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# SOLVING VOLUME AND CAPACITY PLANNING PROBLEMS IN SEMICONDUCTOR MANUFATURING: A COMPUTATIONAL STUDY

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## ABSTRACT

In this paper, we suggest a linear programming formulation that allows for solving volume and capacity planning problems in semiconductor manufacturing systems. We assume a general product structure that includes commodities, custom products, finished products between these two extreme classes, and several types of unfinished products. Computational experiments with respect to the required level of detail of bottleneck modeling are performed. Furthermore, we investigate the sensitivity of the model with respect to noisy demand data. It turns out that the number of modeled bottleneck is not crucial and that our approach can treat noisy demand data appropriately.

## 1 INTRODUCTION

This research is motivated by mid-term production planning problems in semiconductor manufacturing systems. Here, volumes for non-final products and committed volumes for final products have to be determined taking the finite capacity of the manufacturing systems and the requested demand into account.

We call this type of problems volume and capacity planning problems because production volumes are determined that lead to a certain capacity allocation over time. Volume and capacity planning is challenging in the semiconductor industry (cf. Geng and Jiang 2008 and Gupta et al. 2006) because of

- complex manufacturing processes: usually between 400 and 800 process steps are required on a large number of tools to produce an integrated circuit. Typically, semiconductor manufacturing enterprises are organized as manufacturing networks that contain dozens of facilities around the world.
- frequent changes of technology and products: new type of tools are required to produce state of the art integrated circuits. The life-cycle of products is becoming very short.
- long lead times and large costs for extending capacity: capacity expansions are time consuming and very expensive.
- highly uncertain demand and capacity: the demand for integrated circuits is very volatile. Semiconductor manufacturing systems are stochastic systems because of tool break downs and rework. Therefore, the capacity offered by the manufacturing system is to a certain degree unpredictable.

Volume and capacity planning decisions are important instructions for lower level planning and scheduling decisions, for example for master planning.

There is some work related to strategic capacity planning questions in semiconductor manufacturing (cf. the more detailed discussion in Section 2.2). However, questions of an appropriate level of detail in modeling or questions related to the consideration of stochastic demand are only inadequately addressed so far. Based on a linear programming formulation, we study the question which level of detail is necessary in modeling the bottlenecks that constrain the capacity of the manufacturing system. However, our model is more an operative than a strategic planning model.

The paper is organized as follows. In the next section, we describe the problem addressed in this paper. We also discuss related literature. In Section 3, the suggested linear programming formulation is presented in some detail. Finally, the results of a computational study are shown in Section 5.

## 2 PROBLEM DESCRIPTION

We describe the researched problem in Section 2.1. Then we discuss related literature.

### 2.1 Problem Statement

Figure 1 illustrates a typical divergent product structure in semiconductor manufacturing. Several base wafers (blue) are made from raw wafers (white). Base wafers are produced without any relationship to a corresponding customer order. Here, a certain number of layers is manufactured. When a matching customer order arrives then the remaining layers are produced on top of the base wafer. Different intermediate products (green or pink) are made from each base wafer, and several finished products (red, orange, or yellow) are manufactured from each of them.

In the remainder of this paper, the term product can refer to any finished or unfinished product type. Each product is either a front-end or back-end product. In Figure 1, for example, the first two production stages for base wafers and intermediate products represent the front-end while the third stage for finished products represents the back-end. Note that not necessarily only finished products can be sold.

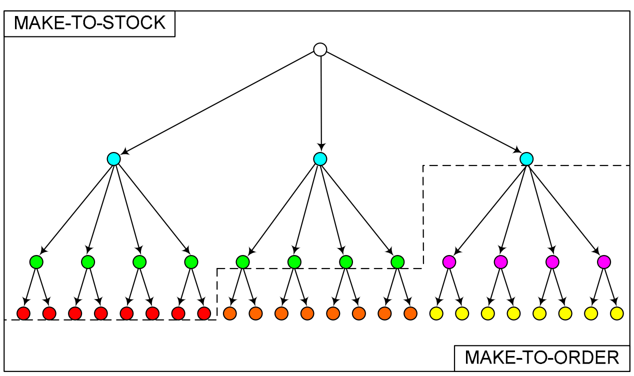


Figure 1: Product Structure

All products are either made-to-stock or made-to-order.

The finished products can be commodities (red) with a quite stable demand, custom products (yellow) with a very volatile demand, or finished products between these two extremes (orange). The demand volatility of the finished products has influence on the question whether their predecessor intermediate products have to be made-to-stock (green) or have to be made-to-order (pink). This decision has to be made on a more strategic planning level and is not the actual decision-making task for the presented model. Nevertheless, sensitivity tests referring to volatility of demand as performed in this paper (see Section 4) can support such decisions.

Each finished and unfinished product is produced by using a manufacturing process (represented by arrows in Figure 1). These processes can be front-end or back-end processes and subsume all manufacturing activities that have to be performed to produce the product they refer to. The data that refers to the processes includes information about cycle times, capacity consumptions, predecessor product consumption, manufacturing costs, and yield. The manufacturing processes are introduced because one product does not necessarily have only one manufacturing process that produces it. Alternative processes with different process data might be available, i.e., production done by a subcontractor. Another reason for the introduction is the more generic way of modeling input and output of a manufacturing process. For example, a process can produce more than one product at the same time when we regard several degrees of output product quality.

Capacity modeling is crucial for volume and capacity planning. In our model, we assume fixed average cycle times for each manufacturing process. Note that the production of a finished product from a raw wafer includes several unfinished product states with a separate manufacturing process for each of them. Therefore, the cumulated cycle time from raw wafer to finished product is not assumed to be fixed because the single processes do not necessarily have to be performed in a consecutive manner. Given the starting period for a process, we can compute when a certain wafer that performs this process will arrive at the bottleneck work centers that occur to execute the process. We accumulate the time that the wafer spends on processing on the tools of the bottleneck work centers for each period of time. This allows us to take the reentrant flows into account. This method is similar to capacity representation approaches used for capacity planning in semiconductor manufacturing (cf. Bermon and Hood 1999, Barahona et al. 2005).

The goal is to find production quantities, i.e., volumes, for a planning horizon of 26 weeks with weekly time buckets taking demand, capacity restrictions, and the current work in progress (WIP) into account. The objective is to maximize revenue for forecasted orders and minimize at the same time production costs, inventory holding costs, and costs for unmet committed orders.

The calculated volumes for “make-to-stock” products are the major output of the volume and capacity planning. They are reported as production requests to lower planning levels such as master planning. For those make-to-stock products that are predecessors of make-to-order products, the volumes are also used as an important input for Capable To Promise (CTP) calculations because they indirectly determine the maximum supply with “make-to-order” products that can be promised to the customer.

### 2.2 Related Research

We discuss first related research for capacity planning. Bermon and Hood (1999) describe a capacity planning system implemented at an IBM wafer fab. A mixed integer programming formulation is suggested. Integer variables are included because the model contains the possibility to extend capacity by purchasing new tools.

Later, this approach was extended in Barahona et al. (2005) to situations where the demand is stochastic. A planning horizon of several years is considered. A similar problem is discussed by Swaminathan (2000). A good source of previous work related to more strategic capacity planning is provided by Geng and Jiang (2008).

In our problem, we have to deal with a medium-term planning problem. Capacity expansion by purchasing new tools is not interesting. Therefore, we are able to avoid integer-valued decision variables. Denton et al. (2006) suggest a mixed-integer program to optimize a semiconductor supply chain. The model contains, for example, discrete lot sizes. Therefore, integer variables are required. However, because we are not interested in daily decisions, we do not need to model discrete details.

A second important stream of research is given by problems that have to deal with demand uncertainty. The idea of robust planning is used, for example, in Leung et al. (2007) and Barahona et al. (2005). However, in the majority of formulations found in the literature the treatment of stochastic demand is not well supported. This is especially true for the interaction of more sophisticated forecasting schemes and production planning approaches (cf. Xie et al. 2007 for some related research). Here, much more research is required.

## 3 LINEAR PROGRAMMING FORMULATION

In this section, we present the linear programming formulation for the volume and capacity planning problem.

### 3.1 Indices

The following indices are used within the model.

| | | |
|---|---|---|
| $p \in P$ : | products, | $p = 1,\dots,P$ , |
| $P^{(S)}$ : | sales products, | |
| $P^{(i,in)}$ : | input products of process $i$, | |
| $P^{(i,out)}$ : | output products of process $i$, | |
| $b \in B$ : | bottlenecks, | $b = 1,\dots,B$ , |
| $i \in I$ : | production processes | $i = 1,\dots,I$ , |
| $I^{(p,in)}$ : | set of all production processes that consume product $p$, | |
| $I^{(p,out)}$ : | set of all production processes that produce product $p$, | |
| $t \in T$ : | periods. | $t = 1,\dots,T$ . |

### 3.2 Parameters

The parameters below are used to formulate the linear programming model.

| | | |
|---|---|---|
| $rev_{pt}$ : | revenue per unit for meeting additional demand for sales product $p$ in period $t$, | $p \in P^{(S)}$ , $t = 1,\dots,T$ , |
| $mc_i$ : | variable cost per process quantity unit to perform process $i$, | $i = 1,\dots,I$ , |
| $hc_p$ : | holding cost per period and unit of product $p$, | $p = 1,\dots,P,$ , |
| $uc_p$ : | assumed penalty costs per unit for unmet confirmed orders of sales product $p$ per period, | $p = 1,\dots,P,$ |
| $C_{bt}$ : | capacity of bottleneck $b$ in period $t$, | $b = 1,\dots,B$ , $t = 1,\dots,T$ , |
| $u_{ibk}$ : | capacity usage of one unit of process $i$ at bottleneck $b$, $k$ periods after the process is launched, | $i = 1,\dots,I$ , $b = 1,\dots,B$ , $k = 0,\dots,ct_i$ -1, |
| $ct_i$ | expected cycle time of process $i$, | $i = 1,\dots,I$ , |
| $ip_{ip}$ : | input quantity coefficient of product $p$ per quantity unit of process $i$, | $i = 1,\dots,I$ , $p \in P^{(i,in)}$, |
| $op_{ip}$ : | output quantity coefficient of product $p$ per quantity unit of process $i$, | $i = 1,\dots,I$ , $p \in P^{(i,out)}$, |
| $q_p^{(l)}$ : | lower bound for the stored quantity of product $p$ at the end of each period, | $p = 1,\dots,P,$ |
| $q_p^{(u)}$ : | upper bound for the stored quantity of product $p$ at the end of each period, | $p = 1,\dots,P,$ |
| $o_{pt}$ : | confirmed orders for sales product $p$ in period $t$, | $p \in P^{(S)}$ , $t = 1,\dots,T$ , |
| $fc_{pt}$ : | additional forecasted demand for sales product $p$ in period $t$, | $p \in P^{(S)}$ , $t = 1,\dots,T$ , |
| $x_{it'}$ : | quantity of process $i$ started in previous period $t'$ , | $i = 1,\dots,I$ , $t' = 1 - ct_i,\dots,0$ , |
| $q_{p0}$ : | initially stored quantity of product $p$, | $p = 1,\dots,P,$ |
| $bl_{p0}$ : | initially found backlog for product $p$. | $p \in P^{(S)}$ . |

### 3.3 Decision Variables

The following non-negative and real-valued decision variables are used within the model:

| | | |
|---|---|---|
| $x_{it}$ : | quantity started in period $t$ for process $i$, | $i = 1,\dots,I$ , $t = 1,\dots,T$, |
| $q_{pt}$ : | quantity of product $p$ stored at the end of period $t$, | $i = 1,\dots,I$ , $t = 1,\dots,T$, |
| $s_{pt}^{(o)}$ | sales quantity of product $p$ in period $t$ to meet committed orders, | $p \in P^{(S)}$ , $t = 1,\dots,T$, |
| $s_{pt}^{(fc)}$ | sales quantity of product $p$ in period $t$ to meet additional forecasted demand, | $p \in P^{(S)}$ , $t = 1,\dots,T$, |
| $bl_{pt}$ | backlog of sales product $p$ at the end of period $t$, | $p \in P^{(S)}$ , $t = 1,\dots,T$ . |

### 3.4 Objective Function and Constraints

The following objective function has to be maximized:

$$\sum_{t=1}^{T}\left[\sum_{p\in P^{(S)}}\left(rev_{pt}s_{pt}^{(fc)} - uc_p bl_{pt}\right) - \sum_{i\in I} mc_i x_{it} - \sum_{p\in P} hc_p q_{pt}\right] \quad (1)$$

subject to the constraints:

$$s_{pt}^{(fc)} \le fc_{pt}, \quad p \in P^{(S)}, t = 1,\dots,T, \quad (2)$$

$$bl_{pt} + s_{pt}^{(o)} = bl_{pt-1} + o_{pt}, \quad p \in P^{(S)}, t = 1,\dots,T, \quad (3)$$

$$q_{pt} + \sum_{i\in I^{(p,in)}} ip_{ip} x_{it} + s_{pt}^{(o)} + s_{pt}^{(fc)} = q_{pt-1} + \sum_{i\in I^{(p,out)}} op_{ip} x_{it-ct_i}, \quad p \in P, t = 1,\dots,T, \quad (4)$$

$$q_p^{(l)} \le q_{pt} \le q_p^{(u)}, \; p \in P, t = 1,\dots,T, \quad (5)$$

$$\sum_{i\in I} \sum_{t'=t-ct_i+1}^{t} u_{ibt-t'} x_{it'} \le C_{bt}, \; b \in B, t = 1,\dots,T. \quad (6)$$

Constraint (2) makes sure that the sales quantity related to additional demand is smaller than the additionally forecasted orders. We use constraint (3) to model backlogs. Equation (4) is used to capture the material flow. Constraint (5) makes sure that the inventory related to each product is bounded. Finally, constraint (6) is a capacity constraint.

## 4 COMPUTATIONAL STUDY

Section 4 presents the computational experiments. To motivate our experiments, we describe the expected effects for which we want to investigate the model behavior in Section 4.1. Detailed information about the design of experiments and the investigated scenarios is given in Section 4.2. Section 4.3 contains the results that are discussed in Section 4.4.

### 4.1 Motivation

We want to investigate the reaction of the model with respect to two important aspects that can affect the solution quality of the presented planning approach: accuracy of bottleneck modeling and demand uncertainty. The goal is to find out how strongly the decision variables vary when facing these effects compared to the case that the full information is given.

Given that the most important task of volume and capacity planning is the determination of production volumes, we concentrate in our investigations on the calculated process quantities and their variation for different types of finished and unfinished products.

### 4.2 Scenarios

The divergent product tree is subdivided into three production stages (as shown in Figure 1). The first two stages (base wafers and intermediate products) are produced in front-end while the third stage (finished products) is produced in back-end. In the remainder of this paper, the stages are denoted as BWS, IMS, FPS.

There are 15 base wafers that are split into 75 intermediate products (five for each base wafer). Intermediate products are split into 300 finished products (four for each intermediate product). Therefore, the total number of products is 390.

Additional to the vertical subdivision into three production stages, the product tree is also horizontally subdivided into three major branches (similar to the situation shown in Figure 1). The first branch is the commodity branch (COB), the third branch is the custom product branch (CPB), and the middle branch (MIB) refers to finished products with an average volatility of demand. Each branch includes the third part of the products, i.e., five base wafers, 25 intermediate products, and 100 finished products with a given volatility of demand. All finished and no unfinished products are sales products.

Each product $p \in P$ is produced by exactly one process. This process generates 0.9 units of product $p$, i.e., the yield is 90 percent and consumes one unit of its predecessor. Base wafers have no predecessor.

We assume that front-end and back-end have four bottlenecks each.

There are 50 periods. The first 12 periods are used for initialization because the model starts empty. The next 26 periods are the actual planning horizon that is investigated. The last 12 periods are necessary in order to avoid invalid results in the later periods of the 26 week planning horizon.

No more processes are started in the later periods because their output is generated beyond the planning horizon. This effect is avoided by adding 12 additional periods with demand. Note that 12 weeks are equal to the maximum net cycle time from raw wafer to finished product in our experiments. Appending additional periods with demand is also necessary for a real-world application to obtain reasonable results for the later periods of the planning horizon.

In the following, we only refer to the actual planning horizon with the periods *1* to *T*.

We assume that the revenues, manufacturing, holding, and unmet demand costs are distributed as shown in Table 1.

The capacities of the bottlenecks are also included in Table 1. Note that bottleneck 1 is the most critical bottleneck for front-end and back-end. The other bottlenecks have 5%, 10%, or 15% percent more capacity.

The capacity usage is distributed as shown in Table 1. The expected cycle time for the different processes is two, three, or four weeks, each with a probability of 1/3. It follows that the total net cycle time from raw wafer to finished product is within the range of six to 12 weeks.

We assume that lower bound for the stored quantity of product *p* at the end of each period is zero. The corresponding upper bound is infinite.

The confirmed orders for sales product *p* in period *t* are distributed as shown in Table 1. The uniform distributions represent the approximately manageable total demand that can be produced. In period 1, the committed order quantity is slightly above this value caused by the factor 1.1 in the distributions. This leads to some backlog quantities in the early periods (see Figure 2). For later periods, the committed orders decrease linearly until they are equal to zero in the last period.

The additional forecasted demand quantities are calculated on the same total manageable demand basis as the committed orders. The difference is that they increase with increasing *t*. Note that the total demand of committed orders and forecasts can not be fully matched in any period because the cumulated factor is always between 1.5 and 1.6, i.e., about maximal two thirds of the total demand can be matched in each period with the given capacity (see Figure 2).

The initial values $x_{it'}$, $q_{p0}$, and $b_{p0}$ are not generated directly. They are a result from the 12 period initialization phase as described above.

The used design of experiments is summarized in Table 1.

Table 1: Design of Experiments

| | |
|---|---|
| $p \in P$ :<br>$P^{(S)}$ : | 390<br>100 |
| $i \in I$ : | one process per product, yield 90 percent |
| $b \in B$ : | four bottlenecks in front- and back-end |
| $t \in T$ : | 26 weeks |
| $rev_{pt}$ : | COB ~U[150,200]<br>MIB ~U[200,250]<br>CPB ~U[250,300] |
| $mc_i$ : | COB ~U[10,20]<br>MIB ~U[20,30]<br>CPB ~U[30,40] |
| $hc_p$ : | *10* |
| $uc_p$ : | *500* |
| $C_{bt}$ : | Front-end 1: 140351 h<br>Front-end 2: 147368 h<br>Front-end 3: 154386 h<br>Front-end 4: 161404 h<br>Back-end 1: 60000 h<br>Back-end 2: 63000 h<br>Back-end 3: 66000 h<br>Back-end 4: 69000 h |
| $u_{ibk}$ : | ~U[10, 30] (in minutes) |
| $ct_i$ | 2 weeks with p = 1/3,<br>3 weeks with p = 1/3;<br>4 weeks with p = 1/3 |
| $q_p^{(l)}$ : | 0 |
| $q_p^{(u)}$ : | ∞ |
| $o_{pt}$ : | COB<br>~U[150*1.1 * (T – t)/T,250*1.1 * (T – t)/T]<br>MIB<br>~U[100*1.1 * (T – t)/T,300*1.1 * (T – t)/T]<br>CPB<br>~U[0, 400* 1.1 * (T – t)/T] |
| $fc_{pt}$ : | COB ~U[150*(0.5 + t/T),250*(0.5 + t/T)]<br>MIB ~U[100*(0.5 + t/T),300*(0.5 + t/T)]<br>CPB ~U[0, 400*(0.5 + t/T)] |

Figure 2 shows a typical example for the given demand quantities and the calculated process, backlog, and sales quantities.

The total demand, represented by a dark blue line, can only be met by about two thirds. This is supported by the observation in Figure 2 that the total sales (light blue) is equal to about 60 percent of the total demand. Backlogs (brown) can be observed in the early periods while in later periods the whole committed orders (light green) are satisfied by sales referring to them (red). The additionally forecasted demand (orange) is never satisfied fully by sales referring to it (dark green) but due to decreasing committed orders for later periods it is satisfied increasingly with increasing periods.

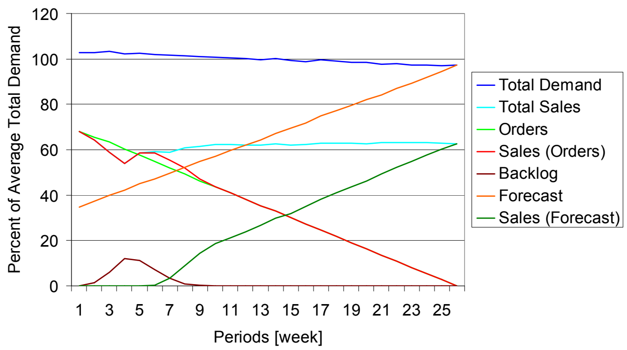


Figure 2: Model Quantity Example

According to the design of experiments, 25 independent test instances are generated. These instances serve as reference instances (RI) for three additional scenarios that are generated for each of these instances. In the first scenario, called SBN, we assume that only information about the most critical bottleneck 1 is given for front-end and back-end. The other three bottlenecks are not taken into account.

In the second scenario, called SFC, we assume that the forecast information is uncertain. Therefore, we delete the forecast data of the reference instance and substitute it by calculation of new forecast data according to the presented distributions. In the last scenario, denoted by SBNFC, we combine the reduced information of the first two scenarios.

### 4.3 Computational Results

In this section, we are interested in evaluating how strongly these scenarios affect the process quantities that are calculated by the model. Here, we distinguish product types by the three production stages and the three branches of the product tree.

As a measure for the deviation between the reference instance and the scenarios, we use the Mean Absolute Percentage Error (MAPE) that can be determined by using the following expression:

$$MAPE_s = \frac{\sum_{e \in E} \sum_{i \in I} \sum_{t=1}^{T} \left| x_{it}^{(e,RI)} - x_{it}^{(e,s)} \right|}{\sum_{e \in E} \sum_{i \in I} \sum_{t=1}^{T} x_{it}^{(e,RI)}}, \quad s \in S. \qquad (7)$$

In expression (7), the notation $S$ is used for the set of considered scenarios, and $E$ stands for the set of the 25 test instances. The MAPE for each scenario is the sum of absolute process quantity errors for all periods, processes, and test instances divided through the sum of all process quantities of the reference instances.

Figure 3 summarizes the results of the computational study. We see that the deviation of the process quantities is only three percent or even less in the SBN scenario for all production stages and all branches of the product tree. For the SFC scenario, we observe that the deviations are strongly dependent on the combination of product tree branch and production stage. The deviations tend to be lower for lower production stages and for product tree branches with lower demand volatility. The deviations in the SBNFC scenario are about equal to the ones in the SFC scenario.

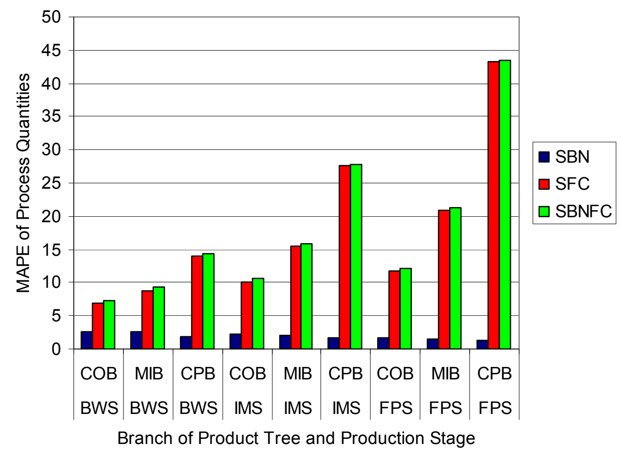


Figure 3: Computational Results

### 4.4 Discussion of the Results

First of all, it is surprising that the reduced information about the capacity in the SBN scenario has a nearly negligible effect on the calculated process quantities, especially when taking into account that even the bottleneck with the highest capacity has only 15% more capacity compared to the most critical bottleneck 1 in front-end and back-end. This implies that a concentration on the most critical bottlenecks in front-end and back-end is sufficient and can lead to near to optimal results.

This is especially useful for real-world application because collecting all the necessary capacity input parameters for the model is expensive and time consuming because of the large number of products and processes. Therefore, neglecting as much capacity information as possible leads to a much faster implementation.

The reaction of the model to demand uncertainty in the SFC scenario shows that the process quantity deviations are of course lower for products in a product tree branch with a lower demand volatility but can also be low for branches with high volatility when they are on a lower production stage.

As already discussed in Section 2.1, such a sensitivity analysis can be used in reality to support the decision which products can be “made-to-stock” and which products must be "made-to-order" because of a too strong reaction to uncertain demand.

## 5 CONCLUSIONS AND FUTURE RESEARCH

In this paper, we described a volume and capacity planning problem found in semiconductor manufacturing. A linear programming formulation is presented that takes important process characteristics of semiconductor manufacturing into account. We presented the results of a computational study where we investigate the necessary number of bottlenecks to be modeled and also the impact of noisy demand. It turned out that the suggested model is not very sensitive to the level of detail in modeling capacities.

There are several directions for future research. We are interested in extending our linear programming formulation to a robust optimization approach or a stochastic programming formulation taking the stochastic behavior of the demand more directly into account.

It is necessary to embed our planning approach into rolling horizon approach. Here, simulation experiments are required to capture the dynamics of the manufacturing process appropriately. In this context, it seems useful to study the interaction of the suggested volume and capacity planning approach with master planning schemes that are more detailed (cf. Ponsignon et al. 2008).

Furthermore, it seems fruitful to study the interaction of more sophisticated demand forecasting strategies and the volume and capacity planning approach described in this paper.

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