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DYNAMIC PRICE AND LEAD TIME QUOTATION UNDER SEMICONDUCTOR INDUSTRY RELATED CHALLENGES

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ABSTRACT

We consider the dynamic price and lead time quotation problem in the practical context of the semiconductor industry. Our model considers an inventory decoupled supply chain and accounts for a limited capacity, stochastic demand and processing times and quote-sensitive customers. We focus on performance evaluation under two decision making strategies. The first is lead time based pricing (LTBP). It follows a sequential approach where the firm decides first on the lead time quote (manufacturing) and then quotes the price under the given lead time (marketing). The second strategy suggests determining the lead time and the price quotes simultaneously. From the practical view-point, it is interesting to first understand the system performance under LTBP and then look for the ways to realize it. Based on our numerical results, we elaborate on the effect of LTBP on the key performance indicators and discuss conditions for close performance to a simultaneous decision strategy.

1 INTRODUCTION

A product manufacturer like a semiconductor company has usually contracts with customers to supply them with a certain quantity of a product by some upfront-agreed lead time and some flexibility in the rolling horizon updated planning. Often, customers request to have a product delivered earlier than the standard time, and could be willing to pay a higher price to make that happen. This is a well-known Revenue Management (RM) situation in the service industry, which in other industries such as process industry is just coming up (Zatta and Kolisch 2014). This paper focuses on lead time based pricing in the context of RM in the semiconductor industry.

In general, based on the manufacturer's information about the system load and inventory availability, lead time based pricing (LTBP) can help the manufacturer to balance capacity utilization rate while increasing the revenue by fulfilling customer orders earlier. This is specifically important for the semiconductor industry as it is characterized by long production lead times, high demand volatility and short delivery lead time requests. Earlier supply dates are valuable for customers due to the potential of lower inventory costs or for responding poor demand forecasts. Furthermore, their customers (the customer of the semiconductor industry e.g. Tier 1 in the automotive industry) tend to sign “Just in Time” agreements with their customers (e.g. OEMs in the automotive industry), leading to a penalization of Tier 1 for delivering products later than agreed and a non-legal but existing pressure on the semiconductor industry to deliver earlier than the contractually agreed lead time. As a result, the semiconductor industry current state is that the manufacturers provide flexibility beyond the contractual agreed date without any price adder.

To introduce revenue management in the semiconductor industry, the characteristics of manufacturing has to be considered (Chien et al. 2011). Semiconductor manufacturers, sit at the low end of the value chain. The long manufacturing times make it difficult to react the customer demand on short notice. In order to decouple the customer orders from long production times and improve responsiveness, semiconductor manufacturers have typically introduced an interim stock point in their supply chains.

Revenue management was researched already in 1960's by Peter P. Belobaba. It was introduced first by American Airlines (Belobaba 1987). Currently, it is successfully implemented in the service industry beyond airlines e.g. for car rentals, hotel industry and more. Zatta and Kolisch (2014) proposed extending it to the process industry. Through their research, they claimed that manufacturing companies could profit from revenue management techniques.

Existing research typically models the following strategies for satisfying customer demand: Make-to-order (MTO), assemble-to-order (ATO) and make-to-stock (MTS). Guhlich et al. (2015) model an ATO system. They consider a finite capacity as well as a limited semi-finished good inventory. However, their work considers that the incoming orders are accepted or rejected, depending on its characteristics and the production capacity. Defregger and Kuhn (2007) also consider revenue management by allowing the manufacturer to choose which order to accept. In practice, however, companies typically do not reject customers but quote a late order lead time. Considering revenue management under a MTO strategy, Öner-Közen and Minner (2017) combine the dynamic price/lead time quotation problem with due date based order sequencing decisions. In their work, order selection was not modeled by direct accept/reject decisions but via the price/lead time quotes. In other words, whenever it is not profitable to serve a customer, the firm quoted an unattractive price/lead time pair. Savaşaneril and Sayın (2017) look at a production system with inventory, used for improving responsiveness. They motivate their model stating that the inventory carries standard products and the customization activities are performed in negligible time. Differently, we assume non-negligible time for composing the final product and also model the processes from the stock point to customer satisfaction.

In this work, we model the main production stage with typically long cycle times, the semi-finished good inventory as well as the final assembly processes with shorter but non-negligible cycle times. We divide customers in to two types: Price sensitive (PS) and lead time sensitive (LS), and apply the strategy that fits to their primary interests (MTO and ATO respectively). In such a system, we analyze the problem of order selection via price and lead time quotes. In this regard, we model and evaluate two decision-making strategies. The sequential decision-making approach considers lead time quotation, considering production capabilities, followed by price quotation of marketing under the given lead time quote. The second strategy makes these decisions jointly, in other words, the firm optimizes order lead time and price decisions at the same time.

1.1 The Situation of Lead Times in the Semiconductor Environment

As mentioned before, semiconductor manufacturers usually sell their products with a shorter than contractually agreed upon lead time. Reasons for that might have been that semiconductor manufacturers came from the ultra competitive time when Moore's Law (Moore 1965) was dominating and with a price decline of 30% and more for memory and microprocessors selling was more important than the classical revenue management approach. For this apparently improved service, beyond the contractually agreed lead time, no higher price is charged. The process may provide a customer independent ATP (Available To Promise) and if supply is available also shorter than the contractual agreed leadtime, due to increased production starts to mitigate risks or cancellations from other customers or other reasons, is confirmed. Introducing lead time based pricing (LTBP) to increase price for an improved service seems to be very attractive especially since it is partially already done today without charging.

Figure 1 shows the current state of order lead times at a typical semiconductor company, where lead time is defined as the latency between an initiation via an order and its completion. The order lead time (OLT) is the time frame between an entry of a new order to one of four different points in time:

1. The wish date: Requested delivery date of the customer.
2. The delivery date: When the goods are actually delivered to the customer.

3. The confirmation date: Delivery is assured to arrive by this date.
4. The contract date: Based on the lead times which have been agreed in the contract.

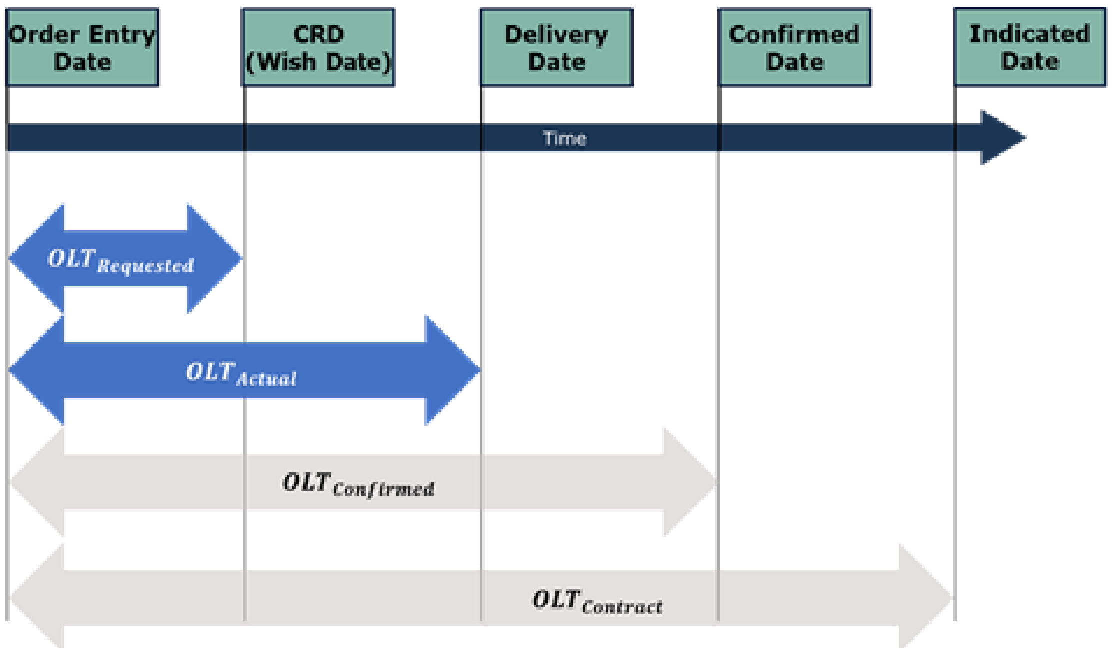

Figure 1: Order lead times.

Figure 1 depicts a scenario where the customer would like to have the chip arrive earlier than the agreed upon time. The semiconductor company confirms an earlier than the contractual date and presents an opportunity where LTBP can be applied. This opportunity arises in several areas but particularly with commodity products as these are typically requested on short notice. Implementation of LTBP here is expected to increase revenue because the company can charge prices that better match the service being provided, i.e. ability to confirm shorter lead times which come together with a better managed supply chain. Figure 1 provides an indication of satisfied orders with a shorter than agreed upon lead time, demonstrating the already existing potential for a way to successfully employ a LTBP strategy. However, a major argument against employing such a strategy is the anticipated high rejection rate of the existing customer base and potential damage to the customer-manufacturer relationship.

2 SIMULATION MODEL

2.1 System

We consider the supply chain structure depicted in Figure 2, where the production process of the final good is mainly divided into two stages. The production lead times are typically long in the first stage (front-end) while in the second stage (back-end) they are shorter. A semi-finished good inventory (die bank) decouples the two stages and enables better customer responsiveness. We model both stages as single server queuing systems.

We make the following assumptions:

- The processing times in both stages are exponentially distributed. The expected processing times of jobs in front- and back-end are $1/\mu_1$ and $1/\mu_2$ respectively ($\mu_2 > \mu_1$). Customers arrive to the system dynamically, according to a Poisson process. The firm applies demand forecasting,

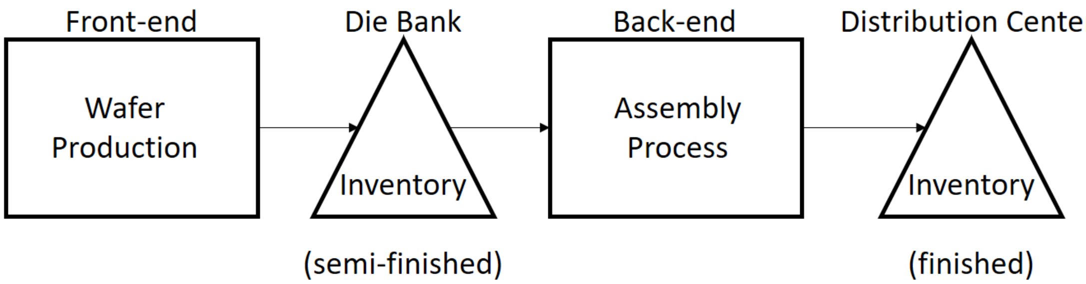

Figure 2: Supply chain of a semiconductor manufacturer.

therefore, has a good estimation of the arrival rate λ. Although in a simulation model many other distributions for the customer inter-arrival and order processing times can easily be incorporated, we model them as exponentially distributed random variables due to the following reason. The coefficient of variation of an exponentially distributed random variable is 1. This describes a high degree of volatility, which also exists in the arrival and service processes of the real-world problem.

- The firm is contractually obliged to deliver within a standard lead time ($OLT_{Contract}$).
- Upon arrival, a customer specifies his wish date. The lead time until this date is called "requested order lead time" and denoted $OLT_{Requested}$.
- The customers are segmented into two groups based on their lead time preferences. Customers with shorter requested order lead times than the standard ($OLT_{Requested} < OLT_{Contract}$) are referred to as lead time sensitive customers (LS). The customers who are not lead time sensitive are called price sensitive (PS). Given that a customer arrives, it is a LS customer with probability ζ. PS customers demand the standard price ($P_{Expected}$) and the contractual lead time ($OLT_{Contract}$). Dynamic price and lead time quotation is considered only for LS customers.

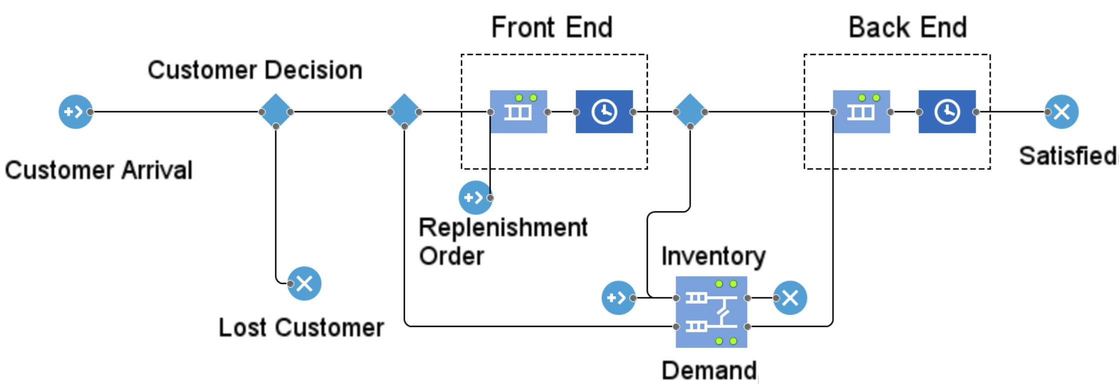

Figure 3: The flow chart of the decision problem (a snapshot from the implemented model).

- Upon the arrival of a LS customer, the company makes a (p,L) quote. In other words, confirms a price p and a lead time L. Then, the customer makes a decision whether to accept it or not. LS customers' reaction to a quoted price and lead time pair, i.e. the probability that a LS customer accepts the (p,L) quote, is modeled with the following probability function (Easton and Moodie 1999; Watanapa and Techanitisawad 2005; Öner-Közen and Minner 2017):

$$P^{LS}(p,L) = \left[1 + \xi_0 e^{\xi_L\left(L - OLT_{Expected}\right) + \xi_p\left(p - P_{Expected}\right)}\right]^{-1} \tag{1}$$

$OLT_{Expected}$ and $P_{Expected}$ reflect LS customers' expectation about a price and lead time offer they can get in the market. This expectation is based on their prior purchases.

Suppose that customers keep data on the lead time realizations for their prior orders (OLT_{Actual}). Based on the historical data, they know that realizing shorter lead times than $OLT_{Contract}$ is typical in the semiconductor industry, since OLT_{Actual} is often shorter than $OLT_{Contract}$. Before asking for a quote from the company (arrival), they shape their expectations accordingly ($OLT_{Expected} \leq OLT_{Contract}$). Similarly they know the standard price quote and expect to be quoted this amount ($P_{Expected}$). Nevertheless, they are willing to pay a premium for receiving shorter lead times than $OLT_{Expected}$. The acceptance probability decreases in both p and L. The negative effect of quoting a longer lead time than $OLT_{Expected}$ on the probability is reflected with parameter ξ_L, while the negative effect of quoting a higher price than $P_{Expected}$ is reflected with parameter ξ_p. These parameters define how sensitive the customers are to the (positive or negative) deviations from these expectations. Note that, even when $(p,L) = (P_{Expected}, OLT_{Expected})$, the customer does not necessarily place an order (if $\xi_0 > 0$).

- The firm follows an Assemble-to-Order (ATO) strategy for serving LS customers. Their orders go through only the back-end stage and consume one item of the available semi-finished-goods inventory. On the contrary, PS customer orders go through both stages, which means that the firm serves them according to a Make-To-Order (MTO) strategy. By doing this, the company exploits customers' willingness to wait for reducing the required inventory levels.
- PS customers place an order with probability one, however the firm does not have to accept all. These customers are rejected if based on the current system state, the expected OLT_{Actual} is estimated to exceed $OLT_{Contract}$.
- Inventory replenishments are made according to an $(S-1,S)$ policy, where S denotes the base stock level. This means that a replenishment order is placed to the front-end process as soon as an item (e.g. a lot) leaves the inventory (die bank).
- If a semi-finished good inventory item is not available at the arrival time of a LS customer, he/she is quoted $(p,L) = (P_{Expected}, OLT_{Contract})$. If he/she places an order, it is backordered (waiting for the completion of a replenishment order from the front-end process). However, a LS customer might reject the quote with a high probability, depending on the parameter ξ_L and the difference between $OLT_{Contract}$ and $OLT_{Expected}$ (1).

Note that OLT_{Actual} for an accepted PS customer order in the system (front-end+back-end) follows a hypoexponential distribution ($\mu_1 \neq \mu_2$). However, it can not be expressed in closed-form because the order processing sequence does not follow a first-come-first-served (FCFS) discipline. Arriving LS customer orders enter the system directly from the second stage, therefore, they can overtake PS customer orders, i.e., they can be processed in the second stage before some PS customer orders that arrived earlier. Furthermore, the arrival rate of the LS customer orders is dependent on the acceptance probability, which depends on the values of decision variables (p,L). In the following we explain how the expected OLT_{Actual} for PS customers is estimated, since the firm rejects them if this amount exceeds $OLT_{Contract}$.

Let $W_i(n_i)$ denote the time an order spends in the i^{th} stage given that it finds n_i jobs there (stage 1: front-end) and let $A_{LS}(n_1)$ denote the expected number of LS customers to arrive (not necessarily to place an order) until the arriving PS order goes through the front-end processes. The criterion to reject a PS customer is mathematically the following.

$$E[W_1(n_1) + W_2(n_2 + A_{LS}(n_1))] > OLT_{Contract} \tag{2}$$

where

$$
\begin{aligned}
E[W_1(n_1)+W_2(n_2+A_{LS}(n_1))] &= E[W_1(n_1)]+E[W_2(n_2+A_{LS}(n_1))] \\
&= \frac{n_1+1}{\mu_1}+\frac{n_2+A_{LS}(n_1)+1}{\mu_2} \\
&= \frac{n_1+1}{\mu_1}+\frac{n_2+\frac{(n_1+1)\cdot\lambda\cdot\zeta}{\mu_1}+1}{\mu_2}.
\end{aligned}
$$

2.2 Decision Strategies

The two decision strategies under our focus are described in the following. Both strategies are myopic, because the decisions are optimized considering solely the profit that is expected to be obtained from the currently arriving customer without any foresight on the long-run impact of these decisions. In other words, the decisions made in this way do not optimize the long-run system performance, e.g. maximize the long-run profit.

2.2.1 Simultaneous Quotation Strategy

The firm decides on the price and lead time quote simultaneously based on a myopic optimization. The objective is to maximize the marginal expected profit of the potential order of an arriving LS customer. In other words, the firm wishes to maximize the expected profit to be obtained solely from the currently arriving potential LS customer.

$$
max_{\substack{P_{min}\leq p\leq P_{max}\\ L_{min}\leq L\leq L_{max}}} E[\Pi_m(p,L)] = P^{LS}(p,L)\,(p-E[T(L,n_2)]\cdot u)+(1-P^{LS}(p,L))\cdot 0 \tag{3}
$$

where u is the unit tardiness cost and $E[T(L,n_2)]$ is the expected tardiness of the order that finds n_2 existing orders in the back-end process and that is quoted a lead time of L. Mathematically,

$$
E[T(L,n_2)] = \int_{w=L}^{\infty} f_{W_2(n_2)}(w)(w-L). \tag{4}
$$

As mentioned before $W_2(n_2)$ describes the lead time of an order that arrives to back-end and finds n_2 orders. $f_{W_2(n_2)}$ is therefore the probability density function of the $Erlang(n_2+1,\mu_2)$ distribution.

This optimization problem considers the following trade-off. If an arriving LS customer accepts the (p,L) quote, i.e. with probability $P^{LS}(p,L)$, a revenue of p is earned and for this order it is expected to incur a tardiness penalty of $E[T(L,n_2)]\cdot u$, considering the fact that there are currently n_2 orders in the back-end process. Therefore, $p-E[T(L,n_2)]\cdot u$ is the expected profit obtained from the arriving customer under this scenario. If the arriving LS customer rejects the quote, i.e. with probability $(1-P^{LS}(p,L))$, he does not place an order. As a result, the firm neither earns a revenue nor incurs a tardiness cost. In this scenario, the profit obtained from the arriving customer is zero. Quoting a higher price, on the one hand, increases revenue earned if the customer accepts, while on the other hand, decreases the probability of acceptance. Similarly, quoting a longer lead time, decreases the expected tardiness cost to be incurred if the customer accepts, while decreasing the probability of acceptance. Intuitively, the optimal decision should be the one that is the most attractive to an arriving customer which results in a positive expected revenue.

2.2.2 Sequential Quotation Strategy

This strategy models in an abstract way, the lead time based pricing (LTBP), a sequential decision making approach in which the firm first decides on the lead time quote and matches this service with an appropriate price in a second step. This approach is easier to be adopted in practice since these decisions are typically under the responsibility of two different departments (e.g. manufacturing and marketing).

The lead time is quoted such that the probability of on-time completion of the arriving order is approximately equal to the service level (α) the company targets.

$$P\{W_2(n_2) < L\} \approx \alpha. \tag{5}$$

The price quote is obtained by solving (3) under the lead time quote (5) suggests.

2.3 System Performance

The system performance is evaluated in steady-state, based on tardiness related and revenue acquisition related measures as well as based on the profit, which combines the two.

- The expected amount of tardiness is denoted $E[T_{LS}]$ and $E[T_{PS}]$ for LS and PS customers.
- The on-time probability is denoted η_{LS} and η_{PS} for LS and PS customers.
- The percentage of LS customers who accept the quote and the percentage of PS customers who are accepted are denoted ϕ_{LS} and ϕ_{PS} respectively.
- The expected revenue, profit and tardiness cost are denoted *Revenue*, $Profit$ and $Tcost$.

We also keep an eye on the quoted (p, L) pairs. $p_{average}$ and $L_{average}$ denote the average price and lead time quotes.

3 NUMERICAL STUDY

The model described in Section 2 is implemented in AnyLogic. The non-linear, constrained optimization problem in (3) was solved using the *fmincon* function of MATLAB via linking the two software. The warm-up period ends upon satisfying $50,000^{th}$ customer and the model terminates once $350,000$ customers are satisfied. We run 50 independent replications. The 95% confidence intervals do not exceed 3% over all experiments.

In the experiments, the parameters ζ (the probability of an LS customer) and α (service level) are varied in three levels since they are the most impactful parameters in the comparison of sequential and simultaneous strategies. $\zeta \in \{0.5, \underline{0.7}, 0.9\}$, $\alpha \in \{0.85, \underline{0.9}, 0.95\}$. The underlined values form a base case. Unless otherwise stated ζ and α are set according to the base case. All other parameters are set as shown in Table 1.

Table 1: Parameter setting in the numerical study.

System Related		Customer Related	
λ (customer arrival rate)	3	ξ_0 (defines acceptance probability of the expected quote)	0.1
μ_1 (processing rate of stage 1)	2.85	ξ_p (price sensitivity of LS customers)	1
μ_2 (processing rate of stage 2)	3.05	ξ_L (lead time sensitivity of LS customers)	1
$OLT_{Contract}$ (contractual lead time)	30	$OLT_{Expected} = P_{Expected}$ (expected lead time and price quote)	10
S (base stock)	50	u (unit tardiness cost)	10

We assume that the minimum quotable lead time in equation (3) is dynamically determined based on the current number of orders in the system, as follows: $L_{min} = E[W_2(n_2)] = \frac{n_2}{\mu_2}$. We assume that the minimum quotable price is equal to this value, $P_{min} = L_{min}$. The maximum quotable lead time and price to a LS customer are $L_{max} = P_{max} = OLT_{Contract}$.

The parameters in the base case are selected in a way that they result in similar values to the industry case in terms of fundamental measures, such as the utilization of the two stages and the average OLT_{Actual}. Figure 4 shows the results from a single run for the base case. As in the industry example, the first processing stage is very highly utilized ($\approx 98\%$ utilization), reflecting its capital intensive nature, while the second stage operates under an $\approx 92\%$ utilization. The average OLT_{Actual} for PS customers, which are produced according to a MTO strategy and therefore go through both stages, is ≈ 11 periods (e.g. weeks), while the average OLT_{Actual} for LS customers that go through only the back-end stage is ≈ 3 periods (e.g. weeks). In the industry example, when the company commits to $OLT_{Contract}$, order tardiness occurs very rarely. We set $OLT_{Contract}$ such that the on-time probability of PS orders is nearly 1 in the base case. The customers know that the quotation of $L < OLT_{Contract}$ is typical in this industry. Therefore, their expectations are already in that direction. Thus, $OLT_{Expected}$, which affects the acceptance probability of customers, is set to one third of the contractual lead time for modeling the demanding market in this industry (Table 1).

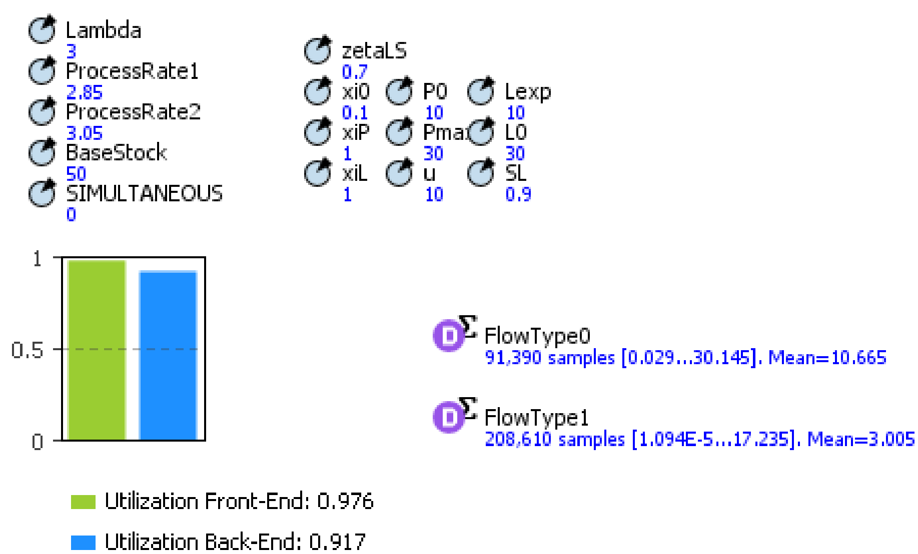

Figure 4: Base case, resulting utilization levels and lead times.

3.1 Performance under Lead Time Based Pricing

As stated earlier, a major practical concern is that, the introduction of a lead time based pricing strategy will result in a high rejection rate of the existing customer base. Therefore, our model for lead time based pricing (sequential strategy) accounts for this. It considers the objective of maximizing the expected marginal profit. Since the marginal profit is zero in the event of a rejection, this model would never suggest (p, L) quotes resulting in such a situation. In contrast, it suggests quotes that are appealing to the customers as far as the expected tardiness occurrence allows.

Table 2 shows how the system performs under LTBP and the effect of firm's service level target on the performance. It is noteworthy to observe that the percentage of LS customers who accept the quote (ϕ_{LS}) is around 92%. This value is higher than the acceptance probability under the "typical" quote ($P^{LS}(P_{Expected}, OLT_{Expected}) = \frac{1}{1+\xi_0} = 0.909$). This means that, the price increase (compared to $P_{Expected}$) is typically *less* than the extra service provided, i.e. the decrease in the lead time (compared to $OLT_{Expected}$).

Furthermore ϕ_{LS} remains stable under varying α. This is a result of quoting safer lead times (see $L_{average}$) always in combination with lower prices (see $p_{average}$). The ability to offer the best combination makes LTBP attractive.

Table 2: Impact of the service level target α (sequential strategy assumed).

α	$p_{average}$	$L_{average}$	ϕ_{PS}	ϕ_{LS}	$E[T_{PS}]$	$E[T_{LS}]$	η_{PS}	η_{LS}	$Profit$	$Revenue$	$Tcost$
0.85	15.757	3.978	0.937	0.925	0.000	0.095	1.000	0.850	13.395	14.064	0.665
0.90	15.483	4.250	0.937	0.925	0.000	0.061	1.000	0.900	13.449	13.872	0.423
0.95	15.100	4.641	0.938	0.924	0.000	0.028	1.000	0.950	13.408	13.605	0.197

The results in Table 3 show the effect of the percentage of LS customers on the system performance. As more and more customers demand short lead times, the average quoted lead time decreases. The revenue potential increases because in return of shorter lead times, higher prices are quoted. Due to tighter lead time quotes, the tardiness costs grow, however, not significantly. As a result, profits increase. Note that the expected amount of tardiness is very low, around 0.06 weeks, corresponding to half a day.

Table 3: Impact of lead time sensitive customer percentage (sequential strategy assumed).

ζ	$p_{average}$	$L_{average}$	ϕ_{PS}	ϕ_{LS}	$E[T_{PS}]$	$E[T_{LS}]$	η_{PS}	η_{LS}	$Profit$	$Revenue$	$Tcost$
0.5	15.281	4.481	0.950	0.920	0.000	0.062	1.000	0.900	12.335	12.643	0.306
0.7	15.483	4.250	0.937	0.925	0.000	0.061	1.000	0.900	13.449	13.872	0.423
0.9	15.595	4.189	0.896	0.924	0.000	0.060	1.000	0.900	14.584	15.121	0.540

3.2 Comparison of LTBP to the Simultaneous Strategy

We compare the performance of alternative decision strategies based on the results in Table 4. The column "SIM" indicates whether a simultaneous (value 1) or a sequential (value 0) strategy is followed.

Table 4: Impact of the decision strategy.

α	SIM	$p_{average}$	$L_{average}$	ϕ_{PS}	ϕ_{LS}	$E[T_{PS}]$	$E[T_{LS}]$	η_{PS}	η_{LS}	$Profit$	$Revenue$	$Tcost$
0.85	0	15.757	3.978	0.937	0.925	0.0	0.095	1.0	0.850	13.395	14.064	0.665
0.85	1	15.459	4.273	0.936	0.925	0.0	0.063	1.0	0.898	13.410	13.856	0.443
0.9	0	15.483	4.250	0.937	0.925	0.0	0.061	1.0	0.900	13.449	13.872	0.423
0.9	1	15.448	4.285	0.936	0.926	0.0	0.063	1.0	0.898	13.404	13.844	0.440
0.95	0	15.100	4.641	0.938	0.924	0.0	0.028	1.0	0.950	13.408	13.605	0.197
0.95	1	15.467	4.264	0.936	0.926	0.0	0.063	1.0	0.899	13.421	13.861	0.437

Clearly, the performance of the sequential policy depends on selection of the service level (α). If the firm makes too safe lead time quotes ($\alpha = 0.95$), then the revenue potential can not be fully used. This is what we see when comparing $p_{average}$ and $L_{average}$ in the last two rows. As a result, the sequential strategy with $\alpha = 0.95$ leads to lower profits via attaining lower revenues. The tardiness cost is also lower, but higher profits are possible to get by increasing it insignificantly. The expected tardiness for LS customers is very low in either case (0.028 and 0.063).

On the other hand, if the firm does not base its decisions on a sufficient "safety" ($\alpha = 0.85$), then higher tardiness costs may interfere with the attain of higher profits. Higher revenue is brought in, but it does not compensate the cost consequences of quoting shorter lead times.

The simultaneous strategy works based on the unit tardiness cost that is assumed to be the true one. Thus, it precisely evaluates the trade-off between positive and negative consequences of a (p,L) quote. It decreases the revenue when necessary for achieving higher profits. The sequential strategy performs closely, if the service level target is correctly set ($\alpha = 0.9$ in this case).

4 DISCUSSION AND CONCLUSION

This work presented an attempt to understand the dynamics of the price and lead time quotation problem in the semiconductor industry. We developed a simulation model capturing important characteristics of the supply chain of a semiconductor manufacturer. Furthermore, we analyzed two decision making strategies: Simultaneous and sequential. Both strategies are simple but sophisticated as they decide on the (p,L) quotes based on a myopic optimization of the expected marginal profit. The sequential strategy (LTBP) is more realistic to consider for a practical implementation, at least in the near future.

Our results showed most importantly that lead time based pricing does not necessarily hurt the attractiveness of the company. In our experiments it even increased the customer acceptance rate. We found that a high customer acceptance probability is maintained even if the service level target is set incorrectly. However, potential consequences of its incorrect specification are that some of the revenue potential might be wasted or tardiness costs may grow beyond the amount of extra revenue can compensate. Furthermore, the percentage of customers who demand more than contractually agreed conditions (LS customers) has a significant impact on firm's profits. Future research should have a closer look on the customer reaction model and setting its parameters as realistic as possible, since it is in the core of the model and crucial for making good decisions. Moreover, the incorporation of a customer arrival process that is not time-homogeneous is a meaningful extension of the model, considering the existing demand seasonality in semiconductor industry.

Since a lead time based pricing strategy would be new in the industry, a practical concern is that the customers may perceive it negatively and doubt its fairness. Hence, a big challenge when introducing such a strategy is doing this without harming the customer-manufacturer relationship. In other words, the implementation challenges move from the technical best solution to a practical one: Convincing customers who are used to lead times shorter than the contractual agreed lead times to the contractual ones for a regular price and for the shorter lead times to a higher price. The results show that LTBP promises a lot, once this hurdle is taken.

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