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IDENTIFYING POTENTIALS AND IMPACTS OF LEAD-TIME BASED PRICING IN SEMICONDUCTOR SUPPLY CHAINS WITH DISCRETE-EVENT SIMULATION

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ABSTRACT

Due to a significant increase in demand fluctuations in the semiconductor industry triggered by the bullwhip effect, global supply chains are experiencing an unprecedented pressure. The industry specific characteristics of short product life cycles, long lead times and a highly competitive market environment are further decreasing flexibility, although a robust and adjustable supply chain is required. In order to enable greater flexibility, this study investigates the hypothesis that Revenue Management is able to offer greater fulfilment of customer expectations, while at the same time initiating a revenue increase in the semiconductor industry. We tested this hypothesis in a discrete-event simulation based on a case study obtained from a semiconductor company. The study indicates that global supply chains, such as the ones in the semiconductor industry, should use Revenue Management methods in order to increase their revenue by 10% to 19% as well as to improve flexibility and customer satisfaction.

1 INTRODUCTION

Supply Chains (SC) are the key factor for an industry to guarantee its competitiveness and flexibility. SCs are currently facing the challenge to become more efficient in an unstable and complex market, where customers are expecting a high service level despite numerous difficulties which the industry might be experiencing. The semiconductor industry is an example for a multifactorial SC that is exposed to different constraints and effects. Product variety, complex production processes, short product life cycles, rapidly advancing technologies and as such products with a perishable character describe only a few of the challenges faced by the semiconductor industry (Ehm and Lachner 2016; Ehm et al. 2019). Besides that, the development is limited by long manufacturing times in global production networks and strong economy of scales due to capital intensive equipment (Ehm et al. 2019; an Kuo et al. 2019). These characteristics combined with the semiconductor's upstream position in the SC, which highly exposes it to the bullwhip, commonly result in severe demand amplifications and dramatic operational consequences (Lee et al. 1997). Being developed under similar circumstances to optimize the sales of perishable inventory, the approach of Revenue Management (RM) presents new opportunities to balance demand and supply (Seitz et al. 2016). RM offers also an opportunity to expand the available-to-promise logic in the advanced planning systems used in the manufacturing domain. This requires the inclusion of RM into the scheduling but this area needs to be the focus of research studies to achieve more benefits in this area (Klein et al. 2020). In addition, by fulfilling the requirements for SC planning in the semiconductor industry, RM enables further benefits by combining capacity planning, inventory management and demand fulfillment (Uzsoy et al. 2018). Despite the promising benefits of greater flexibility and increased revenue, the semiconductor and other business-to-business (B2B) industries failed to transfer ideas of RM into their own SC planning. Consequently, the central research question of this paper is how RM methods impact SCs in the semiconductor industry and to what extent this impact is beneficial regarding SC related Key Performance Indicators (KPI). Contributing to this goal, we additionally answer the question how RM is applied and how it could be transferred to

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the semiconductor industry. Moreover, the paper proposes answers to which methods of RM should be applied as the most beneficial ones and to what extent lead-time based pricing (LTBP) is able to increase flexibility, customer satisfaction and revenue in the semiconductor industry SC.

This paper is structured as follows. The next section presents the research background in which related literature of RM and the semiconductor industry is examined. Section 3 continues with a comparative analysis of the transferability of specific RM methods to the semiconductor industry. Then, Section 4 presents the simulation model and Section 5 focuses on the corresponding computational experiments, by showing the design of experiments and the analysis and the calibration of them. Finally, this paper finishes with a conclusion and outlook in Section 6.

2 RESEARCH BACKGROUND

In the following sections, the research background is presented. This includes first the characteristics of the semiconductor SC and is followed by the overview of RM and its methods.

2.1 Characteristics of Semiconductor Supply Chains

The semiconductor industry has grown steadily since the 1960s. Driven by a constant increase in use of integrated circuits in industrial and commercial products as well as the development of new applications such as the Internet of Things, 5G networks, artificial intelligence, virtual reality, autonomous and electric vehicles and advances in consumer electronics have led to exponential growth (Mönch et al. 2018a; Mönch et al. 2018b; Uzsoy et al. 2018).

To keep up with this growth, the semiconductor industry faces several challenges. Product complexity is one of them. That means, more than 1000 process steps across the Front-End and Back-End stages are required in semiconductor manufacturing. Due to this product complexity, the manufacturing process is characterized by long lead times and uncertainty, since product defects commonly occur. Furthermore, the industry faces a high demand volatility and as such difficulties in forecasting. On the one hand, the semiconductor industry is subject to strong economies of scale, since the manufacturing process requires extremely capital-intensive production equipment and, on the other hand, the industry is in constant need of innovation, driven by the fast-paced consumer electronics market, which results in short product life cycles (Mönch et al. 2018a). In addition to the already increased complexity of the semiconductor SC, the bullwhip effect, adds even greater pressure on the global SC. The bullwhip effect describes the higher variance of orders placed at the suppliers than sales to the customer and is amplified throughout the SC from retailer to wholesaler to manufacturer (Lee et al. 1997). All these challenging factors must be considered in the SC planning process as well as in a possible adoption of RM.

2.2 Revenue Management Overview and Methods

The potential and importance of RM was first identified in the airline industry, with American Airlines being one of the first to conduct research on managing revenue based on their inventories in the 1960s and 1970s (Smith et al. 1992). RM was defined as the "control and management of reservations inventory in a way that increases company profitability" (Smith et al. 1992). Thus, it guides allocation decisions of undifferentiated units of capacity in a way to maximize revenue or profit (Kimes 1989).

After the first successful implementations in the airline industry, one of the earliest adopters of RM was the hotel and lodging industry as seen in Rothstein (1974). Moreover, the car rental industry as presented in Carroll and Grimes (1995) as well as the manufacturing industry as shown in Easton and Moodie (1999), Lan et al. (2008) and Zatta (2016), have adapted methods of RM due to their similarities in industry characteristics. For a complete overview of industries applying RM, interested readers are referred to McGill and van Ryzin (1999). With regards to the semiconductor industry, so far published research that focuses on the implementation of RM in the semiconductor industry is limited. Seitz et al. (2016) developed a framework for RM in the semiconductor industry, in which RM is applied by using dynamic pricing for orders with a requested shorter lead time than the one contractually agreed on (Seitz et al. 2016).

Generally, RM can be classified into quantity-based and price-based RM, depending on whether it uses capacity-allocation or prices for managing demand (Talluri and van Ryzin 2009). Firstly, the quantity-based RM mainly considers availability control of limited capacities. One can divide this type of RM into the three controls of Single-Resource Capacity Control, Network Control and Overbooking. Single-Resource Capacity Control deals with allocating one single resource as for example the seats on a single flight. Network capacity control deals with the same problem of controlling resources, but instead of the single setting, multiple resources are considered, as for example controlling multiple flights legs. Overbooking is widely used to compensate for no-shows and short-term cancellations (Talluri and van Ryzin 2009). Secondly, the price-based RM can typically be found in the retail or manufacturing industries since only dynamic pricing and auctions are considered. Dynamic pricing deals with the question how to set and when to change prices according to market fluctuations, demand uncertainty and capacity availability (Talluri and van Ryzin 2009).

3 CASE STUDY: TRANSFERRING REVENUE MANAGEMENT TO THE SEMICONDUCTOR INDUSTRY

Kolisch and Zatta (2009) designed a framework detailing the main key points of applying RM to the process industry. Their work is based on similar research published by Kimes (1989) or Harris and Pinder (1995). In order to transfer the concept of RM to the semiconductor industry, this framework is used, since its main aspects suits our case study.The eight different key points are as follows:

1. The framework requires not only heterogeneous and stochastic, but also dynamic demand. Table 1 shows an analysis of the order behavior based on the difference in time between the communicated standard delivery time (SDT) and the requested lead time (the time interval between order entry and requested delivery date). It becomes obvious that customers adhere overall to the standard delivery time, but in 38% of observed orders for the exemplary customer selection, the requested lead times varied between 1% earlier than the respective standard one to a solicitation of immediate delivery. The different customer group dynamics and short-term order adaptations combined with the bullwhip effect and a general demand uncertainty lead to heterogeneous, stochastic and dynamic demand in the semiconductor's industry, which provides the rational to implement RM (Seitz et al. 2016; Mönch et al. 2018a).
2. The required perish-ability can be identified in the semiconductors' short life span and their highly innovative character.
3. Moreover, the semiconductor industry feature capacities, which cannot be extended in the short-term, since an enhancement of capacity is not only capital, but especially time extensive.
4. The semiconductor industry experiences high fix costs and applies economy of scales to recover these.
5. Advance reservations of demanded products are strongly advised in the semiconductor industry, due to long lead times.
6. The framework requires economic freedom as well. The semiconductor industry experiences standard regulations in terms of pricing and competitiveness.
7. Data availability and gathering systems are of utmost importance for a potential application of RM. Companies operating in the semiconductor industry usually employ beyond an Enterprise Resource Planning tool huge Data retrieval system, which gathers data from incoming orders and is connected to further functions such as capacity and supply planning or the order management.
8. Management support and a certain innovative open culture in order to accept approaches of RM are required as well. Since the semiconductor industry focuses heavily on the research and development

of new technologies within semiconductors, this industry is likely to support any active measures that relaxes capacity utilization and increases revenue (Moore 2006; Seitz et al. 2016; Mönch et al. 2018a).

In summary, the conditions of the framework based on Kolisch and Zatta (2009) are fulfilled by the semiconductor industry. Thus, methods of RM are applicable for this industry.

Table 1: Compliance of requested delivery time with SDT. If customers comply to the contract, their required order lead time is equal to or greater than the SDT. In contrast, the medium compliance presents the case in which the customers' required lead time is 1%-50% faster than the SDT and no compliance represents the case in which the customers' required lead time is 50%-100% faster than the SDT.

Compliance to contract	61.8%
Medium compliance to contract	18.6%
No compliance to contract	19.6%

3.1 Transferability of Revenue Management Methods

Considering the two types of RM mentioned previously, quantity-based RM is not practically applicable to the semiconductor industry. More concisely, single-resource capacity control is not suitable, since in the semiconductor industry a broad variety of products are sold with different demand and supply characteristics. Network control solves the problem of the diversity of products, however the various demands from different customer groups make the introduction of similar booking limits or bid-price controls difficult and consequently lead to an increased complexity. The method of overbooking presents no option for the semiconductor industry, due to the long cycle times. That means, if a customer's requested date of product availability cannot be fulfilled due to overbooking, the customer would have to wait for up to 12-18 weeks. In this case, the loss of good will and the negative impact on the industry-wide reputation makes overbooking not feasible.

Secondly, price-based RM methods focus on how to dynamically price different customer groups over time (Talluri and van Ryzin 2009). Auctions require a different buyer and seller platform, meaning a secure environment to share the customer's willingness to pay (WTP) as well as a fixed point in time when the auction between potential customers takes place. Due to stochastically arriving customers, auctions in which customers enter the personal bids at the same time are not possible. Dynamic Pricing, the second method of price-based RM, offers great potential in the semiconductor industry, due to its price-sensitivity. Thus, by using dynamic pricing, demand maximum and minimum can be smoothed and steered to unused capacities as well as unforeseen short-term demands can be fulfilled (Seitz et al. 2016). Moreover, Seitz et al. (2016) even proposes to increase revenue at the same time by differentiated pricing of urgent orders due to higher service level. According to Mönch et al. (2013), the competitiveness of a semiconductor manufacturer usually depends on the ability to not only rapidly incorporate advanced technologies or to improve the manufacturing processes, but also to meet the customer due dates.

From a customer's perspective, an early delivery means that products will be available faster and the production can start earlier than expected, which in return benefits the company regardless of the increase in the price payed for the faster delivery, since costs for postponing the production are usually greater than the paid price premium. In addition, this is underlined by Hummels and Schaur (2013), who state that faster delivery respectively "each day saved in [...] time is worth 0.8% ad-valorem for manufactured goods" (Hummels and Schaur 2013), underpinning a steady price increase for faster service times. This approach, to base the price increase on the shorter or longer order lead time compared to the communicated SDT, is described as LTBP (Öner-Kozen and Ehm 2018). Albeit, the idea of LTBP was not yet implemented in the semiconductor industry, its core approach of quoting short lead times can be found in Keskinocak and Tayur (2004), Liu et al. (2007) and Esmaeili et al. (2018).

In summary, price-based RM methods are most suitable to be applied in the semiconductor industry, due to their capabilities to easily impact and guide customer's demand decisions and enable additional revenue streams. Moreover, LTBP is the most promising concept in the semiconductor industry, since it enables advantages on the supplier as well as customer side.

4 DISCRETE-EVENT SIMULATION FOR LEAD-TIME BASED PRICING

In simulation modeling the three different levels of abstraction discrete-event (DE), agent-based (AB) and system dynamics modeling can be distinguished. Based on the required low granularity for this study, the combination between DE and AB modeling is applied, whose advantageous for simulations at this level of detail has been identified by Ehm and Lachner (2016). Moreover, DE simulation makes use of process-centric modelling, which is usually applied to simulate the base system of SCs according to Kleijnen (2005). The individual customers are modeled by decentralized agents, which include their own individual behavior rules and in which the global behavior emerges as a result of the individual activities. Consequently, the AB approach enables a much more detailed consumer behavior than the system dynamics approach (Garifullin et al. 2007). In order to create the simulation model, this study follows the 12 step simulation model development process as proposed by Banks et al. (2005).

4.1 Simulation Model

This simulation model should analyze potential impacts of LTBP on the overall SC in the semiconductor industry. Offering the faster delivery of products might trigger additional, yet not in the scope of RM researched consequences within the SC. In order to assess the impact of LTBP as the chosen method of RM in the presented simulation on the SC, several KPIs are observed. According to Sürie and Wagner (2008) delivery performances, referred also as service levels, have a significant influence on the competitiveness in demand driven markets and thus simultaneously represent an essential measure for total SC performance. Consequently, an improved delivery performance leads to customer satisfaction and reflects flexibility within the SC. Sürie and Wagner (2008) define this indicator as the comparison between the actual delivery date and the originally promised one. In this study, delivery performance is defined as the delivery reliability, which compares the initially promised date with the actual delivery date. It is calculated as presented in Equation 1.

$$Delivery\ Reliability = \frac{number\ of\ orders\ delivered\ according\ to\ promised\ date}{total\ number\ of\ deliveries} \tag{1}$$

Moreover, Sürie and Wagner (2008) differentiate on time deliveries as an additional indicator within delivery performances. These on time deliveries are defined as the percentage of orders which can be delivered on or before the customer request date. This KPI will be defined as the actual delivery performance that compares the customer request date with the actual delivery date called proof of delivery. It is calculated within a defined delivery window as presented in Equation 2.

$$Delivery\ Performance = \frac{number\ of\ orders\ delivered\ according\ to\ requested\ date}{total\ number\ of\ deliveries} \tag{2}$$

Since the semiconductor industry faces long lead times and high capital costs, operating at a high utilization is beneficial to recoup fixed costs of manufacturing equipment (Mönch et al. 2018a). Consequently, the capacity utilization in FE and BE is critical and as such a KPI to maximize. Furthermore, due to the short product life cycles, inventory build-ups need to be avoided, albeit safety inventories could relax the overall SC. During the simulation, different scenarios are observed which differ in safety stocks as well. Thus, inventory is a KPI to monitor. Lastly, revenue will be considered as another important KPI in order to demonstrate potential revenue increases initiated by LTBP.

The model conceptualization focuses on the abstraction level as well as on the applied assumptions, which are presented in the following. Only one single product is considered in the simulation which does not change in its properties nor quantities. That means, products are simulated as one agent each, which simplifies the assembly of final end products consisting of different modules. Furthermore, customer arrival dates and the respective customer requested dates are modelled by an uniform distribution. Moreover, only two types of customers are considered: lead-time sensitive and price-sensitive customers as introduced by Öner-Kozen and Ehm (2018). The lead-time sensitive customers request the product earlier than the SDT, whereas the price-sensitive customers comply with the SDT. The requested quantities are again modelled by a uniform distribution. In addition, orders are not prioritized based on any customer related characteristics or the latency of the product. Instead, customer orders are simply sorted by their customer requested date. The forecasting and planning process follows the overall general forecasting and SC processes as presented by Mönch et al. (2018a) and Uzsoy et al. (2018). However, simplifications led to the removal of a daily re-planning of all orders and products as well as capacity corridors or yield effects.

The production process, as displayed in Figure 1, starts from one of the two product sources. The product agents are differentiated by their product identifier. The Front-End processes are modelled as a queue and a delay block, which delays the product agents with the from the semiconductor company fixed cycle time. The queue stores waiting products. Then, based on the product's identifier, the agents are either passed directly to the Back-End or shipped to the Die Bank and stored until release. The Die Bank is modelled as a wait block with unlimited capacity. When product agents are released from the Die Bank, they enter the Back-End which is again modeled by a queue and a delay. The delay features the specific given cycle time. Once the product agents leave the Back-End, they arrive at the Distribution Center, yet another wait block. The agents are stored in the Distribution Center until shortly before their customer requested date to be released to the batch block. Here the single agents, each representing one product, are bundled together to the by customer requested batches. Then, customers are matched with the correct product batch based on product identifiers. After two agents have been combined to one fulfilled order agent, an additional delay block mirrors the goods in transit delay before the order is marked as delivered and the agent destroyed at the sink.

From the customer's point of view, customer agents are either treated as a lead-time sensitive or as a price-sensitive customer based on their order characteristics and the customer's acceptance of faster orders for price premiums. If a lead-time sensitive customer does not accept the price premium, the customer is not rejected, instead transformed into a price-sensitive customer by delaying the customer's requested date complying with the SDT. Then, the planning functions start with netting the customer's demand to the forecasted demands. If the netting fails, inventories are checked and in instances of low inventory levels, an additional demand signal for production is created. Moreover, in order to mirror the dynamic customer behavior between the purchase order date and the actual delivery, an order change function has been implemented. This function triggers stochastic order quantity changes as well as short-term order cancellations which are typical in the semiconductor industry Ratusny et al. (2020).

Since LTBP is based on price premiums paid by customers for faster deliveries, the calculation of these price premiums as well as the acceptance of higher prices is of great importance when creating this simulation model. More concisely, the algorithm applied in this study, which is used for the pricing and the acceptance of the increased price by shorter lead times is based on the research of Berger et al. (2021) and shown in Equation 3. The price premiums are modelled by a convex function, which has been chosen due to its progression that features small price premiums for relatively smaller faster delivery requests and stronger increasing price premiums until a premium of 100% for next day delivery. The rationale behind this lies in the fact that for decreasing lead-times, the opportunity costs increase not only for the manufacturer due to (pre-) production of products but also for the customer due to high risks of production down-times triggered by missing parts. Consequently, the WTP increases with shorter lead-times (Berger et al. 2021).

$$P_{\text{Premium}} = -\frac{1}{2} \cdot \log\left(\frac{\textit{Order Lead Time}}{\textit{SDT}}\right) \cdot \textit{Price}_{\text{normal}} \tag{3}$$

The rejection rate for the price premium by customers is based on a beta distribution, which includes on the y-axis the rejection rate and on the x-axis the percentage of faster delivery. Berger et al. (2021) assumes that customers do not reject an order when there is no price increase. Furthermore, he assumes that the rejection rate steadily increases up to 25% earlier delivery and more than 80% rejected orders, since a 25% deduction in delivery time represents already a remarkable price increase. He concludes that the customer is more willing to wait for the product without any price increase instead of paying the price premium as the underlying theoretical principle. For a profound explanation and justification of the presented rejection rates, interested readers are referred to Berger et al. (2021).

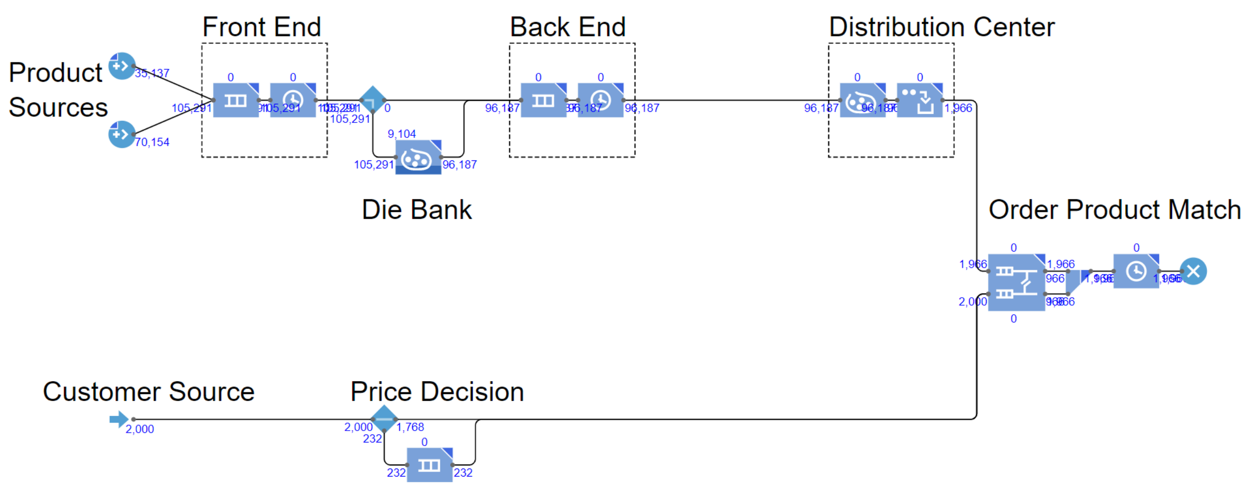

Figure 1: Simulation Model view on process modeling level.

5 COMPUTATIONAL EXPERIMENTS

In the following section the computational experiments are presented and analysed. The section presents as well the calibration experiments which were conducted mainly to compare the model results to reality and make adjustments to the model parameters to fit historical trends.

5.1 Experimental Design

The experimental design defines the experiments and scenario settings. The simulation covers an initialization time of two years before the one-year observed time period starts. Moreover, the model takes into account a cool-down period of one year once the observed time period ends. The initialisation period is needed to produce safety stocks and start production according to forecasts already earlier, while the cool-down period assures orders that could not be served within the requested delivery time, will be fulfilled later than the end of the observed model time period.

The different covered scenarios are structured in two dimensions: Firstly, the global industry dimension features different demand capacity ratios ranging between -25%, -10%, 0%, 10% to 25% in order to display different demand situations in the semiconductor industry. Secondly, the semiconductor company specific dimension features different characteristics concerning production parameters such as forecasting accuracy, share of lead time sensitive customers or safety stock levels at the DB as shown in Table 2. This dimension includes a baseline scenario characterized by parameters typical of the semiconductor industry. Based on this standard scenario, the second scenario features a larger, medium share and the third an even larger, high share in lead-time sensitive customers. The fourth and fifth scenarios differ concerning their inventory safety levels and feature a medium share in lead-time sensitive customers. That means the fourth one is characterized by a small inventory and is thus called lean inventory scenario, whereas the fifth scenario features a much higher inventory safety level. The smaller and larger inventory safety levels scenarios aim to investigate the balance between costs for a higher inventory but at the same time for greater flexibility. In summary, both dimensions create 25 scenario combinations.

Table 2: Overview of simulation model relevant parameters per company specific scenario.

Scenario / Input	Standard	Medium Lead-time Sensitive	High Lead-time Sensitive	Lean Inventory	High Inventory
Forecast accuracy [%]	60	60	60	60	60
Forecasted Lead-time Sensitive customers [%]	40	60	80	60	60
Not forecasted Lead-time Sensitive customers [%]	40	60	80	60	60
SDT [days]	142	142	142	142	142
Cycle Time FE [days]	105	105	105	105	105
Cycle Time BE [days]	35	35	35	35	35
Goods in Transit Delay [days]	2	2	2	2	2

5.2 Result Analysis and Discussion

The analysis of the results is based on the 25 different scenario associations and the three KPIs: revenue, delivery performance and inventory, respectively capacity utilization. Table 3 provides an overview of the most beneficial scenario combinations for each demand scenario in the first 5 rows and of the least beneficial combinations in the last two rows. In order to achieve an optimal scene, both revenue and delivery performance should be maximized, while inventory should be minimized.

On the one hand, it becomes obvious that especially two scenario combinations feature low performances in delivery performance (15% and 28%), comparably lower revenue increases (11% to 11.6%) and on average very low inventory utilization (1.3% and 3.6%). As a consequence, the combinations of a high demand with either a high share of lead-time sensitive customers or the lean inventory configuration represent as expected the less performing scenarios. First, demand exceeds the production capacity by 25% within the high demand scenario. Second, the high share of lead-time sensitive customers as well as the lean inventory configuration decreases the SC's flexibility to fulfill short-term orders sufficiently. That means, without adequate safety stocks and a medium to high share of orders characterized by short order lead times, these incoming orders cannot be fulfilled on time, due to the missing SC's flexibility. Consequently, this results in a reduced revenue increase, a low delivery performance and consequently deteriorated customer satisfaction.

On the other hand, the most beneficial scenarios with revenue increases from 16.05% to 19.69% are the ones that feature a medium to high share of lead-time sensitive customers. Only the high demand scenario favors the high inventory configuration. The justification is whether the SC's flexibility is capable of handling the increased amount of short-term orders. During the first four demand capacity ratios, SC's planning and forecasting functions are able to supply enough capacity at the right time to satisfy the incoming short-term orders, whereas during the high demand scenario, the supplied capacity is not able to match the short-term demand. Generally, the greater the share of this type of demand, the greater the revenue increase, since customers are usually more willing to accept the price premium and receive the products earlier than the SDT. Higher inventory levels allow greater flexibility in terms of capacity allocation, therefore enable faster deliveries and are necessary to cope with the added pressure on the SC. Accordingly, for these scenarios, the delivery performance still continues satisfying, varying from 89.18% to 99.64%. However, the greater the share of lead-time sensitive customers, the larger inventory levels are required to supply the high amount of short-term orders. This leads to increased inventory related costs which are not yet considered. Otherwise, the two KPIs delivery performance and revenue decrease.

Consequently, the execution of each scenario is a combination of all three revenue increase, delivery performance and inventory level and as such one cannot analyze each one separately. That means, the share of lead-time sensitive customers combined with the defined inventory safety level influences the delivery performance, revenue and capacity or inventory utilization. Nevertheless, the overall simulation results show that in all different scenarios the revenue increase is positive, even in those business environments that put additional pressure on the entire SC such as during the high demand scenario under a high share of lead-time sensitive customers. In addition, the delivery performance is unexpectedly rather constant and varies only between 90% to 100% disregarding the two described cases and depending on configurations in inventory levels and share of lead-time sensitive customers. Because of the increased share of short-term orders, a larger decrease in delivery performance was expected. It becomes obvious that the demand pressure did not exceed the SC's flexibility extensively. In summary, the trade-off between inventory levels and share of lead-time sensitive customers defines the characteristics of revenue, delivery performance and inventory utilization.

Furthermore, it is worth noting that the presented delivery performance values are derived from the simulation and do not present the actual current delivery performance characteristics that the semiconductor industry experiences. In addition, the increase in revenue, which is created by RM, do not result in an increase of operating costs and as such would result in much greater earnings before interest, taxes, depreciation and amortization (EBITA).

Table 3: Overview of simulation model relevant parameters per company specific scenario.

KPI / Scenario	Delivery Performance	Revenue	Average inventory utilization at DB level
Low Demand x High Lead-time Sensitive	99.34%	19.69%	7.94%
Decreased Demand x High Lead-time Sensitive	99.39%	19.33%	7.27%
Stable Demand x High Lead-time Sensitive	97.86%	19.01%	7.30%
Increased Demand x High Lead-time Sensitive	92.68%	18.78%	8.42%
High Demand x High Inventory	99.54%	16.05%	2.48%
High Demand x High Lead-time Sensitive	15.18%	11.59%	1.35%
High Demand x Lean Inventory	28.34%	11.14%	3.64%

5.3 Calibration Experiments

The simulation model validation followed a similar approach as Maximiliano Udenio and Peels (2015) described. Firstly, operational parameters were developed following experts interviews. Secondly, the historical data provided by the semiconductor company was used for calibrating the model in AnyLogic 8. This historical data represents the weekly shipped-out quantities for an exemplary product family for a two year time horizon. The product family features a large share of opportunistic customers resulting in dynamic order behavior. The time period was chosen due to its varying demand and shipment quantities. The sharp decrease in demand in the beginning of 2019 and the increase in the summer of 2020 can be observed in the historical data. The calibration is used for minimizing the cumulative sum of squared errors between the historical data and the simulation result data. This method mainly compares the simulation with the real data in an iterative approach while doing adjustments to the model. Thus, the calibration validated the model's behavioral parameters.

6 CONCLUSION

In this paper, we provide an overview of RM characteristics and methods and present its application in different industries in order to enable greater customer satisfaction and SC flexibility while increasing revenue. We introduce a DE and AB simulation model based on a case study for a semiconductor industry in order to underline the possible beneficial effects of implementing LTBP.

The paper indicates that based on the applied framework, RM generally is applicable to the semiconductor industry, due to similar demand and SC characteristics. Moreover, the different methods of RM are presented and LTBP is introduced as the so far most promising method of RM for the semiconductor industry.

The model indicates that regardless of the scenario, LTBP enables revenue increases between 10% to 20%, while in the non-favorable combinations achieving only moderate reductions in delivery performance. We further demonstrate that the trade-off between a higher share of lead-time sensitive customers and the inventory safety levels can negatively affect the possible revenue increase and delivery performance. That means, a high share of lead-time sensitive customers leads to an increase in revenue, albeit to a decrease in delivery performance. However, the reduction in delivery performance can be offset by increased inventory safety levels, although these additional inventories come with additional costs and risks, especially in the fast-paced semiconductor industry. Consequently, the share of lead-time sensitive customers is an important control parameter and should be set by the semiconductor company itself based on the capacity allocation and demand situation.

The simulation study applies different assumptions, which limit the model's degree of explanation and accuracy. The model currently only simulates one product and disregards typical modular manufacturing of semiconductors. Thereby, shared capacities, additional bottlenecks and waiting times for other modules are disregarded. In addition, the simulation study assumes a one-time planning and forecasting step. However, re-planning of production is conducted on a daily basis and products might be rescheduled based on priority rules. Furthermore, the customer's acceptance is based on a theoretical approach, which assumes increased acceptance rates for short-term orders due to increasing opportunity costs at the customer's side for later product delivery.

Therefore, it is recommended to extend the model to a wider variety of products and a more detailed production as well as planning processes. Further research should focus on the customer acceptance model, in order to proof its validity in real supplier customer environments. Moreover, we would like to put emphasis on possible future research to focus on whether LTBP is able to mitigate or delay the bullwhip effect in the semiconductor SC.

Since supply management in the semiconductor industry evolves to be the main competitive advantage, RM management methods could offer more service-oriented perspectives enabling greater customer satisfaction and SC flexibility. Consequently, managers should therefore not delay any opportunity to implement RM applications.

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