Simulation Based Study of Safety Stocks under Short-Term Demand Volatility in Integrated Device Manufacturing

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Abstract

A problem faced by integrated device manufacturers (IDMs) relates to fluctuating demand and can be reflected in long-term demand, middle-term demand, and short-term demand fluctuations. This paper explores safety stock under short term demand fluctuations in integrated device manufacturing. The manufacturing flow of integrated circuits is conceptualized into front end and back end operations with a die bank in between. Using a model of the back-end operations of integrated circuit manufacturing, simulation experiments were conducted based on three scenarios namely a production environment of low demand volatility and high capacity reliability (Scenario A), an environment with lower capacity reliability than scenario A (Scenario B), and an environment of high demand volatility and low capacity reliability (Scenario C). Results show trade-off relation between inventory levels and delivery performance with varied degree of severity between the different scenarios studied. Generally, higher safety stock levels are required to achieve competitive delivery performance as uncertainty in demand increases and manufacturing capability reliability decreases. Back-end cycle time are also found to have detrimental impact on delivery performance as the cycle time increases. It is suggested that success of finished goods safety stock policy relies significantly on having appropriate capacity amongst others to support fluctuations.

Keywords
Finished Good Safety Stock, Integrated Device Manufacturing, Short-term demand volatility, Simulation.

1. Introduction

Technological evolution over the last decades has enabled semiconductor industry to build increasingly complex integrated circuits (ICs) formed by tiny transistors into individual chips able to perform complex tasks. This trend is continuing. ICs constitute a fundamental part of sophisticated electronics systems and they play a central role in the design of end products (Rao, 2015). The semiconductor industry is one of the manufacturing industries that present a highest level of complexity. Companies in this specific segment of the semiconductor industry are known as Integrated Device Manufacturers (IDMs).

A problem faced by IDMs relates to fluctuating demand particularly regarding market interests for ICs that show variations over time. The fluctuating demand impacting IDMs can be of three components in different timescales, namely, long-term demand forecast (more than six months horizon). middle-term demand forecast (between six weeks and six months horizon), and short-term demand fluctuations (less than six weeks horizon). Each of the components can be addressed using appropriate inventory management strategies.

There are two main challenges to address in the development of inventory management strategies for Integrated Device Manufacturers: a) on one hand is the gap between the manufacturing cycle time and the industry lead time and b) on the other hand is the dilemma around the optimal balance between inventory holding costs and stockout costs. Small fluctuations in the demand of the final consumer market tend to result in large swings in the production and inventory levels in the upstream (Tan & Mathews, 2010).

This paper focuses on demand fluctuation in the short term. It reports a simulation study of a finished goods safety stock strategy under fluctuating demand in the manufacture of integrated circuits. Emphasis is placed on delivery performance levels under different utilisation levels and various average safety stock as a ratio of average weekly demand.
The remainder of the report is in four sections. Section 2 contains an overview of the relevant process stages of IC product manufacturing. Also contained in Section 2 is a brief literature review of related work. A simple model of finished goods safety stock policy is presented in Section 3. The model is used in the simulation experiments carried out and reported in Section 4. The report ends in Section 5 with conclusions and suggestions for future work.

2. Background and Related Work

This section contains an introduction to the manufacturing processes involved in IC production and an overview of related work on safety stock in IC manufacturing.

2.1 Background

In this work, we describe the manufacturing processes involved in IC production as mainly grouped into two major stages referred to front-end and back-end stages. The front-end consists of two main manufacturing processes known as wafer fabrication and probe sort. The back-end entails two different activities known as assembly and final test. Figure 1 below shows the manufacturing flow of interest.

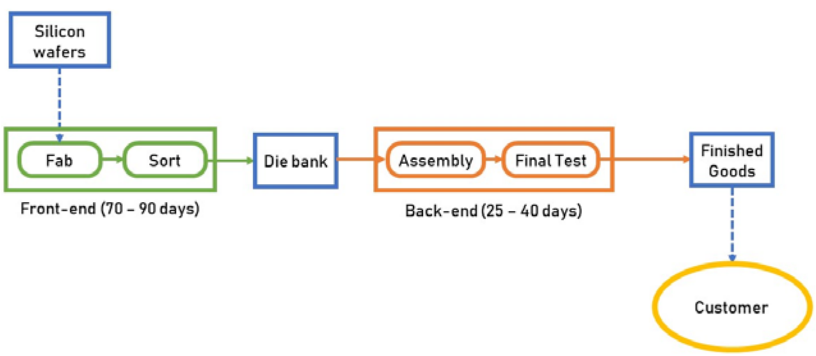

Figure 1 Integrated circuits manufacturing flow

The elementary component in the process is called die and it is created through a multi-step sequence of photolithographic and chemical processing, during which electronic circuits are gradually created on wafers made of semiconducting material, typically silicon. This manufacturing process takes place in highly specialised facilities called 'fabs' and the industry average cycle time ranges from 70 to 90 days, depending on the complexity of the circuit. Once wafers complete processes at fab, the wafers are subjected to test to determine the functionality of each individual die and those with defects are removed from production. This operation is typically referred to as Electronic Die Sort (EDS).
Back-end processes start with die being processed through assembly, in which die are encapsulated in a supporting case that prevents physical damage and corrosion as well as supports the electrical contact that connects the IC with a circuit board. Following assembly, die are subjected to multiple tests to ensure their correct functionality. These tests, called Final Test, often involve different temperature ranges depending on the environment that the devices are going to operate in. Similar to the EDS process, integrated circuits not fully functional are removed from production (May, G. & Sze, 2007). The statistical percentage of final products that offer perfect functionality is known as yield. Back-end cycle time typically ranges from 25 to 40 days. The total manufacturing cycle time typically ranges from 95 to 130 days.
It is particularly important to highlight some of the key inventory points along the manufacturing flow. The inventory point of semi-finished goods between front-end and back-end is known as die bank. At this point, ICs are considered semi-finished products since the main specifications of the integrated circuit have already been conferred

to the die. Nonetheless, these die generally support several end products, which are obtained by specific processes at assembly and final test. Hence, while die bank adds complexity to the overall inventory management they nonetheless provide flexibility to place different safety stock levels along the manufacturing flow instead of concentrating all safety stock at finished goods where the unit costs are higher.

Uncertainty around middle-term demand forecasts is typically addressed by a die bank (DB) stock policy. The DB stock policy aims to ensure the availability of semi-finished goods supply at die bank to support work releases (also known as assembly loads) to back-end in timely manner. The main element of the die bank stock policy is the 'wafer starts logic', which governs the release of raw wafers into 'fab'. Demand fluctuation in the short-term (less than six weeks horizon) can typically be addressed by implementing a Finished Goods (FG) safety stock strategy or through the expedition of WIP at the back-end. Both options can be costly but expediting WIP through the back-end operations entails a high risk of disruption in the back-end manufacturing environment by de-prioritising material causing supply gaps on other end products. For this reason, IDMs look towards developing FG safety stock policy to minimise supply gaps to deliveries according to their business needs.

The three main inventory points in the IC manufacturing process (raw wafers, die bank and finished goods) allow IDMs to place different levels of inventory along the manufacturing flow. The Finished Goods (FG) safety stock is a powerful tool for absorbing short-term demand fluctuations (less than six weeks horizon). The horizon, covering the next six weeks ahead, is regarded as short-term horizon in the industry since the majority of products present a back-end cycle time between four and six weeks. Any demand upside outside the six-weeks horizon could theoretically be supported provided that two conditions are met: first, there is enough die bank supply to be released to back-end and second, back-end capacity is available to support the production. Thus, it is essential to plan the right amount of FG safety stock if an integrated device manufacturer is willing to offer competitive order fulfilment lead times.

2.2 Related Work

Safety stock plays a significant role in preventing stockouts in demanding manufacturing environments. There is evidence in the literature on the convenience of planning safety stock to guarantee an agreed service level from the point of view of a reorder point in a single stage (e.g. Natarajan and Goyal (1994) and Korponai et al. (2017)). However, IC manufacturing extends beyond a single stage. Natarajan and Goyal (1994) explore the relation between lot size and safety stock in the context of JIT productions and reviewed several statistical based methods for determining safety stock, service level and demand distribution follow a probabilistic distribution. Another common feature of the methods is that safety stock determination is through reorder point level: a level of inventory which triggers an action to replenish the inventory stock. Korponai et al. (2017) developed an approach to determine safety stock from the point of view of the minimisation of three different costs involved: procurement activity, stock holding and stockout costs. The resolution of the model is initiated with the definition of an agreed service level, which is the acceptance of a probability of shortage occurrence. They observed that by increasing safety stock, the probability of the stockout occurrence decreases. Arguably, a complete safety can only be guaranteed by an infinite stock level.

The location of the safety stock in the supply chain can be fairly insensitive to the demand whereas the size of the safety stock does depend directly on the demand characterization (Graves and Willems, 2000). Graves and Willems (2000) explored the optimal distribution of safety stock in a supply chain modelled as a network of nodes representing different manufacturing stages. Each stage operates with a periodic-review base-stock policy where the demand between nodes is bounded and a service level is defined at each node. Funaki (2010) presented a strategic multi-echelon safety stock placement model optimisation combined with supply chain design for assembly-type products with due-date based demand allowing back-ordering, which is very similar to practices in the semiconductor industry. In their work, production is planned to support the due-based demand in a Make-to-Plan scheme, supply chain network design is incorporated into safety stock placement model, and their model can incorporate non-stationary demand patterns. Hung (1996) developed a deterministic approach for addressing uncertainty in semiconductor production and considered two main sources of uncertainty: time in manufacturing operations and manufacturing yield. Hung formulates a framework that incorporates cycle time and yield distributions being partly inspired in the reorder point approach but there was no significant reference to demand uncertainty, which is one of the main sources of uncertainty in the semiconductor industry.

The importance of demand forecast updates in safety stock determination has also been emphasized. Schoenmeyr and Graves (2009) developed a safety stock policy emphasising the benefit of updating demand forecasts in production planning. With each forecast revision, a company can review its supply chain plans and tactically reallocate resources to support changing demand. They observed that incorporating demand forecasts updates results in less safety stock and that the magnitude of the savings depends on the quality of the forecasts, rather than the variability of demand. Boulaksil (2006) presented Martingale Model of Forecast Evolution (MMFE) as a model that reflects realistically the demand pattern for many products in a real-world scenario compared to other models that assume independent and identically distributed demand. Using simulation, they observed that a big portion of safety stock should be placed downstream in the supply chain to achieve a high customer service level.

Safety stock models applied to semiconductor manufacturing have been developed but, as noted by Albey et al. (2015), there is limited literature exploring the application of demand forecast information in production planning. Albey et al. (2015) integrates demand forecast evolution and inventory theory applied to semiconductor manufacturing to plan work releases into a production facility in the face of stochastic demand. Demand forecasts are updated over time as customers adjust the quantity and timing of their orders and the model is solved on a rolling horizon basis, managing the inventory, backorder and shortfall levels at each planning epoch. The results of the study indicate that considering forecast evolution in the production planning model can lead to improved performance. The idea of integrating future demand requirements into inventory management policy is present in recent literature given the extraordinary technological progress made in the last decade in data handling. The framework developed in this project can be regarded as part of that trend. Schwartz et al. (2006) developed an approach to manage inventory in a semiconductor supply chain inspired by control-oriented techniques. The idea is to anticipate future events in the system and take control actions accordingly. Model Predictive Control (MPC) strategies have recently been applied to inventory management for multi-echelon supply chains using WIP as liquids in a chemical system as an analogy. Every time WIP is required downstream to support future demand, the valves are opened to release material into the manufacturing system. Based on predicted inventory in the horizon considering the forecasted demand, Schwarz et al. developed a starts policy that automatically selects the right amount at the right time for starts at each echelon. Their simulation results reveal its potential to control inventory in uncertain manufacturing.

Simulation has featured remarkably in the literature as a technique for evaluating the suitability of the safety stock strategies. There is a strong support on modelling and simulation as a robust technique to evaluate semiconductor supply chains as well as to identify areas in safety stock policy for improvement. Godding et al. (2003) argue that simulation of physical flows of material and decision policies governing these flows facilitate the development of improved control in a manufacturing system. In their work, simulation is regarded as the best methodology to develop a deep understanding of a supply chain since it allows extensive experimentation to validate control policies without financial risk. To facilitate the use of simulation, Yuan and Ponsignon (2014) presented a library with a collection of simulation objects that can be used to model supply chains of various scales in the semiconductor industry with the clear purpose of progressing towards standardisation and benchmarking. Some authors cover the direct application of simulation techniques to optimise safety stock placement in semiconductor manufacturing. An example is Morrice et al. (2005) in which the dilemma between minimising inventory and keeping on-time service levels at an optimum point was explored. They developed a discrete-event simulation model to study and better understand the relationship between inventory, internal on-time delivery and customer delivery metrics which facilitates detection of inefficiencies as well as establishing guidance on safety stock relocation along the supply chain.

3. Model and Implementation

A model of the back-end operations of integrated circuit manufacturing in the context of short-term demand fluctuation is developed in this study. The model is described as follows.

1. New demand signal: A new demand forecast over a short-term horizon is provided by the customer and revealed in the system.
2. Demand realisation: Customer demand requirements for current period are realised and FG safety stock level after demand realisation is determined. If customer demand requirements are not fully met, FG safety stock would be fully exhausted and unmet demand would be considered demand backlog. This backlog would be fulfilled with production output in future period(s).
3. Assembly Loads determination: The Assembly Loads logic determines the die bank release.
4. Die bank release: Die bank supply determined by the Assembly Loads logic is released to back-end manufacturing area.
5. Stocks hits Finished Goods: WIP material completing all back-end manufacturing processes on current week is transitioned to FG stock being available to support customer demand.

The implementation of assembly loads logic adopted in this paper is based on the principle of incorporating demand forecast update and WIP and FG inventories to plan die bank releases to back-end. This implementation projects future safety stock levels and releases die bank material to maintain a pre-determined safety stock level target in the future. This approach makes an intensive use of the customer forecast and its updates. It employs all available data at each event time to determine assembly loads; each event time occurs weekly. Model data is composed by the following data: a) WIP levels at the back-end manufacturing area, b) Finished Goods safety stock level, c) Customer demand requirements and d) Customer demand requirements updates. The implementation employs above data to project future FG safety stock levels over the back-end cycle time horizon (i.e. n weeks ahead). Based on these projections, the Assembly Loads logic calculates the necessary amount of die bank to be released to maintain a pre-defined FG safety stock level target within a back-end cycle time horizon (i.e. week n ahead). The process described above is repeated at each event time i.e. weekly. The FG safety stock level targeted by the Assembly Loads logic ultimately determines the customer delivery performance and the inventory holding costs that the FG safety stock policy entails.

Let i = 1, 2, …, M denote the week number representing the system state and j = 0, 1, …, n the week ahead. The vector $(\vec{d_i})$ generated on week i contains the demand requirements for the future n weeks including the current week, which will be represented by superscript 0. The model developed only employs demand requirements within the back-end cycle time (n weeks ahead) to determine die bank releases; therefore, the demand vector $(\vec{d_i})$ have n+1 components.

$$\vec{d_i} = \left(d_i^0, d_i^1, \dots, d_i^j, \dots, d_i^n\right) \qquad 1.$$

The approach developed to determine the WIP position at the back-end considers the division of the back-end manufacturing processes into n+1 subsections, being n the back-end cycle time in weeks of the specific product. Following this approach, WIP is transferred from one section to another on a weekly basis until all back-end manufacturing processes are completed and units are transferred to Finished Goods. Equation 2 below shows the components of the supply position vector $\vec{s_i}$ on week i.

$$\vec{s_i} = \left(s_i^0, s_i^1, \dots, s_i^j, \dots, s_i^n\right) \qquad 2.$$

Each component of $\vec{s_i}$ represents the WIP level at each division. The subscript i indicate the snapshot week. The superscript j indicates the section in which WIP is positioned. The superscript j also indicates the remaining number of weeks to complete the back-end manufacturing processes assuming no delays of any nature.

The components of the supply position vector $\vec{s_i}$ are updated every week i based on Equation 3 below.

$$s_i^j = \begin{cases} C_i, when\ s_{i-1}^{j+1} + es_{i-1}^{j+1} \geq C_i\ and\ j < n \\ s_{i-1}^{j+1} + es_{i-1}^{j+1}, when\ s_{i-1}^{j+1} + es_{i-1}^{j+1} < C_i\ and\ j < n \\ L_i, when\ j = n \end{cases} \qquad 3.$$

The component n of the supply position vector $\vec{s_i}$ is the assembly load on week i represented as L_i. The projected safety stock is represented in this model as a vector $\vec{ss}$ composed by n+1 components as shown in Equation 4 below.

$$\vec{ss_i} = \left(ss_i^0, ss_i^1, \dots, ss_i^j, \dots, ss_i^n\right) \qquad 4.$$

The component ss_i^j of the projected safety stock vector $\vec{ss}$ represents the projected safety stock level on week i for week j ahead. These projections are based on demand vector $\vec{d_i}$ and back-end WIP supply vector $\vec{s_i}$. The model employs projected safety stock levels to determine die bank releases on week i. Projected safety stock components are calculated according to Equation 5 below.

$$ss_i^j = \begin{cases} ss_{i-1}^0 + s_i^0 - d_i^0; when\ j = 0 \\ ss_i^{j-1} + min(s_i^j + es_i^j, C_0) - d_i^j; when\ 0 < j < n \\ ss_i^{n-1} + L_i^{I1} - d_i^n; when\ j = n \end{cases} \quad 5.$$

Following the notations and equations described above, the assembly load, L_i^{I1} , is calculated as follows.

$$\hat{L}_i^{I1} = fg_T + d_i^n - ss_i^{n-1}$$

$$L_i^{I1} = \begin{cases} 0, when\ \hat{L}_i^{I1} \leq 0 \\ \hat{L}_i^{I1}, when\ 0 < \hat{L}_i^{I1} < C_0 \\ C_0, when\ \hat{L}_i^{I1} \geq C_0 \end{cases} \quad 6.$$

4. Simulation Experiments and Results

The setup of the simulation experiment is first described in this section, followed by a presentation and discussion of results.

4.1 Set-up of the Experiments

The simulation period is set to1000 runs (weeks) and entails the simulation of at least 160 full back-end cycles. This is considered sufficient to obtain representative results. The warm-up period is 10 weeks allowing the system to reach the desired conditions of demand and supply stochasticity from an initial system state. It is assumed in all the simulation experiments that the system is initiated on week i = 0 in which the supply position vector $\overrightarrow{s_0}$ is aligned with the demand vector $\overrightarrow{d_0}$. All the components of these two vectors follow a normal distribution with demand μ and standard deviation σ. Three different scenarios of demand volatility and capacity reliability are studied. The scenarios are defined as Scenario A (low volatility), Scenario B (medium volatility) and Scenario C (high volatility). Table 1 below contains parameter settings for the scenarios.

Table 1. Demand parameters in Scenarios A, B and C

Parameter	Scenario A (low volatility)	Scenario B (medium volatility)	Scenario C (high volatility)
Average weekly demand	μ = 10,000 units/week		
Standard deviation	σ = 2,000 units/week		
Possible demand adjustment magnitude (in % of average weekly demand)	b_a = 5% b_b = 10% b_c = 20%	b_a = 10% b_b = 15% b_c = 25%	b_a = 10% b_b = 20% b_c = 30%
Probability of each demand adjustment magnitude	p_a = 0.85 p_b = 0.10 p_c = 0.05	p_a = 0.50 p_b = 0.35 p_c = 0.15	p_a = 0.50 p_b = 0.25 p_c = 0.25
Probability of occurrence of demand adjustment	p_{CH} = 0.15	p_{CH} = 0.2	p_{CH} = 0.3
Probability of demand adjustment occurring upwards	p_{CH} = 0.5		

Along with the demand volatility and the capacity reliability, utilisation represents another key element in the discussion regarding FG safety stock policy. A back-end system with high utilisation is hypothesised as not able to absorb the swings in production required to maintain an efficient FG safety stock policy. Three settings have been considered: low utilisation, medium utilisation and high utilisation as shown in Table 2 below.

Table 2. Utilisation levels adopted in simulation experiments

Parameter	Low Utilisation	Medium Utilisation	High Utilisation
Utilisation	U = 0.5	U = 0.8	U = 0.9
Theoretical capacity	C_0 = 20,000 units/week	C_0 = 12,500 units/week	C_0 = 11,111 units/week

4.2 Results and Discussion

The results of the simulation experiments are presented in Figures 1 and 2 below.

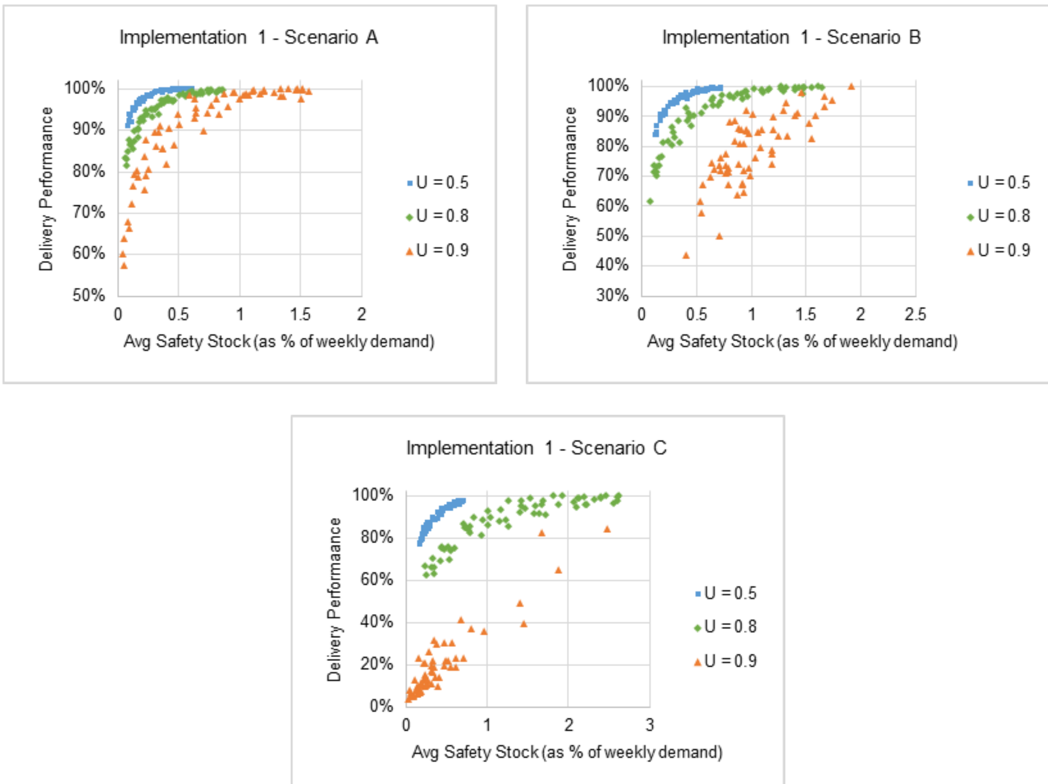

Figure 1: Delivery Performance vs Average Safety Stock for Scenarios A, B, and C.

Scenario A replicates a production environment of low demand volatility and high capacity reliability. This is the most desirable environment given the challenges explored in this study. The results show high delivery performance levels even when implementing an inventory strategy of low Finished Goods carrying inventory. Another interesting area for discussion is the influence of utilisation in a scenario of low uncertainty. The results clearly indicate that the influence of utilisation is significant. The drop recorded in delivery performance caused by a constrained back-end environment (U = 0.9) is remarkable. Scenario B replicates a manufacturing environment with lower capacity reliability than scenario A. In addition, the demand volatility intensifies compared to scenario A. The results confirm that higher FG inventory levels are required in scenario B to achieve similar delivery performance levels than in scenario A. Scenario C reproduces an environment of high demand volatility and low capacity reliability. This scenario recreates the most unfavorable conditions. The results of simulation experiments in this scenario indicates that higher FG inventory levels are required to achieve the same delivery performance levels than in scenario A and B. As in the Scenarios A and B, the influence of utilisation is remarkable and the influence is particularly highest in scenario C. The results show a concentration in the lower range of delivery performance (below 40%), which is unacceptable for most customers in the semiconductor industry. This behaviour is a consequence of several aspects

of the assembly loads logic developed in this work that might be refined in future work. For instance, the assembly loads logic developed entails the projection of FG safety stock levels on future weeks. This projection is made by assuming an effective capacity at the back-end of 100% of the theoretical capacity. This assumption might be perfectly reasonable in a scenario of high capacity reliability but might require some adjustments in an environment of low manufacturing system reliability.
Figure 2 represents the simulation results for different back-end cycle times. These results are simulated in an environment of high uncertainty (scenario C) and low utilisation levels (50%).

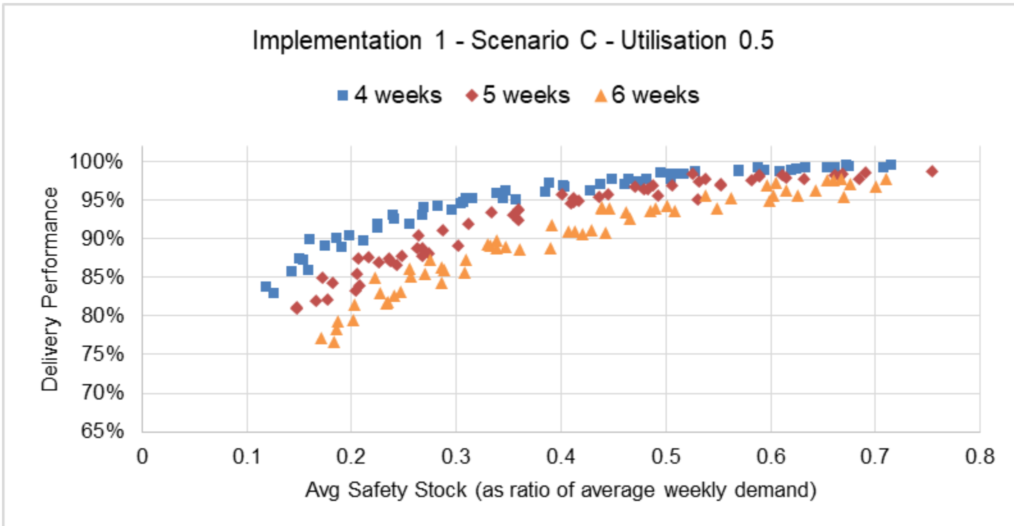

Figure 2 Delivery Performance vs Average Safety Stock for different back end cycle times.

A clear trend is observed in the simulation results: a longer back-end cycle time is detrimental to address short-term demand volatility. A way to compensate the higher exposure to uncertainty for products with long back-end cycle time is by carrying higher levels of FG safety stock. It is interesting to highlight that these results can motivate Integrated Device Manufacturers to dedicate resources to develop new manufacturing processes, reducing the back-end cycle time. Otherwise, manufacturers must assume higher FG inventory holding costs to obtain the same delivery performance results than products with shorter back-end cycle times.

5. Conclusions and Future Work

This paper explores safety stock under short term demand fluctuations in integrated device manufacturing. The manufacturing flow of integrated circuits is conceptualised into front end and back end operations with a die bank in between. A model of the back-end operations of integrated circuit manufacturing in the context of short-term demand fluctuation is developed in this study and implemented using a simple assembly load logic. Simulation experiments based on three scenarios, namely a production environment of low demand volatility and high capacity reliability (Scenario A), a manufacturing environment with lower capacity reliability than scenario A (Scenario B) and an environment of high demand volatility and low capacity reliability (Scenario C). The analysis of simulation results confirms a trade-off relation between inventory levels and delivery performance in all cases and scenarios evaluated. This trade-off relation varies between the different scenarios. Generally, higher safety stock levels are required to achieve competitive delivery performance as uncertainty in demand increases and manufacturing capability reliability decreases. In addition, capacity utilisation is found to be key. The results indicate that the success of the Finished Goods safety stock policy relies on having the sufficient capacity to support swings in production. In addition, the influence of the back-end cycle time of the product shows a detrimental impact on performance as cycle time increases. The model presented considers the uncertainty in both demand and capacity reliability within the back-end cycle time. Statistically, it is more likely that this uncertainty manifests more frequently if the back-end cycle time is longer. In other words, a manufacturing system with shorter back-end cycle time is able to react quicker to sudden changes in the demand requirements by adjusting the assembly loads. Long manufacturing cycle times are regarded as one major challenge given the impossibility to react to sudden changes in demand. The results are indicative of the manufacturing flow studied, more so the simple assembly load logic experimented with. The main assumptions that there exist strategies to address demand uncertainty in the long term and the middle term permits a focus on the short-term perspectives. Therefore, the only component of demand uncertainty considered in the development of the framework is strictly related to short-term demand volatility. In addition, the parameters determining the demand generation do not evolve over time or, in other words, the demand is stationary. Areas of future work should include: a) implementations using a more rigorous smart assembly load logic inclusive of wafer starts policy and b) explorations of the influence of long-term and middle-term demand uncertainty or non-stationary demand behaviour in the development of a Finished Goods safety stock strategy.

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Biographies

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