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PRODUCTION PLANNING MODELS WITH PRODUCTIVITY AND FINANCIAL OBJECTIVE FUNCTIONS IN SEMICONDUCTOR MANUFACTURING

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ABSTRACT

In the semiconductor manufacturing literature, production planning models mainly aim at minimizing total production, inventory and backlog costs. Solving these models may lead to a poor utilization of the production capacity when there are not enough demands. In this paper, after presenting a first generic linear programming model with fixed lead times when total costs are minimized, a model where productivity is maximized is introduced. Then, a model is proposed that includes the maximization of profit and considers the net present value of the financial objective function. These models are then compared using a data set from the literature. The numerical results show that, although the model with productivity maximization is performing as expected, the model with profit maximization is more relevant since it also helps to increase productivity. The impact of the actualization rate is analyzed, and also the limitations of the production of some products.

1 INTRODUCTION

Semiconductor manufacturing probably includes the most complex production systems. This complexity is mainly due to the size of facilities, with hundreds of machines and complex production characteristics, such as reentrant flows that link hundreds of operations to be performed on products, resulting in long cycle times of several weeks or months. Semiconductor manufacturing is decomposed into two main phases: "Front-end" and "Back-end". In this paper, we address production planning in the first phase, also called wafer manufacturing, in which raw wafers are transformed into finished wafers with integrated circuits, ready to be diced and packaged. Front-end facilities can produce many products, each one requiring hundreds of operations to be processed on different sets of heterogeneous parallel machines. In addition, during its long production route, each product is processed many times on the same set of machines (more than 80 times for advanced processes).

Planning the production of wafers is not an easy task. An important issue is to model the planned activity of each resource of the production facility. When the demand is high or/and when the production is characterized by a high mix of products and a low volume, this modeling becomes particularly important. The literature dealing with production planning in semiconductor manufacturing is relatively recent. The first proposed models suggest to model this congestion by integrating a "fixed Lead Time" (LT) per product. This means that a product that enters the system at time period t exits the system at time period $t+LT$. In these models, resource consumption is modeled by a linear function. This lead time is fixed *a priori* (calculated based on historical data) and does not depend on the workload. In real situations, the lead time depends on the workload and the production plan. In order to consider the workload, (Hung and Leachman 1996) propose an iterative approach based on an optimization (linear programming) model to

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determine a production plan with fixed lead times and a (discrete event) simulation model that updates the lead times by evaluating the production plan. These two steps are repeated until the values of the lead times are converging. More recently, several studies (Albey et al. 2017; Kacar et al. 2013; Asmundsson et al. 2006) address this issue using mathematical formulations that model congestion with "Clearing Functions". Clearing Functions are nonlinear functions that model the congestion by quantifying cycle times based on the workload. The notion of "Clearing Functions" is not new, and was introduced in the 80s by (Graves 1986). This recent keen interest is mainly due to the development of more realistic clearing functions. Recently, Albey et al. 2014 propose a clearing function that considers product mix.

These research works emphasize congestion modeling. The studied objective functions are mainly based on a combination of inventory and backlogging costs. However, one of the most important objectives in semiconductor manufacturing is also to maintain a high productivity level. This activity is measured by the *number of operations* performed during the planning time horizon. This performance indicator is also called the number of "moves" in the industrial jargon. In this paper, we propose new objective functions and integrate them in a classical model with fixed lead times in order to enhance productivity and maximize the profit. An actualization rate is used to model the net present value of the profit. In Section 2, linear programming models for production planning are presented, first a generic model where the total cost is minimized, then a model where the number of "moves" is maximized and finally a model where the total profit is maximized. Numerical experiments are conducted in Section 3. The models are compared and analyzed using a data set from the literature with different demand profiles and actualization rates. The impact of limiting the production of some products is also studied. Section 4 concludes the paper and provides some perspectives.

2 MATHEMATICAL MODELS

In this section, we generalize the classical model that considers fixed lead times (see Kacar et al. 2013). First, contrary to most studies, two timescales are considered. The first timescale (in weeks) is used to model demands, while the second timescale (in days) is used to model production processes. In Section 2.1, a generic model is introduced that is based on the classical objective function (an aggregation of inventory costs and backlogging costs). Then, in Section 2.2, a first objective function is proposed that maximizes the total number of performed operations, i.e. the "moves". Finally, in Section 2.3, a second objective function is proposed that considers the Net Present Value (NPV) of the profit.

2.1 Generic model with two timescales

In this section, a generic model is introduced for planning the production of of wafers, namely the production of P products over a discrete time horizon that has two timescales. The time horizon is decomposed into T days and S weeks. Demands D_{ps} are expressed per product p and per week s. Each product p needs a sequence of operations $\mathscr{L}_p$ to be processed on a set of K workshops. Each workshop k can process a finite set of operations $\mathscr{L}^k$ and has a finite capacity C_k.

The plan is determined by optimizing internal production flows. The goal is to decide quantities X_{plt} to be released per product p, per operation l and per period t (one day). The set of operations of product p and their resource consumption α_{pl} provide the timing of operations. In order to trace production flows, a variable W_{plt} that represents the work in progress per product p, per operation l and per period t (a day) is introduced. An unitary work in progress cost w_{pl} is associated to each product p and each operation l.

The goal is to to satisfy demands while minimizing inventory, backlogging and work in progress costs. We introduce an unitary inventory cost h_{ps} and an unitary backlogging cost b_{ps} for each product p and each period s (a week). Let us also introduce two decision variables I_{ps} and B_{ps}, that respectively model the inventory and the backlog of product p at time period s (a week).

To consider congestion in our model, a fixed lead time LT_{pl} per product p and per operation l is used. This way of modeling congestion is known to be less efficient than iterative approaches or clearing function based models (Asmundsson et al. 2006), but is both practical and relevant (Kacar et al. 2016). Its main advantage is that it is easier to analyze and is a special case of more sophisticated models. In this model, we assume that transportation times and costs between two workshops are negligible or constant. Products that complete a given operation are placed in a waiting queue for the next operation (the waiting queue is supposed to be uncapacitated). We also assume that the processing time of each operation is lower than one day (this assumption is justified since the longest operation usually needs less than half a day). All lead time are expressed in days.

Due to the large industrial data sets we want to address, only continuous variables are considered in our models. All sets, parameters and decisions variables are summarized below.

2.1.1 Notations

Sets

- $\mathscr{L}_p$: Sorted list of operations of product p;
- $\mathscr{L}_p^k$: Set of operations for product p processed in workcenter k.

Parameters

- P: Number of products;
- K: Number of workshops;
- T: Number of periods in the planning horizon for production;
- S: Number of periods in the planning horizon for demands;
- ts_s: First period of $\{1,\dots,T\}$ included in $s \in \{1,\dots,S\}$;
- tf_s: Last period of $\{1,\dots,T\}$ included in $s \in \{1,\dots,S\}$;
- α_{pl}: Unitary resource consumption of operation l of product p;
- C_k: Daily available resource capacity of workcenter k;
- LT_{pl}: Lead time of operation $l \in \mathscr{L}_{(p)}$ for product p;
- D_{ps}: Demand of product p at the end of period s;
- h_{ps}: Unitary inventory cost of product p at the end of period s;
- b_{ps}: Unitary backlogging cost of product p at the end of period s;
- w_{pl}: Unitary work in progress cost;
- B_{p0}: Initial backlog of product p;
- I_{p0}: Initial inventory of product p;
- W_{pl0}: Initial work in progress of product p at operation l.

Decision variables

- X_{plt}: Quantity of product p to be released in period t to operation $l \in \mathscr{L}_p$;
- $X_{pt}^{\text{in}} = X_{p1t}$: quantity released for product p at period t (also known as fab-in plan);
- Y_{plt}: Quantity of product p completing its operation $l \in \mathscr{L}_p$ at period t;
- $Y_{pt}^{\text{out}} = Y_{p|\mathscr{L}_p|t}$: output quantity of product p at period t;
- W_{plt}: Work in progress of product p, at operation $l \in \mathscr{L}_p$ at the end of period t;
- I_{ps}: Inventory level of product p at the end of period s;
- B_{ps}: Backlogging level of product p at the end of period s.

2.1.2 Mathematical formulation

$$\min \quad \sum_{p=1}^{P}\sum_{l\in\mathscr{L}_p}\sum_{t=1}^{T} w_{pl}W_{plt} + \sum_{p=1}^{P}\sum_{s=1}^{S}(h_{ps}I_{ps}+b_{ps}B_{ps}) \tag{1}$$

$$\text{s.t.} \quad Y_{plt} = X_{p(l+1)(t)} \qquad \forall p\in\{1,\ldots,P\} \quad \forall l\in\mathscr{L}_p \quad \forall t\in\{1,\ldots,T\} \tag{2}$$

$$W_{plt} = W_{pl(t-1)} + X_{plt} - Y_{plt} \qquad \forall p\in\{1,\ldots,P\} \quad \forall l\in\mathscr{L}_p \quad \forall t\in\{1,\ldots,T\} \tag{3}$$

$$X_{plt} = Y_{pl(t+LT_{pl})} \qquad \forall p\in\{1,\ldots,P\} \quad \forall l\in\mathscr{L}_p \quad \forall t\in\{1,...,T-LT_{pl}\} \tag{4}$$

$$D_{ps} + B_{p(s-1)} = \sum_{\tau=ts_s}^{tf_s} Y_{p\tau}^{\text{out}} + I_{p(s-1)} - I_{ps} + B_{ps} \qquad \forall p\in\{1,\ldots,P\} \quad \forall s\in\{1,\ldots,S\} \tag{5}$$

$$\sum_{p=1}^{P}\sum_{l\in\mathscr{L}_p^k} \alpha_{pl}Y_{plt} \le C_k \qquad \forall k\in\{1,\ldots,K\} \quad \forall t\in\{1,\ldots,T\} \tag{6}$$

$$X_{plt}, Y_{plt}, W_{plt}, I_{ps}, B_{ps} \ge 0 \qquad \forall p\in\{1,\ldots,P\} \quad \forall l\in\mathscr{L}_p \quad \forall t\in\{1,\ldots,T\} \quad \forall s\in\{1,\ldots,S\} \tag{7}$$

The objective function (1) minimizes the total inventory, backlogging and work in progress cost. In the remainder of this paper and in the numerical experiments, for simplicity, we assume that the unitary work in progress cost w_{pl} is equal to zero. Constraints (2)-(5) model flow conservation. Constraints (2) ensure the link between the output of one operation X_{plt} and the input of the next operation Y_{plt}. Constraints (3) balance the work in progress over the time horizon for each operation. Constraints (4) guarantee the fixed lead time for each operation of each product. Constraints (5) are flow conservation constraints for final products, ensuring the satisfaction of demands through the inventory and the production at the current period or their backlogging to subsequent periods. The capacity constraints in each workshop are modeled through Constraints (6). Constraints (7) ensure the non-negative of decision variables.

2.2 Maximizing number of "Moves"

In the semiconductor industry, an important indicator for productivity is the number of performed operations, also called "moves". It corresponds to the number of completed operations multiplied by the number of products processed, per tool, workshop and plant. For example, with 8 machines and if each machine processes 100 products, then the number of "moves" is set to $8\times 100 = 800$. We propose to include this indicator in the previously defined objective function (1) with a scaling factor E. The new objective function is given by the equation below that maximizes the number of moves while minimizing the objective function (1).

$$\max \quad E\sum_{p=1}^{P}\sum_{l\in\mathscr{L}_p}\sum_{t=1}^{T} Y_{plt} - \sum_{p=1}^{P}\sum_{s=1}^{S}(h_{ps}I_{ps}+b_{ps}B_{ps}) \tag{8}$$

2.3 Maximizing profit

Mixing the minimization of the costs and the maximization of the number of "moves" is not really a natural way to improve productivity. In the following, let us introduce a profit per finished product G_p, leading to a more homogeneous objective function. In addition, using this new objective function, it is possible to model the fact that future profits and their associated decisions are less important than the current profits. This is done by introducing the notion of Net Present Value (NPV), which is often used in Economics to calculate the return on investment taking into account the time value of money (one monetary unit today is larger than the same monetary unit tomorrow). All future financial flows are included in a single function with an actualization rate $\beta_s \in (0;1]$, in order to emphasize the importance of good financial results in first periods. In our model, this actualization rate is applied each week, which means that the present value of the profit in week s reduces as s increases. Equation (9) below models the new objective function.

$$\max \quad \sum_{p=1}^{P}\sum_{s=1}^{S}\beta^{(s-1)}(-h_{ps}I_{ps} - b_{ps}B_{ps} + \sum_{t=ts_s}^{tf_s} G_p Y_{pt}^{out}) \tag{9}$$

3 NUMERICAL EXPERIMENTS

In Section 3.1, the data set is described. Then, in Section 3.2, we analyze the impact of the scaling parameter E on the objective function (8). In Section 3.3, the impact of the net present value on the objective function (9) is analyzed. Finally, in Section 3.4, since maximizing the profit induces a surplus of production, we propose to limit the excess of production and analyze the impact of this limitation.

3.1 Data set

Our experiments are conducted on a small data set extracted from (Kacar et al. 2012). It contains three different products with routes with 14 to 23 operations and 11 workstations. The first product has the longest route. The second product shares a large part of its route with the first product. Finally, the last product has a short route and some of the workstations are not shared with the two other products.

We fixed lead times based on the instance characteristics presented in (Kacar et al. 2012):

- Bottleneck machines are given a lead time of 5 days,
- Unreliable machines are given a lead time of 3 days,
- Batching machines are given a lead time of 1 day,
- Remaining machines are given a lead time of 0 day.

Let us recall that, in our experiments, the work in progress costs are fixed to zero. The horizon is divided into 61 days, i.e. 9 weeks. Three profiles of static (not time-dependent) demands are considered.

- Scenario 1. High infeasible demands: $\{45;15;15\}$.
- Scenario 2. Medium feasible demands: $\{33;11;11\}$.
- Scenario 3. Low feasible demands: $\{15;5;5\}$.

As in (Kacar et al. 2012), the backlog cost is fixed to 50, the inventory cost to 15 and the profit per unit of product to 60.

3.2 Analysis of Productivity Maximization

Let us first analyze the impact of the scaling factor E on the total cost, the number of moves and the total output (denoted respectively “Total Cost”, “#Moves” and “Total Output” in the following tables) when using the objective function (8). The scaling factor E is fixed to 0, 1, 5 and 10. Tables 1, 2 and 3 summarize the results for the three profiles of demand (resp. high demand, medium demand and low demand). Column “$E = 0$” corresponds to the generic model (1)-(7) and provides reference values. The deviation in percentage from these reference values is given between brackets.

Table 1: Impacts of scaling factor (E) on “Moves” for high demands.

	$E=0$	$E=1$	$E=5$	$E=10$
Total Outputs	565	565	628 (+11.1%)	691 (+22.2%)
Total Costs	22,515	22,534 (+0.1%)	25,715 (+14.2%)	31,457 (+39.7%)
#Moves	9,750	10,473 (+7.4%)	11,464 (+17.6%)	12,341 (+26.6%)

Table 2: Impacts of scaling factor (E) on "Moves" for medium demands.

	$E = 0$	$E = 1$	$E = 5$	$E = 10$
Total Output	495	495	576 (+16.4%)	649 (+31.2%)
Total Costs	0	0	4,020	10,849
#Moves	8,940	10,003 (+11.9%)	11,251 (+25.9%)	12,295 (+37.5%)

Table 3: Impacts of scaling factor (E) on "Moves" for low demands.

	$E = 0$	$E = 1$	$E = 5$	$E = 10$
Total Output	225	227 (+0.7 %)	446 (+98.4%)	564 (+150.6%)
Total Costs	0	636	8,595	21,713
#Moves	4,138	7,525 (+81.9%)	9,927 (+139.9%)	11,900 (+187.6%)

Tables 1, 2 and 3 show that productivity can significantly be improved. Even with a small scaling factor E, the number of "moves" increases from 7% for high demands up to 82% for low demands. With larger values of E, larger improvements are obtained on the number of moves. This is done at the expense of the total cost. There is a trade-off to make between productivity and inventory/backlog costs. Note also from Tables 1, 2 and 3 that the total output increases when productivity is improved. Through these results we were not able to find a correlation factor between E and $\#Moves$.

However, this first objective function is a naive way to improve productivity. This is why we explore in the following the impact of considering the objective function that maximizes profit.

3.3 Impact of Using a Financial Objective

The profit maximization objective function helps us to move from a pure cost-driven model to a profit-driven model. As shown in the following, the NPV model also improves productivity.

The NPV model with different actualization rates β is compared to the results of the Generic model (Column "Generic"), where β is fixed to 1 (i.e. no depreciation), 0.95 and 0.8. The indicators "Total output" and "#Moves" are kept. Two others indicators are introduced: The total profit considering no depreciation and the total profit considering an actualization rate of 0.95. Tables 4, 5 and 6 summarize the results considering high, medium and low demand profiles, respectively.

Table 4: Variations of actualization rate β for high demands.

Models	Generic	NPV β=1	NPV β=0.95	NPV β=0.8
Total output	565	633 (+12.0 %)	643 (+13.8%)	713 (+26.0%)
#Moves	9,750	10,645 (+9.2%)	10,787 (+10.6%)	11,727 (+20.3%)
Total profit with β=1	11,407	13,571 (+19.0%)	13,563 (+18.9%)	11,361 (-0.4%)
Total profit with β=0.95	11,249	12,761 (+13.4%)	12,793 (+13.7%)	11,588 (+3.0%)

First, note that the objectives with the actualization rates $\beta = 1$, $\beta = 0.95$ and $\beta = 0.8$ are different by definition. From Tables 4 to 6, note that the actualization rates $\beta = 1$ and $\beta = 0.95$ provide similar results, while the actualization rate $\beta = 0.8$ provides a larger total output which induces a larger number of moves (#Moves). By comparing the generic model to models with a profit per product, the total output increases from 12% for instances with high demands to 193% for instances with low demands. The total profit increase is also not negligible, varying from 11% to 63%. A detailed analysis of the results shows that, even if the total profit increases for high demands are greater in percentage compared to profit increases for medium demands, the absolute increase of total profit for medium demand (3,370) is larger than the absolute increase of total profit for high demands (2,164). This larger total profit can be explained by the

Table 5: Variations of actualization rate β for medium demands.

Models	Generic	NPV β=1	NPV β=0.95	NPV β=0.8
Total output	495	595 (+20.2 %)	610 (+23.2%)	697 (+40.7%)
#Moves	8,940	10,266 (+14.8%)	10,458 (+17.0%)	11,672 (+30.6%)
Total profit with β=1	29,700	33,070 (+11.3%)	33,065 (+11.3%)	30,564 (+2.9%)
Total profit with β=0.95	24,404	26,747 (+9.6%)	26,795 (+9.8%)	25,421 (+4.1%)

Table 6: Variations of actualization rate β for low demands.

Models	Generic	NPV β=1	NPV β=0.95	NPV β=0.8
Total output	225	469 (+108.4 %)	487 (+116.7%)	660 (+193.2%)
#Moves	4,138	8,060 (+94.8%)	8,316 (+101.0%)	10,243 (+147.6%)
Total profit with β=1	13,500	22,105 (+63.7%)	22,104 (+63.7%)	17,543 (+29.9%)
Total profit with β=0.95	11,093	17,035 (+53.6%)	17,097 (+54.1%)	14,687 (+32.4%)

fact that demands of instances with medium demands can be met while demands of instances with high demands cannot be met.

Figures 1a, 1b and 1c show weekly total outputs for each experiment compared to actual demands for respectively high, medium and low demands. Note that the generic model is not depicted in Figures 1b and 1c since it follows the demands.

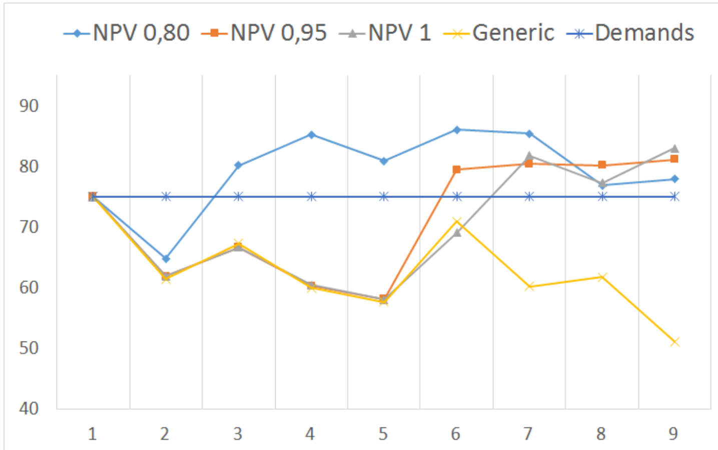
From Figures 1b and 1c, note that all methods start by producing the required demand at the first period, then quickly the model with the lowest actualization rate produces more than the demand. The other models start overproducing at the end of the horizon since no inventory cost is induced. In our instances, profits are lost if a product stays more than four weeks in the inventory. The same remarks can be drawn for Figure 1a, where the NPV model with $\beta = 1$ and $\beta = 0.95$ follows the behavior of the generic model until the end of the horizon where the NPV model starts overproducing. These end-of-horizon effects were expected. In fact, financial results are increased at the expense of meeting demands. This end-of-horizon overstock can be too large, and this anticipated production may have to be limited if demands after the end of the horizon are not expected to be large enough. A deeper analysis of the production plan shows that two products are anticipated. These products are the ones with shorter routes, i.e. requiring less capacity.

3.4 Limiting Excessive Production

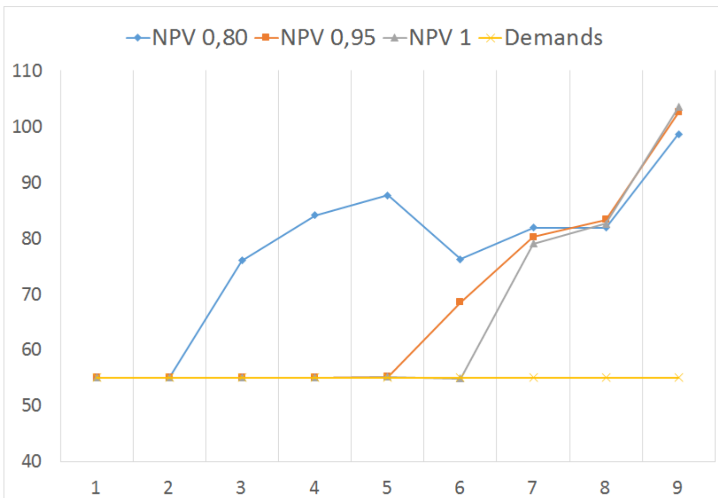
One way to limit the end-of-horizon effect is to limit the inventory at the end of the horizon for some specific products. In the following, we only consider the case with medium demands and the NPV model with an actualization rate of 0.95. Figure 2a details the results obtained in Section 3.3 by depicting weekly outputs of the three products. This figure shows that the first product follows the demand profile while Products 2 and 3 are overproduced at the end of the horizon.

First, in Figure 2b, we start by limiting the inventory of the last period of Product 3 to four times the demand of the last period. Recall that Product 3 shares few non critical machines with other routes. Limiting its last period inventory has almost no impact on the production plan of other products. Note that this additional constraint reduces the total profit by 2% (considering the actualization rate of 0.95).

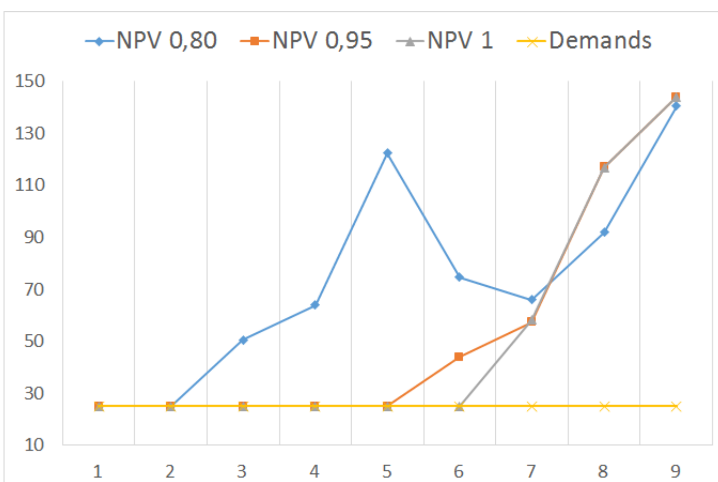
In Figure 2c, the inventory of the last period of Product 2 is limited to the demand of the last period. This new constraint causes a transfer of production from Product 2 to Product 1. This is due to the fact that the routes of Products 1 and 2 share several critical machines. Note that, in this case, adding a limit at the end of horizon for Product 2 does not significantly impact the total profit (a reduction of 0.3%).



(a) High demands

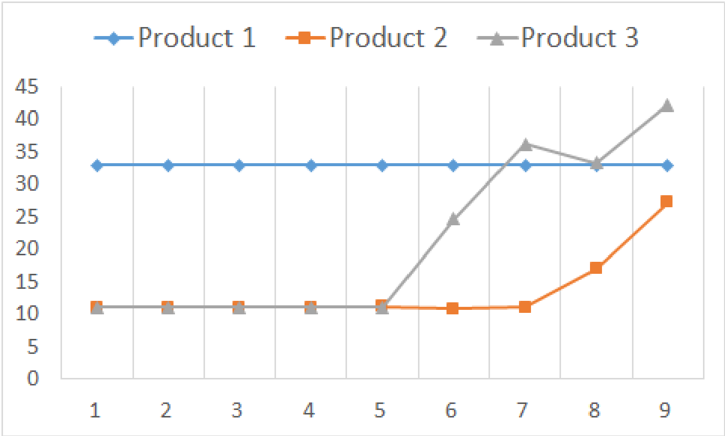


(b) Medium demands

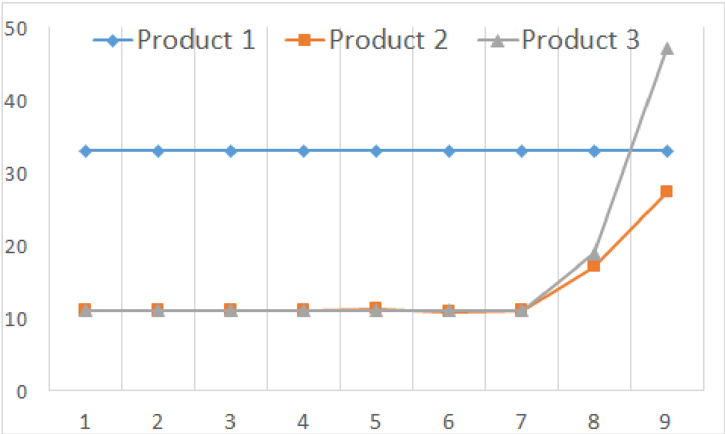


(c) Low demands

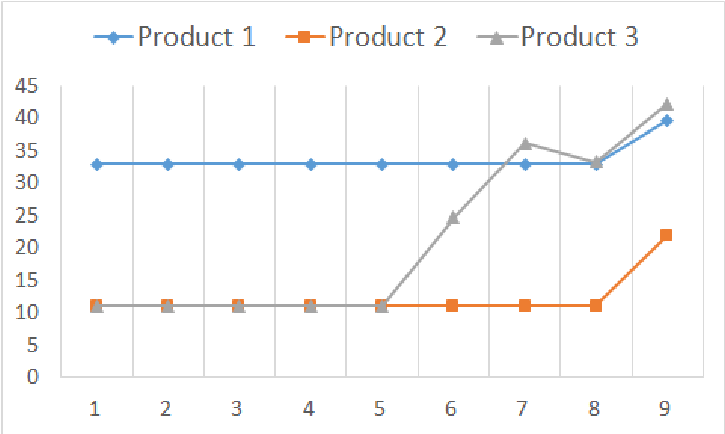
Figure 1: Weekly outputs.



(a) No inventory limit



(b) Inventory limit on Product 3



(c) Inventory limit on Product 2

Figure 2: Weekly outputs by product (NPV model with β=0.95 and medium demands).

4 CONCLUSION AND PERSPECTIVES

In this paper, we introduced models with new objective functions that aim at optimizing productivity and financial objectives for wafer manufacturing. These models were tested on a data set of the literature. First, we proposed a model that considers a classical industrial indicator (number of "moves"). The experiments showed that there is a trade-off to find between productivity and classical costs (inventory costs and backlog costs). Second, we developed a profit-driven model by introducing the Net Present Value in a profit function. The experiments illustrated that the profit-driven model ensures a better productivity than a pure cost-driven model, but it can lead to overproduction (notably at the end of the horizon). Thus we proposed to limit the inventory level at the end of the horizon. These limits are important for products that share capacities with non-overproduced products.

In the future, it will be interesting to propose an approach to bind these limits to forecasted demands (after the planning horizon). It will also be interesting to study the Net Present Value objective with financial closure dates (e.g. quarters) in order to analyze the impact of closure dates and the end-of-horizon effects. We are currently working on testing the proposed models on real industrial instances of large size (with tens of products and hundreds of operations). Finally, another limit of our models is the use of fixed lead time constraints. We are currently working on new constraints to model flexible lead times, and the preliminary results are promising.

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