Simulation Modelling Practice and Theory 117 (2022) 102498

Contents lists available at ScienceDirect

Simulation Modelling Practice and Theory

journal homepage: www.elsevier.com/locate/simpat

Inventory policy for postponement strategy in the semiconductor industry with a die bank

D. Kim [a], Y.S. Park [a], H.W. Kim [b], K.S. Park [a,c], I.K. Moon [a,c,*]

[a] Department of Industrial Engineering, Seoul National University, Seoul, Republic of Korea
[b] LTD Entrue Consulting Optimization Team, LG CNS Co., Seoul, Republic of Korea
[c] Institute for Industrial Systems Innovation, Seoul National University, Seoul, Republic of Korea

ARTICLE INFO

Keywords:
Inventory control
Semiconductor manufacturing
Postponement strategy
Simulation
Die bank

ABSTRACT

We propose inventory models that can be directly applied to the industrial field by adapting from the order-up-to policy and investigate how a die bank can be used to reduce inventory of finished goods and to improve customer responsiveness. This study was motivated by the cooperation with one leading semiconductor company in Korea that wishes to develop inventory-management policy for a die bank, a facility in which the intermediate and generic forms of fabricated wafers are stored. Our simulation experiments, implemented with Arena® software, show that a die bank makes the supply chain more responsive in adjusting demand changes by postponing the differentiation point of finished goods in the production process. We have sufficiently demonstrated the need for a die bank to the company through pilot tests, and laid a good foundation for the introduction of a die bank.

1. Introduction

The semiconductor industry has grown to encompass a market share of more than $450 billion, with an ever-increasing demand driven by continuous advances in technology and innovation in end-use applications [15]. The Korean semiconductor industry, led by Samsung Electronics and SK hynix, ranks second in the world in terms of market share. In particular, Korea is unrivaled when it comes to DRAM (dynamic random access memory) chips, accounting for about 75% of the 2018 global supply [24]. However, a semiconductor supply and demand crisis came again as global IT companies were putting their investments on hold due to the U.S.–China trade conflict. The recent decline in global demand for semiconductors has severely affected Korea's outbound shipments, and companies have been forced to offer a gloomy outlook. Indeed, business reports and financial statements of companies working in the semiconductor sector clearly show that the demand cycle is going downhill [44]. Semiconductor products that had been out of stock due to a supply shortage are now piling up. The Korean semiconductor companies are struggling to break the current situation.

Before going into the core contents of the study, it is worth noting the characteristics of the semiconductor industry. The semiconductor industry is characterized by long production lead times. Lead time is usually the most powerful single factor influencing the performance of inventory control and supply chain management. With such long production lead times, companies in the semiconductor industry have no choice but to hold a lot of WIP (work-in-process). In addition to this, increased uncertainty, due to long lead times, requires more safety stocks, resulting in higher inventory levels of WIP and finished goods. Another issue to be considered is that companies in these sectors release new or enhanced versions of their products even though existing products are still popular in

* Corresponding author.
E-mail address: ikmoon@snu.ac.kr (I.K. Moon).

https://doi.org/10.1016/j.simpat.2022.102498
Received 23 July 2021; Received in revised form 22 December 2021; Accepted 21 January 2022
Available online 31 January 2022

the market. Thus, semiconductor manufacturers suffer from proliferation of product diversity because of overlapping product life-cycles [6]. Last but not least, the semiconductor industry's cyclical demands further compound the challenges of inventory management. Given this inefficiency in the supply chain structure, the recent sharp decline in demand has dramatically increased the inventory of finished goods in the warehouses of the company.

Faced with too much inventory in warehouses, executives of the anonymous company felt the need for change and focused on introducing a die bank to ameliorate high overall inventory levels. A die bank is a facility in which the intermediate and generic forms of wafer-formated inventory are stored. Using generic dies and delaying the point of product differentiation are effective postponement techniques employed by companies to hold less inventory. Therefore, companies have utilized a die bank to delay the point of product differentiation. Although detailed logic for employing this practice is not disclosed, a die bank has already been adopted by some leading companies [6,27,30,33]. A further description of a die bank is presented in Section 4.

Given the high capital investment of introducing a die bank, a thorough cost-effectiveness analysis is required. Therefore, the company must carefully analyze the effect of introducing a die bank and design its process to use a die bank effectively. The most important research questions now for the company are what inventory-management policy to develop and how to determine production quantity after the new system is introduced. If an inventory-management policy suitable for the advanced system is not developed in tandem with these considerations, the company's enormous investment may produce poor returns. Such motivation led us to explore new inventory-management techniques to reduce inventory costs while simultaneously improving customer service levels.

This paper studies the effectiveness of a die bank using simulation at an industrial site. Different from existing approaches developed in the semiconductor field, this study analyses the effectiveness of a die bank from the perspective of the inventory-management policy. In particular, this study is characterized by the development of an inventory policy that shows an excellent performance and is easy-to-apply by appropriately utilizing forecasts from the past demand data. Service-constrained models and policies are often preferred over real-life settings, as many firms do not know their cost functions including backorder costs exactly [41]. Specifically, service levels are the most used performance measures [46]. In our study, we focus on practically implementable inventory-management policy based on target service level, which is suitable for new semiconductor manufacturing process and does not necessarily have to be cost-optimal.

The remainder of this paper is organized as follows. Section 2 summarizes literature review and highlights the research gap. An overview of the company's supply chain and production process are outlined in Section 3, and advanced inventory policies considering a die bank are provided in Section 4. Section 5 summarizes simulation experiments and the effects of introducing a die bank. Finally, concluding remarks on this study are provided in Section 6.

2. Literature review

This study has two major features: that it is a case study on inventory management in the semiconductor industry and that a postponement strategy is verified through simulation. Section 2.1 reviews the flow of research on production planning and inventory management in the semiconductor industry. Multi-echelon inventory problems and postponement are dealt with in detail in Section 2.2.

2.1. *Case studies on inventory management in the semiconductor industry*

An extensive overview on modeling and analysis of the semiconductor supply chain can be found [38,39,52]. In the existing body of literature, many studies have focused on improving the production system in the semiconductor industry; (see [23,30,32,33,42]). On the other hand, relatively few researchers are conducting research from the perspective of inventory and operation management [22,31,49]. Below we review prior literature that has focused on case studies in the semiconductor industry.

Intel introduced a prolonged period of works to develop an automated inventory target-setting system that enables the company to be ranked at the top level regarding supply chain management [34]. At Intel, rule-of-thumb heuristics have been continually replaced with automatic optimization tools, which significantly reduce the inventory levels of the products while maintaining customer service levels. Particular challenges in this project include forecast bias and non-stationary demand variance. Intel developed a new methodology to adjust the forecast bias directly from the demand variance estimate by modifying the variance parameter, assuming stationary bias and a predetermined service level [35]. Afterward, Intel proposed an adjustment procedure to deal with the product families whose service levels are dynamic and an inventory optimization system as a function of a single demand variance estimate [36]. The firm applied a non-parametric approximation of the product error-density function, allowing a kernel-smoothing technique to support the determination of a weighted, localized error pattern. In Wieland et al. [59], Intel summarized how the project team was organized and the applied inventory optimization tools based on the guaranteed service model of safety stock. According to Manary et al. [34], Intel generated more than $400 million in returns, due to reduced inventory levels and increased service levels over the first five years of the pilot phase. Also, it took nearly another decade to transform the inventory optimization model from an initial pilot into an automated system that manages most parts of the supply chain. In virtue of continued efforts, this newly applied system managed approximately 85% of all finished-goods inventory in 2018. Intel has been taking innovative steps for a long time to internalize inventory-management policies as corporate know-how. However, their research scope does not include a die bank.

Similar to Intel, IBM Systems and Technology Group developed a mixed-integer programming-based model and supporting heuristics to implement production planning of its semiconductor manufacturing system [9]. The company also developed OR-based software solutions, including a central planning engine, to balance resources against demand. The central planning engine and efforts to develop it changed IBM's business processes. IBM has improved on-time deliveries by 15% and reduced inventory by more than 25%. Furthermore, IBM Research developed another tool based on the model proposed by Gallego et al. [14] to support its inventory management process. The pilot implementation of inventory policies demonstrated improvement in both inventory levels and on-time delivery performance. IBM obtained excellent results by mathematically analyzing inventory-management policies in the semiconductor production process. The difference from this study is that IBM did not consider a die bank in the mathematical model.

Xilinx, another leading semiconductor company, adopted a postponement strategy in regard to both products and processes [6]. In process postponement, a generic part is created at an early stage of the manufacturing process, which is customized to produce finished goods at a later stage. Xilinx can take advantage of these generic parts to have less finished-goods inventory. In addition, the postponement strategy enables Xilinx to customize some of its product families fast enough such that the production system works as a make-to-order system. The postponement technique is now a crucial part of Xilinx's supply chain strategy. This process postponement motivates us to introduce a die bank in the semiconductor production processes. Brown et al. [6] proposed an excellent strategic idea, but they did not provide a detailed model and computational analysis. In this study, we developed an inventory-management policy suitable for the anonymous company based on their ideas, and we quantitatively demonstrated the effectiveness of the postponement strategy through simulation.

Infineon introduced a die bank to ensure agility and competitiveness when supplies were tight. Advanced planning systems (APS) at Infineon provide computer-based optimization for the allocation of available finished goods. However, APS are not enough to manage overall inventory, and humans are involved in making decisions about the systems, relying solely their experience rather than on any rules. To overcome this situation, Infineon presented a mathematical model for the optimization of "available-to-promise" allocation to customers to analyze all possible allocation scenarios [37]. The results of Millauer et al. [37] supported allocation managers to efficiently allocate supplies to customers and evaluate the decision. Unfortunately, Infineon did not succeed in adapting the mathematical model to industrial sites because of the complexity and dynamic nature of the model. On the other hand, the intuitive and easy-to-use inventory-management policy developed in this study is being pilot tested in the field.

As can been seen from the case studies above, research on the application of a die bank has been a subject of great interest in the semiconductor supply chain as introduced in Brown et al. [6] and Millauer et al. [37]. Although such a system has been studied in the semiconductor industry, few studies have focused on presenting an inventory-management policy. To the best of our knowledge, this paper is the only case study that verified the effect of the inventory-management policy considering a die bank through simulation in the South Korean semiconductor industry. that. Therefore, this study, which establishes an inventory-management policy, is original and practical, applicable to actual production planning.

2.2. Multi-echelon inventory problems and postponement strategy

Over the last few decades, considerable interest has been focused on developing optimal replenishment policies for multi-echelon inventory systems. A drawback of attaining an exact analysis using stochastic dynamic programming is long computation required for the enormous state space. Hence, the focus has been shifted to the analysis of policies that have a relatively simple structure. Graves [19] developed an order-up-to policy in a multi-echelon inventory model with stochastic demand and fixed replenishment intervals. Diks and de Kok [10] introduced an approach to determine a cost optimal replenishment policy for a divergent multi-echelon inventory system under a periodic review of order-up-to policies. Based on the results from that study, the optimal order-up-to level can be determined easily by solving a similar version of the classical newsboy problem. Developing inventory-management policies from a service measure perspective has been the most popular research topic. Graves and Schoenmeyr [20] examined the guaranteed-service model for safety-stock placement in supply chains with capacity constraints. They developed a heuristic inventory-management policy based on order-up-to policy. For the other important contributions on multi-echelon systems and service measures, we refer to Diks et al. [11] and Eruguz et al. [12].

Multi-echelon inventory problems cannot be discussed without considering the rationing policy. Rationing policy allocates all available material following simplified logic. Hence, rationing can be viewed as a special case of an allocation problem, where an upstream inventory point distributes material to downstream players [26]. The best-known practical rule, fair share (FS) rationing, was proposed by Clark and Scarf [7]. FS rationing aims to equalize end players' stockout probability. However, by imposing the same stockout probability at all end inventory points, FS rationing limits system flexibility. This motivated de Kok [8] to propose consistent appropriate share (CAS) rationing. CAS rationing aims to maintain a fixed fraction of the projected net inventory at each end inventory point. By jointly determining rationing fractions and respective order-up-to levels, a supply chain can achieve individual service objectives of downstream players. An important contribution in the development of rationing policies is the priority rationing (PR) rule defined by Lagodimos [25]. Using a priority list, PR rationing policy satisfies all orders of downstream players in the sequence listed until available material is exhausted. We close literature review regarding rationing policy with the linear rationing (LR) rule. Instead of rationing the projected net inventory, LR policy allocate inventory based on system-wide shortage [53]. Therefore, the shortage rationing fractions and order-up-to levels need not be jointly determined under the LR policy,.

A postponement strategy has long been another important research topic in multi-echelon inventory systems, and it evolved from risk and cost management strategies into a powerful tool used to implement mass customization. The concept of postponement was first introduced in the marketing field by Alderson (1950), and it was brought into the scope of logistics research and has been used quite extensively in business. Postponement strategy can be implemented in two different ways [65]. One is to use common parts to design products to maintain commonality until later stages of the production process. The second approach is to design the product as a module that can be combined with various options at later stages in the production process. A representative example in which the point of differentiation is delayed can be found in Zinn [64]. Benetton keeps textiles undyed and manufactures them after receiving customer orders specifying a desired color. By delaying product differentiation, companies can cope with uncertainty and consequently reduce inventory and holding cost. The concept of modular production was explored by Hoek and Weken [21]. By using the example of producing SMART cars in Europe, they showed how suppliers and distributors can collaborate to enable modular production. A detailed description of the mechanisms by which manufacturing characteristics affect the modularity to be embedded into the product family architecture is well explained by Salvador et al. [47].

Inventory savings that resulted from postponement and delayed differentiation is a topic that has been addressed by many studies [3,4,16,17,48]. Lee [28] presented simple inventory models that can be used to delay product differentiation that are essentially adaptations of the multi-echelon inventory system. The limitation of the models is that it assumes no safety stock until the end of the production process. Therefore, the only possible inventory savings of delayed product differentiation come from reduced inventory of finished goods. In the following year, Lee and Tang [29] formalized various mechanisms for delayed product differentiation such as standardization, modular design, and process restructuring. They applied their model to special cases that are motivated by real cases and analyzed the costs and benefits associated with the redesign strategy. Recently, Ramon-Lumbierres et al. [43] analyzed a case study for introducing additive manufacturing technologies and determined the optimal degree of postponement. The focus of the literature is on the impact of the component inventory as a result of commonality.

Although there have been many studies on analysing a postponement strategy, the investigation of the system considering delayed differentiation with order-up-to policy to satisfy the target service level in various settings is relatively insufficient. Therefore, we presented order-up-to policies suitable for a postponement strategy in the following sections.

3. Existing manufacturing system operation and its inventory management policy in the semiconductor supply chain

A brief overview of the semiconductor production process is provided to assist readers in understanding the work in this paper. The semiconductor production process consists of four major stages: fabrication, probing, packaging, and testing.

The facility in which the wafer fabrication and subsequent probing processes take place is referred to as the "*Fab*". In the fabrication stage, numerous identical dies are created on a silicon wafer through an intricate process of adding and removing patterned layers of various materials. The specific operations may vary greatly, depending on the product and technology used. Thereafter, the individual die is tested electrically using thin probes. A wafer is sliced into the individual die, and the defective dies are discarded. Wafer fabrication and probe stages are generally referred to as *front-end* operations. The following stages, packaging and testing (P&T), are referred to as *back-end* operations. In packaging and testing stages, each die is assembled in a specific package format to test for its functionality and speed. Dies that all processes have been completed are stored in the FGS (finished goods storage).

The focus of this study is on minimizing finished-goods inventory and on increasing a production chain's responsiveness through establishing a scientific inventory-management system. The company in our research runs the production facilities nonstop. Hence, a fixed cost for production does not affect inventory decisions. Additionally, due to the continuous expansion of facilities and the ongoing cycle of declining demand, production capacity has little impact on input decisions. Therefore, we assumed that fixed costs are negligible, and the company follows an incapacitated version of an order-up-to policy. In its classical form, order-up-to levels are fixed, but there exists a dynamic policy that allows for adjusting these levels using forecast information at each review period. We adapted the classical base-stock formula to apply it to the case of the dynamic ones used by the company under consideration in our research. Detailed information about the order-up-to policy can be found in various sources including Vassian [56], Veinott [57], and Gilbert [18].

Inventory status is reviewed periodically at regular time intervals and a replenishment order is placed to restore inventory at a predetermined order-up-to level. The periodic review version of the order-up-to policy only generates an order at the moment when the inventory is inspected. Syntetos et al. [50] proposed a modified order-up-to policy for intermittent demand items in a periodic review system. The empirical performance of their approach is assessed on a large demand data set from the Royal Air Force, and they find insights on the interactions between forecasting and inventory control. Teunter and Sani [51] showed how the generated forecasts can be used to determine order-up-to levels for controlling stock levels. We also adopt the periodic review analogue of the order-up-to policy and use forecasts to develop an inventory-management policy.

An order-up-to policy is intuitively appealing and hence are often applied in practice because of this simple mechanism. In a single-period situation, an order- up-to policy can be easily solved with a newsvendor model. On the other hand, in a multi- period model, advanced order-up-to levels, which may vary from period to period, must be determined. Under such a policy, an input quantity is set in each period to bring the end-of-period inventory position to a given target level, S, and unsatisfied demands are backordered. Some of our policy makes use of the assumptions and results by Wijngaard and Wortmann [61] and Manary and Willems [35]. We use the following notations and parameters to describe the developed inventory policy.

- $D_{i,t}$: demand for product i realized at time t
- $F_{i,t}$: forecast of demand for product i at time t
- $S_{i,t}$: order-up-to level of product i at time t
- $IL_{i,t}$: inventory level of product i at time t
- $IP_{i,t}$: inventory position of product i at time t
- $X_{i,t}$: input quantity of product i realized at time t, $\max\{S_{i,t-1} - IP_{i,t-1}, 0\}$
- τ: production lead time for Fab and P&T

Inventory level is the inventory on hand, which is different from inventory position, which is equal to the sum of the inventory level

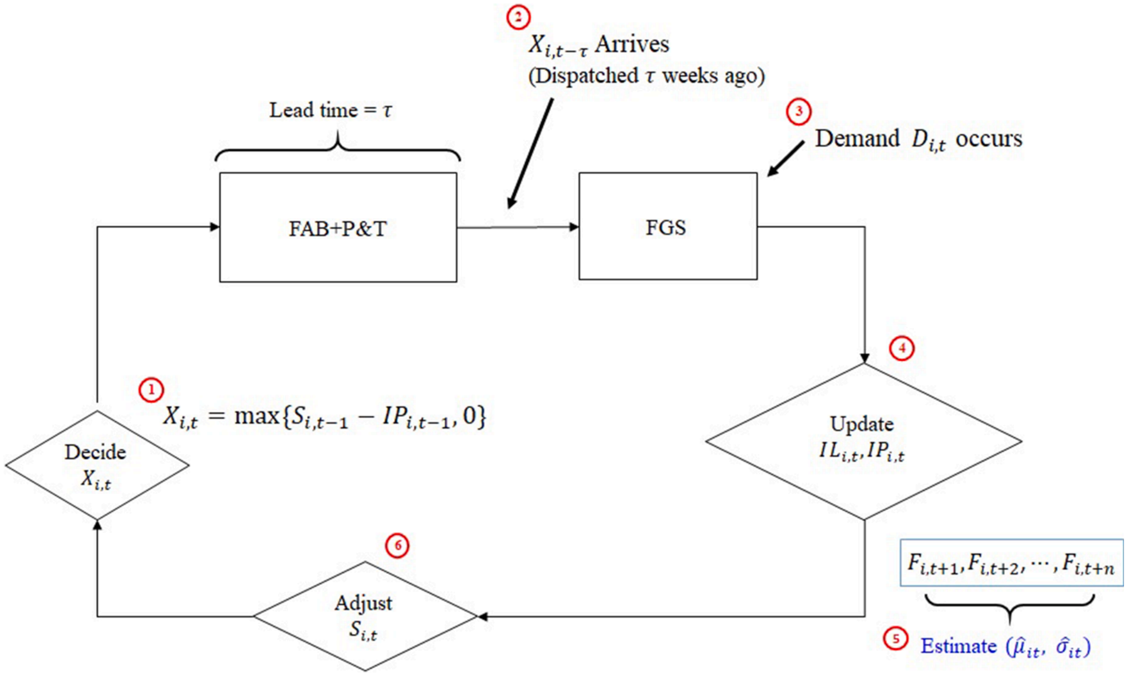

Fig. 1. Flowchart to determine input quantities (As-Is).

and quantity on order minus backordered quantity. A negative inventory level indicates a backordered quantity, and backorders are given priority over the demand in the following period. We assumed that the demand per period for each product follows a probability distribution characterized by mean and standard deviation, denoted as $\mu_{i,t}$ and$\sigma_{i,t}$, respectively. We also assumed that the demand per period for each product is independent and identically distributed to calculate order-up-to level simply. For a given service level, $\alpha_{i,t}$, the order-up-to level of product i at time t is represented as:

$$S_{i,t} = \sum_{k=t}^{t+\tau} \mu_{i,k} + \sqrt{\sum_{k=t}^{t+\tau} \sigma_{i,k}^2}\, \Phi^{-1}(\alpha_i) = (\tau + 1)\hat{\mu}_{i,t} + \sqrt{\tau + 1}\hat{\sigma}_{i,t}\Phi^{-1}(\alpha_i)$$

where $\Phi^{-1}()$ is the inverse cumulative distribution function and the hat symbol denotes estimated value. Estimations of $\mu_{i,t}$ and $\sigma_{i,k}$ rely on the forecasts provided by the sales and marketing group. The demand for semiconductor products is significantly affected by the global economic outlook, product life cycles, and market cannibalization. A sales forecast captures these deviations better than merely using actual historical demand. Supply chain management group in this company use the current forecasts over the next 12 weeks, $F_{i,t}$, $F_{i,t+1}, \cdots, F_{i,t+12}$, similar to the time frame of production lead times, to determine the order-up-to level of product i at time t. To estimate the standard deviation of demand, realized demands for the past Δ weeks, $D_{i,t-1}, \cdots, D_{i,t-\Delta}$, are used. $\overline{D}$ is the average of the demands realized during the data collection period, Δ, and the appropriate data collection period is derived from the pilot test. Consequently, the order-up-to inventory level of product i at time t for service level α_i is represented as:

$$S_{i,t} = \sum_{k=t}^{t+12} F_{i,k} + \sqrt{\frac{\sum_{k=t}^{t-\Delta} \left(D_{i,k} - \overline{D}\right)^2}{\Delta - 1}}\Phi^{-1}(\alpha_i)$$

Fig. 1 gives an overview of the company's current system. As can be seen in Fig. 1, a serial production-inventory system is considered. The current system is called As-Is, and the system that applied die bank is called To-be. As depicted in Fig. 1, decisions related to inventory management within a time period are made in the following order: The input quantity is determined based on the order-up-to level of the previous period, $S_{i,t-1}$. After demands are realized, both the inventory level, $IL_{i,t}$, and the inventory position, $IP_{i,t}$, are updated as:

$$IL_{i,t} = IL_{i,t-1} + X_{i,t-\tau} - D_{i,t}$$

$$IP_{i,t} = IP_{i,t-1} + X_{i,t} - D_{i,t}$$

The mean and standard deviation of the demand are re-estimated based on updated demand forecasts. Finally, order-up-to level, $S_{i,t}$, is updated. This process is repeated throughout the planning horizon to manage inventory and wafer inputs.

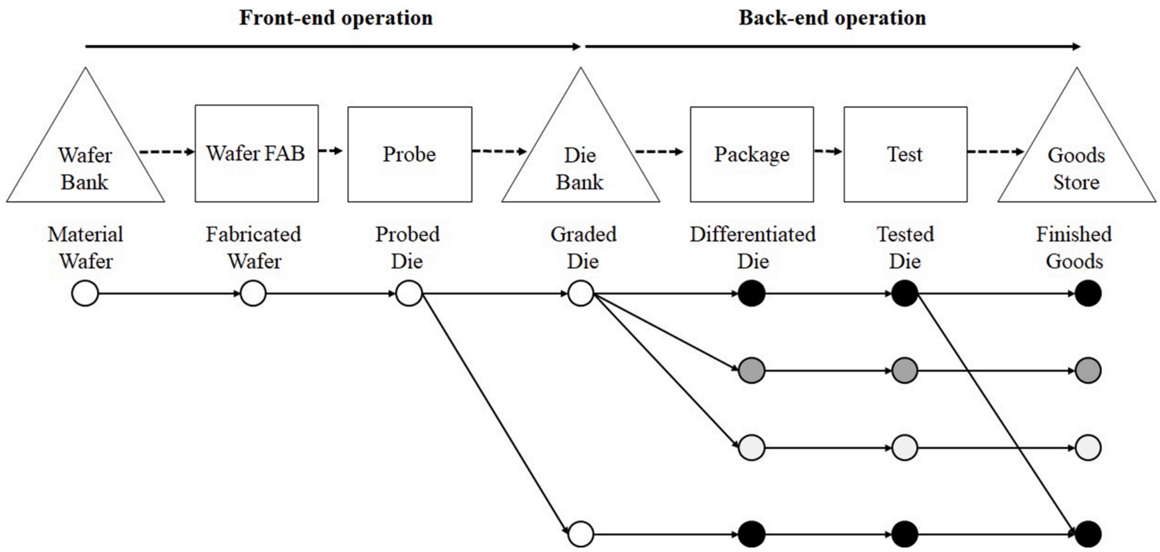

Fig. 2. Semiconductor production process considering a die bank.

4. Postponement strategy with a die bank

This section presents new semiconductor production process after a die bank is introduced. An advanced manufacturing system with a die bank is described in Section 4.1. A new ordering system and its inventory policy are described in Section 4.2 and Section 4.3, respectively.

4.1. Manufacturing system with a die bank

The semiconductor industry is characterized not only by long production lead times but also by short product life cycles and greater variety with customized products. It is almost impossible to achieve a target service level with rule-of-thumb-based inventory management because demands for finished goods are highly uncertain, and product lead times are longer than three months. Faced with such challenges, the company considered in our research attempted to introduce a die bank to delay the point of product differentiation, which could be a powerful technique to economize on supply chain costs and improve customer responsiveness.

A common postponement technique is to buffer the production process in order to respond flexibly to fluctuations in external demand by holding wafer-formated WIP, referred to as "a die bank inventory," between front-end and back-end processes. Fig. 2 shows a brief overview of the semiconductor production process and product flow when a die bank is applied. Instead of using the projected demands for individual finished goods to determine each production quantity at an early stage, the company aggregates the demands for finished goods into generic die demands. Then, front-end production starts based on aggregated die demands. After completing the front-end operations, generic dies are held in a die bank immediately. Generic dies are then customized into different finished goods at the back-end stage according to customer demands. Therefore, a die bank can postpone the point of product differentiation, moving it from the beginning to the end of the front-end stage.

In our application here, finished goods are on average about twice as valuable as die bank inventories. Hence, the major value of commonality is not on die bank inventory reduction, but on the resulting finished goods inventory reduction due to delayed product differentiation. By operating a die bank, less safety stock of finished goods is needed to maintain the same target service level than is needed in the original process. This is because the lead time from order placement to finished-goods shipment is shortened. In addition, volatility of demand has a smaller impact on the inventory level. This observation is known as the risk-pooling effect, which is described in detail in Eppen [13]. Consequently, the utilization of a die bank enables a more robust response to the volatility of demand.

4.2. Ordering system with a die bank

A new ordering system with a die bank corresponds to a divergent two-echelon system. Before describing an ordering system and an inventory-management policy, we have first reviewed some of the related literature, concentrating on papers that have studied two-echelon inventory systems. Donselaar and Wijngaard [55] developed analytic service models for a two-echelon serial network using order-up-to level policies. Assuming stationary demands, they derived an exact model for the stockout probability occurring at any period, and subsequently extended their results for divergent two-echelon networks under the assumptions of balanced inventories and identical lead times. de Kok [8] introduced a service-related approach to achieve some target service levels at different end-stock points in a divergent two-echelon system with a stockless depot. Verrijdt and de Kok [58] described a distribution planning procedure for a

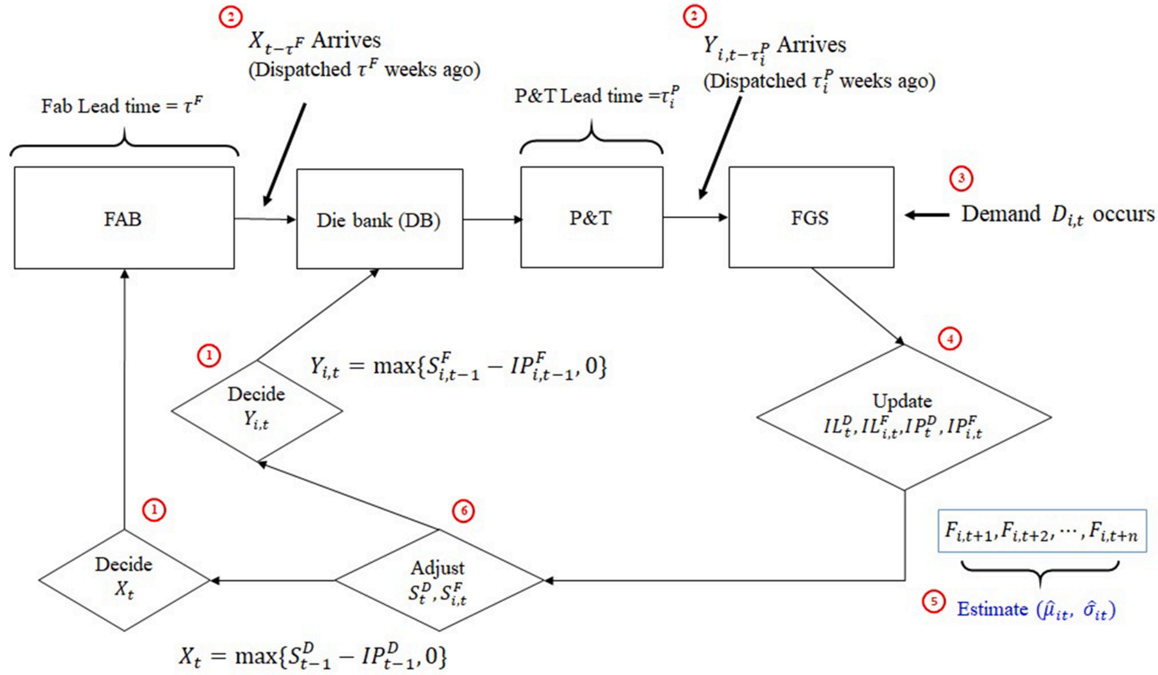

Fig. 3. Flowchart to determine input quantities (To-Be).

divergent two-echelon distribution network, one central depot and a number of stock points, under service constraints. Their decomposition algorithm evaluated the required echelon order-up-to-level and the allocation. In addition, an analytical approximation of the probability of imbalance was presented, and the analytical results were validated through an extensive simulation study.

Because of notational difficulties, we restrict our attention to one product family that can be differentiated from the same wafer. We assume that all products within the same product family have one identical target service level. The model can be extended to inventory management with different service levels for each product, which will be discussed in Section 4.3. We use the following notations in defining the new ordering system with a die bank.

- S^D_t: order-up-to level in a die bank at time t
- $S^F_{i,t}$: order-up-to level of product i in FGS at time t
- IL^D_t: inventory level in a die bank at time t
- $IL^F_{i,t}$: inventory level of product i in FGS at time t
- IP^D_t: inventory position in a die bank at time t
- $IP^F_{i,t}$: inventory position of product i in FGS at time t
- X_t: Fab process input at time t
- $Y_{i,t}$: P&T process input of product i at time t
- τ^F: lead time for Fab process
- τ^P_i: lead time of product i for P&T process

After a die bank is introduced, decisions made within a time period are revised in the following order (see Fig. 3): The input quantities for Fab and P&T processes are determined based on the order-up-to levels of the previous period, $S^F_{i,t-1}$ and $S^D_{i,t-1}$, respectively. Fabricated wafers that have been put into the process at $t-\tau^F_i$ are stored in the die bank as WIP, and wafers that launched the additional process at time $t-\tau^P_i$ arrive in the FGS after being processed at the P&T stage. After demands are realized, the inventory levels, IL^D_t and $IL^F_{i,t}$, and the inventory positions, IP^D_t and $IP^F_{i,t}$, are updated as:

$$IL^D_{i,t} = IL^D_{i,t-1} + \sum_i \left(X_{i,t-\tau^F_i} - Y_{i,t} \right)$$

$$IL^F_{i,t} = IL^F_{i,t-1} + Y_{i,t-\tau^P_i} - D_{i,t}$$

$$IP^D_t = IP^D_{t-1} + X_{i,t} - Y_{i,t}$$

$$IP^F_{i,t} = IP^F_{i,t-1} + Y_{i,t} - D_{i,t}$$

A new order-up-to-level is then calculated, and the subsequent decision flow is similar to that of the As-Is model. After a die bank receives the order, two different cases occur. The former case is that the inventory on hand at the die bank is large enough to raise the inventory positions of all types of finished goods to their order-up-to levels and the remainder is held at the die bank. The latter case is that the inventory on hand at the die bank is insufficient to satisfy the expected demand of all finished goods. When such a shortage occurs, the order-up-to level of the finished goods which generally incur more expensive back-order costs due to the higher product value is satisfied first. For finished goods of the same value, wafers are processed according to a randomly selected priority. The allocation strategy in the company is similar to the priority rationing introduced by Lagodimos [25].

4.3. Inventory policy with a die bank

This section provides existing literature that forms the basis of our policy and formulas used for quantifying order-up-to levels. What follows are the details of the inventory-management policies we studied in relation to those implemented by some well-established inventory control systems. Clark and Scarf [7] first introduced the echelon inventory concept and demonstrated that order-up-to policies considering echelon inventory are optimal for serial inventory systems with periodic review and some assumptions related to cost functions. They also proved that recursive computation of optimal policies using installation inventory does not compromise the optimality of the solution if several assumptions are incorporated in the model. For the inventory system that we consider in our study, such a simplification can be obtained. Neither the installation inventory nor the echelon inventory gives a complete representation of the optimal inventory-management of a multi-echelon inventory system [2]. It is important to use these concepts appropriately for the purpose of an inventory-management policy. Therefore, we developed the inventory-management policy based on installation inventory.

All demands for finished goods at each period are merged into a demand for wafers to be put into the fabrication process. Input to the fabrication process is equal to the sum of all the original demand for finished goods. Demand for front-end production is characterized by the mean and the standard deviation, denoted as $\widehat{\mu}^{\mathrm{D}}_t = \sum_{\mathrm{i}} \widehat{\mu}_{i,t}$ and $\widehat{\sigma}^{\mathrm{D}}_t = \sqrt{\sum_{\mathrm{i}} \widehat{\sigma}^2_{i,t}}$, respectively. The target service level of the die bank is set equal to those of the products in this scenario. For a given service level, α, the order-up-to inventory levels in a die bank and an FGS are represented as:

$$S^D_t = \left(\tau^F + 1\right)\widehat{\mu}^D_t + \sqrt{\tau^F + 1}\,\widehat{\sigma}^D_t \Phi^{-1}(\alpha)$$

$$S^F_{i,t} = \left(\tau^P + 1\right)\widehat{\mu}_{i,t} + \sqrt{\tau^P + 1}\,\widehat{\sigma}_{i,t} \Phi^{-1}(\alpha)$$

In order to deal with heterogeneous service levels, a complicated and advanced service-constrained model is necessary to ensure a target service level while minimizing costs and inventory levels. Rosenbaum [45] developed a heuristic for determine target service level through the use of simulation. Van der Heijden et al. [54] analysed inventory allocation policies in multi-echelon distribution systems to achieve differentiated target service levels. Alptekinoğlu et al. [1] proposed a model of inventory pooling to satisfy heterogeneous service levels for different customers and characterized the optimal solution in several inventory-management policies. Noordhoek et al. [41] developed a simulation-optimization approach to optimize order-up-to policies for a service-constrained multi-echelon distribution network. As can be seen from many previous studies, inventory-management policies for heterogeneous service levels require additional assumptions and intractable model. However, what piqued interest the most in industry practice is whether the model is commercially available. Therefore, we proposed a simple heuristic of determining order-up-to level to implement postponement strategy.

When determining wafer input for the product family consisting of products with heterogeneous service levels, setting the appropriate target service level for a die bank requires further investigation and requirements. Therefore, in this case it is preferable to approach the challenge from the viewpoint of each product rather than to set the service level for the die bank. To cover heterogeneous service levels, the products were rearranged in a descending order, from the products with the highest target service level to the products with the lowest target service level. Let (1) be the product with the highest service level, and $S^D_{(1),t}$ denotes the projected order-up-to level of product (1) at time t. After that, wafers are loaded in the order of $(1), (2), \cdots, (n)$. When $D^F_{i,t}$ is the total demand during the lead time of product i for the Fab process estimated at time t, the service level constraint for each product can be expressed as:

$$Prob\left\{S^D_{(1),t} \geq D^F_{(1),t}\right\} \geq \alpha_{(1)},$$

$$Prob\left\{S^D_{(2),t} \geq D^F_{(1),t} + D^F_{(2),t}\right\} \geq \alpha_{(2)} \Leftrightarrow$$

$$\int_0^\infty Prob\left\{S^D_{(2),t} \geq D^F_{(1),t} + D^F_{(2),t} | D^F_{(1),t} = x\right\} Prob\left\{D^F_{(1),t} = x\right\} dx \geq \alpha_{(2)}, \cdots,$$

$$Prob\left\{S^D_{(n),t} \geq D^F_{(1),t} + D^F_{(2),t} + \cdots + D^F_{(n),t}\right\} \geq \alpha_{(n)} \Leftrightarrow$$

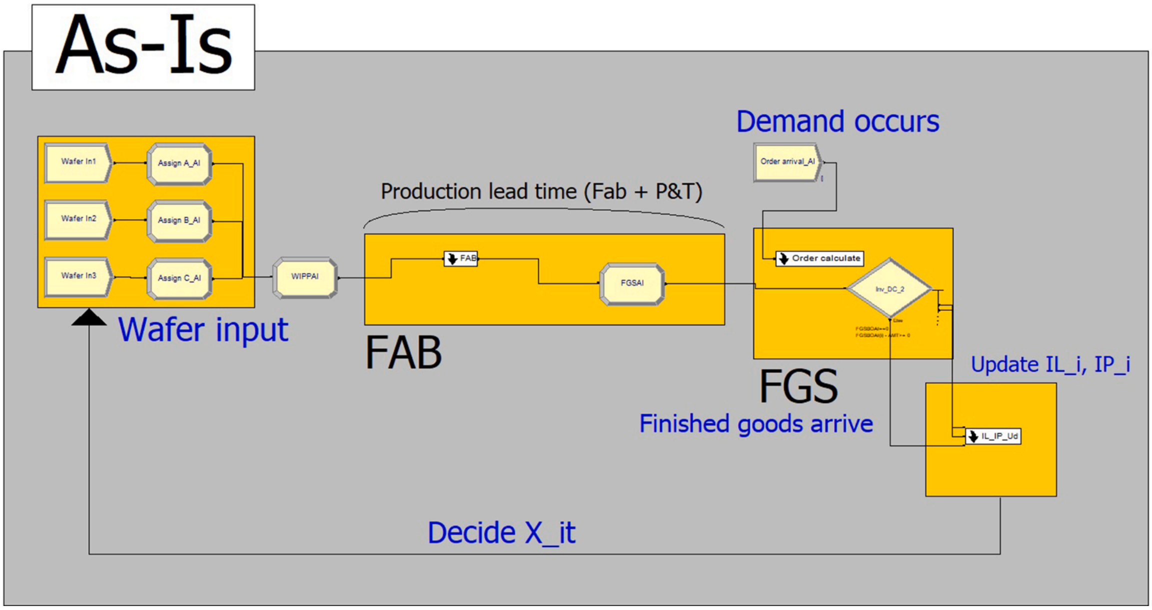

Fig. 4. Arena simulation model for As-Is system.

$$\int_0^\infty Prob\left\{S^D_{(n),t} \geq D^F_{(1),t} + \cdots + D^F_{(n),t} | D^F_{(1),t} + \cdots + D^F_{(n-1),t} = x\right\} Prob\left\{D^F_{(1),t} + \cdots + D^F_{(n),t} = x\right\} dx \geq \alpha_{(n)}$$

Therefore, the order-up-to level for a die bank must satisfy the following constraints to manage all products in the same product family.

$$S^D_t = \max\left\{S^D_{(1),t}, \cdots, S^D_{(n),t}\right\}$$

where

$$S^D_{(k),t} = \left(\tau^F + 1\right) \sum_{i=1}^{k} \widehat{\mu}_{(i),t} + \sqrt{\left(\tau^F + 1\right) \sum_{i=1}^{k} \widehat{\sigma}^2_{(i),t}} \Phi^{-1}\left(\alpha_{(k)}\right)$$

5. Simulation experiments

Simulation experiments are widely used in industrial sites to verify the effectiveness of production-system design [60,62,66]. Various simulation experiments are conducted to illustrate the performance of the proposed inventory management policy and the impact of the die bank for the system. Sections 5.1 and 5.2 present simulation models with a deterministic production lead time and a probabilistic production lead time, respectively. Section 5.3 introduces additional experiments with demand changes, which show the improved responsiveness of the new production process. A managerial insight is provided in Section 5.4.

Illustrative examples provided in this section are manufacturing systems with three types of finished goods from the same product family and one type of the wafer that can be shared among different finished goods. To show the impact of the implementation of the die bank, the supply chains with and without the die bank are compared in each setting. The simulation models are developed as follows:

(1) The order-up-to level and the production input quantity are decided at the beginning of each time period.
(2) The demand for finished goods is realized at the beginning of each time period.
(3) The decision-maker estimates future demand based on the sample mean and standard deviation with moving averages at the end of each time period.
(4) The inventory level and the inventory position are updated at the end of each time period.
(5) We assumed that the demand follows the rectified normal distribution with given parameters which are different among finished goods.
(6) The decision-maker finally establishes the production plan of each period.

The order-up-to levels of the simulation models are determined based on the models presented in Sections 3 and 4.1. Real demand

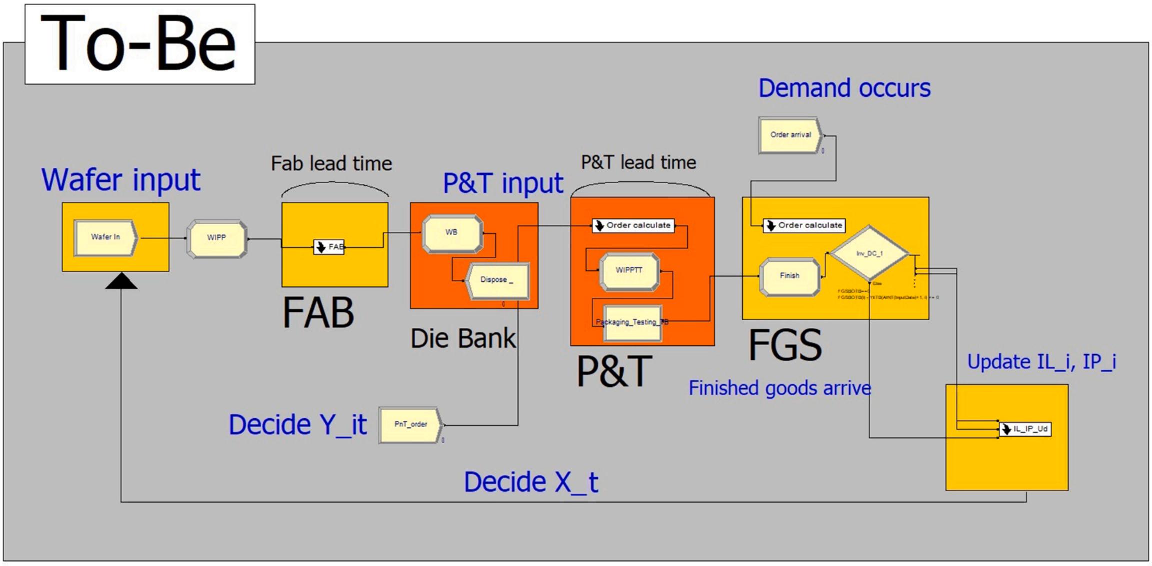

Fig. 5. Arena simulation model for To-Be system.

Table 1
Demand distributions and initial inventories of the illustrative examples.

Product	Mean	Standard deviation				Initial inventory
		Scenario 1	Scenario 2	Scenario 3	Scenario 4	
A	7,000	1,500	3,500	5,500	7,000	105,000
B	5,000	1,000	2,500	3,500	5,000	75,000
C	3,000	1,000	1,500	2,000	3,000	45,000
DB						400,000

at industrial sites is not simply expressed as a probability distribution, and it is difficult to perfectly estimate the distribution of demand. Although we used rectified normal distribution to generate demands, we employed the z-score of standard normal distribution, which is different from the demand distribution in our policy, because it is popular and easy for practitioners to use.

In the illustrative example, three finished goods share the same wafer and Fab process. Therefore, the production lead time of the front-end stage is identical. Even though finished goods can have different back-end stage processing times among products, identical processing times are assumed to analyze the impact of introducing a die bank clearly. Considering that the order-up-to level policy quickly neutralizes the effect of the initial inventory, setting a warm-up period that is 5 times the production lead time can sufficiently eliminate errors that may occur in simulation experiments. The simulation starts with a warm-up period of 60 weeks and terminates at Week 600, with a one-week unit time frame. Thus, the time horizon of simulation includes 540 data points to ensure sufficient reliability of the experimental results. In addition, we repeated 500 experiments for each setting to provide reliable results.

Four key performance indicators–average inventory levels of finished goods and WIP, service level, and fill rate–are proposed by the semiconductor company and used for the comparison. For a reasonable comparison, not only the inventory levels of finished goods are compared, but also the amount of WIPS, service level, and fill rate are reported. The average inventory levels are time-averages of the inventory levels of WIPs and finished goods. Cycle service level represents the frequency of out-of-stock, regardless of the total size. On the other hand, fill rate is a ratio of the fulfilled demand over the total demand, measured with the quantities of wafers and products.

The simulation experiment was conducted with Rockwell Automation Arena® software. Two Arena models were presented in Figs. 4 and 5. A rectangular box with a down arrow contains submodels. Note that the Arena models resemble the flowcharts in Figs. 1 and 3, which spring from the activity-based modeling formalism of Arena simulation. The deterministic/probabilistic production lead times are managed by the parameter settings in the process module of Arena.

5.1. *Deterministic production lead-time model*

The simulation experiment in this section assumes a deterministic production lead time. To consider the variability of the production process, in Section 4.2, a stochastic lead time is considered. Demand distributions and initial inventories used for the illustrative example are presented in Table 1. All other parameters were set based on real data from industrial sites. The lead times for Fab and P&T Processes are 10 weeks and 2 weeks, respectively. The target service level is set to 90%. In the deterministic production lead-time model, each production order is finished and arrived after a fixed production lead time. With the aforementioned warm-up period and the duration of the simulation, the average inventory level, service level, and fill rate are calculated from the following formula:

- AIL_i^F: average inventory level of product i

$$AIL_i^F = \frac{1}{540}\sum_{t=61}^{600} IL_{i,t}^F$$

- WIP(Fab, P&T, Total = Fab + P&T): sum of WIPs at each level.
- $FO_{i,t}$: fulfilled order of product i at time t (If the order was fulfilled, $FO_{i,t} = 1.$ 0, otherwise)
- SL_i: service level of product i

$$SL_i = \frac{\sum_{t=61}^{600} FO_{i,t}}{540}$$

- $FD_{i,t}$: fulfilled demand of product i at time t

$$FD_{i,t} = \min\left\{IL_{i,t-1}^F + Y_{i,t-\tau^P}, D_{i,t}\right\}$$

- FR_i: fill rate of product i

$$FR_i = \frac{\sum_{t=61}^{600} FD_{i,t}}{\sum_{t=61}^{600} D_{i,t}}$$

Tables 2 and 3 show the average of 500 repeated experiments with the same setting. In each experiment, As-Is and To-Be models share the same demand generated as an input for each time period. Let the average number of wafers in the system (WIP+DB+FGS) be the sum of the average total WIP, the average inventory level of the die bank, and the average inventory level of finished goods. In Table 2, we observe that the average inventory of finished goods reduces significantly when a die bank is implemented. The effectiveness of a die bank is more pronounced as the coefficient of variation in demand increases. That is, a die bank can play a more important role in a market with high uncertainty, such as in the semiconductor market. When the coefficient of variation is high, the company is able to cut the inventory of the finished goods by almost half with little change in the total inventories in the overall production system. In other words, a die bank functions to hold inventory as WIPs rather than as finished goods, and implements a postponement strategy. Fig. 6 summarizes the experimental results of Scenario 4, and the effect of the die bank can be visually confirmed.

Table 3 shows that regardless of the decreased average inventory level of finished goods in the To-Be model, the company can secure higher service levels and fill rates. When a die bank is applied to the production system, the company can perfectly achieve its target service level and fill rate under any circumstances.

5.2. Probabilistic production lead-time model

Given the intricate process of semiconductor production and long production lead times, it is necessary to analyze the impact of variability of lead time. In the probabilistic production lead-time model, the production lead time is modeled as a random variable with a given distribution. Because the demand for finished goods is realized at the beginning of each period, the service level, SL_i and fill rate, FR_i, can be calculated in the discrete time period, as they are in the deterministic production lead-time model. However, the inventory level is calculated over a continuous time dimension as:

- AIL_i^F: average inventory level of product i

$$AIL_i^F = \frac{1}{540}\int_{t=61}^{600} IL_{i,t}^F \, dt$$

The production lead time for each product is assumed to follow a triangle distribution. For a fair comparison to the deterministic production lead-time model, the production lead times for front-end (Fab) and back-end (P&T) stages follow triangle distributions, with a minimum value of 9 (and most likely a value of 10), and a maximum value of 11; and a minimum value of 1.5 (and most likely a value of 2), and a maximum value of 2.5, respectively.

Table 2
Average inventory levels and WIPs of deterministic production lead-time models.

Scenario	Model	AIL_A^F	AIL_B^F	AIL_C^F	AIL_{FGS}^F
1	As-Is	15,772.09	8995.46	7769.89	32,537.44
	To-Be	11,174.75	7783.17	5788.19	24,746.11
	Ratio	−29.15%	−13.48%	−25.50%	−23.95%
	Model	AIL_{DB}	WIP(total)	$WIP+DB$	$WIP+DB+FGS$
	As-Is	–	179,900.88	179,900.88	212,438.31
	To-Be	19,173.53	180,091.77	199,265.30	224,011.42
	Ratio	–	0.11%	10.76%	5.45%
2	Model	AIL_A^F	AIL_B^F	AIL_C^F	AIL_{FGS}^F
	As-Is	28,294.88	18,578.56	11,008.99	57,882.43
	To-Be	16,633.41	11,881.54	7137.08	35,652.03
	Ratio	−41.21%	−36.05%	−35.17%	−38.41%
	Model	AIL_{DB}	WIP(total)	$WIP+DB$	$WIP+DB+FGS$
	As-Is	–	180,621.72	180,621.72	238,504.15
	To-Be	32,600.71	180,797.68	213,398.39	249,050.42
	Ratio	–	0.10%	18.15%	4.42%
3	Model	AIL_A^F	AIL_B^F	AIL_C^F	AIL_{FGS}^F
	As-Is	40,575.84	24,830.60	14,161.92	79,568.36
	To-Be	21,530.06	14,368.20	8392.53	44,290.80
	Ratio	−46.94%	−42.14%	−40.74%	−44.34%
	Model	AIL_{DB}	WIP(total)	$WIP+DB$	$WIP+DB+FGS$
	As-Is	–	185,174.94	185,174.94	264,743.29
	To-Be	43,684.63	185,350.12	229,034.75	273,325.55
	Ratio	–	0.09%	23.69%	3.24%
4	Model	AIL_A^F	AIL_B^F	AIL_C^F	AIL_{FGS}^F
	As-Is	49,408.70	33,727.29	20,149.97	103,285.95
	To-Be	24,978.72	17,844.58	10,730.12	53,553.42
	Ratio	−49.44%	−47.09%	−46.75%	−48.15%
	Model	AIL_{DB}	WIP(total)	$WIP+DB$	$WIP+DB+FGS$
	As-Is	–	194,820.29	194,820.29	298,106.25
	To-Be	54,364.05	195,000.51	249,364.56	302,917.98
	Ratio	–	0.09%	28.00%	1.61%

Table 3
Service levels and fill rates of deterministic production lead-time models.

Scenario	Model	Product A		Product B		Product C		FGS		DB	
		SL_A	FR_A	SL_B	FR_B	SL_C	FR_C	SL_{FGS}	FR_{FGS}	SL_{DB}	FR_{DB}
1	As-Is	89.12%	94.46%	79.36%	87.95%	82.36%	87.67%	83.61%	90.93%	–	–
	To-Be	93.61%	98.74%	93.61%	98.83%	93.49%	98.02%	93.57%	98.63%	88.78%	91.74%
2	As-Is	88.57%	91.23%	85.72%	88.80%	84.48%	87.62%	86.26%	89.69%	–	–
	To-Be	93.50%	97.08%	93.51%	97.10%	93.41%	97.04%	93.48%	97.08%	89.39%	90.36%
3	As-Is	88.65%	89.60%	86.84%	88.35%	85.58%	87.23%	87.02%	88.68%	–	–
	To-Be	93.22%	95.62%	93.27%	96.02%	93.22%	96.11%	93.23%	95.85%	89.38%	89.17%
4	As-Is	88.67%	88.54%	87.58%	87.37%	86.60%	86.19%	87.62%	87.63%	–	–
	To-Be	93.10%	94.78%	93.07%	94.75%	92.97%	94.66%	93.05%	94.75%	89.78%	88.51%

Simulation results show that probabilistic production lead times do not significantly affect the average inventory level. Because the results of both probabilistic and deterministic models show similar trends, experimental results can be found in the Appendix. We observe in the case of probabilistic lead time that the introduction of the die bank slightly increases the average number of wafers. Likewise, the service level and the fill rate in Table 4 increase consequently from those in Table 3. When a die bank is applied, every product achieves the average service level and fill rate higher than 95% and a target service level of 90%.

Additional simulation experiments were conducted with different distributions of production lead time. The production lead time for each product is assumed to follow a normal distribution. The production lead times for the front-end (Fab) stage follow a normal distribution with a mean of 10 and a standard deviation of 1, and production lead times for the back-end (P&T) stage follow a normal distribution with a mean of 2 and a standard deviation of 0.5. Similar conclusions were reconfirmed in experiments using the new

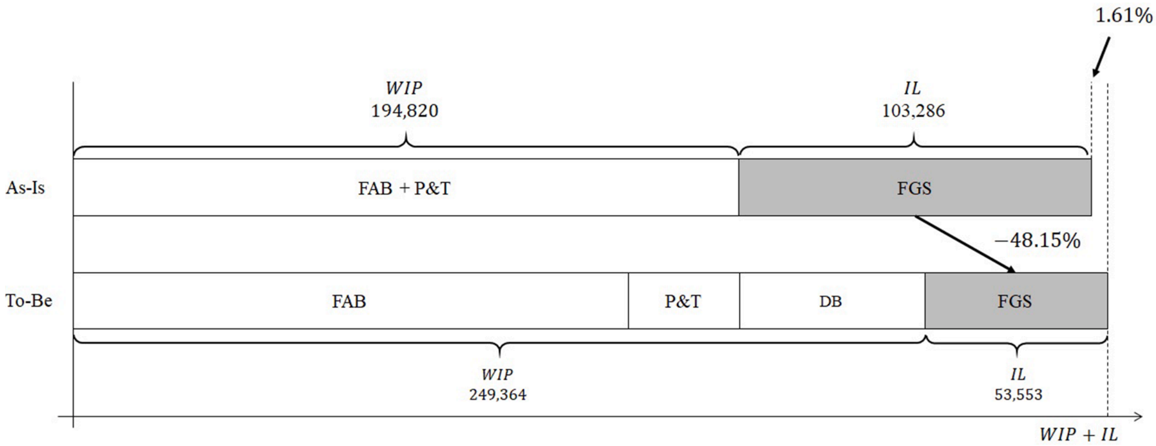

Fig. 6. Comparison of the average number of wafers between two manufacturing systems.

distribution of lead times. The results of probabilistic models with normally distributed lead times are also attached in the Appendix.

5.3. Responsiveness to demand changes

One of the main interests of the semiconductor company is to retain a high degree of responsiveness in the production system. In the existing production system, any reaction to the sudden change could be reflected only after the extremely long production lead time. The introduction of a die bank facilitates the responsiveness to the supply chain because WIP and wafers are used as a shared buffer that absorbs the shock of any change in demand. An illustrative example is presented in this section to show the increased responsiveness of a production system using a die bank. We simulated scenarios in which product preferences changed or in which semiconductor demand doubled or halved. During the simulation, the system faced demand changes after a warm-up period. To focus on the impact of changes in demand, we simulated the experiment up to Week 100. We also set coefficients of variance to 0.5 and used a deterministic production lead-time model to eliminate the impact of other variables. The detailed settings of the simulation are presented in Table 5.

Tables 6 and 7 show the results of the experiments with demand changes. First, in Product-mix-transition scenario, the semiconductor production process to which a die bank is applied responds sensitively to changes in demand. Fig. 7 summarizes the experimental results of Product-mix-transition scenario. Compared to the As-Is model, the To-Be model achieved higher service levels and fill rates while maintaining lower inventory levels. In particular, the To-Be model keeps high inventory levels of popular products while keeping relatively low inventory levels of outdated products. However, the As-Is model failed to keep up with changes in demand

Table 4
Service levels and fill rates of probabilistic models with triangular distribution lead times.

Scenario	Model	Product A		Product B		Product C		FGS		DB	
		SL_A	FR_A	SL_B	FR_B	SL_C	FR_C	SL_{FGS}	FR_{FGS}	SL_{DB}	FR_{DB}
1	As-Is	93.19%	96.61%	84.66%	91.17%	86.96%	91.12%	88.27%	93.70%	–	–
	To-Be	96.53%	99.31%	96.50%	99.35%	96.43%	98.92%	96.49%	99.25%	89.34%	92.00%
2	As-Is	91.38%	93.49%	88.33%	90.89%	87.81%	90.52%	89.17%	92.02%	–	–
	To-Be	96.34%	98.38%	96.33%	98.37%	96.28%	98.36%	96.32%	98.37%	89.92%	90.83%
3	As-Is	90.81%	91.66%	88.92%	90.24%	88.21%	89.83%	89.31%	90.80%	–	–
	To-Be	95.895	97.42%	96.01%	97.68%	96.00%	97.78%	95.97%	97.58%	89.83%	89.60%
4	As-Is	90.54%	90.51%	89.25%	89.14%	88.56%	88.40%	89.45%	89.59%	–	–
	To-Be	95.63%	96.80%	95.61%	96.79%	95.53%	96.75%	95.59%	96.79%	90.09%	88.85%

Table 5
Demand changes in illustrative examples.

Scenario	Time	Product A		Product B		Product C	
		Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Product mix transition	1–60	7,000	3,500	5,000	2,500	3,000	1,500
	61–100	5,000	2,500	2,000	1,000	8,000	4,000
Surge in demand	1–60	7,000	3,500	5,000	2,500	3,000	1,500
	61–100	14,000	7,000	10,000	5,000	6,000	3,000
Decline in demand	1–60	7,000	3,500	5,000	2,500	3,000	1,500
	61–100	3,500	1,750	2,500	1,250	1,500	750

Table 6
Inventory levels and WIPs of simulation models with demand changes.

Scenario	Model	AIL_A^F	AIL_B^F	AIL_C^F	AIL_{FGS}^F	$WIP + DB + FGS$
Product mix transition	As-Is	33,030.14	33,785.78	14,847.59	81,663.52	259,674.43
	To-Be	13,861.11	8063.75	15,424.80	37,349.67	249,452.16
Surge in demand	Model	AIL_A^F	AIL_B^F	AIL_C^F	AIL_{FGS}^F	$WIP + DB + FGS$
	As-Is	30,489.40	21,351.18	11,863.41	63,703.99	467,542.16
	To-Be	28,020.70	19,974.10	11,899.15	59,893.95	452,517.33
Decline in demand	Model	AIL_A^F	AIL_B^F	AIL_C^F	AIL_{FGS}^F	$WIP + DB + FGS$
	As-Is	40,339.72	28,311.90	16,907.71	85,559.33	151,539.72
	To-Be	12,032.31	8550.52	5137.86	25,720.68	155,675.16

Table 7
Service levels and fill rates of simulation models with demand changes.

Scenario	Model	Product A		Product B		Product C		FGS		DB	
		SL_A	FR_A	SL_B	FR_B	SL_C	FR_C	SL_{FGS}	FR_{FGS}	SL_{DB}	FR_{DB}
Product mix transition	As-Is	91.60%	93.69%	91.77%	93.22%	73.45%	64.45%	85.60%	84.91%	–	–
	To-Be	97.19%	98.77%	97.46%	98.83%	89.84%	87.87%	94.83%	95.71%	97.33%	96.72%
Surge in demand	As-Is	77.74%	74.01%	76.69%	72.28%	75.04%	71.44%	76.49%	72.81%	–	–
	To-Be	91.27%	91.64%	91.07%	91.42%	91.13%	91.94%	91.16%	91.60%	83.51%	69.85%
Decline in demand	As-Is	92.07%	93.71%	91.66%	93.30%	90.16%	92.16%	91.30%	93.18%	–	–
	To-Be	97.38%	98.84%	97.38%	98.80%	97.29%	98.90%	97.35%	98.84%	99.51%	99.65%

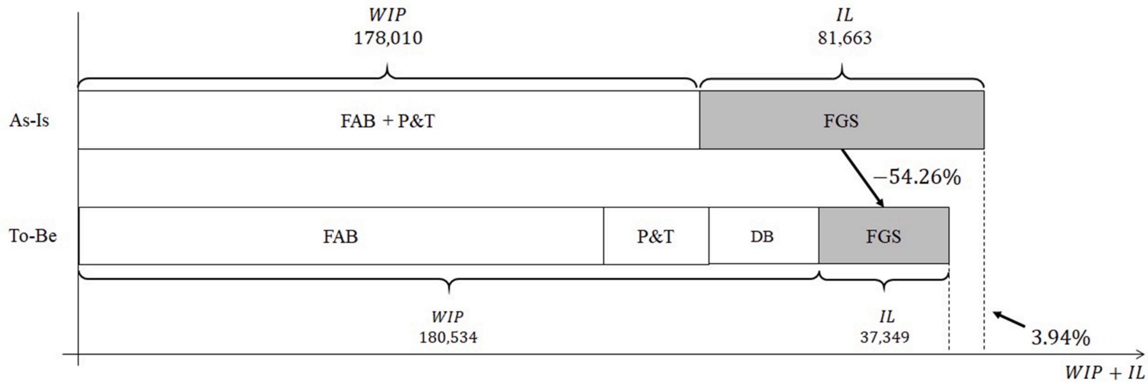

Fig. 7. Comparison of the average number of wafers between two manufacturing systems with a product mix transition.

and did not distribute inventory properly. Despite of the high average inventory level in the As-Is model, the As-Is model shows that the service level and the fill rate dropped from those in the experiments in Section 5.1. Compared to a target service level of 90%, in Table 7, the average service level of Product C dropped dramatically to below 80%.

In Surge-in-demand scenario, the To-Be model outperforms the As-Is model again. Because of the failure to keep up with the growing trend of demand, the inventory levels of finished goods in the As-Is model is still low. A large amount of inventory was backordered, and WIPs increased dramatically as a belatedly high order volume had been requested to compensate for this. Eventually, the As-Is model held a high inventory because of the increased WIPs, but the service levels and fill rates plummeted to about 80%. In Decline-in-demand scenario, the As-IS model maintained higher inventory levels of finished goods compared to the To-Be model, but had lower service levels and fill rates. To summarize the simulation results, sudden changes in demands can be responded more quickly with a die bank. In other words, a die bank offers flexibility and responsiveness to the semiconductor production process. Therefore, the effectiveness and efficiency of applying a die bank is further emphasized when unexpected events occur in the market.

5.4. *Managerial insights*

The application of the die bank shows overwhelming performance in terms of service level and fill rate. However, the total number of wafers in a system sometimes increases slightly when a die bank is applied to a semiconductor production process. Accordingly, additional analysis is needed from the perspective of total costs. As stated in Section 4, there is a gap between the monetary value of the finished goods and the wafers in process. Therefore, the total monetary value of the wafers in the system can be decreased along with the decrease of the finished goods' inventory level.

Table 8
Economic analysis of the application of die bank.

Model	Scenario	Value (WIPs)	Value (FGS)	Inventory value	Backorder cost	Total cost
As-Is	1	179,900.88	65,074.88	244,975.8	2,193.42	247,169.22
	2	180,621.72	115,764.9	296,386.6	6,275.85	302,662.45
	3	185,174.94	159,136.7	344,311.6	8,752.60	353,064.20
	4	194,820.29	206,571.9	401,392.2	10,595.20	411,987.40
	Average	185,129.46	136,637.10	321,766.55	6,954.27	**328,720.82**
To-Be	1	199,265.30	49,492.22	248,757.52	1.15	248,758.67
	2	213,389.39	71,304.06	284,693.45	63.33	284,756.78
	3	229,034.75	88,581.60	317,616.35	308.19	317,924.54
	4	249,364.56	107,106.80	356,471.36	744.76	357,216.12
	Average	222,763.50	79,121.17	301,884.67	279.36	**302,164.03**

Based on the evaluations of the experts in the industry, all finished goods are assumed to have twice the value of the wafer in the process. The backorder cost was estimated to be 2.5 times higher than the inventory value of the same product based on the recent literature [5,40,63]. Numerical analysis was performed using the simulation results of different scenarios. Based on the result of the deterministic lead time model, the total relevant cost is estimated in Table 8. Economic analysis for other scenarios can be found in the Appendix. Value (WIPs) column shows the monetary value of wafers being fabricated and WIPs in a die bank, and Value (FGS) column shows the inventory values of all finished goods. Except in few cases in which demand is very stable, introducing a die bank into the production process is an economically strategic dominance. Although the number of wafers flowing through the supply chain was large, the system incorporating the die bank had a lower value of inventory considering the difference in monetary value according to the completeness of the product. The economic benefits of the new system are further emphasized when considering backorders. In addition, as demonstrated in Section 5.3, implementing a postponement strategy through a die bank has incalculable benefits in improving supply chain responsiveness and flexibility. Consequently, introduction of a die bank has proved to be economically efficient for the company.

6. Conclusions

Thanks to the supercycle with overwhelming demand, the Korean semiconductor industry has experienced an unprecedented boom and solidified its dominant position in the industry. However, when downturns in demand occur, many problems arise in the production and operation systems. A major problem, in particular, is the inventory constantly filling up warehouses, which is due to the gap between plentiful supply and decreasing demand. To address the problems caused by a high inventory level, one major Korean semiconductor manufacturer looked into establishing of a die bank in its supply chain.

Initiated to successfully utilize the die bank, our study proposed an inventory- management policy adapted from the order-up-to policy to determine appropriate inventory levels of WIP and finished goods. Under the proposed policy, a die bank enables a company to hold a reasonable inventory of fabricated wafers, thus reducing the finished-goods inventory and improving response times. The inventory levels of finished goods are decreased by almost half in some cases. Inventory costs are sometimes slightly high due to additional WIP, but considering the backorder cost, the introduction of a die bank outperforms the original system in terms of economic efficiency. The latter results from the postponement strategy, which moves the differentiation point of finished goods (semiconductor chips) to the back of the production process. Our Arena simulation experiments also support these results. In particular, the merit of introducing a die bank is more salient when market demand fluctuations increase. In other words, by introducing a die bank, semiconductor companies can cope with the long-standing challenges that arise from high market volatility and uncertainty in the semiconductor industry. Therefore, this study verified that the company under consideration would reap great benefits by introducing a die bank and managing inventory systematically.

Through this case study, the executives and field staff at this company unquestionably recognized the need to introduce a die bank in order to achieve their goals. While the company has learned that it is necessary to apply a scientific inventory control model, it will take additional time and effort to accommodate the actual model in practice. Extensive computer simulations are further required to validate the effect of the model. In addition, additional pilot test should be conducted to apply the model to other product families. All of these efforts will ensure that the die bank is effectively applied to the company's supply chain, making it a competitiveness for the company.

Our current inventory management models assumed an incapacitated production facility. For future research, we believe it would be promising to consider inventory management models for capacitated Fabs and die banks. Another extension to our existing study would be to develop an inventor-management policy that can be used in industrial settings while taking into account the correlation of demands. Lastly, if the rationing policy, a major issue of the multi-echelon inventory problem, is also studied together, the contribution of this study will be further increased. Following research on these problems would be the cornerstones for an advanced semiconductor supply chain.

CRediT authorship contribution statement

D. Kim: Methodology, Investigation, Formal analysis, Validation, Writing – original draft, Writing – review & editing. **Y.S. Park:** Data curation, Software, Investigation, Visualization, Writing – original draft. **H.W. Kim:** Data curation, Software, Formal analysis. **K. S. Park:** Methodology, Investigation, Formal analysis, Validation, Writing – review & editing. **I.K. Moon:** Conceptualization, Methodology, Validation, Writing – review & editing, Supervision, Project administration.

Acknowledgment

We are grateful to the editor-in-chief and three anonymous reviewers for their constructive comments and suggestions on the previous version of this manuscript. We also express our deepest gratitude to an anonymous Korean semiconductor company that worked with us on the study.

Appendix A. Simulation results' details

Tables A1 and A2 present the average inventory levels and WIPs of probabilistic models with triangular lead times and normally distributed lead times, respectively. Table A3 shows service levels and fill rates of probabilistic models with normally distributed lead times.

Table A1
Inventory outputs of probabilistic models with a triangular distribution of lead times.

Scenario	Model	AIL_A^F	AIL_B^F	AIL_C^F	AIL_{FGS}^F
1	As-Is	15,848.01	8666.76	7728.96	32,243.72
	To-Be	11,185.91	7787.15	5794.38	24,767.44
	Ratio	−29.42%	−10.15%	−25.03%	−23.19%
	Model	AIL_{DB}	WIP(total)	$WIP + DB$	$WIP + DB + FGS$
	As-Is	–	179,980.61	179,980.61	212,224.33
	To-Be	21,088.42	179,970.51	201,058.94	225,826.37
	Ratio	–	−0.01%	11.71%	6.41%
2	Model	AIL_A^F	AIL_B^F	AIL_C^F	AIL_{FGS}^F
	As-Is	28,355.95	18,217.21	10,962.62	57,535.79
	To-Be	16,659.99	11,892.97	7146.10	35,699.06
	Ratio	−41.25%	−34.72%	−34.81%	−37.95%
	Model	AIL_{DB}	WIP(total)	$WIP + DB$	$WIP + DB + FGS$
	As-Is	–	180,695.07	180,695.07	238,230.68
	To-Be	34,480.34	180,690.26	215,170.60	250,869.65
	Ratio	–	0.00%	19.08%	5.31%
3	Model	AIL_A^F	AIL_B^F	AIL_C^F	AIL_{FGS}^F
	As-Is	40,619.05	24,480.46	14,117.93	79,217.44
	To-Be	21,570.46	14,384.03	8403.76	44,358.25
	Ratio	−46.90%	−41.24%	−40.47%	−44.00%
	Model	AIL_{DB}	WIP(total)	$WIP + DB$	$WIP + DB + FGS$
	As-Is	–	185,243.73	185,243.73	264,461.17
	To-Be	45,595.48	185,246.88	230,842.36	275,200.61
	Ratio	–	0.00%	24.62%	4.06%
4	Model	AIL_A^F	AIL_B^F	AIL_C^F	AIL_{FGS}^F
	As-Is	49,444.82	33,382.33	20,110.71	102,937.86
	To-Be	25,027.16	17,864.90	10,743.94	53,635.99
	Ratio	−49.38%	−46.48%	−46.58%	−47.89%
	Model	AIL_{DB}	WIP(total)	$WIP + DB$	$WIP + DB + FGS$
	As-Is	–	194,879.23	194,879.23	297,817.09
	To-Be	56,361.72	194,897.42	251,259.14	304,895.14
	Ratio	–	0.01%	28.93%	2.38%

Table A2
Inventory outputs of probabilistic models with normally distributed lead times.

Scenario	Model	AIL_A^F	AIL_B^F	AIL_C^F	AIL_{FGS}^F
1	As-Is	15,935.78	8821.89	7779.64	32,537.31
	To-Be	11,212.96	7794.97	5804.03	24,811.96
	Ratio	−29.64%	−11.64%	−25.39%	−23.74%
	Model	AIL_{DB}	WIP(total)	$WIP+DB$	$WIP+DB+FGS$
	As-Is	–	180,002.37	180,002.37	212,539.68
	To-Be	21,272.44	179,934.23	201,206.67	226,018.63
	Ratio	–	−0.04%	11.78%	6.34%
2	Model	AIL_A^F	AIL_B^F	AIL_C^F	AIL_{FGS}^F
	As-Is	28,405.12	18,289.62	10,990.72	57,685.45
	To-Be	16,696.53	11,911.93	7159.18	35,767.64
	Ratio	−41.22%	−34.87%	−34.86%	−38.00%
	Model	AIL_{DB}	WIP(total)	$WIP+DB$	$WIP+DB+FGS$
	As-Is	–	180,716.81	180,716.81	238,402.26
	To-Be	34,663.50	180,652.94	215,316.45	251,084.09
	Ratio	–	−0.04%	19.15%	5.32%
3	Model	AIL_A^F	AIL_B^F	AIL_C^F	AIL_{FGS}^F
	As-Is	40,644.43	24,533.90	14,130.54	79,308.87
	To-Be	21,614.93	14,409.67	8419.91	44,444.51
	Ratio	−46.82%	−41.27%	−40.41%	−43.96%
	Model	AIL_{DB}	WIP(total)	$WIP+DB$	$WIP+DB+FGS$
	As-Is	–	185,270.05	185,270.05	264,578.91
	To-Be	45,781.12	185,210.68	230,991.81	275,436.32
	Ratio	–	−0.03%	24.68%	4.10%
4	Model	AIL_A^F	AIL_B^F	AIL_C^F	AIL_{FGS}^F
	As-Is	49,461.22	33,417.68	20,103.47	102,982.38
	To-Be	25,075.43	17,897.23	10,764.24	53,736.89
	Ratio	−49.30%	−46.44%	−46.46%	−47.82%
	Model	AIL_{DB}	WIP(total)	$WIP+DB$	$WIP+DB+FGS$
	As-Is	–	194,909.74	194,909.74	297,892.11
	To-Be	56,567.08	194,847.21	251,414.29	305,151.18
	Ratio	–	−0.03%	28.99%	2.44%

Table A3
Service levels and fill rates of probabilistic models with normally distributed lead times.

Scenario	Model	Product A		Product B		Product C		FGS		DB	
		SL_A	FR_A	SL_B	FR_B	SL_C	FR_C	SL_{FGS}	FR_{FGS}	SL_{DB}	FR_{DB}
1	As-Is	91.30%	95.21%	82.64%	89.21%	85.96%	90.19%	86.63%	92.20%	–	–
	To-Be	95.89%	98.95%	95.84%	98.95%	95.97%	98.64%	95.90%	98.89%	87.56%	90.24%
2	As-Is	90.98%	93.14%	87.84%	90.39%	87.39%	90.04%	88.74%	91.59%	–	–
	To-Be	96.12%	98.23%	96.11%	98.22%	95.99%	98.15%	96.07%	98.21%	89.33%	90.23%
3	As-Is	90.70%	91.59%	88.75%	90.03%	88.00%	89.56%	89.15%	90.64%	–	–
	To-Be	95.79%	97.35%	95.88%	97.57%	95.80%	97.60%	95.82%	97.48%	89.54%	89.34%
4	As-Is	90.58%	90.51%	89.16%	89.06%	88.54%	88.36%	89.43%	89.55%	–	–
	To-Be	95.56%	96.77%	95.54%	96.71%	95.42%	96.61%	95.51%	96.72%	89.97%	88.75%

Appendix B. Economic analysis of the application of a die bank

Tables B1 and B2 show the economic analysis of the application of a die bank for probabilistic models with triangular lead times and normally distributed lead times, respectively.

Table B1
Economic analysis with probabilistic models with a triangular distribution of lead times.

Model	Scenario	Value (WIPs)	Value (FGS)	Inventory value	Backorder cost	Total cost
As-Is	1	179,980.61	64,487.44	244,468.05	3598.95	248,067.00
	2	180,695.07	115,071.58	295,766.65	7281.10	303,047.75
	3	185,243.73	158,434.88	343,678.61	9548.25	353,226.86
	4	194,879.23	205,875.72	400,754.95	11,263.75	412,018.70
	Average	185,199.66	135,967.41	321,167.07	7923.01	**329,090.08**
To-Be	1	201,058.94	49,534.88	250,593.82	112.97	250,706.79
	2	215,170.60	71,398.12	286,568.72	297.03	286,865.75
	3	230,842.36	88,716.50	319,558.86	630.04	320,188.90
	4	251,259.14	107,271.98	358,531.12	1141.63	359,672.75
	Average	224,582.76	79,230.37	303,813.13	545.42	**304,358.55**

Table B2
Economic analysis with probabilistic models with normally distributed lead times.

Model	Scenario	Value (WIPs)	FGS	Inventory value	Backorder cost	Total cost
As-Is	1	180,002.37	65,074.62	245,076.99	5004.20	250,081.19
	2	180,716.81	115,370.90	296,087.71	7974.30	304,062.01
	3	185,270.05	158,617.74	343,887.79	9978.30	353,866.09
	4	194,909.74	205,964.76	400,874.50	11,533.60	412,408.10
	Average	185,224.74	136,257.01	321,481.75	8622.60	**330,104.35**
To-Be	1	201,206.67	49,623.92	250,830.59	284.72	251,115.31
	2	215,316.45	71,535.28	286,851.73	581.23	287,432.96
	3	230,991.81	88,889.02	319,880.83	1003.70	320,884.53
	4	251,414.29	107,473.78	358,888.07	1590.92	360,478.99
	Average	224,732.31	79,380.50	304,112.81	856.14	**304,977.95**

References

[1] A. Alptekinoğlu, A. Banerjee, A. Paul, N. Jain, Inventory pooling to deliver differentiated service, Manuf. Serv. Oper. Manag. 15 (1) (2013) 33–44.
[2] S. Axsäter, K. Rosling, Installation vs. echelon stock policies for multilevel inventory control, Manag. Sci. 39 (10) (1993) 1274–1280.
[3] K.R. Baker, Safety stocks and component commonality, J. Oper. Manag. 6 (1) (1985) 13–22.
[4] K.R. Baker, M.J. Magazine, H.L. Nuttle, The effect of commonality on safety stock in a simple inventory model, Manag. Sci. 32 (8) (1986) 982–988.
[5] G.R. Bitran, S.M. Gilbert, Co-production processes with random yields in the semiconductor industry, Oper. Res. 42 (3) (1994) 476–491.
[6] A.O. Brown, H.L. Lee, R. Petrakian, Xilinx improves its semiconductor supply chain using product and process postponement, Interfaces 30 (4) (2000) 65–80. Providence.
[7] A.J. Clark, H. Scarf, Optimal policies for a multi-echelon inventory problem, Manag. Sci. 6 (4) (1960) 475–490.
[8] A.G. de Kok, Hierarchical production planning for consumer goods, Eur. J. Oper. Res. 45 (1) (1990) 55–69.
[9] B.T. Denton, J. Forrest, R.J. Milne, IBM solves a mixed-integer program to optimize its semiconductor supply chain, Interfaces 36 (5) (2006) 386–399. Providence.
[10] E.B. Diks, A.G. de Kok, Optimal control of a divergent multi-echelon inventory system, Eur. J. Oper. Res. 111 (1) (1998) 75–97.
[11] E.B. Diks, A.G. de Kok, A.G. Lagodimos, Multi-echelon systems: a service measure perspective, Eur J Oper Res 95 (2) (1996) 241–263.
[12] A.S. Eruguz, E. Sahin, Z. Jemai, Y. Dallery, A comprehensive survey of guaranteed-service models for multi-echelon inventory optimization, Int. J. Prod. Econ. 172 (2016) 110–125.
[13] G. Eppen, Note-effects of centralization on expected costs in a multi-location newsboy problem, Manag. Sci. 25 (5) (1979) 498–501.
[14] G. Gallego, K. Katircioglu, B. Ramachandran, Semiconductor inventory management with multiple grade parts and downgrading, Prod. Plan. Control 17 (7) (2006) 689–700.
[15] J. Garfinkel, G. Omale, Gartner says worldwide semiconductor revenue grew 13.4% in 2018; increase driven by memory market, Gart. Newsroom (2019). Retrieved from <, https://www.gartner.com/en/newsroom/press-releases/2019-01-07-gartner-says-worldwide-semiconductor-revenue-grew-13-. >.
[16] Y. Gerchak, M. Henig, An inventory model with component commonality, Oper. Res. Lett. 5 (3) (1986) 157–160.
[17] Y. Gerchak, M.J. Magazine, A.B. Gamble, Component commonality with service level requirements, Manag. Sci. 34 (6) (1988) 753–760.
[18] K. Gilbert, An ARIMA supply chain model, Manag. Sci. 51 (2) (2005) 305–310.
[19] S.C. Graves, A multiechelon inventory model with fixed replenishment intervals, Manag. Sci. 42 (1) (1996) 1–18.
[20] S.C. Graves, T. Schoenmeyr, Strategic safety-stock placement in supply chains with capacity constraints, Manuf. Serv. Oper. Manag. 18 (3) (2016) 445–460.
[21] R.I.V. Hoek, H.A. Weken, The impact of modular production on the dynamics of supply chains, Int. J. Logist. Manag. 9 (2) (1998) 35–50.
[22] Y.F. Hung, I.R. Chen, A simulation study of dispatch rules for reducing flow times in semiconductor wafer fabrication, Prod. Plan. Control 9 (7) (1998) 714–722.
[23] C. Johnzeń, S. Dauze`re-Peŕe`s, P. Vialletelle, Flexibility measures for qualification management in wafer fabs, Prod. Plan. Control 22 (1) (2011) 81–90.
[24] E.J. Kim, Samsung electronics and sk hynix led global semiconductor industry last year, Bus. Korea (2019). Retrieved from, http://www.businesskorea.co.kr/news/articleView.html?idxno=29678.
[25] A.G. Lagodimos, Multi-echelon service models for inventory systems under different rationing policies, Int. J. Prod. Res. 30 (4) (1992) 939–956.
[26] A.G. Lagodimos, S. Koukoumialos, Service performance of two-echelon supply chains under linear rationing, Int. J. Prod. Econ. 112 (2) (2008) 869–884.
[27] R.C. Leachman, R.F. Benson, C. Liu, D.J. Raar, IMPReSS: an automated production-planning and delivery-quotation system at Harris Corporation—Semiconductor Sector, *Interfaces* 26 (1) (1996) 6–37. Providence.

[28] H.L. Lee, Effective inventory and service management through product and process redesign, Oper. Res. 44 (1) (1996) 151–159.
[29] H.L. Lee, C.S. Tang, Modelling the costs and benefits of delayed product differentiation, Manag. Sci. 43 (1) (1997) 40–53.
[30] Y.H. Lee, Supply chain model for the semiconductor industry of global market, J. Syst. Integr. 10 (3) (2001) 189–206.
[31] Y.H. Lee, S. Chung, B. Lee, K.H. Kang, Supply chain model for the semiconductor industry in consideration of manufacturing characteristics, Prod. Plan. Control 17 (5) (2006) 518–533.
[32] J. Lin, V.L. Spiegler, M.M. Naim, Dynamic analysis and design of a semiconductor supply chain: a control engineering approach, Int. J. Prod. Res. 56 (13) (2018) 4585–4611.
[33] J.J. Lowe, S.J. Mason, Integrated semiconductor supply chain production planning, IEEE Trans. Semiconduct. Manuf. 29 (2) (2016) 116–126.
[34] M.P. Manary, B. Wieland, S.P. Willems, K.G. Kempf, Analytics makes in – ventory planning a lights-out activity at Intel Corporation, Inf. J. Appl. Anal. 49 (1) (2019) 52–63.
[35] M.P. Manary, S.P. Willems, Setting safety-stock targets at Intel in the presence of forecast bias, Interfaces 38 (2) (2008) 112–122. Providence.
[36] M.P. Manary, S.P. Willems, A.F. Shihata, Correcting heterogeneous and biased forecast error at Intel for supply chain optimization, Interfaces 39 (5) (2009) 415–427. Providence.
[37] C. Millauer, R. Azzouz, B. AlizadehMousavi, C. Heavey, K. Randolph, Mathematical modelling of product allocation to customers for semiconductor industry, in: Proceeding of the European 2019 Conference Abstract Book, Dublin, Ireland, 2019.
[38] L. Mönch, R. Uzsoy, J.W. Fowler, A survey of semiconductor supply chain models part iii: master planning, production planning, and demand fulfilment, Int. J. Prod. Res. 56 (13) (2018) 4565–4584.
[39] L. Mönch, R. Uzsoy, J.W. Fowler, A survey of semiconductor supply chain models part i: semiconductor supply chains, strategic network design, and supply chain simulation, Int. J. Prod. Res. 56 (13) (2018) 4524–4545.
[40] P. Neuner, S. Haeussler, Rule based workload control in semiconductor manufacturing revisited, Int. J. Prod. Res. 59 (19) (2021) 5972–5991.
[41] M. Noordhoek, W. Dullaert, D.S. Lai, S. de Leeuw, A simulation–optimization approach for a service-constrained multi-echelon distribution network, Transp. Res. Part E Logist. Transp. Rev. 114 (2018) 292–311.
[42] C. Peng, F. Erhun, E.F. Hertzler, K.G. Kempf, Capacity planning in the semiconductor industry: dual-mode procurement with options, Manuf. Serv. Oper. Manag. 14 (2) (2012) 170–185.
[43] D. Ramón-Lumbierres, F.J. Heredia Cervera, J. Minguella-Canela, A. Muguruza-Blanco, Optimal postponement in supply chain network design under uncertainty: an application for additive manufacturing, Int. J. Prod. Res. 59 (17) (2021) 5198–5215.
[44] M. Rimol, Gartner says worldwide semiconductor revenue declined 11.9% in 2019, Gart. Newsroom (2020). Retrieved from, https://www.gartner.com/en/newsroom/press-releases/2020-01-14-gartner-says-worldwide-semiconductor-revenue-declined-11-point-9-percent-in-2019.
[45] B.A. Rosenbaum, Service level relationships in a multi-echelon inventory system, Manag. Sci. 27 (8) (1981) 926–945.
[46] E.A. Silver, D.F. Pyke, R. Peterson, Inventory Management and Production Planning and Scheduling, 3, Wiley, New York, 1998, p. 30.
[47] F. Salvador, C. Forza, M. Rungtusanatham, Modularity, product variety, production volume, and component sourcing: theorizing beyond generic prescriptions, J. Oper. Manag. 20 (5) (2002) 549–575.
[48] J.C. Su, Y.C. Lin, V. Lee, Component commonality in closed-loop manufacturing systems, J. Intell. Manuf. 23 (6) (2012) 2383–2396.
[49] Y. Sun, J.W. Fowler, D.L. Shunk, Policies for allocating product lots to customer orders in semiconductor manufacturing supply chains, Prod. Plan. Control 22 (1) (2011) 69–80.
[50] A.A. Syntetos, M.Z. Babai, Y. Dallery, R. Teunter, Periodic control of intermittent demand items: theory and empirical analysis, J. Oper. Res. Soc. 60 (5) (2009) 611–618.
[51] R. Teunter, B. Sani, Calculating order-up-to levels for products with intermittent demand, Int. J. Prod. Econ. 118 (1) (2009) 82–86.
[52] R. Uzsoy, J.W. Fowler, L. Mönch, A survey of semiconductor supply chain models part II: demand planning, inventory management, and capacity planning, Int. J. Prod. Res. 56 (13) (2018) 4546–4564.
[53] M.C. van der Heijden, Supply rationing in multi-echelon divergent systems, Eur. J. Oper. Res. 101 (3) (1997) 532–549.
[54] M.C. van der Heijden, E.B. Diks, A.G. De Kok, Stock allocation in general multi-echelon distribution systems with (R, S) order-up-to-policies, Int. J. Prod. Econ. 49 (2) (1997) 157–174.
[55] K. van Donselaar, J. Wijngaard, Practical application of the echelon approach in a system with divergent product structures, in: Sven Axsäter, Christoph Schneeweiss, Edward Silver (Eds.), Multi-stage Production Planning and Inventory Control, Springer, 1986, pp. 182–196.
[56] H.J. Vassian, Application of discrete variable servo theory to inventory control, J. Oper. Res. Soc. Am. 3 (3) (1955) 272–282.
[57] A.F. Veinott, Optimal policy for a multi-product, dynamic, nonstationary inventory problem, Manag. Sci. 12 (3) (1965) 206–222.
[58] J.H.C.M. Verrijdt, A.G. De Kok, Distribution planning for a divergent depotless two-echelon network under service constraints, Eur. J. Oper. Res. 89 (2) (1996) 341–354.
[59] B. Wieland, P. Mastrantonio, S.P. Willems, K.G. Kempf, Optimizing inventory levels within Intel's channel supply demand operations, Interfaces 42 (6) (2012) 517–527. Providence.
[60] R.A. Williams, User experiences using FLAME: a case study modelling conflict in large enterprise system implementations, Simul. Model. Pract. Theory 106 (2021), 102196.
[61] J. Wijngaard, J.C. Wortmann, MRP and inventories, Eur. J. Oper. Res. 20 (3) (1985) 281–293.
[62] S. Zhong, M. Bushell, Impact of the built environment on the vehicle emission effects of road pricing policies: a simulation case study, Transp. Res. Part A Policy Pract. 103 (2017) 235–249.
[63] T. Ziarnetzky, L. Mönch, R. Uzsoy, Simulation-based performance assessment of production planning models with safety stock and forecast evolution in semiconductor wafer fabrication, IEEE Trans. Semiconduct. Manuf. 33 (1) (2019) 1–12.
[64] W. Zinn, Should you assemble products before an order is received? Bus. Horiz 33 (2) (1990) 70–74.
[65] W. Zinn, A historical review of postponement research, J. Bus. Logist. 40 (1) (2019) 66–72.
[66] X. Zhang, Y. Sun, Y. Zhang, S. Su, Multi-agent modelling and situational awareness analysis of human-computer interaction in the aircraft cockpit: a case study, Simul. Model. Pract. Theory 111 (2021), 102355.