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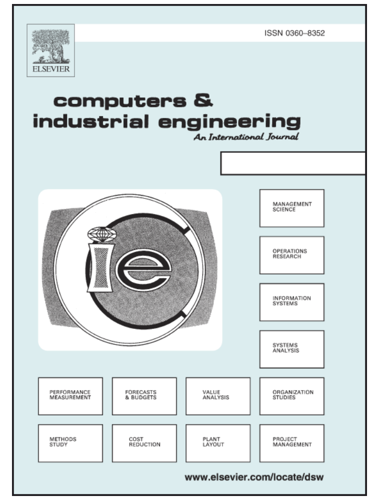

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Quantitative Analysis of Semiconductor Supply Chain Contracts with Order Flexibility under Demand Uncertainty: A Case Study

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December 9, 2014

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Abstract

The evidence base for the configuration of rolling horizon flexibility (RHF) contracts (a type of quantity flexibility contract) used in the semiconductor industry to coordinate production and demand remains meagre, more art than science. Informed by the characteristics of actual clauses and demand behaviors drawn from a company's experience, a discrete-event simulation model is developed to represent the company's supply chain. It comprises of three parties: a customer, a supplier (semiconductor manufacturer), and a capacity provider. Through analysis of customer forecasted demand the paper characterizes forecast demand as being under, over or unbiased.

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Models of these forecasted demands drives both long and short term planning. In long term planning, which is given twelve months before an order is delivered, capacity at the capacity provider is booked. Short term planning is also driven by this forecast which, within a binding period, is governed by an RHF contract. Results from the model report inventory levels, and delivery compliance, namely Delivery Performance (DP) and Delivery Reliability (DR), measures widely used in this sector. A comparison is made between symmetrical and asymmetrical flexibility bounds in RHF contracts, under conditions of the three forecasted demand behaviors above. A conclusion of the paper is that asymmetrical flexibility boundaries perform better than symmetrical boundaries for demand data that is biased in either direction (i.e. both over and under planning).

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Quantitative Analysis of Semiconductor Supply Chain Contracts with Order Flexibility under Demand Uncertainty: A Case Study

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27th May 2015

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Abstract

The evidence base for the configuration of rolling horizon flexibility (RHF) contracts (a type of quantity flexibility contract) used in the semiconductor industry to coordinate production and demand remains meagre, more art than science. Informed by the characteristics of actual clauses and demand behaviors drawn from a company's experience, a discrete-event simulation model is developed to represent the company's supply chain. It comprises of three parties: a customer, a supplier (semiconductor manufacturer), and a capacity provider. Through analysis of customer forecasted demand the paper characterizes forecast demand as being under, over or unbiased. Models of these forecasted demands drives both long and short term planning. In long term planning, which is given twelve months before an order is delivered, capacity at the capacity provider is booked. Short term planning is also driven by this forecast which, within a binding period,

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is governed by an RHF contract. Results from the model report inventory levels, and delivery compliance, namely Delivery Performance (DP) and Delivery Reliability (DR), measures widely used in this sector. It is concluded from this work that on the balance of performance measures RHF contracts with asymmetrical flexibility bounds are substantially better than those with symmetrical boundaries, and that this conclusion is robust with regard to both over-planning and under-planning behaviors. This robustness is a critical attribute with respect to the endemic medium-term vacillation between both states experienced in practice in this sector.

1 Introduction

The semiconductor industry is one of the most productive but also one of the most volatile industries (Tan and Mathews, 2010). The permanent progress in innovation, reduction of the product life cycle time and growing competition from Asia raise a lot of challenges for this advanced technology industry, especially with regard to responding to uncertain emergent demand realization. To stay competitive semiconductor manufacturers must provide their customers with a high level of order flexibility in order to support them in adapting to their emergent markets, such as is manifested in economic up and down turns at medium and long-term levels. The lead-time from firm order commitment to actual delivery adds to the complexity of responding, and this is dependent on the degree of customization of the product, being in practice a constant within a product class and with a strict regime of compliance. Rolling-horizon flexibility (RHF) contracts are seen as a means to coordinate demand and supply under such conditions, whereby early indications of anticipated future demands are transmitted from customer to manufacturer, providing some forewarning to facilitate the planning of capacity and material supply commitments.

The supply chain modeled consists of three parties: a customer, a supplier (semiconductor manufacturer), and a capacity provider. The paper first studies and characterizes customer demand received by the supplier into three types of forecasted demand: over-planning, under-planning or unbiased forecasted demand. The paper proposes an approach to model these three types of forecasted demand, with this approach validated against customers within the case study company. Under the contract, customers send order forecasts twelve months in advance to support long term capacity planning,

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which is used to purchase capacity from the capacity provider. The capacity provider is assumed to have infinite capacity to be mobilised as capacity is booked twelve months prior to delivery of the order, an assumption used within the case study company. To support short term planning, the supplier provides the customer with the flexibility to adjust order quantities within the order lead time and within a binding period customer demand is governed using a RHF contract. Within the binding period in the RHF contract the quantity flexibility clause defines the upper and lower boundaries (in percentages) within which the customer is allowed to update their forecasted demand quantity, as per Tsay (1995); Lee et al. (1997); Wang and Tsao (2006).

The motivation for this paper is to evaluate the RHF contract to understand better how to set the quantity flexibility clauses in order to minimize inventory and maximize Delivery Performance (DP) and Delivery Reliability (DR), performance measures used by the supplier.

The remainder of the article is organized as follows. Section 2 provides an overview of relevant literature. Section 3 presents in more detail the case study company, focusing on supply chain contract clauses and forecast accuracy, which gives the industrial context to this work. Section 4 presents the simulation model used in this paper with section 5 presenting results. Finally, conclusions and future research are presented.

2 Literature Review

A supply chain contract is a coordination mechanism in decentralized supply chains to motivate the supply chain partners to behave like an integrated supply chain and to benefit therefore from improved operational performance (Wang, 2002). Supply chain contracts have been studied extensively in the context of conventional supply chains.

However, there are several unique characteristics that make semiconductor supply chains differ from supply chains generally studied within the literature: semiconductor supply chains have long cycle times; they are capital intensive with long investment cycles; to keep unit cost low, utilization of capital equipment needs to be very high; products must be moved with a high velocity performance and low flow factors; products tend to have short product life-cycles, especially with greater application-specificity and higher variety product families; demand is highly volatile as Original Equipment

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Manufacturer (OEM) customers adapt to emergent demand, and forecasting can have low accuracy especially due to heavy over and under planning bias (Katircioglu and Gallego, 2011).

Supply chain contracts in general are reviewed comprehensively by Cachon (2003) and Lariviere (1999) with focus on specifying contract design parameters to achieve better supply chain coordination under different circumstances. Cachon (2003) provides a comprehensive study of prices and volumes for different contract types and, among others, the quantity flexibility contract is analyzed under conditions which coordinate a supply chain.

A detailed analysis of quantity flexibility contracts is carried out by Tsay (1999), who propose the quantity flexibility contract as a method for material and information flow coordination in a supply chain with rolling horizon planning. They investigate the incentives for which a customer and seller would participate in a quantity flexibility contract, that is, would a customer be willing to commit to a certain order quantity for a lower price, and would the seller derive benefits from certainty of sales.

Bassok and Anupindi (2008) analyzed an open loop feedback control based heuristic algorithm for the contract and demonstrated that the order process variability decreases significantly as flexibility is decreased. They also provide insights on deciding how much flexibility is sufficient from a customer's perspective and how it effects customer satisfaction. They suggest that for tighter flexibility bounds, the seller could give a discount.

Walsh et al. (2008) simulated two types of a RHF contracts. They modeled a supply chain consisting of an original equipment manufacturer (OEM) and a contract manufacturer (CM). One contract type had constant flexibility boundaries and the other had decreasing flexibility boundaries over the contract horizon. They concluded that measured by fill rate, bullwhip effect and inventory level, both contracts have favorable performance outcomes for both the OEM and the CM parties. Regarding the design parameters of the quantity flexibility contract, the upper and the lower boundaries of the flexibility profile were assumed stationary and symmetric (in percentages), following Bassok and Anupindi (2008).

Wang (2008) added delivery lead-time flexibility to order quantity flexibility, and concluded that lead time flexibility allows the customer to improve their service level and reduce their shortage cost when the penalty cost per shortage is relatively high. Furthermore they note that service level should be maintained at least at a certain level to keep customers loyal.

Kim (2011) analyzed a quantity flexibility contract between a customer

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and a supplier, and demonstrated the supplier's trade-off between the customer service level and the inventory risk. Whereas for the customer, the benefit keeps increasing and then remains constant as the flexibility rate increases. In general the author stated that in a decentralized system, the quantity flexibility contract can provide an effective coordination mechanism for the supply chain.

The notion of flexibility on order lead time is extended in various ways. For example, Das and Abdel-Malek (2003) propose a model with a minimum delivery lead time for the supplier to ship orders. When the customer requests a faster delivery, then a price penalty is imposed. In Wang (2008)'s model a regular lead time is set at 7 days, and an option is included to change a regular order into a "hot" order so as to reduce the lead time at an extra cost. Chan and Chan (2006) studied the relationship between flexibility in both delivery quantity and due date and outcomes in terms of cost fill rate. The flexibility range of delivery due dates is determined through a coordination mechanism between supplier and retailer.

The focus of this work is on the order flexibility in terms of quantity and in the context of different customer forecast demand behavior (unbiased, over and under planning) and production and delivery lead times. This work is not intended to derive optimal ordering and inventory policies given that the implementation of the contract for optimal policies associated with quantity flexibility would be extremely complex and unattractive for implementation (Bassok and Anupindi, 2008). In the model we use production and delivery lead times as observed in the case study company which depends on the product type.

While in Kim (2011), the customer demand signal was modeled as a stochastic process without any bias, experience recorded in the case company indicates substantial periods of demand signal bias with over- and under-ordering. Thus in the present work the demand signal is subject to forecast error, which is explicitly modeled with an over or under planning bias to reflect reality. The simulation experiments in this article use a stochastic process to generate initial customer demand, according to Walsh (2009) but extends this by an additional stochastic process for the weekly demand forecast updates in order to model forecast error more explicitly. This is achieved by modeling forecast variability changes over the forecasted horizon, where the forecast error decreases as the delivery date approaches, in order to simulate realistic customer demand behaviors received by the supplier (i.e. case study company).

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Cyclicity is a constant concern in the semiconductor industry sector, especially at a periodicity above individual contract duration: Tan and Mathews (2010) (Figure 5) through a fourier analysis show that there is a dominant repetitiveness period in the order of 0.5 cycles per year with significant shorter cyclics. They note that this industry is characterized by more volatility than most other sectors. This is taken to underly the recurring predilection for over- and under-ordering bias.

The model also includes long term capacity planning where the customers send order forecasts twelve months in advance which is used to purchase capacity from the capacity provider by provided by the supplier. Due to this long forecast (twelve months) a realistic assumption is to assume unlimited capacity by the capacity provider, as capacity is provided either within the case study company or purchased externally. However, in reality, this long term capacity forecasting process includes more complex processes (market development simulation and risk analysis) and information (marketing and sales insights), which are not considered in this study.

3 Case Study

This research originates in a project completed at a major semiconductor manufacturer in Europe. At the start of the project in the beginning of 2010, the semiconductor industry market faced a strong upturn which came in stark contrast to the heavy downturn during 2008 and especially 2009. With a rather more conservative expansion policy than in the past, the manufacturer's available capacity and supply was significantly below market demand. As a consequence the semiconductor industry globally faced allocation problems (i.e. manufacturers were rationing component supplies to their customers). In a rapidly growing market, the manufacturer has of course the incentive to adapt its temporarily scarce capacity to the actual market demand for higher revenue by "cherry-picking" the orders placed from those who will pay highest at the time. However the decision to invest in new capacity to match emergent demand is a risky business decision due to the high cost of capacity and the high and cyclic demand volatility which indicates the possibility that the investor will have at another time surplus capacity without revenue.

A study was made of operations-relevant aspects of contracting within the case study company. Besides studying the contracts, customer order behavior

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was also investigated, especially in terms of demand volatility, in order to gain insights on the the current nature of customer-requested quantity flexibility.

3.1 SC Contract Clauses

To understand better the observed contract clauses, they were documented and mapped onto classifications found in the literature, as in Tsay et al. (1999). Many of these contract clauses were observed being practiced in the company, including the following: decision rights, pricing, minimum purchasing commitments, quantity flexibility, buyback or returns policies, allocation rules, lead time and quality. Further clauses were also found in the company such as the following: demand signal, rescheduling, stock and run rate. As typically found in the semiconductor sector, the range of product classifications included the following: Commodity Products (COMM), Application Specific Standard Products (ASSP) and Customer Specific Products (CSP).

In the simulation study, three of the clauses are represented, namely demand signal, quantity flexibility and lead time clauses as in our earlier work (Knoblich et al., 2011). These are detailed as follows

Demand Signal – this contract clause determines the method and the granularity of the shared demand information between the customer and the supplier. For example, it could be used to define that the customer has to provide the supplier with weekly updated unconstrained forecast of estimated future demand for the next 12 months.

Quantity Flexibility – this contract clause allows one of the parties to deviate from an initially committed quantity. For example, a customer wants to change their previously committed purchasing quantity of a component because additional knowledge of demand has become available. How much and at what cost a supply chain partner can deviate from the initial quantity is determined by the quantity flexibility contract, as per Tsay (1999).

Production and Delivery Lead Time – The production and delivery lead time (PDL) here is defined as the time from the start of physical production to the delivery of the product to the customer. In practice, the PDL in a contract is fixed in advance and is uniformly enacted without any element of random variation. In the present model, two

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product types with different PDT times are included: COMM with a PDL time of 4 (+/-0) weeks and ASSP with a PDL time of 8 (+/-0) weeks. The third group found, CSP, are not considered as their order lead time depends on the complexity of the particular product being designed.

3.2 Customer Forecast Accuracy

Demand volatility naturally arises when the customer demand forecasts are based on preliminary information and made at a point in time at which the customer still faces substantial uncertainty about their eventual actual needs for the products (Huang and Ahmed, 2009). To complicate matters, it is commonly recognized that the customer has an incentive to forecast extra orders (phantom orders), above the required orders, if the supplier's capacity is rationed, as for example in Lee et al. (1997) who call this phenomenon "supply gaming" or "shortage gaming" with customers hoping that the partial shipments they receive will be sufficient. The result is that there is poor visibility of the true customer demand, resulting in the substantial over and under-supply, characterized in "bullwhip" or "Forrester" effects. When there is a large build-up of product, then there is the risk of curtailing supply of those products that are actually moving, so in a situation of apparent plenty, there are also shortages.

As both the long and short term supply planning relies on the customer demand forecast the accuracy of this forecast is crucial. In practice within the case study company, the accuracy of the customer demand forecast is quantified using the measure Symmetric Mean Absolute Percentage Error3 (SMAPE3) (Armstrong, 1985; Flores, 1986). Unlike Mean Absolute Percentage Error (MAPE) this measure protects against distortion caused by low data values and uses a summation of both the negative error and the positive error, in order to identify any potential bias towards under or over-forecasting (Ott et al., 2013):

$$SMAPE3 = 1 - \sum_{t=1}^{n} \frac{Abs(A_t - FC_t)}{(A_t + FC_t)} [\%] \tag{1}$$

where A_t is the customers actual final demand and FC_t the customers forecasted demand at time t over n periods.

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Using SMAPE3, customer demand accuracy in the company is presented in Figure 1 for 2012, aggregated over all products and customers. It shows the forecast accuracy (black line) improving during the planning process on a count-down from week 12 to week 1 before the order is delivered to the customer. Furthermore the graph shows the over-planning (white bars) and under-planning (hashed bars) bias over this time. The graph shows a slight net over planning bias, which means that the customers were forecasting less than they actually ordered.

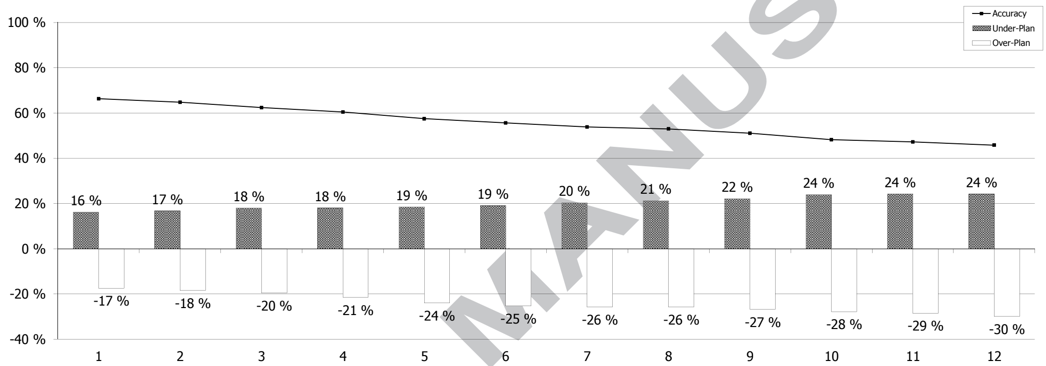

Figure 1: Case study company - aggregated forecast accuracy over all products and customers according to SMAPE3 - y-axis deviations and forecast accuracy and x-axis forecasting horizon [weeks]

By analyzing individual customer demand data three planning categories were identified: unbiased, over and under planning. The following graphs (see Figure 2) show customer forecast accuracy for representative customers. Figure 2a shows an unbiased customer planning behavior, while Figure 2b shows an example an over planning bias, and lastly Figure 2c shows an under planning bias, which reflects a customer who forecast more than actually required. It is clear that in all examples, forecast accuracy improves as the delivery date is approached (i.e. week 1).

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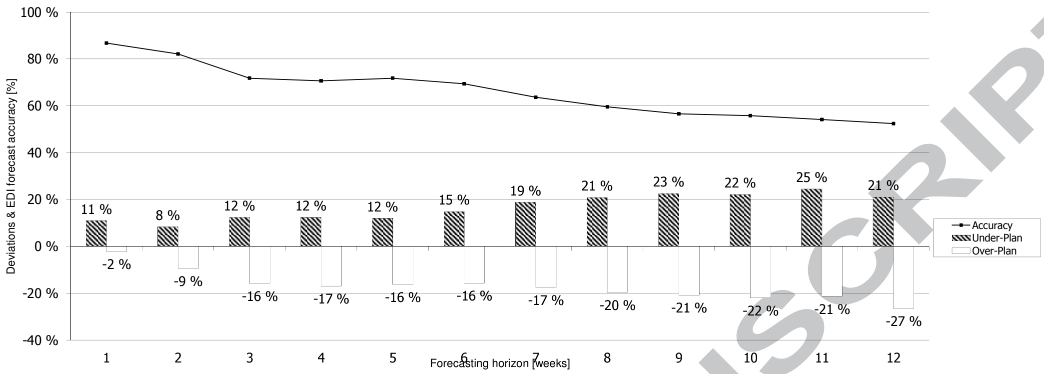
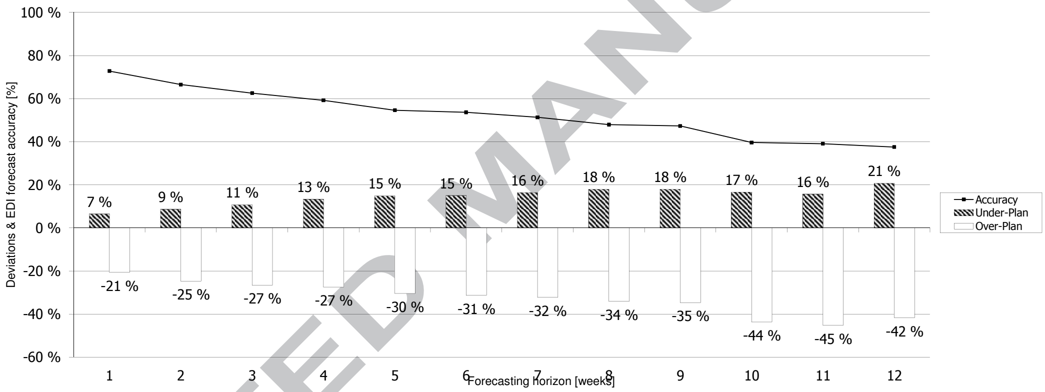
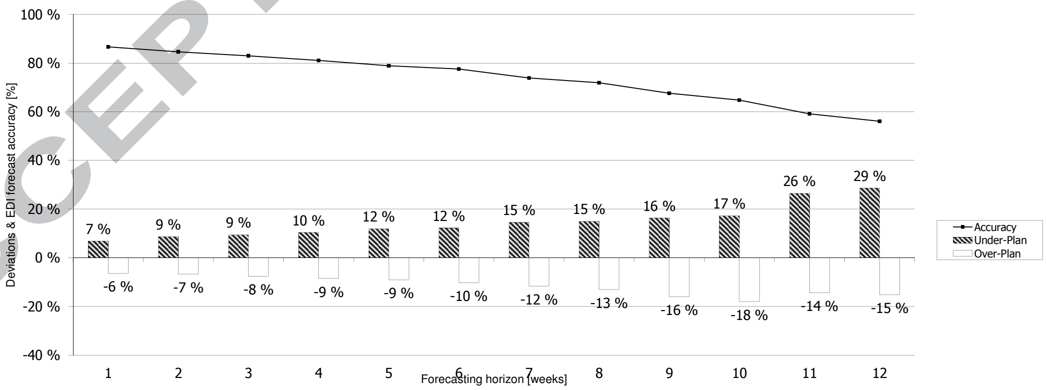


(a) Unbiased customer forecast accuracy



(b) Over planned customer forecast accuracy



(c) Under planned customer forecast accuracy

Figure 2: Examples of customer forecast accuracy (SMAPE3)

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4 Supply Chain Simulation Model

Discrete-event simulation (DES) was chosen as the tool to model the case study company as it facilitated the choreographing of the rolling horizon demand instantiation, which included both long and short-term planning, the modeling of forecasting error and capturing of the resultant performance information. The simulation model is presented in Section 4.1, this is followed by a description of the performance metrics (Section 4.2) and finally verification and validation steps presented in section 4.3.

4.1 Model Overview

The conceptual model of the supply chain is shown in Figure 3. As noted earlier, it consists of three partners: the customer, supplier (semiconductor manufacturer) and the capacity provider (see Figure 4). The customer indicates their demand by sending their forecast with an agreed lead time of 12 months to the supplier. Then on a weekly basis the forecast is updated with the latest demand information and it is used to drive short-term planning modules. The capacity provider (the supplier to the semiconductor manufacturer) is assumed to have unlimited capacity. This is a realistic assumption used within the case study company as supply is provided through internally owned fabrication facilities or through outsourced facilities, which can typically be sourced within the 12 months lead time.

Also, the analysis in the contract market is limited to one customer. However, competition by other customers is included indirectly via the demand function. The extension of the model to multiple customers is straightforward: The current single customer can be interpreted as the aggregation of all customers.

A RHF contract is used between the customer and the semiconductor manufacturer. In this contract there are two operational clauses that govern the contract: (i) the binding period for the contract; (ii) quantity flexibility and periods that governs the changes in the quantity of the customer's order. These values will be agreed through negotiation between a customer and the semiconductor manufacturer.

The objective of the simulation study is to analyze a RHF contract under different customer demand behaviors. The processes that describe how

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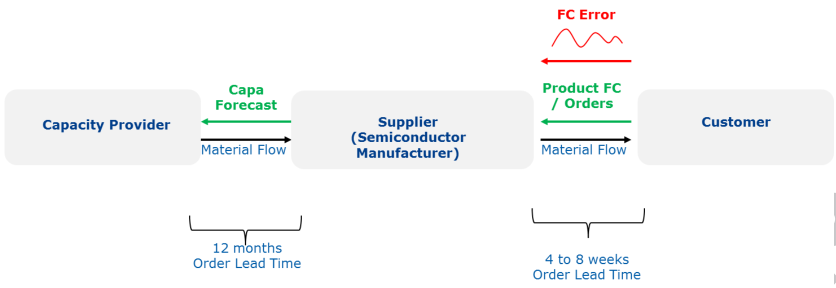

Figure 3: Supply chain model

the three partners (see Figure 4, customer, semiconductor manufacturer and capacity provider) are modeled are described as follows.

4.1.1 Customer

The process starts with the customer forecasting demand for 52 weeks in a rolling horizon basis (1.0 in Figure 4), which is then sent to the semiconductor manufacturer (2.0), who uses this forecast to source capacity in the capacity provider. Recent forecasted demand information also drives short-term planning within the *Supply Chain RHF Contract*, with the customer receiving an order confirmation (1.1) and the process ends after receiving the supply from the semiconductor manufacturer (1.2).

4.1.2 Semiconductor Manufacturer

The semiconductor manufacturer receives (2.0) the customer demand information and uses it for *Long Term Capacity Forecasting* (2.1-2.3), for the *Supply Chain RHF Contract* (2.4-2.10) and for *Inventory Policy* (2.11 and 2.12).

Long Term Capacity Forecasting (2.1-2.3) Within the *Long Term Capacity Forecasting* process the semiconductor manufacturer uses the received customer demand information (2.0) to forecast its long term capacity. This is done by aggregating the demand from a weekly to a monthly granularity (2.1) and based on a 12 months customer demand information, a new

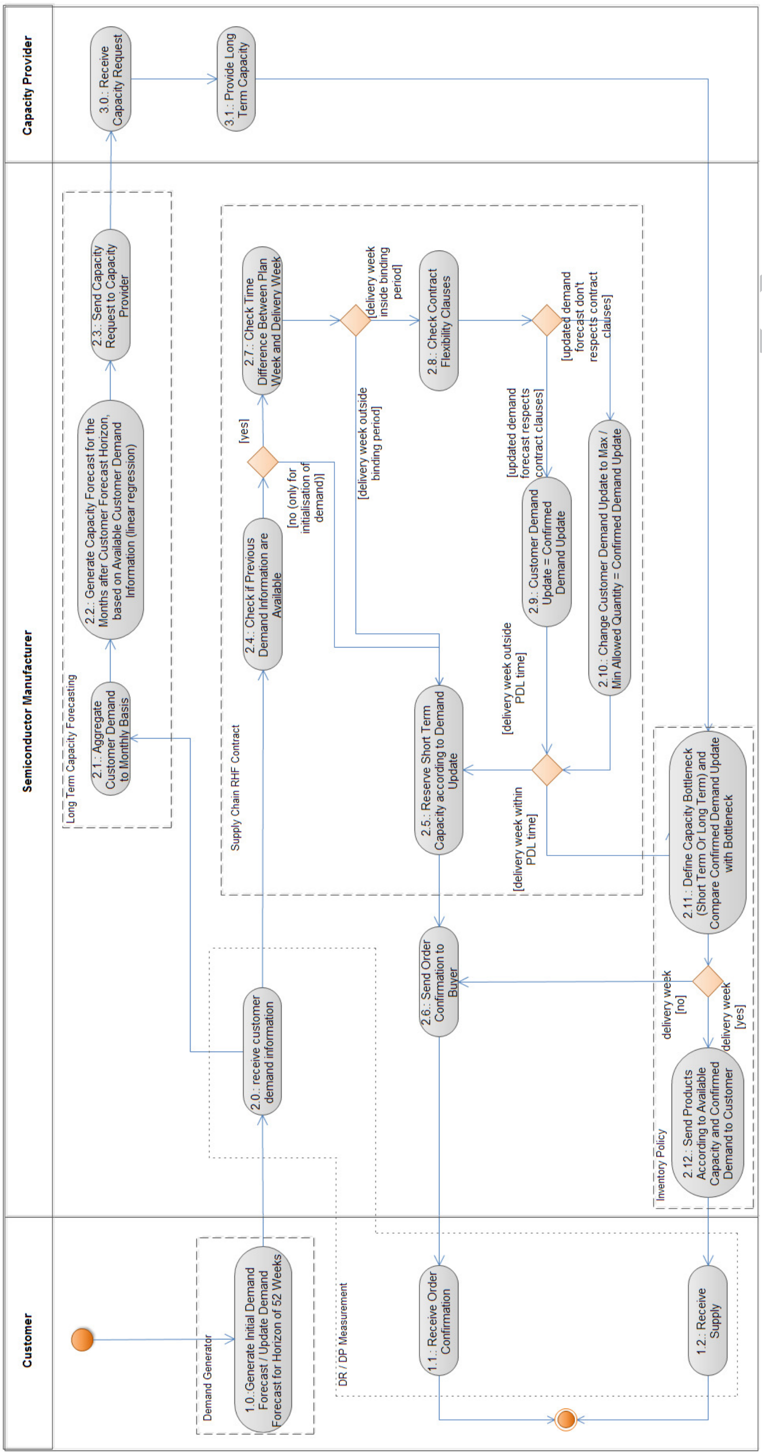

Figure 4: Overview of simulation model

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forecast for the 13th month is calculated (2.2). This is graphically shown in Figure 5.

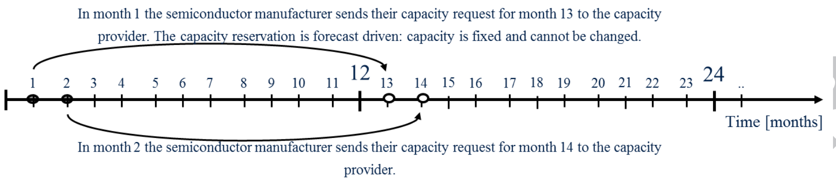

Figure 5: Long term forecasting of capacity

The semiconductor manufacturer's long term capacity forecast, C_{fc}, is based on a linear regression forecasting technique. Linear regression is a statistical method to model the relationship between variables by fitting a linear equation to observed data (Hillier and Lieberman, 2005). A linear regression model is used:

$$C_{fc} = a + px \tag{2}$$

where C_{fc} denotes the forecasted capacity, a and p are coefficients and x denotes time. Let

$$a = \bar{y} - p\bar{x} \tag{3}$$

with y equal to quantity and the values $\bar{x}$ and $\bar{y}$ are the sample means, respectively. Then

$$p = \left(\frac{\sum_{i=1}^{12} (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{12} (x_i - \bar{x})^2} \right) \tag{4}$$

resulting in

$$C_{fc} = \left(y - \frac{\sum_{i=1}^{12} (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{12} (x_i - \bar{x})^2} \right) \bar{x} + \left(\frac{\sum_{i=1}^{12} (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{12} (x_i - \bar{x})^2} \right) x_i \tag{5}$$

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This forecasting process happens every month on a rolling horizon principle as shown in Figure 5. Through the use of forecasting the semiconductor manufacturer and its outsourced capacity providers are assumed to have unlimited capacity, which is realistic as long term forecasting has a fixed lead time of 1 year. Finally, the semiconductor manufacturer will send this forecasted capacity request to the capacity provider (2.3) and it is important to note that this forecasted capacity request cannot be changed and is therefore fixed.

Supply Chain RHF Contract (2.4, 2.5, 2.7- 2.10) Besides long term capacity forecasting, the customer demand is used to drive short-term planning which is executed in the *Supply Chain RHF Contract*. First of all, the manufacturer will check if the customer demand is an initial demand or an update from a previous request (2.4), and will act as follows:

1. In the case of initial demand information, the demand will be used to reserve short term capacity (2.5) and will be immediately confirmed to the customer (2.6) who will receive a demand confirmation (1.1).

2. If previous demand information is updated, the manufacturer will check the time difference between the current plan week and the requested delivery week (2.7). When the requested delivery week is outside of the binding period the semiconductor manufacturer will always accept the customer's request and reserves capacity accordingly (2.5) as well as sending the customer an order confirmation (2.6).

3. If the provided demand forecast is within the binding period (2.7), the contract clauses will be applied on the updated demand forecast (2.8) and a decision will be made to change the customer demand forecast in order to fit the contractual clauses (2.10) or confirm the change (2.9).

The generation of each instance of demand per week is choreographed from generation of an initial demand estimate, through progressive applications of refinement under the respective quantity-flexibility plan towards a final commitment. The variability in the simulated demand reflects the type of variability observed in practice in the company over a representative range of individual products.

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Each instantiation of the customer's initial forecasted demand is modeled using a gamma distribution. After Walsh et al. (2008), the reasons for choosing this distribution are as follows: it is bounded to the left (i.e. does not generate negative demand instances); it is positively skewed in that it has a right-sided tail with occasional large demands; it is not restricted in its range of variation in that it allows high values of coefficient of variation. The standard gamma is a continuous distribution with two parametersLaw and Kelton (1991):

$$f(x) = \frac{\beta^{-\alpha} x^{\alpha-1} e^{-\frac{x}{\beta}}}{\Gamma(\alpha)}, \quad x > 0 \tag{6}$$

with mean equal to $\alpha\beta$ and variance $\alpha\beta^2$.

Auto-correlation in demand is frequently encountered in the forecasting literature in relation to inventory control (Silver et al., 1998; Box and Jenkins, 1976). More specifically, it is deployed in some important analyzes of RHF contracts such as Barnes-Schuster et al. (2002). However, sufficient evidence was not found in the data to justify adding auto-correlation, so it is not deployed in the present model. Forecasting is modeled using a normal distribution, where

$$D_{j-1} \sim \mathcal{N}\left(\left(D_j + \mu_f\right), \sigma_j^2\right), \quad j = 52, t-1, \cdots 0 \tag{7}$$

Furthermore, the variance of the forecast error decreases with the decreasing time difference (Δt) between the period of time t in which the forecast is generated and the requested delivery period of time j. Let

$$\sigma_j = \sigma_f + m \times \Delta t \quad \triangle t \text{ and } j = 52, 51, \cdots, 0 \tag{8}$$

where σ_f equals the fitted forecast error for a customer and $m = 1$ in this case. A mean of $\mu_f = 0$ is used to model an unbiased customer or a shifted normal ($\mu_f \neq 0$) for a customer that over or under forecasts. These relationships allow modeling of a forecast accuracy error which gets smaller as the delivery date approaches, which was observed in the case study company. The tightening of the normal distribution as time advances within the contract binding period is illustrated in Figure 6.

A RHF contract is used between the customer and the semiconductor manufacturer. Orders within the binding period, b, are subject to quantity flexibility clauses. Demand, D_j, within the binding period, $(b, b-1, \cdots, 0)$, are subject to the following RHF clauses:

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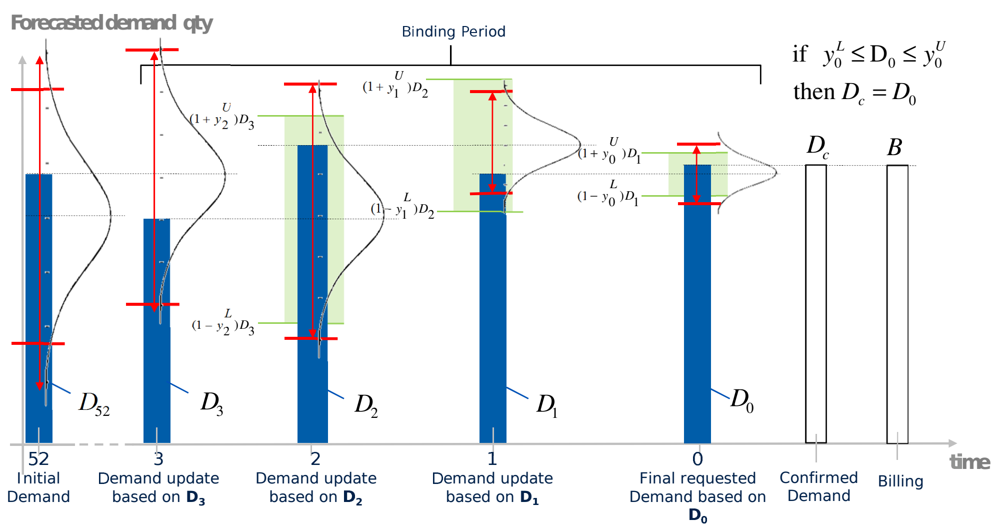

Figure 6: Demand generator and contractual boundaries

$$
\begin{array}{ccccc}
(1-y_{b-1}^L)D_b & \leq & D_{b-1} & \leq & (1+y_{b-1}^U)D_b \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
(1-y_0^L)D_1 & \leq & D_0 & \leq & (1+y_0^U)D_1
\end{array}
\tag{9}
$$

with y_i^L and y_i^U $i = b-1, b-2, \cdots, 0$ denote the lower and upper flexibility bounds for period i and are positive real numbers. Based on these equations, demand can be adjusted by the customer during the binding period according to movements in market demand within specified limits.

Assuming no loss of generality, let $b = 3$ as shown in Figure 6. This diagram shows customer demand updates as bars, from week 52, D_{52} to week 0. Figure 6 illustrates the projected change of demand until final demand, D_0, is reached. As shown in Figure 6 demand in period 2 is dependent on demand in period 3, D_3, and subjected to a forecasting error modeled using a normal distribution as shown in Equation 7. Specifically, forecast error is modeled using a normal distribution with a mean or shifted value μ_f and variance σ_j. As long as the demand updates are within the contractual boundaries, the customer requested quantity is confirmed and the confirmed demand, D_c, is set equal to the final demand D_0 (see Figure 6) or if D_0 is

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outside the flexibility clauses at time 0 then

$$\begin{aligned} D_c &= (1 - y_0^L)D_1 \quad if \quad D_0 < (1 - y_0^L)D_1 \\ D_c &= (1 + y_0^U)D_1 \quad if \quad D_0 > (1 + y_0^U)D_1 \end{aligned} \tag{10}$$

Inventory Policy (2.11 - 2.12) If the current week is within the binding period b of the contract the flexibility bounds will change according to Equation 9, which for the simulation experiments carried out in this paper (detailed in Section 5) is 16 weeks. Two different products, COMM and ASSP, are experimented on which have a PDL of 4 weeks and 8 weeks. After the PDL of each product is reached production of what has been ordered by the customer cannot change. The semiconductor manufacturer can only deliver to the customer the remaining capacity available in this time period (2.11). Both (2.11) and (2.12) will send an order confirmation to the customer (2.6, 1.1). If the delivery week is due, the semiconductor manufacturer will send products according to their available capacity (2.12) which will be received by the customer (1.2).

4.1.3 Capacity Provider

The capacity provider receives the semiconductor manufacturing forecast (3.0) and provides long term capacity accordingly (3.1). As stated earlier the capacity provider's potential capacity is assumed to be unlimited, but with capacity fixed with a lead time of 52 weeks.

4.2 Performance Measures

The performance measures used in the experimentation are the delivery performance (DP), the delivery reliability (DR) and the Inventory level (I). Delivery Performance is calculated as the total number of products delivered on time and in full based on a customer requested date (Council, 2010; Vickery et al., 1997). DP is a demand fulfillment measurement which compares the customers final requested demand, D_0, with the quantity of delivered products (Billings), B. Let the delivery performance equal DP_i for a product delivered to a customer be

$$DP_i = \frac{B}{D_0} \times 100 \tag{11}$$

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with $DP = \sum_{i=1}^{K} DP_i$ for all products delivered to a customer during the simulation model of length K in which results are collected.

This measurement can be seen as a performance index of customer satisfaction, i.e. the customer final demand D_0 is 100 pieces, but the semiconductor manufacturer is only delivering 90 pieces (B), then the DP would be 90%. A body of empirical work confirms that customer satisfaction influence customer retention positively (Mittal and Wagner, 2001; Anderson and Sullivan, 1993). Increasing customer retention secures future revenues (Fornell, 1992; Rust et al., 1994) and can reduce the cost of future customer transactions (Reichheld and Sasser, 1996). As a consequence, net cash flows should be higher and prediction of future revenues should be more accurate as greater customer retention indicates a more stable customer base (Anderson and Sullivan, 1993; Narayandas, 1998).

DR (Equation 12) gives insights into a supplier's capability to meet delivery schedules promised to the customer (Leong et al., 1990) and is measured as the total number of products delivered on time and in full based on an agreed delivery date (Council, 2010). DR is a demand fulfillment measurement that compares the confirmed order quantity, D_c, according to the flexibility rules stipulated in the contract with the quantity of delivered products (B). This measure can be seen as a performance index of a supplier's contract compliance, i.e. how well the RHF contract flexibility can be satisfied by the supplier. Therefore let delivery reliability equal DR_i for a product delivered to a customer be

$$DR_i = \frac{B}{D_c} \times 100 \tag{12}$$

with $DR = \sum_{i=1}^{K} DR_i$ for all products delivered to a customer during the simulation model of length K in which results are collected.

4.3 Verification and Validation

Simulation experiments were conducted in order to verify the different customer order behaviors generated by the model. In total 312 different trials were simulated, comprising combinations of 6 customer order behaviors, 2 PDL times, and 26 different contract flexibility settings. In addition, each of the modules were individually verified, including the interaction with cus-

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tomer order behavior, in terms of customer forecast accuracy, inventory levels, and the amount of billings. Furthermore the measures DP and DR were recorded and charted and specific examination of the graphs of forecast accuracy behavior over time.

The forecast error was validated against real customer demand. Real customer data from the case study company were analyzed and curve fitting methods were applied, to derive realistic values for the gamma distribution parameters. Based on the analysis of a representative customer, a shape parameter α of 80 and the inverse scale parameter β of 20 were identified as being representative of real data. These parameters were used for the experiments, see Table 1.

The normal distribution was used to model forecast error as described in subsection 4.1.2. Analyzing actual forecast error data of an unbiased customer order yielded a forecast error variance of $\sigma_f = 40$, with the time-dependent variation of the variance parameter modeled according to Equation 8. A representative range of bias across several customers lies in the range of means from -20 to +20. In order to represent the three different order behaviors of unbiased, over-planning, and under-planning, the mean μ_f of the normal distribution was set to 0, -20 and +20.

Table 1: Demand values for forecast error distributions

Initial Customer Demand Signal	$\alpha = 80$	$\beta = 20$
Forecast error	σ_f	μ_f
UB - Unbias	40	0
O - Over planning bias	40	-20
U - Under planning bias	40	20

Based on these settings, the different forecast accuracy behaviors were generated by the simulation model and were validated by comparing the outputs with real customer forecast accuracy behaviors in the case study company. Figure 7 shows the result of comparing actual customer forecast accuracy against real data with the generated output of the simulation model for an unbiased customer. It also shows the proportion of over and under planning bias measured using SMAPE3.

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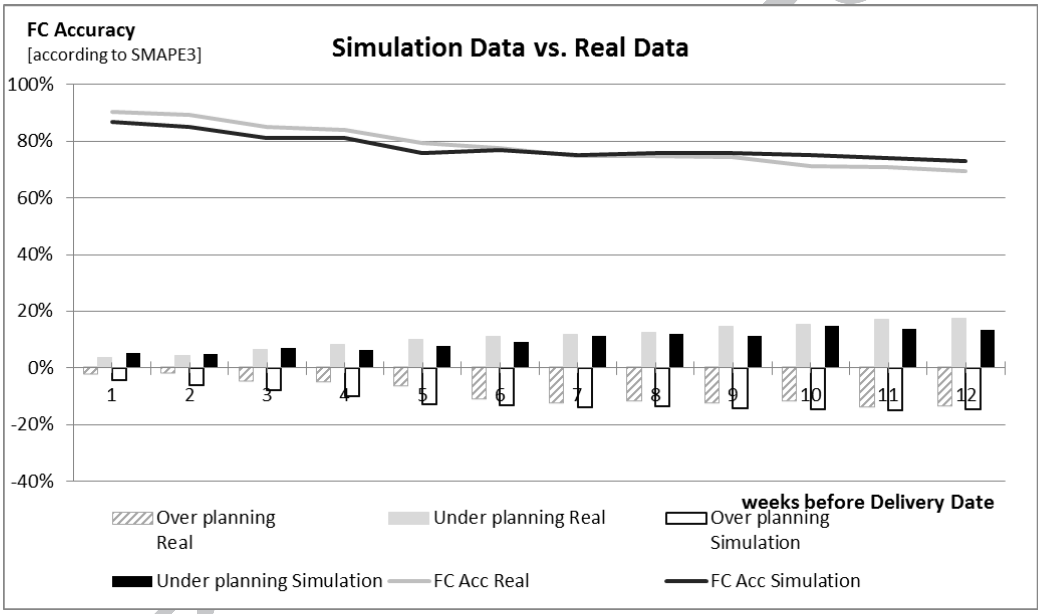

Figure 7: Comparison of simulation forecast data for an unbiased customer against actual customer forecast accuracy over time using SMAPE3

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Furthermore in order to evaluate the correct modeling of the RHF contract, the output of the model in terms of average fill-rate which is comparable to our delivery performance was compared to the output of the model from Bassok and Anupindi (2008). Figure 8 generated from the simulation model presented in this paper shows a similar operating characteristic for the average fill rate versus the contractual flexibility bounds with constant flexibility and stationary demand with a CV of 0.5 to those presented in Bassok and Anupindi (2008).

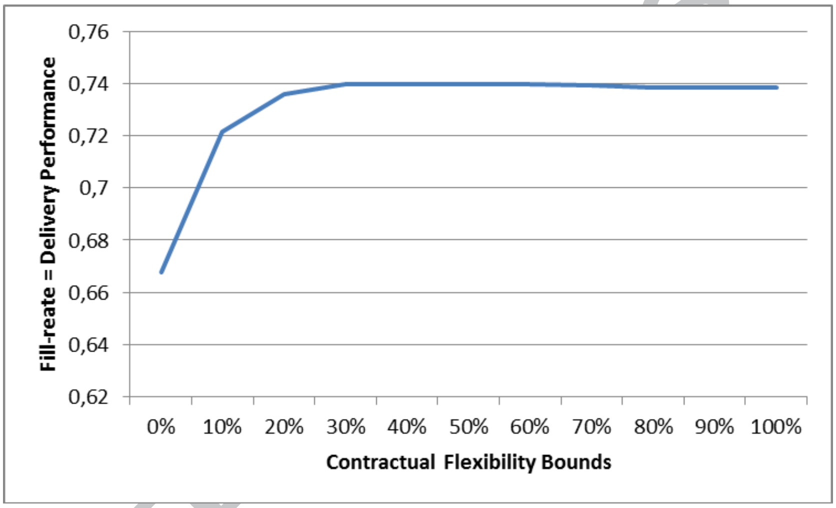

Figure 8: Average fill rate versus flexibility for stationary demand with CV=0.5 of the model

5 Experimentation

The following experiments analyze contracts with symmetrical and asymmetrical RHF clauses under a demand signal with forecast error, three categories of demand signal (unbiased, over-planning and under-planning) and for two different PDL times. Before presenting these results first the simulation settings under which the experiments were carried out are given.

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5.1 Simulation Settings

The simulation length was 208 periods, with each period equating to a week. The simulation model was ran for 52 periods (one year) to warm up and reach steady-state (Alwan et al., 2008). This was followed with results gathered for the remaining 156 periods (three years). The model was run under two different PDL time settings, the COMM product which is 4 weeks and the ASSP product which is 8 weeks. For each of these products the semiconductor manufacturer (supplier) allocates supply based on the customer's forecast at the 4th and 8th week for each product type, respectively (see Figure 4 (2.5, 2.9, 2.10 and 2.11)). However, the customer will still update their forecast right up until the final demand D_0 is issued when the semiconductor will try to fulfill based on current inventory levels.

5.2 Symmetrical Flexibility Boundaries

Table 2 shows the different supply chain contract settings for the different time periods t [1 to 4; 5 to 8; 9 to 16] before final demand is delivered. First a contract (UL) with unlimited upside and downside flexibility was simulated, in order to analyze the case of "no contract". This is because within the case study company we observed that the quantities (as opposed to the timing) of supply chain contracts are not always accurately executed. The contract setting UL should give insights into the advantages and disadvantages of having no contract or having the contract not linked to the supply chain execution system. Then a contract (Z) with zero downside and upside flexibility was experimented with. This setting reflects the case where the customer has no flexibility to update their demand information. The contract settings LF (Low Flexibility) and HF (High Flexibility) are based on real customer examples.

5.2.1 Results

Figure 9 shows the results for the symmetrical rolling horizon contracts for the demand signals UB, O and U (see Table 1) for COMM (4 weeks PDL time) and ASSP (8 weeks PDL time). In general it can be seen, that the performance measures DR, DP and I, show better results for COMM than for ASSP. This is explained by the more upstream decoupling point of 8 weeks for ASSP. Whereas for the COMM more recent demand information is con-

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sidered, which improves the performance. In general for both product types it can be observed that the over planning behavior shows higher DR and DP than for unbiased and under planning demand behavior. This is explained by the fact, that the customer is forecasting more than he actually required. This has the effect, that the supplier builds up more I then necessary, which works as a hedge against demand volatility.

Table 2: Symmetrical flexibility boundaries experiments

Contract	Upper and Lower Contract Bounds	Time period t 1 to 4	5 to 8	9 to 16
UL	y_{tj}^U	*unlimited*	*unlimited*	*unlimited*
	y_{tj}^L	*unlimited*	*unlimited*	*unlimited*
Z	y_{tj}^U	0	0	0
	y_{tj}^L	0	0	0
LF	y_{tj}^U	0	0.1	0.2
	y_{tj}^L	0	0.1	0.2
HF	y_{tj}^U	0.1	0.2	0.4
	y_{tj}^L	0.1	0.2	0.4

In the case of an over planning behavior, disregarding UL, the best DP result is obtained with a contract with upside flexibility (LF and HF). Furthermore, contract HF and UL show very similar performance results, for both product types. This could be explained by the fact that the upside and downside flexibility boundaries of HF are high enough to not restrict the customer demand signal similar to UL (with unlimited contract boundaries).

Summarizing, these results shows the trade off between service level (DP and DR) in the form of delivery performance and inventory level. In order to obtain improved supply chain performance, the right contract settings are required to match the correct customer demand signal, which here is classified as unbiased, over-planning or under-planning. However, the results presented do not indicate which contract settings would be the best for each categorized demand signal. Therefore the impact of downside and upside flexibility were analyzed individually with results presented next.

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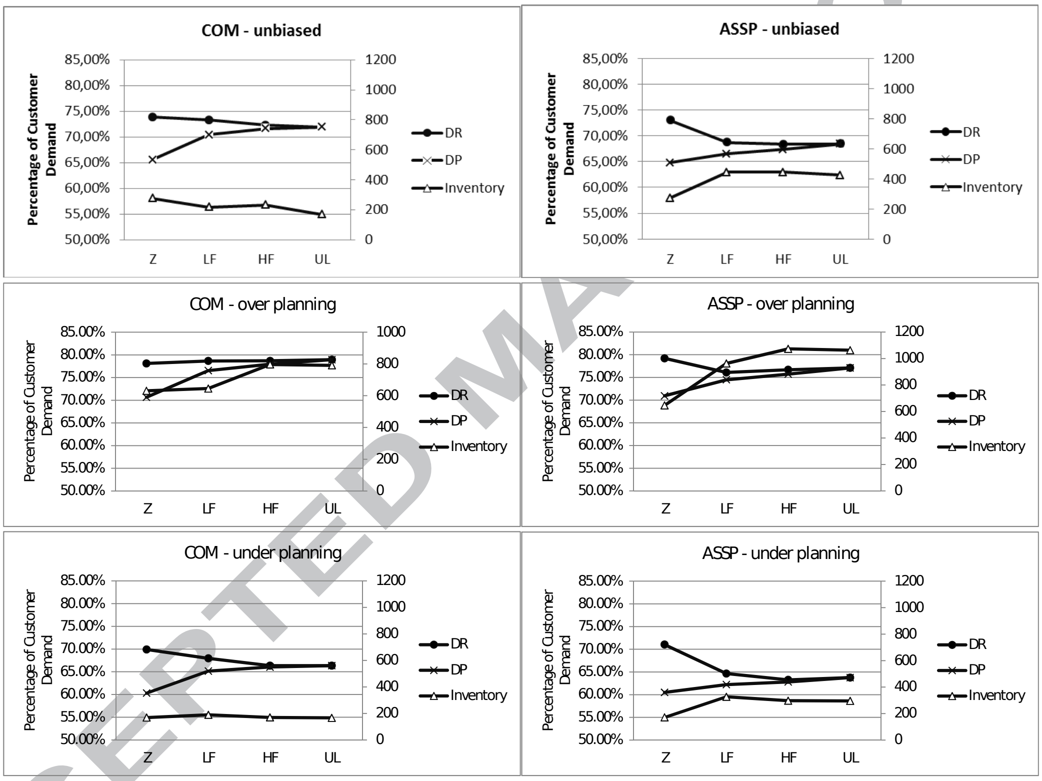

Figure 9: Impact of contract flexibility on DP and DR and inventory

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5.3 One Sided Flexibility Boundaries: Impact Of Upside And Downside Flexibility

The simulated upside and downside flexibility rates y_j^L and y_j^U, $j = b, b-1, \cdots, 0$ were set to {0,0.1,0.2,0.3,0.4,0.5}, respectfully, as shown in Table 3, to provide a deeper insight into how y_j^L and y_j^U impact the SC performance measures. First, a contract with unlimited upside flexibility and different downside flexibility was simulated for each demand signal UB, O and U (see Table 1). Then a contract with unlimited downside flexibility and different upside flexibility was simulated for the same demand signals. For all following experiments, products with a PDT Time of 4 weeks were considered.

Table 3: One sided flexibility boundaries

Contract Settings	Contract	Upper and Lower Contract Bounds	Time period t 1 to 4	5 to 8	9 to 16
Unlimited Upside/Downside Flexibility	1	y_j^L or y_j^U	0	0	0
	2	y_j^L or y_j^U	0	0	0.1
	3	y_j^L or y_j^U	0	0.1	0.2
	4	y_j^L or y_j^U	0.1	0.2	0.3
	5	y_j^L or y_j^U	0.2	0.3	0.4
	6	y_j^L or y_j^U	0.3	0.4	0.5

5.3.1 Results

Figure 10 shows on the left side, the result for a contract with unlimited downside flexibility and different upside flexibility for the demand signals UB, O and U. The results show that with increasing upside flexibility the DR decreases whereas the DP increases. This is explained by the fact, that with tight upside flexibility boundaries the customer is not allowed to increase their demand abruptly, which helps the manufacturer keep their commitments resulting in a higher DR. However, the restricted upside flexibility on the customer side impacts the DP. The over planning customer order behavior (O) shows the best DR and DP performance, however it shows also the highest I compared to UB or U.

On the right side of Figure 10, the results of a contract with unlimited upside flexibility and different downside flexibility is shown for UB, O and

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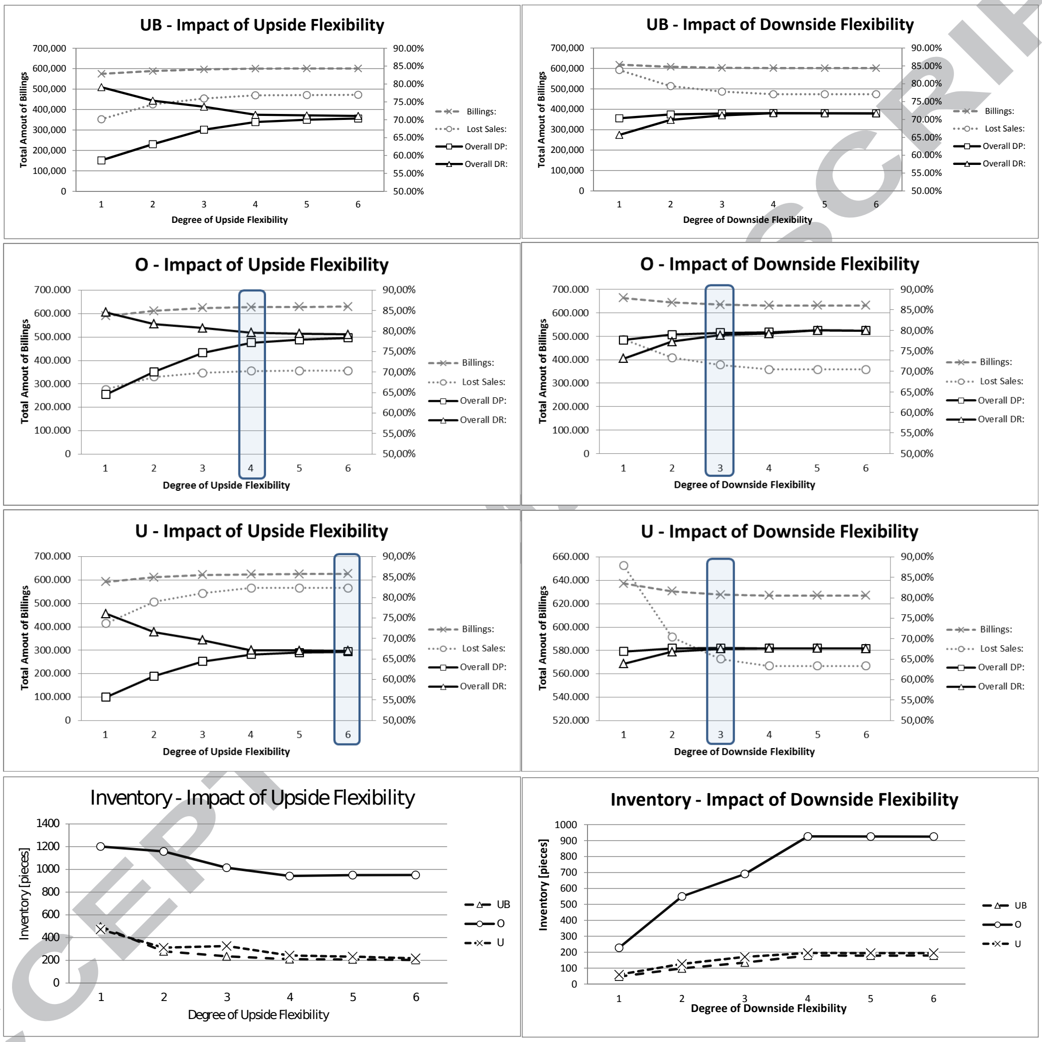

Figure 10: Impact of upside and downside flexibility on DR, DP and I under UB, O and U

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U. The results show that with increasing downside flexibility, the DR and DP for all demand signals increase, with better performance for U than for UB and O. Significant in these results is the steep ramp of I for customer demand signal O, with increasing downside flexibility. This is explained by the fact that the customer with O are forecasting more than they actually need, which when combined with the unlimited upside flexibility leads to a steep ramp increase in I.

These results of the analysis of one sided flexibility show that upside and downside flexibility should be chosen independently from each other, resulting in an asymmetrical RHF contract. Asymmetrical RHF contracts provide a means to improve DP and DR while lowering I in the case of O and U customer order behavior. It is concluded from this that that asymmetrical bounds offer the possibility to outperform symmetrical bounds. Thus, in the following section, their performance is compared.

5.4 Asymmetrical Flexibility Boundaries

Based on the results from the previous subsection, here we compare asymmetrical RHF contracts with symmetrical, under the two demand profiles (O and U) for COMM products. Depending on the cost of inventory, revenue from sales, and the relative benefit accruing to service level measures (DP and DR), a multicriteria optimization method could in theory be used to find the optimal settings. However, this would require many additional assumptions, so to compare performance with regard to RHF symmetry in an objective fashion, we compare a best or near-best parametrization to represent each alternative as follows.

In chosing the most beneficial asymmetrical contract parameter, we focused for over- and under- planning bias on reducing I whilst providing stable values for DR, DP and Billings. Referring to Figure 10 we chose for O contract parameter 3 for the downside flexibility (0 for $t = 1$ *to* 4; 0.1 for $t = 5$ *to* 8, and 0.2 for $t = 9$ *to* 16), contract parameter 4 for the upside flexibility (0.1 for $t = 1$ *to* 4; 0.2 for $t = 5$ *to* 8, and 0.3 for $t = 9$ *to* 16). These were chosen because contract 3 (for downside flexibility, see right side of Figure 10) showed a high level of DR, DP and Billings and a low I in contrast to contract 4 which has a higher level of I and similar values for DR, DP and Billings. For U, contract 3 was selected for the downside flexibility (0 for $t = 1$ *to* 4; 0.1 for $t = 5$ *to* 8, and 0.2 for $t = 9$ *to* 16) and contract 6 for the upside flexibility (0.3 for $t = 1$ *to* 4; 0.4 for $t = 5$ *to* 8, and 0.5 for

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t = 9 *to* 16). Again these were chosen because contract 3 for downside flexibility shows a high level for DR and DP and Billings, whereas contract 6 for upside flexibility shows the lowest I and also stable performance for DR and DP. Similarly, we made a beneficial choice of parameters for symmetrical bounds.

5.4.1 Results

The results of the comparison are shown in Table 4. For demand signal O and U, the asymmetrical contracts perform better than the symmetrical contracts LF and HF and, especially, the I is reduced for U by over 54% and for O by over 48%. The DR (0.68% and 2.06%) and DP (3.35% and 2.75%) are slightly improved for U. For O, DR (0.9% and 0.31%) and DP (2.64% and 1.64%) increased slightly too. The asymmetrical contracts for both demand profiles show negligible performance changes in terms of Billings compared to the symmetrical contracts.

Examining Figure 10 in the case of O, DP can only be improved by increasing the downside flexibility, which will increase I. This shows again the discrepancy between service level (DP and DR) and I, which is most visible for the over planning forecasting behavior.

Table 4: Results of the comparison of symmetrical and asymmetrical contract performance

Demand	Contract Performance				Comparison A against S	
	Result	Asymmetrical, A	Symmetrical, S			
			LF	HF	LF	HF
O	I	501	963	1073	-48%	-53%
	DP	77,38%	74,74%	75,74%	2,64%	1,64%
	DR	77,00%	76,10%	76,69%	0,9%	0,31%
	Billings	614,095	624,323	624,599	-1,6%	-1,7%
U	I	138	327	298	-58%	-54%
	DP	65,56%	62,21%	62,81%	3,35%	2,75%
	DR	65,32%	64,64%	63,26%	0,68%	2,06%
	Billings	652,259	614,416	616,232	+6,2%	+5,8%

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6 Discussion

This study is premised on the assumption that according to a customer's demand behavior, changes in the RHF clauses afford improved system-wide performance. It is important that a supplier understands it's customer demand pattern with respect to bias (unbiased, over or under planning) in order to adjust RHF boundaries accordingly. Depending on this pattern, the model shows that by choosing the right upper and lower flexibility boundaries, demand fluctuations can be effectively absorbed by the system.

In subsection 5.2 the experiments on symmetrical flexibility boundaries show the trade off between service level (DP and DR) in the form of delivery performance and inventory level. However, the results did not directly indicate which contract settings would be the best. Therefore the individual impact of downside and of upside flexibility were analyzed in subsection 5.3. These results show that upside and downside flexibility should be chosen independently from each other, resulting in an asymmetrical RHF contract.

In subsection 5.4 it is found that asymmetrical RHF contracts provide a means to improve DP and DR while lowering I in both cases, for over- and under- planning. Especially for under planning behavior, the inventory level could be reduced by approximately 50% with an asymmetrical RHF contract, with an increase in DP of approximately 3%, and in DR by 2% when compared to symmetrical contract clauses. In the case of over planning whilst inventory remained unchanged or slightly dis-improved, DP and DR had an approximate increase of 3%. The use of asymmetrical RHF clauses on biased customer demand signals is thus expected to enable better inventory management and better customer service. This appears to be because the RHF contract works as a countermeasure for a customer's demand bias.

The outcomes appear to be robust with respect to both cases: over- (O) and under-planning (U). This means that the planner's approach does not need to be changed when a medium- run cyclic changes direction. It is known that the semiconductor industry is volatile. In a study of the global semiconductor industry, Tan and Mathews (2010) confirmed the semiconductor industry as being highly volatile, and especially their data suggest a recurrent component of medium-term cyclicity at around 0.5 years. This indicates that a contract will generally happen within a period of over- or under-planning.

However, while a RHF contract adjusted to a customer's demand signal bias may be beneficial for both the customer and the manufacturer, in reality

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a customer may hesitate to enter into such a contract. This can arise due to power asymmetry: in this sector, such as in the case study company, it is generally the customer who has the advantage of power in reaching a contract agreement, and who seeks more flexibility through a preference for shorter planning horizons with higher upper and lower flexibility bounds as well. Therefore, in a decentralized supply chain, the contract clauses between customer and supplier will often be determined in practice, by the partner with the most negotiation power. In practice however, knowledge of the effect of symmetric and asymmetrical RHF clauses on a customer demand profile when entering negotiations would be beneficial to a supplier, affording situation awareness with regard to excessive risk.

7 Conclusions

While there is considerable variation in model behavior as between performance measures and across experimental conditions and replications, the following conclusions are considered to be supported by the experimental evidence:

1. Asymmetrical contracts substantially outperform symmetrical contracts under the comparable conditions examined.
2. The advantage was found to be of similar degree under both over-planning (O) and under-planning (U) conditions.
3. The advantage found against symmetric contracts was regardless of the degree of flexibility examined (LF and HF).
4. The robustness with respect to O and U conditions is of particular comfort in this industry sector in which buying behavior oscillates between degrees of O and U with a medium-term regularity.

Overall, this paper contributes a significant insight with respect to the design of RHF contracts in relation to a semiconductor supply chain.

Being exploratory, the work has its limitations. In particular, optimal rather than globally optimum positions are adopted to represent both general cases of asymmetric and symmetric RHF bounds. However, we claim that the test cases used are reasonably representative of the balance in practice.

It would be interesting to examine cyclicity in O and U using the cyclicity explicated by Tan and Mathews (2010) and others who have looked at this dimension. It would also be interesting to investigate the performance of

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other contract types. For example, option contracts as explored in (Gomez-Padilla and Mishina, 2009) , using the approach developed in this work.

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Highlights

- We model a 3 echelon SC with uncertain & biased customers demand and RHF contract
- Case Study: Over 200 SC contracts were reviewed & customer order behavior analyzed
- Changes in performance for different order behavior and RHF contracts were observed
- RHF contracts need to be altered acc. to order behavior to increased performance
- Asymmetrical RHF contracts perform better than symmetrical for biased demand data

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