chiplots. Production starts and sales are shown across the five levels of deviation from mean. Panel A shows the results when there is positive correlation (*r*) between the demands of the two products. Panel B has *r* at zero and Panel C has *r* as –0.4, negative correlation.

Panel A (*r = +0.4*)

	10%	**20%**	**30%**	**40%**	**50%**
	(Demand deviation from mean)				
Fab	193245	191796	186170	183090	175758
Sort	183582	182126	175991	173936	166970
Assembly	917913	910629	879951	863731	833982
Test	917912	910629	879951	863731	833982
Demand	899554	892416	862351	845477	813970

Panel B (*r = 0*)

	10%	**20%**	**30%**	**40%**	**50%**
	(Demand deviation from mean)				
Fab	193521	191305	189059	183550	179694
Sort	183845	181739	179606	174373	170709
Assembly	919226	908696	898029	868418	852413
Test	919226	908696	898028	868418	852414
Demand	900841	890522	880068	851050	834420

Panel C (*r = -0.4*)

	10%	**20%**	**30%**	**40%**	**50%**
	(Demand deviation from mean)				
Fab	193804	183964	191129	190136	185832
Sort	184114	174766	181572	179947	176414
Assembly	920570	873831	907856	899739	879704
Test	919226	873831	905268	891419	874411
Demand	900841	856354	887162	872870	855176