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AN OPTIMIZATION FRAMEWORK FOR MANAGING PRODUCT TRANSITIONS IN SEMICONDUCTOR MANUFACTURING

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ABSTRACT

The highly competitive nature of semiconductor manufacturing requires firms to constantly introduce new products with improved features and cost. Product divisions, which are responsible for product specification and demand forecasting, must collaborate with manufacturing and product engineering groups to develop new products and bring them into high-volume production for sale. We present a centralized optimization model for resource allocation across the different units. Computational experiments indicate that the model captures the interactions between agents in a logically consistent manner, providing a basis for decentralized approaches and stochastic formulations.

1 INTRODUCTION

In highly competitive industries such as semiconductor manufacturing firms must continually introduce new products to replace older ones in the market (Billington et al. 1998) in a process known as *product transitions* or *product rollovers*. A Product Division (PD) manages the product portfolio for each market segment the firm serves, determining the timing and pricing of new products introductions (Bilginer and Erhun 2010). Each PD must forecast the demand for their products and request capacity from the Manufacturing Group (MFG) to fulfill the expected demand, and the Product Engineering Group (PEG) for product development. MFG can only produce a product for sale if its development has been completed by PEG. Several of PEG's development activities require prototype fabrication, for which MFG must allocate factory capacity. Corporate Management (CORP) allocates budgets to the Product Divisions, who must compensate PEG for development work and MFG for the production of their products for sale. Hence a product generation currently in the market will compete for MFG capacity with other PDs' products in the market, and with its own products and those of other PDs that are in development. Effective management of product transitions requires coordination between CORP, the PDs, MFG, and PEG to maintain revenue from sales of current products while ensuring the timely development of new products for future revenue. The broad scope and technical complexity of the decisions requires a decentralized solution, since each unit only has knowledge of its own capabilities and constraints. Thus our ultimate aim is to develop decentralized decision making mechanisms that can operate effectively in an uncertain environment.

This paper takes a first step towards this objective by formulating a centralized, logically consistent optimization model that can provide a basis for alternative stochastic formulations and decentralized approaches, as well as a benchmark against which their performance can be assessed. To validate the correctness of our model we perform computational experiments analyzing the effects of manufacturing capacity, product development capacity and product sale price on profitability. The results highlight the the importance of the pricing strategy across product generations and cash-flow constraints for resource allocation decisions. Finally, we explore the effects of disruptions within the planning horizon.

2 LITERATURE REVIEW

2.1 Introduction

Being first to market with a product allows a firm to establish itself as a new market standard, improving brand recognition and helping to capture market share by responding faster to customer feedback (Bilginer and Erhun 2010; Billington et al. 1998). However, many new products fail in the marketplace for different reasons (Erhun et al. 2007). In a single-product rollover, a new product is introduced only after its predecessor is discontinued. However, any disruption in the development of the new product will leave the firm with no product in the market. To mitigate this risk, the firm can choose a dual-rollover strategy where the old and new products share the market. However, this requires efficient coordination of the manufacturing, distribution, and marketing of both products. Erhun et al. (2007) reported on a three-year study at Intel Corporation on the risks and drivers affecting the product transitions, examining how the failure of a product introduction can damage the company. They identify eight factors affecting the adoption rate of a new product: product features (product capability); process features (internal execution); supply chain features (external alignment and execution); managerial policies (pricing, timing and marketing); and externalities (environmental indicators and competition).

Bilginer and Erhun (2010) define a product introduction as the process of introducing a product without considering its interactions with previous and future generations. In contrast, a product transition involves both introduction of the new product and displacement of a previous one. Since we study the interaction of multiple product divisions over a period long enough to develop several generations this paper focuses on product transitions. Drawing upon previous reviews by Bilginer and Erhun (2010) and Katana et al. (2017), we will examine the literature from the following perspectives: i) Demand Modeling, ii) Pricing Strategy, iii) Product Life-Cycle Events, iv) Supply Chain Decisions, and v) Integrating Studies that consider two or more of these aspects simultaneously.

2.1.1 Demand Forecast Determination

Diffusion models Bass (1969) are the most common approach to modelling demand for a new product. Norton and Bass (1987) extend the Bass model to multiple product generations. Wu et al. (2010) exploit sources of predictive information available over the product life-cycle using Bayesian updating to leverage new data as it becomes available. Reviews of the Bass model and its extensions are given by Robinson and Lakhani (1975), Norton and Bass (1987), Mahajan and Muller (1996), Padmanabhan and Bass (1993), Wilson and Norton (1989) and Dockner and Jorgensen (1988).

2.1.2 Pricing Strategy Determination

Product transitions can be managed by using price to influence the demand of successive product generations (Erhun et al. 2007). In the Bass model, reducing a product's price should increase its adoption rate. Robinson and Lakhani (1975) incorporate pricing into the Bass diffusion model such that product prices affect the adoption rate in any period, but the potential demand remains unchanged. Clarke and Dolan (1984) develop a game theory approach by studying different pricing strategies in a duopoly, while Dockner and Jorgensen (1988) introduce competition to the Bass model. Padmanabhan and Bass (1993) extend the Norton and Bass (1987) model by introducing prices, deriving the optimal pricing policy of a monopolist marketing successive product generations.

2.1.3 Product Life-Cycle Events

Some of the most important decisions in managing product transitions relate to the timing of events in the product life-cycle. Wilson and Norton (1989) study the optimal entry time of a new product using a diffusion model, proposing the "now or never" rule that it is best to either introduce the new product as early as possible or not introduce it at all. Mahajan and Muller (1996) extend this model by increasing the number of generations to four and allowing more than two product families in the market.

The previous models assume some cannibalization between generations of the same family, assuming a dual rollover strategy that is not necessarily optimal. Lim and Tang (2006) and Koca et al. (2010) developed analytical models to analyze the profits of single- and dual-product rollovers. They find that lower market risk and higher performance improvement for the new generation are associated with the single rollover strategy, consistent with Billington et al. (1998). Carrillo (2005) uses the rate of introduction of new product generations into the marketplace to analyze the relationship between a firm's own new product development activities and the industry clockspeed, finding that both technological and organizational barriers can be significant in fast-paced industries.

2.1.4 Supply Chain Decisions

A firm cannot benefit from the right pricing and time-to-market strategy if it is operationally unable to meet customer requirements. Diffusion models suggest that the demand will increase as the product penetrates the market until the demand reach a peak, after which the market is flooded by the new product and demand will decrease. The firm must decide how much production capacity to allocate to each product at different points in its life-cycle, particularly when to initiate production and when to terminate it. These production ramp-up and ramp-down decisions determine the amount of product available to meet demand over time. Carrillo and Franza (2006) study the linkage between time-to-market and ramp-up time decisions.

Product transitions often lead to increased uncertainty in the firm's supply chain due to the possibility of severe demand and supply mismatches. On the demand side, the degree to which the new product will be accepted is uncertain. From the production side, the increased frequency of adverse events induced by the new product can negatively affect delivery of both the new product and others that share capacity with it (Manda and Uzsoy 2020). Li et al. (2010) address inventory planning decisions for product upgrades when there is no replenishment opportunity during the transition period and show that the optimal substitution decision is a time-varying threshold policy.

2.1.5 Integrating Papers

Since the management of product transitions is a complex multidimensional problem, recent studies emphasize decisions integrating the several aspects discussed above. Shen et al. (2014) consider how a capacity-constrained firm prices products during new product introductions using a control-theory framework to model integrated optimal pricing, production, and inventory decisions. Demand is modelled using a generalized Bass Model where volume is influenced by price. When manufacturing capacity is insufficient they split the current unfulfilled demand into lost sales and backlogged demand, which affects the penetration parameters of the diffusion model. They find that the benefits of pricing flexibility are highest when capacity is neither very large nor very small and when word-of-mouth dominates direct impact from media. The ability to adjust prices is significantly more important than the option of producing in advance and holding inventory.

Özalp Özer and Uncu (2015) propose a dynamic programming model considering time to market decisions, sales channels, pricing and production decisions. They show that a threshold policy relating the number of competitors in the market to the time-to-market decisions is optimal. The firm needs to adjust its pricing and production policy in conjunction with its time-to-market decision. The firm's optimal policy during pricing and production stage is a state-dependent, base-stock list-price policy. Şeref et al. (2016) give an analytical model of coordinated product timing and pricing decisions for two product generations, characterising the optimal timing and pricing strategies for a single rollover scenario.

Wu and Lai (2019) use a multistage game between two asymmetric firms to examine different product launching strategies under a single-rollover. The firms may simultaneously launch new products that interact with each other in a two-stage game; or each firm may introduce their new products earlier or later than their rival leading to a three-stage interaction. They derive the firms' equilibrium pricing decisions using a dynamic programming approach, concluding that introducing a new product later than the rival is often a dominant strategy for firms. However, in some cases, a firm may prefer to launch their new product earlier than their rival to allow for a longer sales period, contradicting the "now or never" of Wilson and Norton. Schwarz and Tan (2021) examine how limited production capacity affects the optimal rollover strategy.

2.2 Decentralized Approaches

The complexity of managing product transitions renders effective coordination of the firm's activities crucial to success. However, since the information and technical skills required for decisions are located within different units and are not easily available outside them, many decisions are taken individually by the agents involved. This creates situations where agents' decisions may not always be mutually supporting, and may emphasize their local objectives over corporate ones. The difficulty of centralized planning in this environment motivates decentralized decision making approaches to this problem. The most common approaches use the ideas of market and mechanism design from economics, in which agents requiring resources submit bids to those who allocate them. Bids are then refined through a bargaining process until a final allocation of the resources commensurate with the current prices is achieved (Bichler 2017).

Wu et al. (2005) discuss the problem of capacity planning in high-technology industries which is heavily influenced by the need for continuous updating of the product portfolio. They classify the literature in three different categories: strategic models, tactical models and operational models and identify two general types of approaches. One body of research uses game theoretic and economic analysis to model multiple independent decision makers in the context of supply chain management. The second approach uses centralized models that employ tools such as dynamic programming or expected utility. Karabuk and Wu (2002) examine a decentralized coordination scheme at a major US semiconductor manufacturer. They construct a centralized stochastic programming model as a benchmark for the decentralized model in which each agent optimizes its own local decisions based on the available resources and information.

Karabuk and Wu (2005) design an incentive scheme through bonus payments and participation charges that elicits private demand information from the agents, and does not require external transfers to reach equilibrium. The mechanism also guarantees voluntary participation from the agents. A similar approach is presented by Kutanoglu and Wu (2006) for a collaborative production scheduling problem that arises when schedulers must coordinate their schedules with internal or external customers. They design a schedule selection auction where all agents state their preferences via a valuation scheme, and the mechanism selects a final schedule based on their collective input. They show that the proposed scheme is a direct revelation mechanism (Bichler 2017) that implements the optimal schedule selection under agents' dominant strategies.

The papers presented above treat one agent as an auctioneer who seeks to coordinate operations by allocating resources among the other agents, the bidders, who reveal their valuation of the resource bundle that is being offered. In our problem the agents act as buyers of some resources and sellers of others, resulting in interdependent bids. Bansal et al. (2020) approach the problem of effective coordination between manufacturing and product development activities with MFG acting as auctioneer. Since the product development teams request production capacity from MFG for prototype fabrication, MFG is not a simple auctioneer, since it also requires the use of some of the resource that is offering. The product development groups, in turn, offer MFG dates by which new products will complete development and be ready for production. The authors solve this coordination problem with an iterative combinatorial auction for that seeks to maximize the firm's profit while motivating all units to share information truthfully.

Most of the studies cited above approach the problem of managing product transitions from a strategic perspective, using simplified models that do not consider the complex technological and resource constraints affecting the production and development processes. Our model expands the number of agent types by including the budget allocation decisions that allow CORP to subsidize a PD that is temporarily unprofitable. The inclusion of separate PDs for different market segments, each of which must interact with MFG, CORP and PEG to fulfill their demand, also extends previous work Bansal et al. (2020).

3 MODEL FORMULATION

Our model seeks to maximize the firm's total profit over a finite planning horizon subject to constraints on the capabilities of the individual agents (CORP, PEG, PDs and MFG) and the external market conditions.

3.1 Corporate Management (CORP)

The CORP agent representing corporate management assigns initial budgets to the other agents at the start of each planning period. At the end of each period CORP receives the surplus generated by each of the PDs, given by the difference between the sales revenue from their products and the PD's payments to MFG and PEG for production and development activities. This allows CORP to subsidize some PDs that may be temporarily unprofitable in order to obtain increased profit in the future. Cash flow balance constraints ensuring that the firm's expenditures are commensurate with its revenues and borrowing capability.

3.2 Product Divisions (PDs)

Each Product Division (PD) operates as a profit center responsible for managing the product portfolio for the market segment it serves. The PD is responsible for developing demand forecasts for its products, developing specifications for new products and working with PEG to complete their development, and with MFG to have them produced for sale. At the beginning of each period each PD will receive a budget from CORP to cover its operating costs. From this budget it must pay MFG for each unit produced for sale, and PEG for any development work requested. Each PD is responsible for inventory holding or shortage costs incurred due to its decisions. At the end of the period the PD is credited with the revenue from the period sales of its products, and passes any surplus remaining after costs are met to CORP.

3.3 Manufacturing Group (MFG)

The Manufacturing Group (MFG) is responsible for fulfilling the PDs' requests for products to be sold, and PEG's requests for capacity for development purposes. At the beginning of a period MFG receives payment for each unit that will be produced for any other agent, which is used to pay for their own operations. The production process for high-volume units comprises two stages, transistor fabrication and metal fabrication, each requiring one planning period to complete. The primary constraints for MFG are material balance constraints across planning periods, and capacity constraints for each stage of the manufacturing process.

3.4 Product Engineering Group (PEG)

At the beginning of the period the PEG receives payment from each PD for the development work on its products in the current period. The development process for a semiconductor comprises three design-test-fabricate cycles, each involving three different steps. The first step is transistor design and fabrication, which requires capacity from both MFG and PEG for one planning period. The second step, metal design and fabrication, also consumes MFG and PEG capacity for one planning period. The development cycle ends with a debugging process requiring only PEG resources for one planning period. We assume each new product will be ready for manufacturing after three such cycles. In practice, the number of cycles is uncertain; unexpected technical problems may require an additional cycle, while a new product that is a minor modification of an existing one may require fewer. The primary constraints are precedence constraints between development tasks on each product generation, and resource capacity constraints.

3.5 Demand Modeling

Using a modified Bass diffusion model Wu et al. (2010), the demand for generation p of PD i in period t is given by

$$d_{(p,i,t)} = D^{pot}_{(p,i,t)} \frac{1-e^{-(pR+qR)t}}{1+\frac{pe^{-(pR+qR)t}}{q}} + \varepsilon_t \tag{1}$$

where $D^{pot}_{(p,i,t+1)} = D^{pot}_{(p,i,t)} - d_{(p,i,t)}$ denotes the remaining potential demand of generation p of product i at the beginning of period t, pR the PD's internal rate of adoption and qR the rate of adoption due the environment influence. $\varepsilon \sim Normal(0,\sigma^2)$ is a random variable representing the forecast error.

The literature considers the interaction between products of different generations only from the cannibalization point of view, so that a customer buying the older product will not buy the new one. However, in some industries the firm wants the customer to buy both generations, and a customer who buys the previous generation is more likely to buy the next. This situation can be seen clearly in the case of iOS vs Android cell phone users. A customer using one operating system gets familiar with it and is more likely to buy the next generation of the same product. This suggests that the unfulfilled demand of the older generation due to operational limitation should reduce the potential demand of the newer generations, which has not been considered in the literature to date.

In our experiments we reduce the future potential demand in proportion to the cumulative unfulfilled demand of earlier generations of the the PD's products (same division) as follows:

$$d^{new}_{(p,i,t)} = d_{(p,i,t)}(1-C\frac{\sum_{\forall pp}\sum_{\tau=0}^{t} max\{0, d_{(p,i,\tau)} - x^*_{(p,i,\tau)}\}}{\sum_{\forall pp}\sum_{\tau=0}^{t} d_{(p,i,\tau)}})\forall i \tag{2}$$

where C is a user-specified parameter describing the severity of the impact of missed demand on demand for future generations. We set C = 0.5 in all experiments presented except for those in Section 4.1 where C = 0.05 in order to reduce CPU time.

4 EXPERIMENTAL RESULTS

We present several computational experiments that explore the impact of several parameters regarding the rollover decisions. The experiments were conducted with a time horizon of 40 periods with two PDs each developing two new product generations. Each PD starts the experiment with an existing product, Generation Zero, already developed, while Generation Last represents a new product to be sold after the end of the current planning horizon.

The first set of experiments varies the parameter values for the entire planning horizon. In the second set of experiments, which examine the effects of unexpected disruptions, the firm constructs an optimal plan at the beginning of the planning horizon horizon. At an intermediate point in the planning horizon problem parameters change unexpectedly, returning to their original values after a known duration.

4.1 Impact of Manufacturing and Development Capacity

We first explore the impact of MFG and PEG capacities on the firm's total profit, sales and unfulfilled demand. Both PDs share the same product profitability across generations, with higher revenue for later generations. The introduction time for different PDs' products was only slightly different in order to test scenarios with high utilization of both MFG and PEG capacity. The three graphs in the left column of Figure 1 show the impact of varying PEG capacity on profit for a fixed MFG capacity.

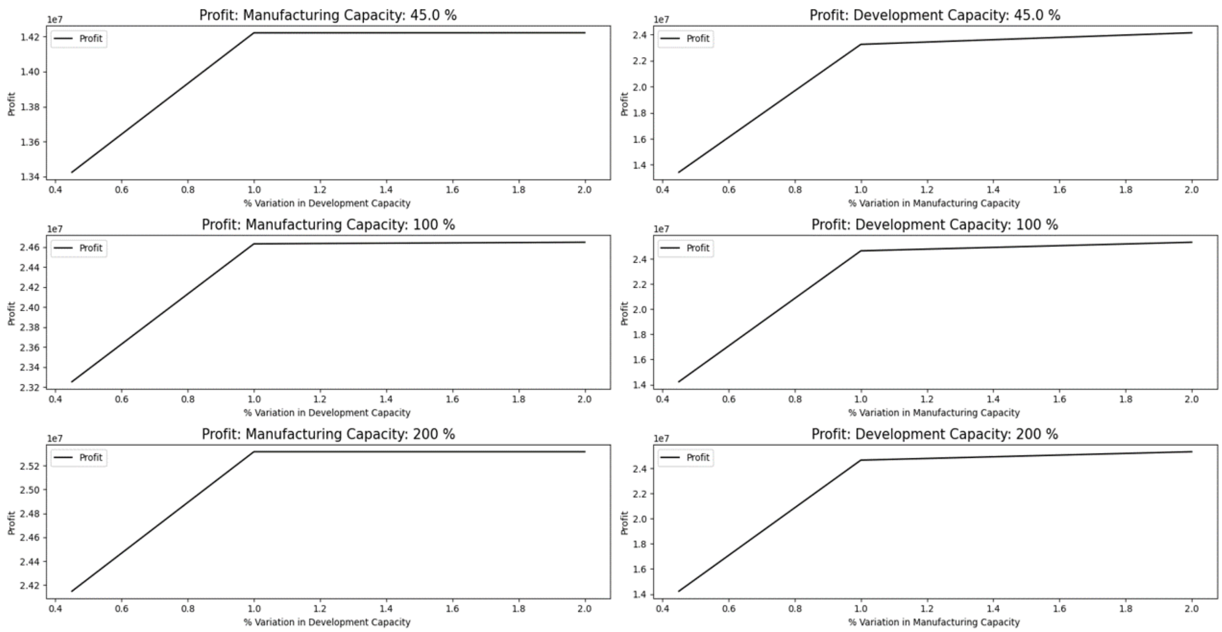

Figure 1: Impact of MFG and PEG capacity on profit.

Those in the right column plot the profit for a fixed PEG capacity as MFG capacity varies. In all graphs the slopes to the left of the base scenario are steeper than those to the right, showing that capacity reduction for one agent reduces profit more when the capacity of the other is already low, as expected. Figure 2 shows the output of the transistor fabrication stage. The line graph on the left side of the figure reflects the units produced for sale, and that on the right those produced for development . Each development stage requires 500 units and one product engineer team to be completed.

Plot a) in Figure 2 reflects the most constrained scenario. The left-hand plot shows that the model struggles to produce Generation Zero because it is using the available capacity to develop more profitable new generations. In this scenario the firm is not able to develop any generation for PD A due to the limited capacity. In b), where the MFG capacity is equal to the base case, the model uses the extra MFG capacity to produce Generation Zero for sale because the limited PEG capacity does not allow additional development, preventing the firm from developing the first generation of PD A. Plots c) and d) have higher capacity and in both scenarios the model develops every generation of every PD. Scenario c) struggles in two segments of the time horizon to fulfill the market demand for Generation Zero in periods 7 to 14 and that of Generation One of both PDs in periods 20 to 35.

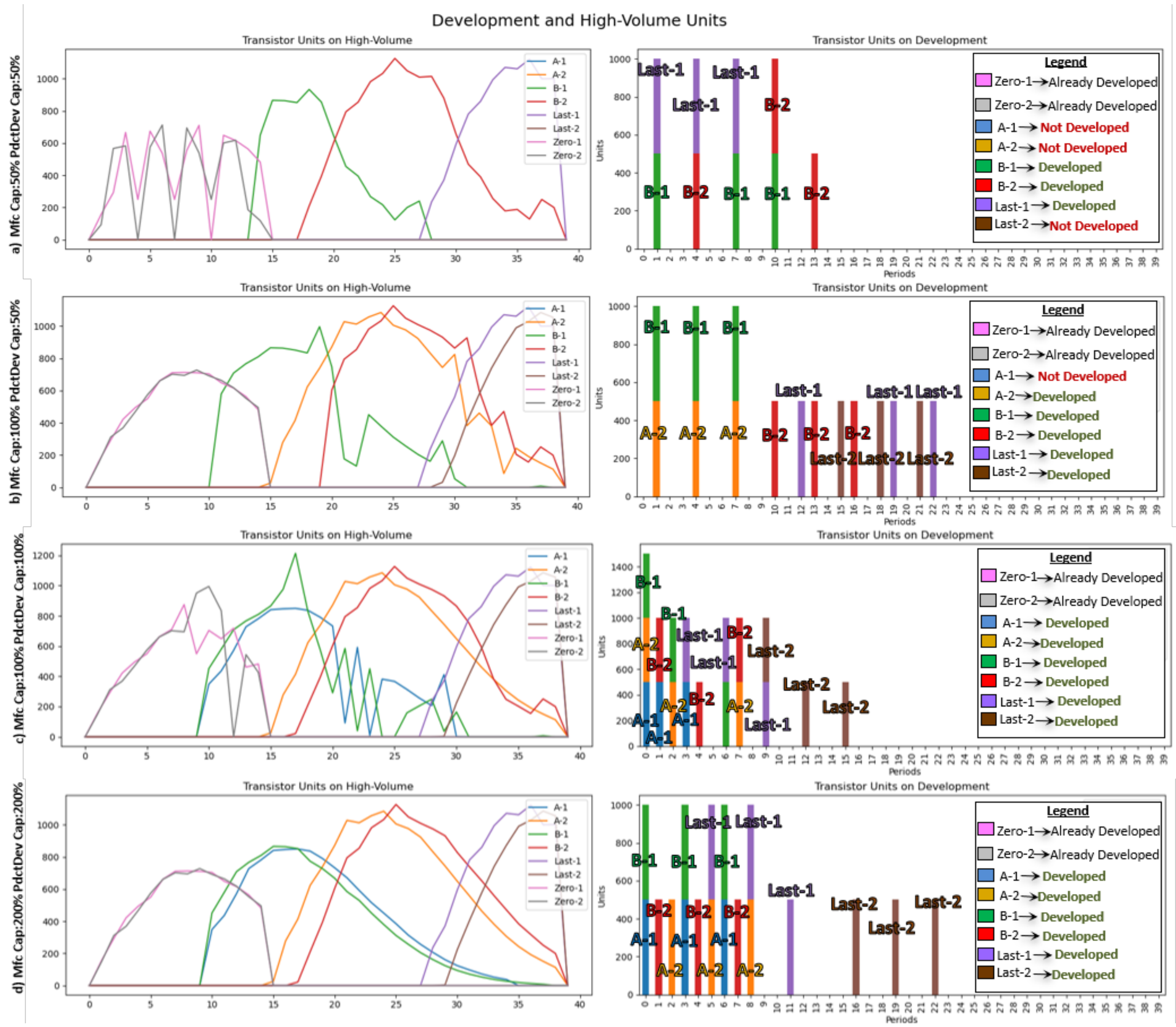

Figure 2: Impact of MFG and PEG Capacity on the Transistor Fabrication Stage

4.2 Impact of product revenue across generations.

Since the model shows a tendency to develop new generations as early as possible, we seek to identify the factors encouraging the firm to allocate MFG capacity to development early in the time horizon despite losing the demand for high volume products. If future generations are more profitable, the tendency to sacrifice present demand to develop new products earlier increases. In Figure 3 the development schedules on both metals and transistors processes differ for two opposite revenue strategies; on the top (a and b) the profitability increases as the generations advance, on the bottom (c and d) the revenue decreases for future generations. Comparing a) and c), where the initial budget is not constraining, we see how in the increasing revenue scenario the model brings the development schedules earlier, sacrificing current high volume demand to free manufacturing capacity in the future when it is more profitable to produce products with higher revenue. The profitability of a product generation is driven by its sales price, its manufacturing cost and the cost of the product development stage. We do not consider any interaction between price and demand, although this will be the subject of future work.

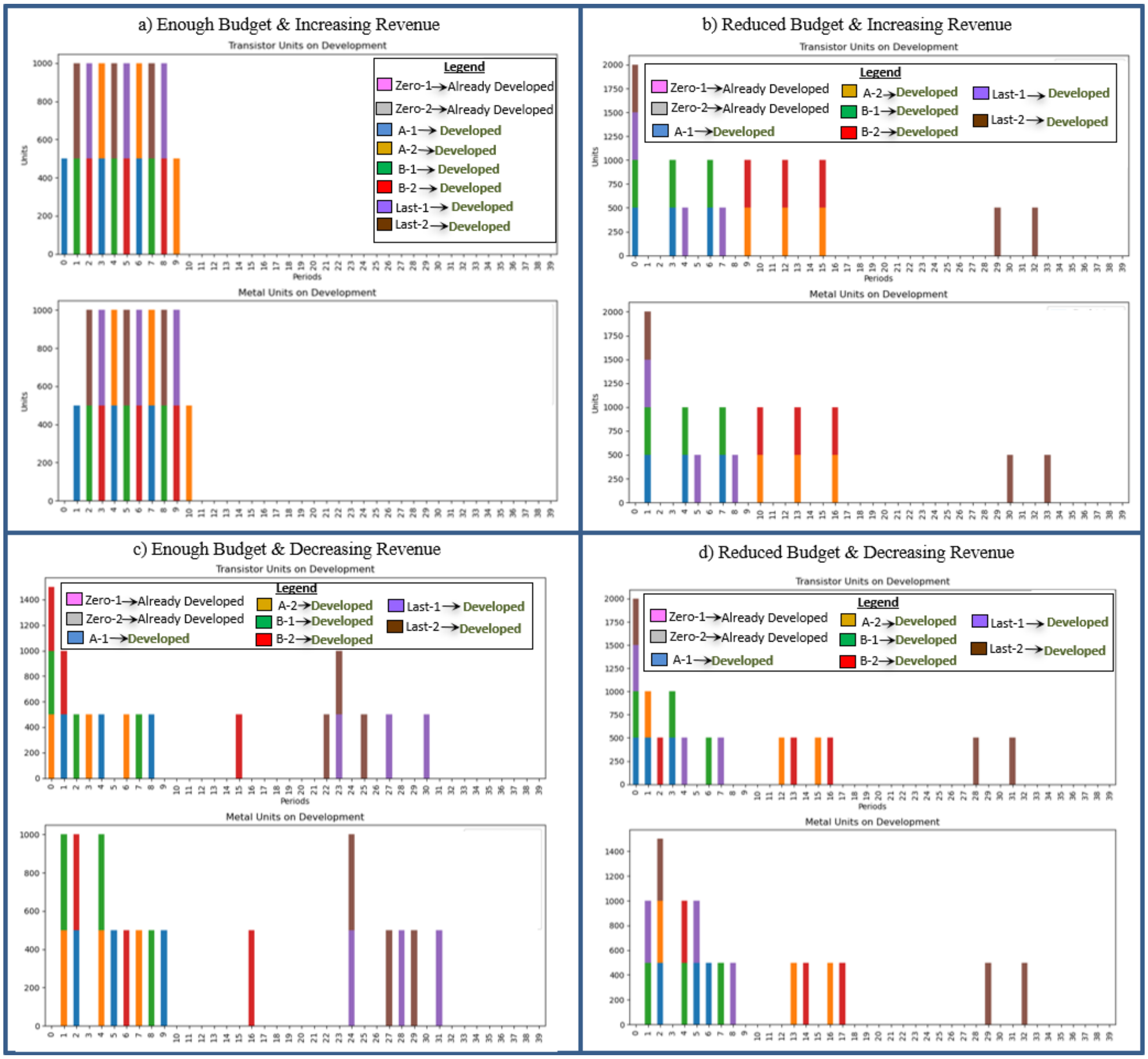

Figure 3: Effect of the Profitability Strategy and the Initial Budget in the Development Schedule

Further analysis identifies two important factors affecting capacity allocation under varying product profitability. The first is the cash available to the firm. If the future generation is more profitable, the incentive to develop earlier increases and current market demand is only partially served because meeting the demand for future generations is more profitable. But if we reduce the firm's initial budget at the beginning of the time horizon, the firm may have to delay some development activity to build enough liquidity by serving the present demand to avoid a cash flow problem. This is the reason why in Figure 3 the differences between scenarios b) and d) are much more subtle than those between a) and c). The second factor driving capacity assignment to the most profitable products is the future potential customers lost due to current unfulfilled demand. Customers who wanted our product but due to stockouts did not get it, will buy the competitor's product, hurting the firm's future demand.

4.3 Disruptions

In this set of experiments we develop a framework in which we simulate a disruption at any period of the time horizon varying the parameters over a time window. The disruption is not predicted at the start of time horizon, but once it occurs the firm has complete knowledge of when it will end. We simulate a disruption of production capacity, reducing MFG capacity by 50% over a time window ranging from 5 to 15 consecutive periods (Table 1). We compare the profit obtained for each instance under three different scenarios. The first is without any disruption to provide a baseline. In the second, the firm develops an optimal plan at the start of the horizon with no prediction of the disruption, and then re-optimizes upon the occurrence of the disruption. In the third case, the firm has full knowledge of the disruption at the start of the planning horizon and can develop an optimal plan accordingly.

Table 1 summarizes the results of these experiments. As expected, scenarios where the firm has knowledge of the disruption are more profitable than those where the disruption was unknown. It is clear that the disruption duration affects performance significantly. In the second experiment, when the firm knows that the disruption is going to occur in period 10, it finds that is better to focus on the current demand by delaying the development of the new generations until after the disruption. This scenario yields less unfulfilled demand than that without disruption, although the latter has better profit because it can focus on developing and selling more profitable future generations.

Table 1: Profit and unfulfilled demand relative to no disruption.

First Period of Disruption	Duration of Disruption	Disruption Scenario	Profit	Unfulfilled Demand
10	15	With Information	-16.90%	299.69%
10	15	Without Information	-28.08%	794.42%
10	5	With Information	-4.72%	-35.24%
10	5	Without Information	-17.71%	535.49%
25	10	With Information	-17.15%	330.22%
25	10	Without Information	-19.10%	405.09%

5 CONCLUSIONS

The experiments presented in this paper show that the proposed centralized model is able to capture the complex interactions between different units of the same firm pursuing different objectives but mutually dependent in terms of resource availability in a logically consistent manner. The experimental results clearly show the interaction between MFG and PEG capacity and their impact on profitability. Furthermore, limited PEG capacity can results in MFG capacity deficits that otherwise would not appear. When the capacity restrictions are tight enough they can force the firm to give up the development and future production of some products. The decision of which product to keep in the firm's portfolio is mainly driven by product profitability. Hence the pricing strategy affects not only sales revenue but also internal resource allocation decisions. These latter are also limited by the available budget, since allocating available capacity to develop a more profitable new products may reduce current sales leading to cash flow problems. In the presence of disruptions, both the duration and the starting period of the disruption affect profitability, and the ability to plan predictively improves performance.

Our future work will pursue two parallel directions. The first of these is to use this centralized model as a basis for decentralized approaches based on combinatorial auctions that will allow the firm to obtain feasible solutions that are near-optimal in terms of profit. A second direction will be the formulation of stochastic versions of the problem that can again be solved through decentralized approaches, taking advantage of information updating that occurs in a rolling horizon environment.

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