國立交通大學
工業工程與管理學系

博士論文

需求不確定下控檔片之管理

Managing Control and Dummy Wafers under Demand Uncertainty

研　究　生：楊懿淑
指導教授：張永佳　博士

中華民國九十八年七月

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摘要

半導體製作過程中控檔片(Control and Dummy Wafers) 的主要功能在於確保晶圓產品的品質與製程穩定。大量的控檔片並非產品卻不可或缺，一但短缺則會導致製程停頓與交期延誤，間接會提高成本和降低獲利。故有效的管理控檔片是晶圓製造過程中重要的議題。

本研究主要探討控檔片之降級法則與需求服務水準兩種問題，目的是在多期多產品不確定需求前提下最小化總成本。本研究以兩階段隨機規劃模型求出新片的供給數量、降級的數量、方式與途徑，探討降級法則；再以機遇限制規劃模型滿足預設的需求服務水準，並提出利用滾動時窗法將機遇限制規劃模型轉換成等價的動態線性規劃模型求解。經由實例驗證，本研究所設計之控檔片管理模式在實務上因將需求不確性列入考慮，故提高其應用上之有效性。

關鍵詞：控檔片、隨機規劃、機遇限制規劃、需求不確定性。

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ABSTRACT

The first subject of this dissertation is to study a realistic planning environment in wafer fabrication for the control and dummy wafers problem (C/DWP) with uncertain demand. A two-stage stochastic programming model is developed based on scenarios and solved by a deterministic equivalent large linear programming model. The model explicitly considers the objective to minimize the total cost of C/D wafers. A real-world example is given to illustrate the practicality of a stochastic approach. The results are better in comparison with deterministic linear programming by using expectation instead of stochastic demands. The model improved the performance of C/D wafers management and the flexibility of determining the downgrading policy. For the inventory management with service level, a chanced-constrained model is developed to minimize the total cost and to keep satisfaction of customer with pre-specified probability level. Based on rolling horizon method, this model is transformed into a dynamically equivalent linear problem. A numerical example problem is illustrated to provide information for setting customer satisfaction levels and unfolding effective inventory management options.

Keywords: control and dummy wafers, stochastic programming, chance-constrained programming, demand uncertainty

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楊懿淑

謹誌於國立交通大學工業工程與管理系

97 年 7 月

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Notation

Index	Definition	Sets		
m	Product	$\boldsymbol{M}$	=	$\{1, 2, \ldots, M\}$
j	Sequencing grade of C/D wafer	$\boldsymbol{J}$	=	$\{1, 2, \ldots, J\}$
k	Number of grades changed	$\boldsymbol{K}$	=	$\{1, 2, \ldots, J\text{-}1\}$
s	Demand scenario	ξ	=	$\{1, 2, \ldots, S\}$
t	Time period	$\boldsymbol{T}$	=	$\{0, 1, \ldots, T\}$

Notations for stochastic C/D downgrading problem and C/D service level problem

$I_j^{[t]}$	Quantity of inventory for the j^{th} grade of C/D wafers in period t
$x_{0j}^{[t]}$	Quantity of new C/D wafers released to the j^{th} grade in period t
$x_{jj}^{[t]}$	Quantity of the j^{th} grade C/D wafers for recycling in period t
$x_{j(j+k)}^{[t]}$	Quantity of the j^{th} grade C/D wafers downgraded to the $(j+k)^{th}$ grade due to demand in period t
$x_{js}^{[t]}$	Quantity of the j^{th} grade C/D wafers scraped in period t
$\boldsymbol{D}_m^{[t]}$	Matrix of demand of the product m in period t
$\boldsymbol{d}_j^{[t]}$	Matrix of the integrated demand for the j^{th} grade C/D wafers in period t.
$\boldsymbol{f}_j^m$	Frequency of using the j^{th} grade C/D wafers in the process for product m
c_0	Cost of the new C/D wafer/ per unit

c_{jj}	Cost of recycling a C/D wafer at the j^{th} grade/ per unit
$c_{ij}^{(n)}$	Cost of natural downgrading a C/D wafer from the i^{th} grade to the j^{th} grade/ per unit
$c_{ij}^{(d)}$	Cost of demand downgrading a C/D wafer from the i^{th} grade to the j^{th} grade/ per unit
$c^{(s)}$	Cost of scraping a C/D wafer
h_j	Cost of holding the j^{th} grade C/D wafer
r_j	times of recycling for a C/D wafer at the j^{th} grade
u	Minimum level of inventory of the C/D wafers at each grade
R_r	Maximum rate of recycled C/D wafers at each grade
R_s	Minimum rate of scraped C/D wafers at each grade
$1-\alpha$	Service level
μ_m	Expected demand of product m
σ_m^2	Demand variance of product m
$d_{j(s)}^{[t]}$	Total demand for the j^{th} grade C/D wafers in period t, (scenario s)
$I_{j(s)}^{[t]}$	Quantity of inventory for the j^{th} grade C/D wafers in period t (scenario s)
$x_{0j(s)}^{[t]}$	Quantity of new C/D wafers released to the j^{th} grade in period t (scenario s)
$x_{jj(s)}^{[t]}$	Quantity of the j^{th} grade of the C/D wafers for recycling or external downgrading in period t (scenario s)
$x_{j(j+k)(s)}^{[t]}$	Quantity of the j^{th} grade of the C/D wafers downgraded to the $(j+k)^{th}$ grade due to demand in period t (scenario s)

1. Introduction

1.1 Motivation

Control and dummy (C/D) wafers are indispensable to manufacturing processes in semiconductor wafer fabrication. Control wafers are used to measure the refraction indices and etching rates in order to test the quality of equipment and monitor the process prior to risking the real product wafer. This ensures process stability and normal equipment operation. Control wafers may also be used with products together as proof of product quality in the process by measuring particle numbers and film thickness. Dummy wafers are used to distribute heat uniformly inside the furnaces. Each inspection item requires C/D wafers for different devices. Figure 1-1 represents an overview of the applications of C/D wafers in a wafer fabrication. Any lack or surplus of C/D wafers may cause the loss of equipment capacity and production movement because they occupy equipment capacity of wafer fabrication, not only affecting production planning but also decreasing process yield.

Besides the cost and quality issues, the lifecycles of C/D wafer make management a real challenge. The major characteristics of C/D wafers is that they can repeat the same functional test several times until they fail to conform to quality specifications related to requirements for cleanliness or thickness. When a qualification is due, the C/D wafers associated with that process is pulled from the inventory. If the number of C/D wafers is not enough, new C/D wafers are released. Once the C/D wafer is used, it has to be checked whether it can be reused or not. If yes, it can either return back to the inventory, or to a lower grade based on the demand. Good management can reduce the number of C/D wafers brought in to the manufacturing process and improve the efficiency of C/D wafer usage.

Therefore, the main challenges of C/D wafer management are downgrading problem and inventory control.

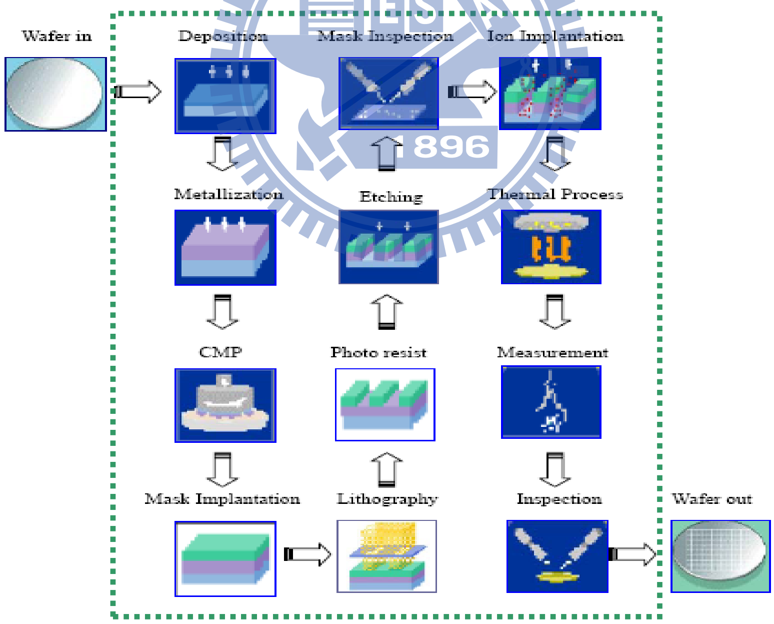


Figure 1-1 Applications of C/D wafers in process

1.2 Objectives

C/D wafer management is a crucial issue of complexity in the wafer fabrication, because it needs to consider not only downgrading policy, release rule, and inventory control, but also service level under demand uncertainty. Even though many researchers have focused on C/D wafers management, little study has been done under demand uncertainty which is a realization of nature. In real world, the manufacturer has to meet the demand for different products according to the service level requirements set by its customers. To capture the trade-off between customers satisfaction and production costs, it makes C/D wafers management effectively and efficiently. This research attempts to:

1. Develop a two-stage stochastic programming model to minimize the total cost of C/D wafers and to set the quantities of new C/D wafers released and C/D wafers recycled or downgraded to meet the stochastic demands of each grade.

2. Develop a chance-constrained programming model to minimize the total cost of C/D wafers and to make production and C/D wafers sourcing decisions during the planning horizon subject to the service level requirements set by customers.

To attain the mission of the stochastic C/D wafers downgrading problem (SC/DWDP), a scenario-base approximation approach is proposed to give advantages in terms of retaining a linear model and easier solutions by utilizing a single large equivalent LP model. Next, to achieve the objectives of C/D wafers service level problem (C/DWSLP) constructed by a chance-constrained programming model, an approach is proposed to decide an appropriate C/D wafer quantity for each grade in each period. The approach includes three phases: (i) transforming the empirical cumulative demand data, if it is non-normal, into a set of data which is approximately normal distributed, (ii) transforming the chance-constrained programming model into an equivalent integer programming, and (iii) using rolling horizon method to solve the problem dynamically.

1.3 Thesis Outline

The remaining of this study is organized as follows.

Chapter 2 reviews four portions, viz., (i) downgrading resource (ii) inventory management (iii) stochastic Programming and (iv) normal Transformation. Chapter 3 describes the background information including: the PUR process of C/D wafers, the resource downgrading characteristics of C/D wafers, demand uncertainty, and assumptions of this study. In chapter 4, a two-stage stochastic programming model is proposed, while a chance-constrained programming model is presented in chapter 5. Finally, conclusion and future research are given in chapter 6. Figure 1-2 illustrates the architecture of these six chapters in this study.

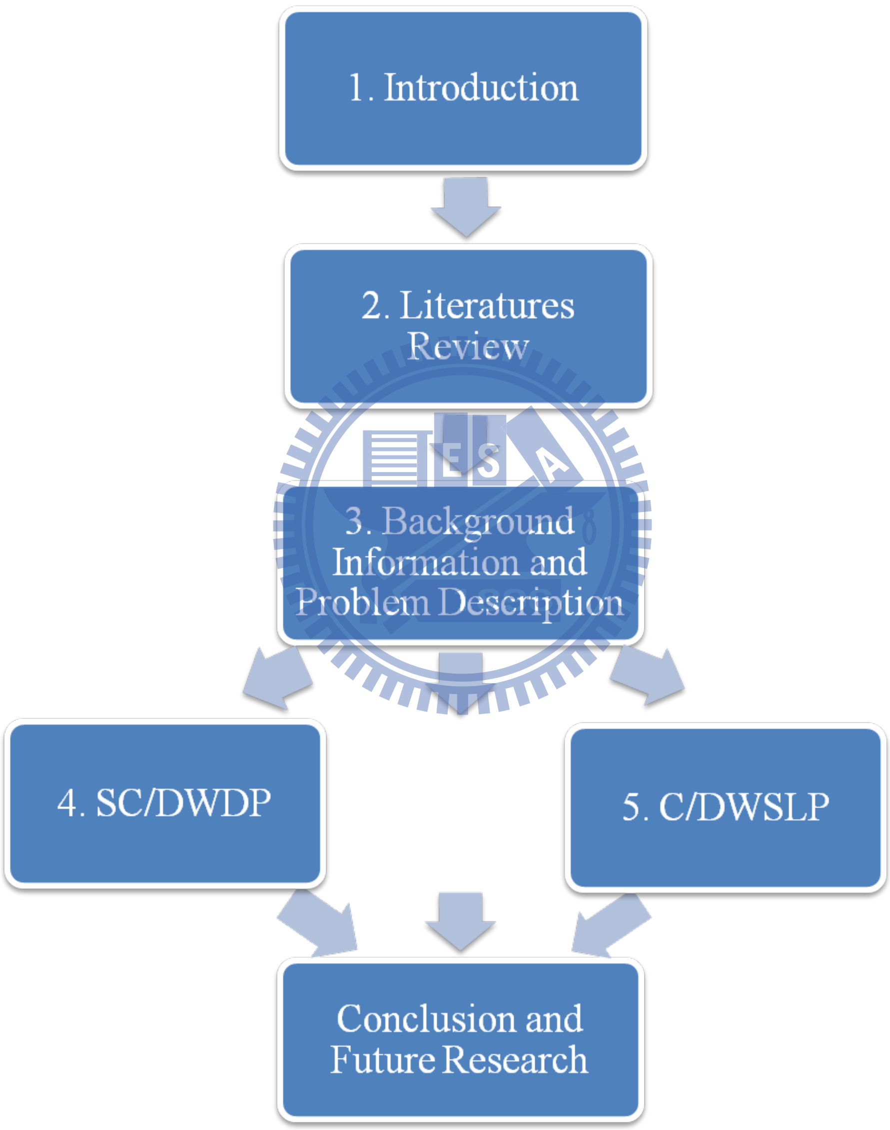


Figure 1-2　Organization of this study

2. Literature Review

The purpose of using C/D wafers is to assure that the wafer manufacturing process operations meet the required manufacturing specifications. Downgrading resources and inventory control are two characteristics of C/D wafer management. To properly account for product demand fluctuate, this research considers that the demand is uncertain.

Rare researches have been conducted on C/D wafer management since Wong and Hood [76] used discrete event simulation to run a hypothetical fab model with an industry-standard CMOS base process. They did not provide a method for efficiently managing test wafers but only examined the impact of test wafers on process cycle time, wafer throughput, and fab line equipment capacity requirements. Chen *et al*. [17] pointed out the issues about C/D wafer management. Later, Chen *et al*. [19] proposed a pull system to manage C/D wafers in order to increase the efficiency of C/D wafers. According to the above, downgrading rules and inventory control are the keys of a good C/D wafers management. Therefore, the literature review includes downgrading resources, inventory management, stochastic programming, and normal transformation. The first two topics are related to the C/D wafer management, while the last two are related to methodologies implemented in this research.

2.1 Downgrading Resource

Due to the reuse and downgrading of the C/D wafers, resource downgrading problem is quite different from other production problems. Some researchers focused on downgrading rules. Chen, *et al*. [18] suggested downgrading and release rules for C/D wafers. Foster, *et al*. [32] studied test wafer consumption by simulation. Although simulation can realize stochastic events and observe the effects by the current state of the system during a specific simulation run, it needs more time to produce results, and the randomness does not guarantee the same results between different runs. On the other hand, Foster, *et al*. [32] also suggested "lowest inventory first" downgrading rule which only can yield suboptimal solution. Chung, *et al*. [23] proposed a linear programming model for the C/D wafers downgrading problem to minimize the total cost of C/D wafers by using expected demand in the photolithography area of a wafer fab. Wu, *et al*. [77] aimed to minimize the long-term daily use of brand-new C/D wafers in a fab by a linear programming model. Özelkan and Çakanyildirim [57] represented a resource downgrading problem as a network model with side constraints, which results in an integer programming formulation. Of the above, little work has been done to include the uncertainty of demands so as to meet the rapidly changing demands of the future. Liou, *et al*. [53] established a capacity forecast model for C/D wafers for decision support instead of basing it on personal experience or the historical reservation data in practice. Popovich, *et al*. [62]

mentioned that Motorola MOS12 designed a re-use matrix to determine the possible uses for C/D wafers. However, it is manual and thus has limitations due to the complexity of identifying downgrading paths and controlling the inventory of C/D wafers.

This downgrading substitution structure also occurs in some other practical settings, for example, in the steel industry by Wagner *et al*. [72], memory chips by Leachman [51], inventory policies of priority by Duran *et al*. [30], and semiconductor chips by Hsu *et al*. [41].

2.2 Inventory Management

Inventory has been one of the most investigated areas of research. Early work done by Harris [38] on inventory management goes back to the classical economic lot size model which assumes a steady demand and holding costs over time. Deterioration of products is realistic in many inventory systems. In determining the optimal inventory policy of product, the loss due to deterioration should be taken into account. Ghare and Schrader [33] initiated the analysis of deteriorating inventory by establishing a classical no-shortage inventory model with a constant rate of decay. Covert and Philip [25] extended Ghare and Schrader's model by establishing an economic order quantity (EOQ) model for a variable rate of deterioration with a two-parameter Weibull distribution. Later, Kar *et al*. [48] proposed a deterministic inventory model for a single product stored in two storage facilities while the demand was assumed linearly increasing, time-dependent over a fixed finite time horizon. To fit a more general inventory feature, Chang and Dye [13] developed an EOQ model to find the optimal total cost savings for deteriorating items with varying rate of deterioration during the special replenishment period. Chung and Tsai [22] developed an inventory model for deteriorating items with the demand of linear trend and shortages during a finite planning horizon. A line search was applied in a simple solution algorithm to determine the optimal interval without considering stock-outs. Chang *et al*. [14] proposed a finite time horizon EOQ model taking into accounts the followings: a time-varying deterioration rate, time value of money, shortages and permissible delay in payments.

In practice, demand and service level may influence safety inventory. Inventory models have been continually modified to accommodate to more practical issues of the production planning and the real inventory systems. For a large family of lead time demand distributions, Platt *et al*. [60] declared that the optimal policy depends on two parameters: the fill rate and the EOQ scaled by the standard deviation of demand over the constant lead time. Silva Filho [68] proposed the cumulative demand is a random variable represented by a compound Poisson process, since the demand affects the inventory system. Gupta *et al.* [36] utilized a stochastic framework to provide quantitative guidelines for setting customer satisfaction levels and uncovering effective inventory management options. Furthermore, Bhunia and

Maiti [5] assumed that the production rate is a variable. They also presented inventory models in which the production rate depends on either on-hand inventory or demand. Das *et al*. [27] developed a multi-item inventory model with quantity-dependent inventory costs and demand-dependent unit cost under imprecise objective and restrictions. Both geometric programming (GP) and gradient-based nonlinear programming (NLP) methods are used to solve the problem. Rao *et al*. [65] modeled a single period multi-product inventory problem with uncertain demand and one-way product substitution in the downward direction. Pal *et al*. [58] constructed a deterministic inventory model with a stock-dependent demand rate and a constant item deteriorating rate. In addition, a fuzzy geometric programming (FGP) method is used to solve two highly nonlinear equations generated from the model. Duran *et al*. [30] provided tools for managing production and inventory tactically when customers differ in their willingness to pay and to wait. Many other references about multi-echelon inventory management in supply chains with uncertain demand and lead times appear in Gumus and Guneri's survey [34].

For C/D wafers in the semiconductor industry, majority of researches have been focused on controlling inventory with deterministic demand, inventory management under uncertain demands has received relatively little attention. Chung, *et al*. [24] used a non-linear program to set a safe inventory level for control wafers. Since they assumed that demand follows an approximately normal distribution, the optimal solutions were based on deterministic expected values to simplify stochastic events and dynamics that might reach misleading solutions.

2.3 Stochastic Programming

A great quantity of research has been conducted on C/D wafer management but most was based on the assumption of known or expected demand. Chung *et al*. [23] assumed the demand of C/D wafers is constant. Later, Chung *et al*. [24] used a non-linear program to set a safe inventory level for control wafers but assumed that demand follows an approximately normal distribution. Their optimal solutions were based on deterministic expected values to simplify stochastic events and dynamics that might reach misleading solutions.

2.3.1 Two-stage stochastic programming

Uncertainty is one of the main characteristics of semiconductor manufacturing systems. To handle uncertainty, it is appropriate to use a two-stage stochastic programming (SP) with recourse, which was first independently presented by Dantzig [26] and Beale [3]. It is a dynamic linear programming model characterized by uncertain future outcomes for some parameters, as follows.

$$Z = \min \boldsymbol{cx} + E_{\omega}[Q(\boldsymbol{x}, \boldsymbol{\omega})] \tag{1}$$

Subject to

$$\boldsymbol{Ax} \geq \boldsymbol{b}, \quad \boldsymbol{x} \geq 0 \tag{2}$$

where $$Q(\boldsymbol{x}, \boldsymbol{\omega}) = \min f(\boldsymbol{\omega}) \cdot \boldsymbol{y} \tag{3}$$

Subject to

$$\boldsymbol{D}(\boldsymbol{\omega})\boldsymbol{y} = \boldsymbol{d}(\boldsymbol{\omega}) + \boldsymbol{B}(\boldsymbol{\omega})\boldsymbol{x} \tag{4}$$

$$\boldsymbol{y} \geq 0, \quad \omega \in \boldsymbol{\Omega}.$$

The model is separated into two stages. At the first stage, referred to Equations (1) and Equation (2), the decision variables are chosen to minimize the direct cost and expected recourse cost that faces the recourse action taken. At the second stage, referred to Equations (3) and Equation (4), the decision variables are chosen due to the future uncertainty defined by probability space ($\boldsymbol{\Omega}$, $\boldsymbol{P}$). Matrix $\boldsymbol{A}$, vector $\boldsymbol{b}$, and vector $\boldsymbol{c}$ are known with certainty. The function $Q(\boldsymbol{x}, \boldsymbol{\omega})$, is referred as the recourse function. The technology matrix $\boldsymbol{D}(\boldsymbol{\omega})$, the right-hand side $\boldsymbol{d}(\boldsymbol{\omega})$, the inter-stage link matrix, $\boldsymbol{B}(\boldsymbol{\omega})$, and the objective function coefficients $\boldsymbol{f}(\boldsymbol{\omega})$ may be random. For a realization $\boldsymbol{\omega}$, the corresponding recourse action $\boldsymbol{y}$ is determined by $\boldsymbol{Q}(\boldsymbol{x}, \boldsymbol{\omega})$. Therefore, the optimal solution of the objective function hedges against all possible events $\boldsymbol{\omega} \in \boldsymbol{\Omega}$ that might occur in the future. Kall [47] suggests that "here and now"

(HN) and “wait and see” (WS) are two different solution approaches to the stochastic programming. The WS approach assumes that the decision maker would not make the optimal decision until the outcome of a random variable can be observed. It is clear that such a solution is not implemented. The HN approach represents the true stochastic optimization solution without knowledge of the realization of random variables. A number of different algorithmic approaches have been proposed for solving the stochastic linear programming stated above, Equations (1) – (4). Refer to Wets [74] for an investigation of the recourse problem. Later, Wets [75] surveyed the use of large-scale linear programming techniques. Using mathematical programming techniques seemed to be one of the promising approaches to solve stochastic problem in some special cases, since stochastic models address the shortcomings of deterministic models directly. There are two measures to evaluate whether stochastic approach can be nearly optimal or nearly accurate: the expected value of perfect information (EVPI) and the value of the stochastic solution (VSS). EVPI and VSS give the motivation for stochastic programming in general and remain a key focus for the sensitivity analysis. EVPI measures the value of knowing the future with certainty while VSS assesses the value of knowing and using distributions on future outcomes.

Uncertain demand is a realized nature of production process, so a lot of researches in production planning implemented stochastic programming to make meaningful planning decisions. Bakir *et al*. [2] studied a realistic planning environment for a multi-product multi-period with stochastic demand. The normally distributed stochastic demand is approximated by a discrete approximation method. Gupta *et al*. [35] proposed a two-stage stochastic programming approach for incorporating demand uncertainty in multisite midterm supply chain planning problem. At the expense of imposing the normality assumption for the stochastic product demands, Gupta *et al*. [35] evaluated the expected second stage costs by analytical integration yielding an equivalent convex mixed-integer nonlinear problem. Zhang *et al*. [82] consider a discrete-time capacity expansion problem involving multiple families and multiple machine types, and non-stationary stochastic demand. They used a novel assumption that demand can be approximated by a distribution in order to allow them to solve the problem as a max-flow, min-cut problem.

There has been a large variety of applications for stochastic programming; for example, fleet assignment by Ferguson and Dantzig [31], capacity planning by Christie and Wu [21], water resource management by Watkins *et al*. [73], and production planning by Leung *et al*. [52]. Many other references appear in King's survey [49].

2.3.2 Chance-Constrained Programming

It is apparent that many real world problems contain uncertainty. Charnes and Cooper

[15] were the pioneers who proposed chance constrained programming (CCP) as a means of managing uncertainty and probability. It provides a powerful means of modeling stochastic decision system which has ability to meet the constraints with certain reliability in an uncertain environment. The general formulation of CCP is as Equation (5) – (7):

$$Z_{ccp} \; = \; min \; \boldsymbol{cx} \tag{5}$$

Subject to

$$\boldsymbol{A_0} \; \boldsymbol{x} \; \geq \; \boldsymbol{b_0} \tag{6}$$

$$P[\boldsymbol{A}_i \boldsymbol{x} \geq \boldsymbol{h}_i] \geq \alpha_i, \quad where \quad \alpha_i \in [0,1], \quad i = 1, \cdots, I \tag{7}$$

Let $\xi_i = (\boldsymbol{A}_i, \boldsymbol{h}_i)$, $\forall i = 1, \cdots, I$, be a random vector on the probability space ($\boldsymbol{\Omega}$, $\boldsymbol{F}$, $\boldsymbol{P}$). If the $\boldsymbol{A}_i$ is a row vector, the i^{th} constraint is called individual constraint. If $\boldsymbol{A}_i$ is a $r \times c$ matrix with $r > 1$, then the i^{th} constraint is referred to as joint chance constraint. When the stochastic variables are independent, then the joint chance-constraint (7) can be decomposed into the product of the constituting chance-constraints as Equation (8).

$$\prod_{j=1}^{r} P\left[\sum_{k=1}^{c} a_{jk} x_j \geq h_{ij}\right] \geq \beta_i \quad i = 1, \cdots, I \tag{8}$$

If the stochastic variables are correlated, then the joint probabilities cannot be decomposed. This complicates the calculation of the probability and requires the simultaneous integration of multivariate probability distributions. Plackett [60] proposed a reduction formula for multivariate normal integrals.

There are a lot of practical problems which always involve uncertainty and probability. Chance-constrained programming has been implemented in a variety of fields. For instance, Petkov *et al*. [59] proposed a stochastic model to maximize the expected profit subject to the satisfaction of product demands with pre-specified probability levels, electrical circuit design by Ji *et al*. [45], routing problem by Wu *et al*. [78], soil conservation problem by Zhu *et al* [82], path planning for autonomous vehicles by Blackmore *et al*. [7], reservoir management by Azaier *et al*. [1], aggregate production planning by Silva Filho *et al*. [67], and production planning and sourcing problem by Yildirim *et al*. [79]. In general, obtaining the optimal solution of chance-constrained programming is not tractable. Bitran and Yanasse [6] considered deterministic approximations to a stochastic production problem on a rolling horizon basis. They showed that the service level constraint can be transformed into a deterministic equivalent constraint by specifying certain minimum cumulative production quantities that depend on the service level requirements. Kumral [50] proposed a combination of the chance-constrained programming and the genetic algorithm to find the optimal mine system parameters simultaneously. Jana *et al*. ([42], [43]) proposed a stochastic simulation based genetic algorithm approach to solve chance constraint programming problem in which the random variables follow some discrete distributions [43] and continuous distributions [42]. Manandhar *et al*. [55] provided a semantic based on scenarios to model combinatorial decision problems involving uncertainty and probability, while Prekopa [63] provides a numerical solution of probabilistic constrained programming models.

2.4 Normal Transformation

For most industrial applications, normality is assumed due to the advantage of the analytical convenience and existing effective statistical methods. For example, Platt *et al*. [60] assumed that the lead time demand is normally distributed, so the asymptotic results can be used as the EOQ from zero to positive infinity to fit a theoretic curve for the order quantity Q and the reorder point R. Silva Filho [68] proposed the cumulative demand is a random variable represented by a compound Poisson process. Because the demand affects the inventory system, a chanced constraint is used to preserve the inventory constraint explicitly in a stochastic optimization model. A Gaussian approximation is also proposed to the compound Poisson process. You *et al*. [80] used Box-Cox transformation method to transform the experiment data investigated from microcircuit process. But, for many engineering operations such as locating pins or automatic sensors, the manufacturing data is often truncated or appears to be non-normal. Pezdek [64] gave a non-normal data example and perform process performance analysis. Pezdek [64] demonstrated how the non-normal characteristic would significantly impact on the data analysis result and the conclusion, thus convey incorrect process information. If the process characteristic is not normally distributed, there are two popular approaches to transform the non-normal data into a normal one. First, Johnson [46] proposed a system of three transformation families for selection of a transformation to normality. Let X be a random variable and Z be a standard normal variable. The three transformation families in Johnson system are, respectively as Equation (9) – (11),

$$Z = \gamma + \eta \, ln\{(X - \varepsilon)/[\lambda - (X - \varepsilon)]\}, \quad \varepsilon < X < \lambda + \varepsilon, \tag{9}$$

$$Z = \gamma + \eta \, ln(X - \varepsilon), \quad X > \varepsilon, \tag{10}$$

$$Z = \gamma + \eta \, sinh^{-1}[(X - \varepsilon)/\lambda], \quad -\infty < X < \infty, \tag{11}$$

where $-\infty < \gamma, \varepsilon < \infty$, $\eta > 0$, and $\lambda > 0$ are four parameters. The distribution determined by (9) is called the S_B distribution denoted by S_B (γ, η, ε, λ). Similarly, the distribution determined by (10) is called the S_L distribution denoted by $S_L(\gamma, \eta, \varepsilon)$, and by (11) called the S_U distribution denoted by S_U (γ, η, ε, λ). The subscripts, B, L, and U, refer to X being bounded, lognormal, and unbounded, respectively. Hahn and Shapiro [37] gave further description of these distributions. In using the Johnson system, the first step is to determine which of the three families should be used. The next step is to estimate parameters of the transformation family selected. A moment approach in the selection step is to choose the transformation family according to which region of the $(\sqrt{\beta_1}, \beta_2)$ plane the estimated third (β_1) and fourth (β_2) standardized sample moments fall into. Slifker and Shapiro [69] pointed out the major shortcomings of this procedure such as high mean-square errors and vulnerability to outliers of the sample third and fourth moments.

Another percentile approach prevails and is in fact mostly adopted in practice. Johnson [46] proposed a method, which uses four percentiles. Based on symmetrical points, Bukac [12] suggested procedures for estimating parameters of SB distribution. Later, Mage [54] presented a method of reducing Bukac's quadratic equations to a quadratic equation. Slifker and Shapiro [69] suggested choosing four symmetric standard normal deviates equally spaced with intervals 2z, i.e. 3z, z, -z, and -3z, admittedly not a serious restriction. Bowman and Shenton [9] proposed a simple algorithmic solution for normal deviates -sz, -z, z, and sz where s and z are arbitrary positive constants and s > 1. Meanwhile, Owen [56] proposed the starship procedure to search out a transformation that most nearly transforms the sample to normality, which is not only tied to Johnson system but also many possibilities exist for the transformations. Chou et al. [20] recommended that use the set Z = { z0: z0 = 0.25, 0.26, …, 1.25}, instead of a single chosen value, to fit all the Johnson distributions which are feasible for the Slifker and Shapiro's estimation formulas. The best-fit Johnson distribution is chosen to be the one that best transforms the data to normality among the z0 values in Z. However, this procedure cannot discriminate the SL distribution family from the other two families. Chen and Kamburowska [16] proposed a procedure, called M procedure, which is consistent by setting a bound on the parameter to prevent from an incorrect selection when the underlying distribution is an SL distribution.

Box and Cox [10] modified the family of power transformation proposed by Tukey [71]. Its simple form defined as T λ: y →y(λ)

$$y^{(\lambda)} = \begin{cases} \dfrac{y^{\lambda}\text{-}1}{\lambda}, & \lambda \neq 0 \\ \ln y, & \lambda y = 0 \end{cases} \tag{12}$$

The transformation in Equation (12) is defined for $y > 0$. It is hoped that for some value of λ, a non-normal data can be fitted to a normal distribution. Box and Cox [10] used the maximum likelihood method to estimate the parameter λ. An analytical expression for the accuracy of maximum likelihood estimate of λ is derived by Draper and Cox [29]. Hinkley [39] used order statistics to estimate the transformation parameter. Later, Hinkley [40] assumed that there might be a value of λ making the transformed data nearly symmetry and proposed a similar method for choosing a symmetrical transformation based on the asymmetry degree of the sample, which is measured by Equation (13)

$$d = \text{(sample mean – sample median)/sample scale} \tag{13}$$

If the underlying distribution is symmetric, then the mean and the median must be identical. Thus, the sample data drawn from such distribution should reflect such property, and a good estimate of λ should minimize the value of d.

Base on the Tukey's [71] recommendation with setting λ to $-2 \leq \lambda \leq 2$, Hinkley [40] proposed a step-by-step procedure for computing the power of Box-Cox transformation based on moment of percentile may be presented as follows:

Step 1: Choose -2 as an initial guess λ_0 of λ for a given random sample.

Step 2: Transform the original sample by taking the power λ_0 and then find the sample mean, sample median, and sample inter-quartile range for the transformed random sample.

Step 3: Calculate d defined in Equation (13) using the inter-quartile range as the sample scale.

Step 4: Check whether d is less than a predetermined precision level. If not, iterate Steps 1-3 by increasing the magnitude of λ by unit of 0.05 as new λ_c, till the difference between λ_0 and λ_c is smaller than the predetermined precision level.

Step 5: Use the λ derived from Step 4 as the optimal estimate $\hat{\lambda}$. Employ Shapiro-Wilk [66] test to check the normality of the transformed sample.

3. Background Information and Problem Description

3.1 The PUR Process of C/D Wafers

Cost is only a part of the C/D wafer issue because they also occupy the capacity of equipment, which is capital intensive. The usage of C/D wafers in wafer manufacturing processes can be divided into five primary categories, viz., (i) product monitoring, (ii) equipment monitoring, (iii) preventive maintenance, (iv) the experiment with engineering lots, and (v) repaired equipment if breakdown. Therefore, good management ought to reduce the number of C/D wafers brought in to the manufacturing process and improve the efficiency of C/D wafer usage since the major characteristic of C/D wafers is that they can repeat the same functional test several times until they fail to conform to quality specifications related to requirements for cleanliness or thickness. The reuse statuses consist of three processes, viz., (i) pre-disposition, (ii) in-use, and (iii) recycle stages, termed the PUR process. Figure 3-1 represents the cyclic relation among PUR process of a C/D wafer used in a specific process.

3.1.1 Pre-disposition

Before control wafers are used to monitor production, they have to finish a series of operations, called pre-dispostion stage, to meet the required specifications. The purpose of this stage is to set up the initial measurements of C/D wafers themselves.

3.1.2 In-use

Control wafers are used to monitor process, qualify tools, and develop new process techniques. To test the wellness of the tool prior to manufacturing the production wafer, control wafers may be run concurrently with them to perform as a witness to the process, or may also be used to pilot a process before wafers are committed to a tool. Therefore, output parameters are taken from the control wafers and adjustments are made to the tool or process correspondingly. On the other hand, dummy wafers are used on two sides of wafer cassette to protect the wafers heated uniformly inside the furnaces.

In engineering lots, control wafers are built the designed structure, similar to built onto the real wafers, to simulate the actual production. The effects of a specific process to the structure can be studied, characterized, and optimized.

3.1.3 Recycle

After in-use stage, there are some remnants and particles left on the surfaces of C/D wafers. To reduce the WIP level of C/D wafer, recycle is a key process which polishes off the contaminants on the top of C/D wafers. This provides a clean C/D wafers re-used back to pre-disposition stage at a much reduced cost.

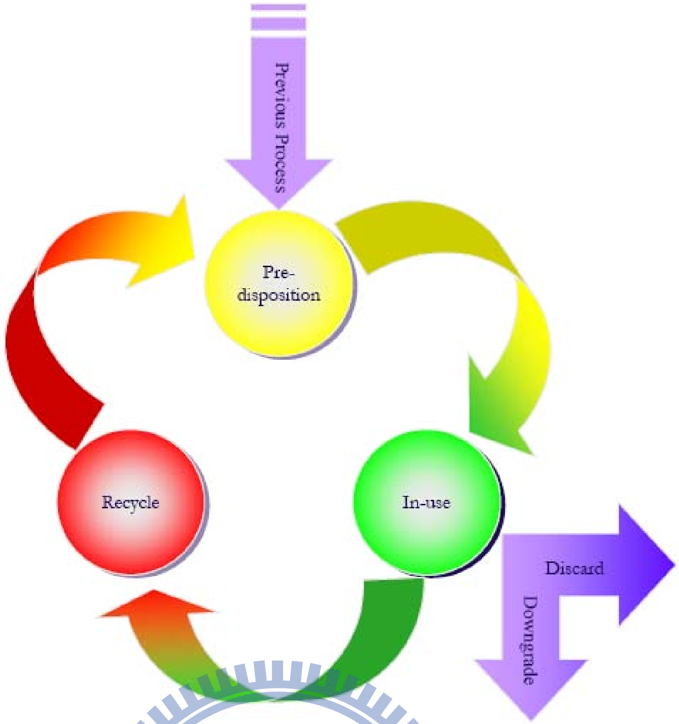


Figure 3-1 The cyclic relation among PUR process of a C/D wafer.

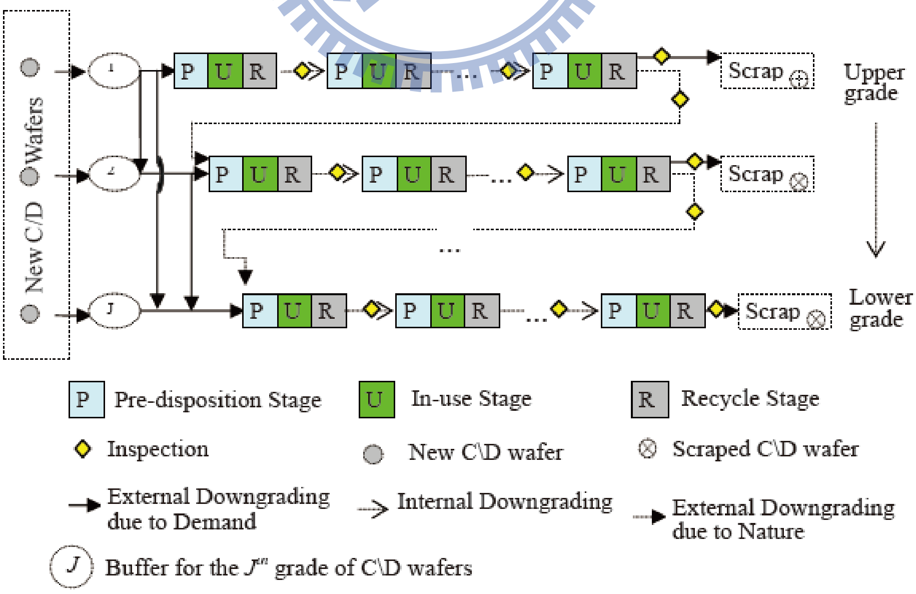


Figure 3-2 Multi-level downgrading diagram for C/D wafer

3.2 The Resource Downgrading Characteristic of C/D Wafers

The major characteristic of C/D wafers is that they can repeat the same functional test several times until they fail to conform to quality specifications related to requirements for cleanliness or thickness. The reuse statuses consist of the pre-disposition, in-use, and recycle stages, termed the PUR process, illustrated in Figure 3-2 with dotted arrows. We called it internal downgrading or recycling. Once a C/D wafer no longer conforms to the pre-defined specifications, it will be scraped or downgraded to lower grade of which the quality specifications are not so high. Hence, such a kind of downgrading is referred to here as external downgrading due to wafer quality, indicated by a dotted line and bold arrows in Figure 3-2. Furthermore, releasing new raw wafers as any grade of C/D wafers or downgrading C/D wafers that directly bypass the PUR process to lower grades where there is a deficit of C/D wafers is regarded as external downgrading due to demand, indicated by a solid line and bold arrows.

Re-use is crucial to cost saving, but without some policy to prioritize and monitor it, the efficiency of C/D wafer could be decreasing. As a result, more expensive new C/D wafers will be brought into the manufacturing process. It is easy to see that C/D wafers are used in very large quantity occupying a significant portion of a fab’s expensive capacity. A good management of C/D wafer must focus on identifying appropriate downgrading rules in order to increase both the recycled usage of C/D wafers and the throughput rates of wafers.

3.3 Demand Uncertainty

The semiconductor industry has become one of the leading industries in the world on account of rapid shrinkage of product design cycles and life cycles in the consumer electronics business. Therefore, competition is fierce and the pace of product innovation and changes in technologies is high. Due to the intensive capital investment, making efficient usage of current tools and well planning the production are of great important. Consequently, the demand for semiconductor products is becoming increasingly hard to predict. In the prevailing intangible business environment, with ever changing market conditions and customer expectations, it is necessary to consider the impact of uncertainties involved in the semiconductor industry.

In the past of researches, deterministic models are assumed widely. But this assumption is rarely true. It is more reasonable to study this kind of “demand-driven” problems under uncertain environment because deterministic approach may thus yield unrealistic results by failing to capture the effect of demand variability on the tradeoff lost sales and inventory holding costs. Moreover, failure to incorporate a stochastic description of the product demand could lead to either unsatisfied both customers and loss of market share or excessively high inventory holding costs. Buffa and Taubert [11] state that the normal, Poisson and negative exponential distributions have been found to be of considerable value in representing demand functions for inventory management. A classification of different areas of uncertainty is suggested by Subrahmanyam *et al.* [70] including uncertainty in prices, demand, equipment reliability, and manufacturing uncertainty.

3.4 Problem Description

3.4.1 Overview of stochastic management system of C/D wafers

The stochastic management system of C/D wafers is depicted on a simplified representation of network system, as shown in Figure 3-3. While t = 1 represents the time period called "here and now", t = 2 is the next time period to "wait and see", and t = 0 is the previous time period. In Figure 3-3, each node represents the random demand for each grade of C/D wafers in each period. The solid arrows refer to external downgrading action due to demand while the segmented arrows refer to external downgrading action due to nature. The recycle or inventory is presented by dotted arrows. Therefore, in a stabilized system, the arrivals of C/D wafers at each node are equal to the departures. The inventory at the end of period t is available for withdrawal in the next period, and is also as the transit matrix that provides the linkage between the periods of the model. To avoid affecting the processes, backlogging is not allowed.

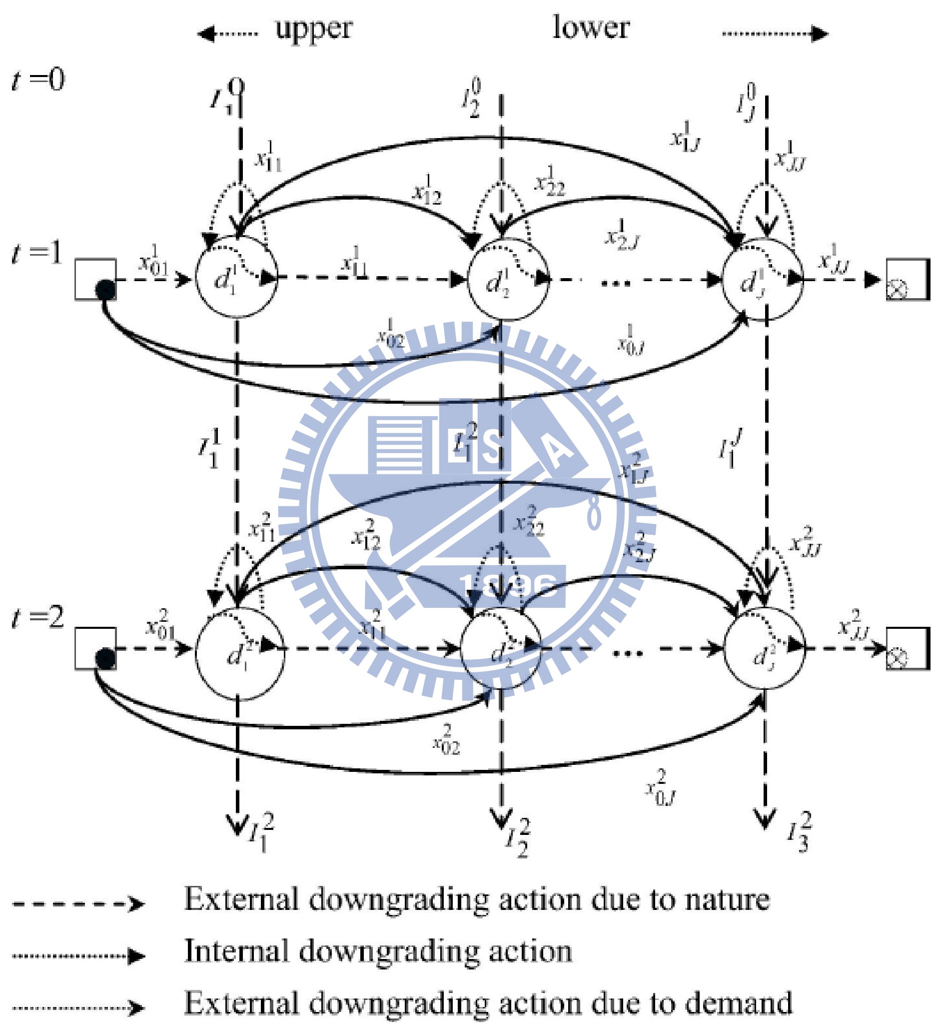


Figure 3-3 Schematic stochastic C/D wafers management system diagram

3.4.2 Assumptions

A two-stage stochastic programming model for stochastic control and dummy wafer downgrading problem (SC/DWDP) and a chanced-constrained programming model for control and dummy wafer service level problem (C/DWSLP) were constructed for a theoretical manufacturing system based on the following assumptions:

1. The product mix is given in period t = 1, which represents “now”.
2. The multi-level downgrading rule is applied.
3. Engineering lots are not considered.
4. A shortage of C/D wafers is not allowed.
5. The C/D wafers are classified into J grades.
6. The downgrading graph for each product must be determined in advanced.
7. A lot is the least unit for release, downgrading, and scrap.
8. Each PUR process consists of three processes of operation.
9. The maximum recycle ratio of C/D wafers for each grade is determined to allow the occurrence of unexpected breakages. (number of recycled to available C/D wafers ratio)

10. The minimum scrap ratio of C/D wafers for each grade is determined to avoid waste due to abundance of inventory (number of scraped to available C/D wafers ratio).
11. The demands of products for all time periods are random and empirical.
12. The integrated demands of C/D wafers of each grade at each period are independent.

3.4.3 Stochastic C/D Wafers Downgrading Problem

To attain the mission of C/D wafers in a fab, we define the stochastic C/D wafer downgrading problem (SC/DWDP) to minimize the total cost of C/D wafers while simultaneously determining their inventory policies, downgrading policies, and release rules for new wafers. We consider that the uncertainty of demands will result in more realistic planning decisions to meet rapidly changing future demands. Therefore, the purpose of this dissertation is to develop a two-stage stochastic programming model for SC/DWDP to minimize the total cost of C/D wafers and to set the quantity of new C/D wafers released and C/D wafers recycled or downgraded to meet the stochastic demands of each grade. The proposed stochastic model, which is balanced and hedges against various scenarios, can describe the real-world production setting more realistically than the static approach can. Furthermore, a discrete approximation of stochastic demand gives advantages in terms of retaining a linear model and easier solutions by utilizing a single large equivalent linear programming model. It is more useful and efficient than a simulation approach.

3.4.4 C/D Wafers Service Level Problem

The influencing uncertainty of demands matters in making production decisions of C/D wafers. This feature makes C/D wafers production management appropriate for the application of chance-constraint programming (CCP), a more practical and general approach. The manufacturer has to meet the demand for multi-products according to the service level requirements set by its customers. And the demand for each product in each period is random. The C/D wafer service level problem (C/DWSLP) in a chance-constraint manner is presented. The chanced constraints will hold at least α of time, where α is referred to as the confidence level provided as an appropriate service level by the customers. The rolling horizon approach is proposed to dynamically transform the model into an equivalent deterministic problem based on the real life data at each time period and the optimal solution of the preceding period.

4. Optimization of Stochastic C/D Wafers Downgrading Problem

4.1 Formulation of Stochastic C/D Wafers Downgrading Problem

The integrated demand of the j^{th} grade C/D wafers in each time period at the first stage is calculated by Equation (14). Given a scenario at the second stage, Equation (15) calculates the integrated demand of the j^{th} grade C/D wafers in each time period.

$$d_j^{[t]} = \sum_{m=1}^{M} f_{jm} \times D_m^{[t]}, \quad j = 1, 2, \cdots, J, t = 1, 2, \cdots, T. \tag{14}$$

$$d_{j(s)}^{[t]} = \sum_{m=1}^{M} f_{jm} \times D_{m(s)}^{[t]} \quad j = 1, 2, \cdots, J; \; s = 1, 2, \cdots, S; \; t = 1, 2, \cdots, T. \tag{15}$$

The production planner's objective is to minimize the total cost of the C/D wafers and to determine the supply quantity of C/D wafers at each grade for each period and inventory quantity at each grade for the next period. The first-stage formulation is given in Equations (16) – (21).

$$\begin{aligned} min\, Z = & \sum_{j=1}^{J} c_0 x_{0j}^{[1]} + \sum_{j=1}^{J} c_{jj} x_{jj}^{[1]} + \sum_{j=1}^{J-1} c_{j(j+1)}^{(n)} x_{jj}^{[1]} + \\ & \sum_{j=1}^{J} \sum_{k=1}^{J-j} c_{j(j+k)}^{(d)} x_{j(j+k)}^{[1]} + \sum_{j=1}^{J} h_j I_j^{[1]} + E_{\xi}\left[Q\left(X, I, \xi^S\right)\right] \end{aligned} \tag{16}$$

Subject to

$$r_j x_{jj}^{[1]} \ge d_j^{[1]}, \quad j = 1, 2, \cdots, J \tag{17}$$

$$I_j^{[0]} + x_{(j-1)(j-1)}^{[1]} + \sum_{k=1}^{j\text{-}1} x_{(j-k)j}^{[1]} = I_j^{[1]} + \sum_{k=0}^{J-j} x_{j(j+k)}^{[1]}, \quad j = 1, 2, \cdots, J \tag{18}$$

$$x_{jj}^{[1]} \Big/ \left(I_j^{[0]} + x_{(j-1)(j-1)}^{[1]} + \sum_{k=1}^{j\text{-}1} x_{(j-k)j}^{[1]} \right) \le R_r, \quad j = 1, 2, \cdots, J \tag{19}$$

$$x_{jJ}^{[1]} \Big/ \left(I_j^{[1]} + \sum_{k=1}^{J-(j+1)} x_{j(j+k)}^{[1]} \right) \ge R_s, \quad j = 1, 2, \cdots, J \tag{20}$$

$$I_j^1 \ge u, \quad j = 1, 2, \cdots, J \tag{21}$$

All variables are non-negative integers.

Equation (16) is the objective function that includes the cost of new C/D wafers, recycling cost, downgrading cost due to natural, downgrading cost due to demand, holding cost, and the expected cost of the second stage. The operative constraints, of which the first stage given a specific scenario, are formulated as follows. Equation (17) presents that the recycling capacity of the C/D wafers must meet the integrated demand of the j^{th} grade. Equation (18) consists of balance constraints representing that the arrivals are equal to the departures at each grade. The recycle ratio is not more than a positive percentage given by Equation (19). The scrap rate is not less than a positive percentage given by Equation (20). The inventory of each grade is kept at a minimum level by Equation (21).

The second-stage formulation is given in Equations (22) – (27).

$$\begin{aligned} min \quad Q(s) = & \sum_{j=1}^{J} c_0 x_{0j(s)}^{[2]} + \sum_{j=1}^{J} c_{jj} x_{jj(s)}^{[2]} + \sum_{j=1}^{J} c_{j(j+1)}^{(n)} x_{j(j+1)(s)}^{[2]} \\ & + \sum_{j=1}^{J} \sum_{k=1}^{J-j} c_{j(j+k)}^{(d)} x_{j(j+k)(s)}^{[2]} + \sum_{j=1}^{J} h_j I_{j(s)}^{[2]} \end{aligned} \tag{22}$$

Subject to

$$r_j x_{jj(s)}^{[2]} \geq d_{j(s)}^{[2]}, \quad j = 1, 2, \cdots, J,\ s = 0, 1, \cdots, S \tag{23}$$

$$\begin{aligned} & I_j^{[0]} + x_{(j-1)(j-1)(s)}^{[1]} + \sum_{k=1}^{j-1} x_{(j-k)j(s)}^{[1]} = I_{j(s)}^{[1]} + \sum_{k=0}^{J-j} x_{j(j+k)(s)}^{[1]}, \\ & j = 1, 2, \cdots, J,\ s = 0, 1, \cdots, S \end{aligned} \tag{24}$$

$$x_{jj(s)}^{[2]} \bigg/ \left(I_{j(s)}^{[1]} + x_{(j-1)(j-1)(s)}^{[2]} + \sum_{k=1}^{j-1} x_{(j-k)j(s)}^{[2]} \right) \leq R_r, \quad j = 1, 2, \cdots, J,\ s = 0, 1, \cdots, S \tag{25}$$

$$x_{jJ(s)}^{[2]} \bigg/ \left(I_{j(s)}^{[2]} + \sum_{k=1}^{J-(j+1)} x_{j(j+k)j(s)}^{[2]} \right) \geq R_s, \quad j = 1, 2, \cdots, J,\ s = 0, 1, \cdots, S \tag{26}$$

$$I_{j(s)}^{[2]} \geq u, \quad j = 1, 2, \cdots, J,\ s = 0, 1, \cdots, S \tag{27}$$

All variables are non-negative integers.

In the second-stage formulation, Equation (22) represents the objective function of the second stage. Given a scenario, Equations (23) – (27) are similar to those at the first stage from Equation (17) – (21). Especially, the inventory for each grade at the end of period $t = 1$

is available for withdrawal in the next period, and provides the linkage between the two stages of the C/D wafer downgrading problem. All variables are non-negative integers. Finally, the first and second stage can be summed up into a single large linear programming model. Therefore, we determine all *x*'s and *I*'s to be optimal over all the scenarios because we solve the large linear programming model for all decision variables simultaneously.

4.2 Optimization Methodology

4.2.1 Demand Model and Scenario Construction

The demands of products are modeled with a geometric Brownian motion process. Geometric Brownian motion (GBM) was firstly proposed to describe the variation of the stock price by Black and Scholes [7]. Benavides *et al.* [4] applied Geometric Brownian motion as the demand model for IC manufacturing industry, since the historical data is consistent with Semiconductor Industry Association data. According to Dixit and Pindyck [28], if $D_m^{[t]}$ is the demand of product *m* in period *t* for C/D wafer downgrading problem, then the rate of change of this demand is assumed to be governed by Equation (28).

$$dD_m^{[t]} = \mu_m D_m^{[t]} dt + \sigma_m D_m^{[t]} dz, \quad t = 1, 2, \cdots, T; m = 1, 2, \cdots, M. \tag{28}$$

In Equation (28) $dz = \varepsilon_t \sqrt{dt}$ and ε_t is assumed as a standard normal random variable with respect to the time interval *t*. This model of demand implies that the variability of demand increases linearly with the length of demand forecast horizon, so that over a finite time interval *t*, the change between the logarithms of demands in two different periods is distributed as Equation (29):

$$ln\left(D_m^{[t]}\right) - ln\left(D_{\boldsymbol{m}}^{[1]}\right) = ln\left(\frac{D_m^{[t]}}{D_m^{[1]}}\right) \sim N\left(\left[\mu_m - \frac{\sigma_m^2}{2}\right] t, \sigma_m^2\, t\right), \tag{29}$$

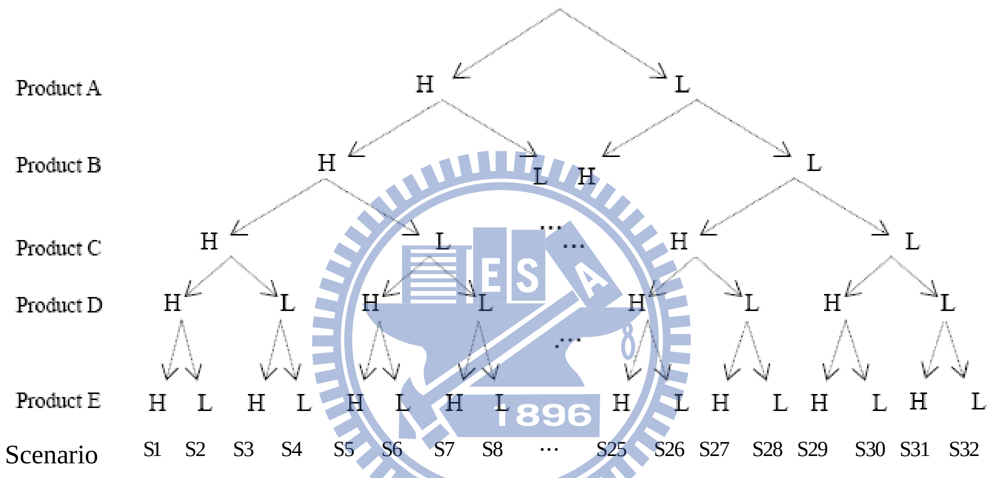
$$m = 1, 2, \cdots, M\,,\ \ t = 1, 2, \cdots, T$$

In models of decision making under uncertainty, it is essential to represent uncertainties in a form suitable for quantitative models. It is the most popular method for stochastic programming to generate a limited number of discrete scenarios that satisfy specified the random variables. Jarrow and Rudd [44] proposed binary tree with equal probability method to generate as small number of scenarios as possible and proved it has reasonably good approximation.

Hence, this method is used to generate the demand distribution of each product at the second. Note that $D_m^{[1]}$ represents the demand of product *m* in the period *t* = 1. There are two possibilities of demands for product *m* in the period *t* with probability 0.5 as Equation (30).

$$D_m^{[t]} = D_m^{[1]}\,exp\left(\left[\mu_m - \frac{\sigma_m^2}{2}\right] t \pm \sigma_m^2 \sqrt{t}\right),\ \ m = 1, 2, \cdots, M\,;\ \ t = 1, 2, \cdots, T \tag{30}$$

As an approximation example of five products, an event tree with 32 scenarios was constructed with two branches in each node, which represents high demand or low demand as shown in Figure 4-1. A scenario is a sequence of events. For example, scenario 1 is the set of event sequences {H, H, H, H, H} as high demands for each product A to E, respectively.



* H represents high demand and L represents low demand

Figure 4-1 Event tree and scenarios for SC/DWD problem model

No need to reticence, there are no guarantees that those scenarios assembled in this particular manner can adequately represent the uncertainty of the C/D wafers demands caused by product mix. To address these potential limitations, sensitivity analyses are presented in a later section.

4.2.2 Solution Procedure

By taking all possible scenarios into account, the first- and second-stage linear programming models can be summed up into a single large linear programming model. The objective function of equation (16) can be extended to equation (31) for large-scale linear programming model. In other words, we are choosing all of x's and I's to be optimal over all the scenarios because we solve for all decisions simultaneously.

$$
\begin{aligned}
min \quad Z = &\sum_{j=1}^{J} c_0 x_{0j}^{[1]} + \sum_{j=1}^{J} c_{jj} x_{jj}^{[1]} + \sum_{j=1}^{J-1} c_{jj}^{(n)} x_{jj}^{[1]} \\
&+ \sum_{j=1}^{J} \sum_{k=1}^{J-j} c_{j(j+k)}^{(d)} x_{j(j+k)}^{[1]} + \sum_{j=1}^{J} h_j I_j^{[1]} \\
&+ \sum_{s=1}^{S} \sum_{j=1}^{J} p_{j(s)} \left[\sum_{j=1}^{J} c_0 x_{0j(s)}^{[2]} + \sum_{j=1}^{J} c_{jj} x_{jj(s)}^{[2]} + \sum_{j=1}^{J-1} c_{jj}^{(n)} x_{jj(s)}^{[2]} \right] \\
&+ \sum_{s=1}^{S} \sum_{j=1}^{J} p_{j(s)} \left[\sum_{j=1}^{J} \sum_{k=1}^{J-j} c_{j(j+k)}^{(d)} x_{j(j+k)(s)}^{[2]} + \sum_{j=1}^{J} h_j I_{j(s)}^{[2]} \right]
\end{aligned}
\qquad (31)
$$

4.3 Implementation of Stochastic C/D Wafers Downgrading Problem

To investigate the effect of the stochastic management system on the planning, real-world data is taken from a wafer fabrication factory located in the Science-Based Industrial Park in Hsin-Chu, Taiwan.

4.3.1 Numerical Example and Input Information

In this production system, regarded as base case, there are five products A, B, C, D, and E with product mix 5: 7: 3: 4: 1 at the first stage. Based on historical data, we applied a geometric Brownian motion model and estimated the drift and variance parameters of the demands for each product, as given in Table 4-1. The monthly throughput target is 640 lots and the planning period is 28 days. C/D wafers can be categorized into three levels according to their conditions suitable for use in process. At the end of period t = 0, the inventory quantity is 30 for grade 1, 40 for grade 2, and 50 for grade 3. The maximum times of recycling a C/D wafer at each grade is 4, 5, and 6 for grade 1, 2, and 3, respectively. Table 4-2 gives the frequencies of using the j^{th} grade C/D wafers for each product and the unit cost for each kind is given in Table 4-4. The multilevel downgrading rule is implemented to minimize the total cost for SC/DWDP. Finally, the large Linear programming model is solved by using LINDO 6.01.

Table 4-1 The parameters of demands for each product

	Product				
Parameters	A	B	C	D	E
μ	0.14	0.18	0.09	0.06	0.07
σ^2	0.22	0.19	0.14	0.14	0.13

Table 4-2 The number of times for C/D wafer consumed by each product at each grade

Product	A	B	C	D	E
Grade 1	6	4	6	7	5
Grade 2	5	6	5	6	9
Grade 3	9	7	8	6	5

Table 4-3 The unit cost for (holding, recycling/natural downgrading, demand downgrading)

	From			
To	New	Grade 1	Grade 2	Grade 3
Grade 1	(-- , 0 ,100)	(6 , 80, --)		
Grade 2	(-- , 0 ,100)	(-- , 70, 80)	(6 , 70, --)	
Grade 3	(-- , 0 ,100)	(-- , --, 80)	(-- , 60, 70)	(6 , 60, --)
Scrap		(-- , -- , 5)	(-- , -- , 5)	(-- , -- , 5)

Table 4-4 Economic benefit analysis for SC/DWDP

Benefit	Optimality	VSS	EVPI	EV	HN	WS
0.78%	0.02%	1139	29	146,414	145,275	145,246

4.3.2 Experimental Results and Sensitivity Analysis

The solution procedure includes the "here and now" (HN), "wait and see" (WS), and "expected value" (EV) approaches. To assess the benefit of the SC/DWDP model, the expected value of perfect information (EVPI) and optimality index are investigated. EVPI measures the value of knowing the future with certainty. Optimality is defined by the ratio of EVPI to the WS optimal solution. It indicates how costly the incomplete information about the future is. To assess the value of knowing and using distributions on future outcomes, the value of the stochastic solution (VSS) and benefit are computed. Since benefit is the ratio of VSS to the HN optimal solution, the larger the benefit of the stochastic solution, the more implemental stochastic optimization is.

The results for SC/DWDP are shown in Table 4-4. With perfect information, the minimized total cost of C/D wafers is 145246 dollars. With a "here and now" decision, we would make a minimized cost of 145275 dollars. Note that the optimality index is 0.02%, which means the stochastic solution is nearly optimal. In other words, the expected value of perfect information is worthless. On the part of the value of the stochastic solution, stochastic programming is superior to the expected approach by 0.78%, as shown in Table 4-4. This implies that, considering demand uncertainty, the accumulated capital could be saved up to 0.3 million US dollars per year for wafer fabrication yielding 30,000 pieces of product wafers a month, since the WIP level of C/D wafers may be as many as 30,000 pieces priced at USD 100 each.

Here sensitivity analysis was conducted to determine how the results of the base case reported above vary with changes in the principal parameters of the model. Cost of new wafers, cost of holding, maximum recycle rate, minimum rate of scrap, and inventory level are included and experimental scenarios are shown in Table 4-5.

The results of the sensitivity analysis are summarized in the “tornado” diagram of Figure 4-2. The figure shows how the percentage of the optimal minimized total cost, compared with the base case, changes as the individual parameter is changed to the high and low values shown in Table 4-5. The dramatic impact of new wafer cost and maximum recycle rate plays the leading role in SC/DWDP management given demand uncertainties. The total cost of C/D wafers varies linearly by 7% while the cost of new wafers varies by 20%. Since the price of new wafers is market-driven, it should be considered as a random variable in future research. Similarly, the impact of the maximum recycle rate on the total cost reflects the importance of reuse characteristic. Nevertheless, a 10% decrease in the recycle rate resulted in 8% increase of total cost. On the contrary, the same amount increase in the recycle rate only saves 4% of total cost. Therefore, one of the thumbs-up rules in C/D wafer management is to keep the recycle rate as high as possible. In contrast, the results show that holding cost, minimum scrap rate, and inventory level restrict the impact that the volatility of demands has on total cost.

Table 4-5 Parameter values for sensitivity analysis

Scenario number	Sensitivity parameter	New wafer cost	Recycle rate	Holding cost	Scrap rate	Inventory
0	Base case	100	80 %	6	10%	40
1	New wafer cost	80	80 %	6	10%	40
2	New wafer cost	60	80 %	6	10%	40
3	Recycle rate	100	70 %	6	10%	40
4	Recycle rate	100	90 %	6	10%	40
5	Holding cost	100	80 %	4	10%	40
6	Holding cost	100	80 %	8	10%	40
7	Scrap rate	100	80 %	6	5%	40
8	Scrap rate	100	80 %	6	15%	40
9	Inventory	100	80 %	6	10%	30
10	Inventory	100	80 %	6	10%	50

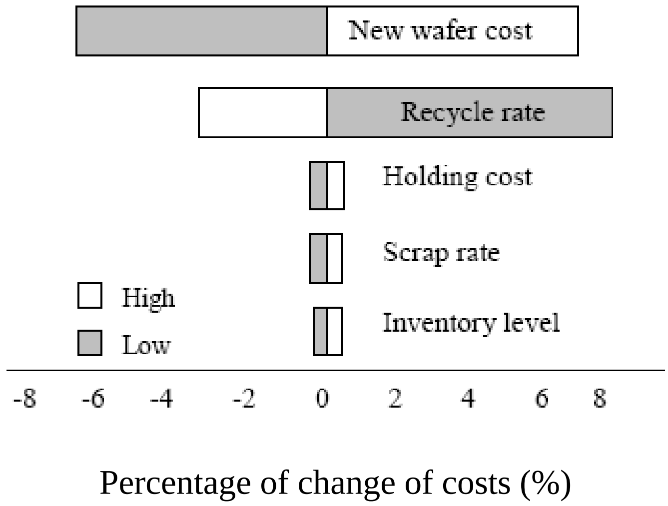


Figure 4-2 Sensitivity of values of optimal alternatives

5. Optimization of the C/D Wafers Service Level Problem

5.1 Formulation of Stochastic C/D Wafers Service Level Problem

In this section, the objective of C/D wafer service level problem (C/DWSLP) is to minimize the total cost of C/D wafers in the system. A chance-constrained programming model is developed to determine how many new C/D wafers to release, how many C/D wafers to be reuse, to be downgraded due to nature or demand, and how many inventories to carry. The C/DWSLP with probabilistic constraints can be formulated as follows:

$$min\, Z =$$

$$min \sum_{t=1}^{T} \left(\begin{array}{l} \sum_{j=1}^{J} h_j I_j^{[t]} + \sum_{j=1}^{J} c_0 x_{0j}^{[t]} + \sum_{j=1}^{J} c_{jj} x_{jj}^{[t]} + \sum_{j=1}^{J-1} c_{j(j+1)}^{(n)} x_{jj}^{[t]} \\ \qquad + \sum_{j=1}^{J} \sum_{k=1}^{J-j} c_{j(j+k)}^{(d)} x_{j(j+k)}^{[t]} + \sum_{j=1}^{J} c^{(s)} x_{js}^{[t]} \end{array} \right) \tag{32}$$

Subject to

$$P\left[\sum_{\tau=1}^{t} r_j x_{jj}^{[\tau]} \geq \sum_{\tau=1}^{t} d_j^{[\tau]} \right] \geq 1-\alpha , \quad j = 1, 2, \cdots, J, t = 1, \cdots, T. \tag{33}$$

$$I_j^{[t-1]} + x_{(j-1)(j-1)}^{[t]} + \sum_{k=1}^{j} x_{(j-k)j}^{[t]} = I_j^{[t]} + x_{jj}^{[t]} + \sum_{k=0}^{J-j} x_{j(j+k)}^{[t]} + x_{js}^{[t]}, \tag{34}$$

$$j = 1, 2, \cdots, J, t = 1, \cdots, T.$$

$$\frac{x_{jj}^{[t]}}{I_j^{[t-1]} + x_{(j-1)(j-1)}^{[t]} + \sum_{k=1}^{j} x_{(j-k)j}^{[t]}} \le R_r, \quad j = 1, 2, \cdots, J, t = 1, \cdots, T. \tag{35}$$

$$\frac{x_{js}^{[t]}}{I_j^{[t]} + x_{jj}^{[t]} + \sum_{k=0}^{J-j} x_{j(j+k)}^{[t]} + x_{js}^{[t]}} \ge R_s, \quad j = 1, 2, \cdots, J, t = 1, \cdots, T. \tag{36}$$

$$I_j^{[t]} \ge u, \quad j = 1, 2, \cdots, J, \quad t = 1, \cdots, T. \tag{37}$$

All variables are non-negative integers.

The objective function, Equation (32), is to minimize the total cost considered. Equation (33) imposes the service level requirement for each grade on cumulative demand from the beginning up to the period t in order to ensure the j^{th} grade C/D wafers satisfying the demand with a predetermined confidence level $1-\alpha$. Equation (34) is representing the balance of the arrival C/D wafers and the departures at each grade in any time period. The recycle ratio is no more than a positive percentage expressed by constraint Equation (35). The scrap rate is no less than a positive percentage represented by constraint Equation (36). The inventory of each grade must be greater than a safety stock level shown by constraint Equation (37). Finally, the production quantities are non-negative integers.

5.2 Optimization Methodology

The solution of the above problem in period 0 for the planning horizon [0, *T*] is referred as the static solution for dynamic problem. The static solution is obtained by using the available information about the distribution of demand in the future periods and the initial inventory. A decision that sets the C/D wafer quantity of each grade at each period is referred to as the dynamic solution. In practice, there are some difficulties with solving the stochastic dynamic problem, such as dimensionality and integrating constraints underlying stochastic processes.

In this section, an integrated approach is proposed for minimizing the total cost of C/D wafers in the system. The approach is developed to decide an appropriate C/D wafer quantity for each grade in each period with a service level predetermined by customers. It integrated three phases as follows:

(i) Transform the empirical demand data of products, if non-normal, into a set of data which is approximately normal distributed,

(ii) Estimate the normal distribution of C/D wafers demand for each grade,

(iii) Transform the chance-constrained programming model into a deterministic one and then solve it dynamically by implementing rolling horizon method.

The detail procedures are in the following:

Step 1: Compute the integrated demands for each grade of C/D wafers in period t by Equation (38).

$$\boldsymbol{d}_{t\times j} = \boldsymbol{D}_{t\times m} \cdot \boldsymbol{f}_{m\times j}, \quad j = 1, 2, \cdots, J, \ m = 1, 2, \cdots, M, \ t = 1, \cdots, T. \tag{38}$$

Step 2: Use method of percentile (MOP) proposed by Hinkley [40] to choose an appropriate power, λ, to transform the empirical demand data into a normal distribution with mean, $\mu_{\boldsymbol{m}}$, and standard deviation, $\sigma^{\boldsymbol{2}}_{\boldsymbol{m}}$.

Step 3: According to normality, the demand of each grade C/D wafer in period t follows a normal distribution as expressed by Equation (39)

$$d_j^{[t]} \sim N\left(\mu_{d_j^{[t]}}, \sigma^2_{d_j^{[t]}}\right), \quad j = 1, 2, \cdots, J, t = 1, \cdots, T. \tag{39}$$

Then, the cumulative demand of each grade C/D wafer from the beginning to the period t also follows a normal distribution as expressed in Equation (40).

$$\sum_{\tau=1}^{t} d_j^{[\tau]} \sim N\left(\mu_{\sum_{\tau=1}^{t} d_j^{[\tau]}}, \sigma^2_{\sum_{\tau=1}^{t} d_j^{[\tau]}}\right), \quad j = 1, 2, \cdots, J, t = 1, \cdots, T. \tag{40}$$

Let $l_j^t = min\sum_{\tau=1}^{t} r_j x_{jj}^{\tau}$ denote the minimum cumulative C/D wafer quantity of the j^{th} grade in period t. Then the chance-constrained Equation (33) can be rewritten as Equation (41).

$$P\left[\sum_{\tau=1}^{t} d_j^{[\tau]} \le l_j^{[t]}\right] = 1-\alpha, \quad j=1,2,\cdots,J, t=1,\cdots,T. \tag{41}$$

After standardization, Equation (41) can be expressed by Equation (42)

$$\Phi\left[\frac{l_j^{[t]} - \mu_{\sum_{\tau=1}^{t} d_j^{[\tau]}}}{\sigma_{\sum_{\tau=1}^{t} d_j^{[\tau]}}}\right] = 1\text{-}\alpha, \quad j=1,2,\cdots,J, t=1,\cdots,T, \tag{42}$$

where $\Phi[\bullet]$ denotes the cumulative distribution function of standard normal. Then the probabilistic constraint Equation (42) can be expressed equivalently by Equation (43).

$$\sum_{\tau=1}^{t} r_j x_{jj}^{[\tau]} \ge \mu_{\sum_{\tau=1}^{t} d_j^{[\tau]}} + \Phi^{-1}[1\text{-}\alpha]\cdot\sigma_{\sum_{\tau=1}^{t} d_j^{[\tau]}}, \quad j=1,2,\cdots,J, t=1,\cdots,T. \tag{43}$$

Step 4: Use Equation (43) to replace Equation (33) of the C/DWSLP formulated in the previous section. The rolling horizon approach repeats this procedure by using the available information in each period until time *T*.

5.3 Implementation of chance-constrained C/D Wafers Problem

5.3.1 Numerical Example and Input Information

To investigate the applicability and effects of the proposed model and approach, actual data is taken from a wafer fabrication factory. There are four products and three grades of C/D wafers. Table 5-1 presents the historical demand records of all products in the last five years.

Table 5-1 The demands of all products in the last five years

Time Period	Past 5 Years	Product			
		A	B	C	D
1	1	126	95	164	304
	2	117	105	182	299
	3	89	69	209	301
	4	78	89	206	345
	5	69	58	219	367
2	1	158	90	198	358
	2	134	88	178	329
	3	117	99	169	432
	4	108	56	159	477
	5	99	63	123	492
3	1	156	149	229	302
	2	105	110	268	295
	3	121	105	201	302
	4	135	103	267	350
	5	98	96	294	368
4	1	123	145	268	327
	2	134	138	259	338
	3	156	135	249	319
	4	89	145	295	323
	5	98	166	283	367

The frequencies of using each grade C/D wafers for products are shown in Table 5-2. Table 5-3 is the cost information. The initial conditions of this system are in the following:

$I_1^0 = 400,\quad I_2^0 = 100,\quad I_3^0 = 100,\quad u_1 = 100,\quad u_2 = 200,\quad u_3 = 400$

Table 5-2 Frequency of using the j^{th} grade C/D wafers for products

Products	Grades		
	1	2	3
A	5	4	3
B	5	3	4
C	3	4	5
D	4	3	5

Table 5-3 The unit cost for

(holding, recycling/natural downgrading, demand downgrading)

	From			
To	New	Grade 1	Grade 2	Grade 3
Grade 1	(-- , 0 ,100)	(6 , 50, --)		
Grade 2	(-- , 0 ,100)	(-- , 50, 80)	(6 , 40, --)	
Grade 3	(-- , 0 ,100)	(-- , -- , 80)	(-- , 30, 70)	(6 , 30, --)
Scrap		(-- , -- , 5)	(-- , -- , 5)	(-- , -- , 5)

5.3.2 Experiment Results and Sensitivity Analysis

The above chanced-constraint C/DWSLP with full downgrading rule, regarded as "base case", was solved to fulfill 95% of service level. Using method of percentile, the best power λ is zero for empirical cumulative demand data in each period. This yields the optimal solution of 733255 by Lingo 8.0. Accordingly to the results, the cost analysis is depicted by Figure 5-1. The new C/D wafers were consumed only at the first grade to ensure as high efficiency as possible (Figure 5-1 (a)). On the contrary, the inventory at the first grade only keeps pre-set minimum safety inventory to avoid running out of stock (Figure 5-1 (b)).

Natural downgrading is the main characteristic for C/D wafers, so it is the best way to increase the utilization. Most of natural downgrading cost is spent at the first grade downgraded to the second grade, shown in Figure 5-1 (c). It means that most of surplus values of the first grade C/D wafers pass on to the next grades. On the other hand, the demand downgrading is a waste of C/D wafer capacity. Therefore, there is no cost for demand downgrading, shown in Figure 5-1 (d), only if unexpected demand occurs. As shown in Figure 5-1 (e), the recycling cost depends on the unit cost and the amount of demand. The highest scraping cost happened at the third grade in each time period, referring to Figure 5-1 (f). This is because the most of C/D wafer capacity has been exhausted. Based on the cost analysis above, the proposed approach performs quite well in fulfilling service level predetermined by customers.

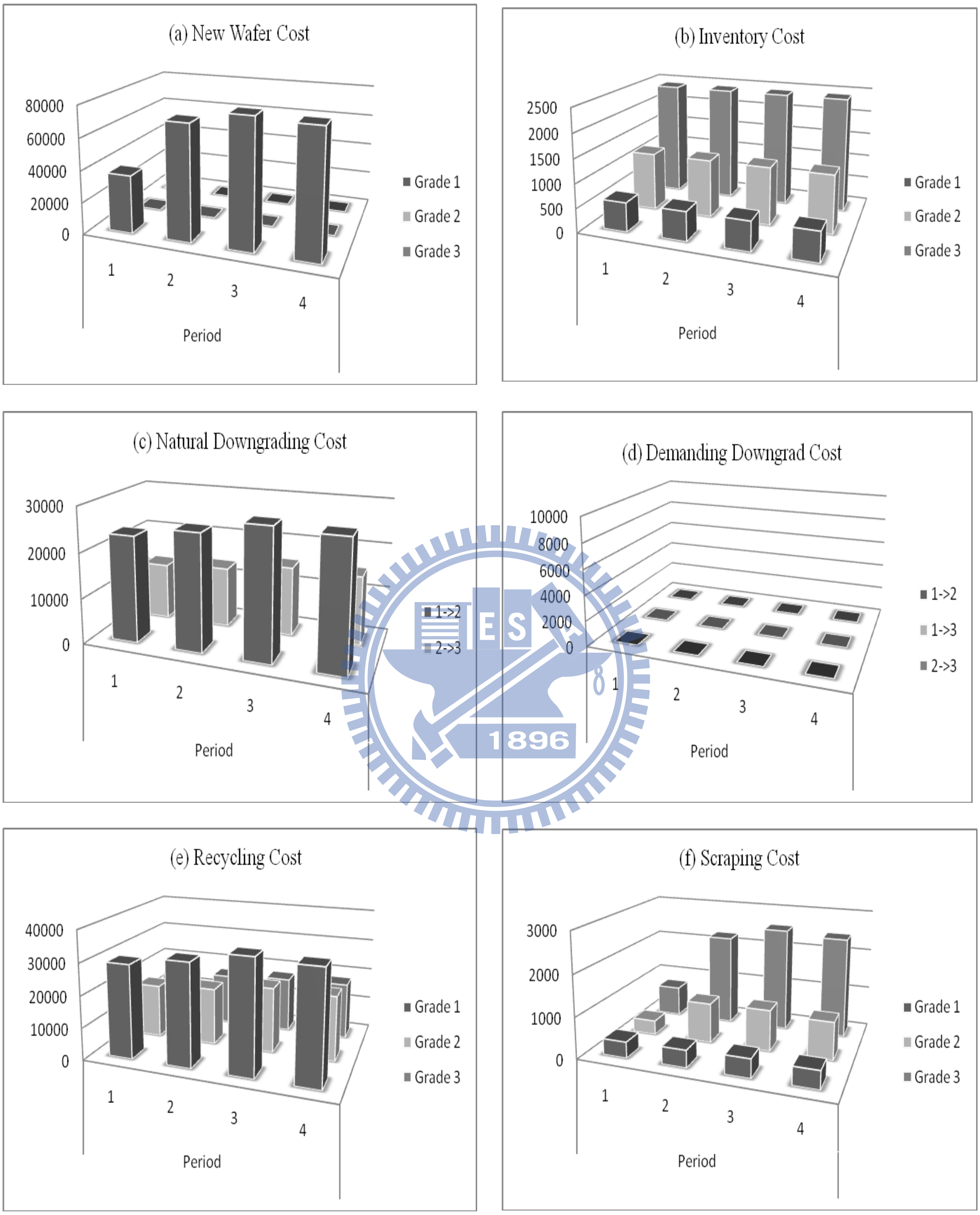


Figure 5-1 Cost analysis for the base case

Next, the base case problem is solved for varying C/D wafers service levels. The optimal total costs incurred are illustrated in Figure 5-2. As shown in the figure, the total cost increases approximately linearly with service level. This initial linear relation changes to an exponential one at service level ranging from 90% to 99%. This indicates that the service level can be improved by 9%, from 90% up to about 99%, at the expense of modest cost increases. Furthermore, the continuously increasing slope of the curve implies that the cost resulted in per percent change in service level increases with service level. This agrees with the classic law of diminishing returns.

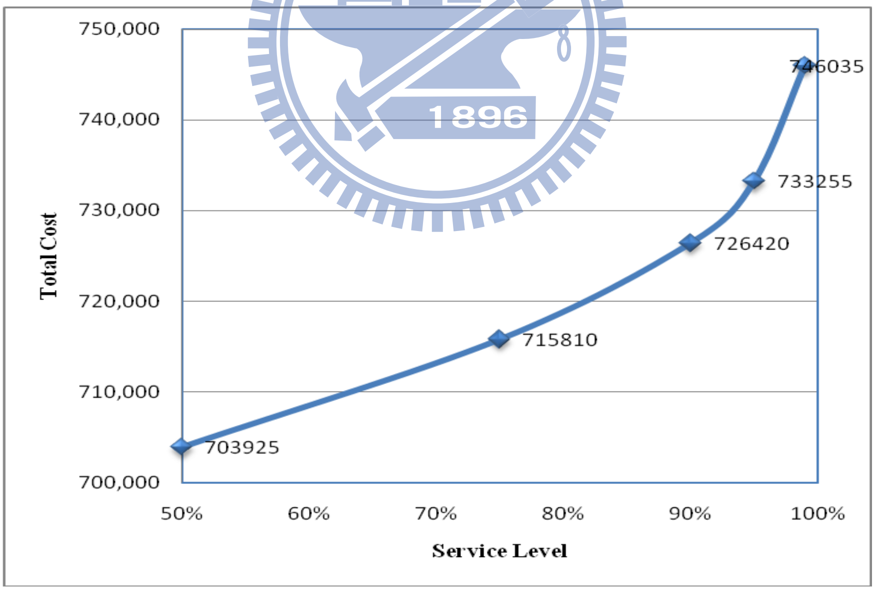


Figure 5-2 Variation of total cost with service level

For sensitivity analysis, seven experiment scenarios are designed and shown in Table 5-4. The first row of the table shows the base case above, while the successive scenarios are 20%

deviations from the base case to capture the model sensitivity with respect to downgrading rule, new wafer cost, natural downgrading cost, and demand downgrading cost. Holding cost is taken the same for all cases, since it only occupies relative small portion of the total cost.

Results presented in the "tornado" diagram of Figure 5-3 summarize the rate of change in total cost with respect to new wafer cost, natural downgrading cost, and demand downgrading cost.

Table 5-4 Experiment scenarios for sensitivity analysis

Scenario number	Sensitivity parameter	New wafer cost	Downgrading Rule	Natural downgrading cost	Demand downgrading cost	Holding cost
1	Base case	100	Full	(40, 30)	(80, 80, 70)	6
2	high new wafer cost	120	Full	(40, 30)	(80, 80, 70)	6
3	low new wafer cost	80	Full	(40, 30)	(80, 80, 70)	6
4	high natural downgrading cost	100	Full	(48, 36)	(80, 80, 70)	6
5	low natural downgrading cost	100	Full	(32, 24)	(80, 80, 70)	6
6	high Demand downgrading	100	Full	(40, 30)	(96, 96, 84)	6
7	low demand downgrading cost	100	Full	(40, 30)	(64, 64, 56)	6

New wafer cost illustrates the leading role in C/D wafers management given demand uncertainties. The total cost of C/D wafers varies linearly by 7% while the cost of new wafers increases or decreases 20%. On the other hand, the results indicate that increasing the natural downgrading cost by 20% has a near 4% increasing effect on total cost. It reveals, instead of releasing new wafers, that reuse downgrading wafers is more efficient and economic. In contrast, demand downgrading cost makes no impact on total cost since it is the last resource to use because its high cost and inefficiency.

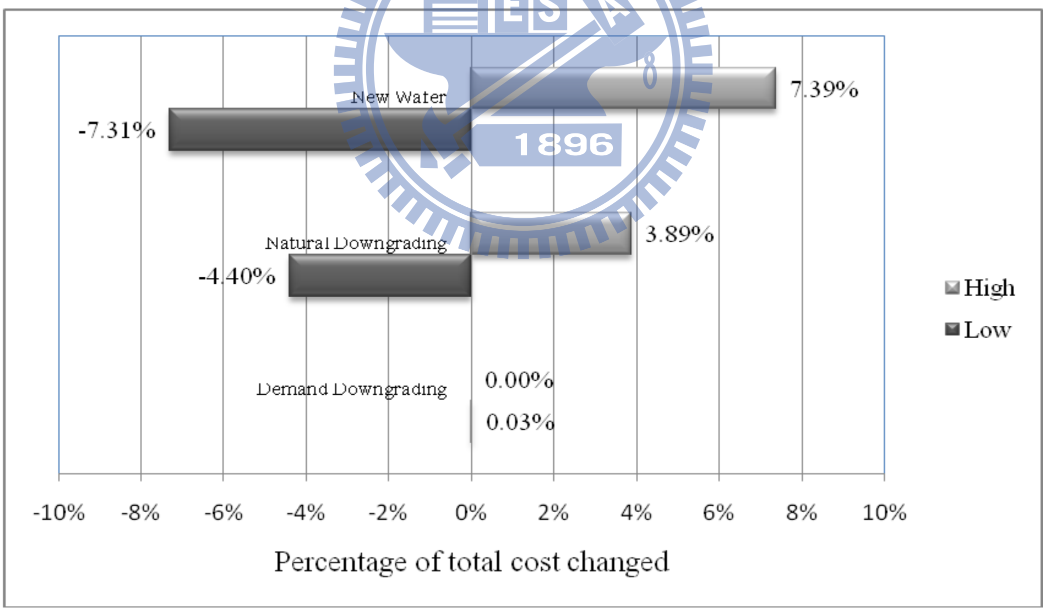


Figure 5-3 Tornado diagram for sensitivity analysis

6. Conclusion Remarks

6.1 Concluding Remarks

C/D wafer management is a challenge to engineers in wafer fabrication. In practice, most C/D wafer management still relies on the experience of field managers. But, setting proper downgrading rule and satisfying service level predetermined by customers becomes a very essential task. There are three contributions of this dissertation. First, uncertain demand condition, the nature of reality, is considered rather than deterministic demand assumed by most other researches. Secondly, a two-stage stochastic programming model for C/D wafer downgrading problem is proposed to determine the quantities of new wafer supply, recycling, and downgrading for each C/D wafer grade. Finally, a chance-constrained programming model is proposed to manage C/D wafers to meet service level set by customers.

A numerical example implements the proposed two-stage stochastic model for C/D wafer downgrading problem (SCDWDP) to minimize the total cost of C/D wafers when demands are uncertain. It verified that this type of model can provide different insights than the deterministic optimization model, in essence, which assumes that future demands are known with certainty. Given the substantial uncertainties of the semiconductor manufacturing business environment, the ability of a stochastic model to deliver the leading performance across a wide range of sensitivity analysis is impressive and valuable. In the presence of uncertainty, it is believed that implementing the multilevel downgrading rule will result in relatively significant savings and increase utilization efficiency by prolonging the life cycle of C/D wafers. However, for C/D wafers downgrading problem, it is impossible to find a solution that is an ideal under all circumstances; even decisions in stochastic models are balanced, or hedged against various scenarios. Therefore, care must be taken not to overstate the benefits of stochastic models.

Secondly, a chance-constrained programming under demand uncertainty was proposed to minimize the total cost subject to constraints for the satisfaction of multiple-product demands with a pre-specified level of probability. In addition, to solve the C/D wafer service level problem, an integrated approach was proposed by combining normal transformation technique and rolling horizon method to solve the resulting mathematical program.

However, uncertain demand is assumed to be normal in most of researches due to its advantages in computations. Normality needs to be tested rather than assumed in order not to induce bias of the analysis. In this paper, we propose implementing Box-Cox transformation as a priori means to the behavior demand distributions. On the other hand, normality of demands gives feasibility that chance-constrained programming can be represented as an equivalent integer programming formulation.

Nowadays, semiconductor manufacturers invest millions of dollars annually to manage control and dummy wafers, so any opportunity that results in savings will be focused. It is believed that both the proposed model and the integrated approach contribute a lot of saving to manufacturers. Both stochastic downgrading and service level problems provide the practical solutions for managing C/D wafers in a fab. With adoption of the proposed stochastic models, a manager can make the utilization of C/D wafers more effective and efficient. And then a wafer fab can create a higher return from investment and be more competing in the market.

6.2 Future Research

Future research directions might include development of efficient dynamic heuristics to solve larger scale dynamic downgrading problem, focus on estimating a demand model and generating economic scenarios to improve the discrete approximation of the probability distribution. In addition, establishing a multi-objective stochastic model for C/D wafers problem to minimize total cost can achieve multiple planning targets at one time.

References

[1] Azaier, M. N., Hariga, M., Al-Harkan, I., A chance-constrained multi-period model for a special multi-reservoir system. *Computers & Operations Research*, 32 (5), 1337-1351, 2005.

[2] Bakir, M. A. and Byrne, M. D., Stochastic linear optimization of an MPMP production planning model. *International Journal of Production Economics*, 55 (1), 87-96, 1998.

[3] Beale, E. M. L., On minimizing a convex function subject to linear inequalities. *Journal of the Royal Statistical Society*, Series B, 17 (2), 173-184, 1955.

[4] Benavides, D. L, Duley, R., Johnson, B. E., As good as it gets: Optimal fab design and deployment. *IEEE Transactions on Semiconductor Manufacturing*, 12 (3), 281-287, 1999.

[5] Bhunia, A. K. and Maiti, M., Deterministic inventory models for variable production. *Journal of the Operational Research Society*, 48 (2), 221-224, 1997.

[6] Bitran, G. R. and Yanasse, H. H., Deterministic approximations to stochastic production problem. *Operations Research*, 32 (5), 999-1018, 1984.

[7] Black, F. and Scholes, M., The pricing of options and corporate liabilities. *The Journal*

of Political Economy, 81 (3) 637-654, 1973.

[8] Blackmore, L., Li, H., and Williams, B., A probabilistic approach to optimal robust path planning with obstacles. *American Control Conference*, 2006.

[9] Bowman, K. O. and Shenton, L. R., Solutions to Johnson's S_B and S_U. *Communications in Statistics, Simulation and Computation*, 17 (2), 343-348, 1988.

[10] Box, G. E. P. and Cox, D. R., An analysis of transformations. *Journal of the Royal Statistical Society*, Series B, 26 (2), 211-252, 1964.

[11] Buffa, E. S., and Taubert, W. H., *Production Inventory Systems: Planning and Control*, Irwin, Homewood, Illinois, 1972.

[12] Bukac, J., Fitting SB curves using symmetrical percentile points. *Biometrika*, 59 (3), 688-690, 1972.

[13] Chang, H. J. and Dye, C. Y., An EOQ model with deteriorating items in response to a temporary sale price. *Production Planning and Control*, 11 (5), 464-473, 2000.

[14] Chang, H. J, Hung, C. H. and Dye, C.Y., A finite time horizon inventory model with deterioration and time-value of money under the conditions of permissible delay in payments. *International Journal of Systems Science*, 33 (2), 141-151, 2002.

[15] Charnes, A. and Cooper, A. A., Chance constrained programming. *Management Science*, 6 (1), 73-79, 1959.

[16] Chen, H. and Kamburowska, G., Fitting data to the Johnson system. *Journal of Statistics in Computation and Simulation*, 70 (1), 21-32, 2001.

[17] Chen, H. C. and Lee, C. E., Control and dummy wafers management. *Journal of the Chinese Institute of Industrial Engineer*, 17 (4), 437-449, 2000.

[18] Chen, H.C. and Lee, C. E., Downgrading and release rules for control and dummy wafers, *International Journal of Industrial Engineering: Theory, Applications and Practice*, 11 (2), 197-206, 2004.

[19] Chen, H. C. and Lee, C. E., Pull system for control and dummy wafers. *The International Journal of Advanced Manufacturing*, 22 (11-12), 805-818, 2003.

[20] Chou, Y. M., Polansky, A. M. and Mason, R. L., Transforming non-normal data to normality in statistical process and control. *Journal of Quality Technology*, 30 (2), 133-141, 1998.

[21] Christie, R. M. E. and Wu, S. D., Semiconductor capacity planning: stochastic modeling and computational studies. *IIE Transactions*, 34 (2), 131-143, 2002.

[22] Chung, K. J. and Tsai, S. F., Inventory systems for deteriorating items with shortages

and a linear trend in demand-taking account of time value. *Computer and Operation Research*, 28 (9), 915-934, 2001.

[23] Chung, S. H., Kang, H. Y., and Pearn, W.L., A linear programming model for the control wafers downgrading problem. *The International Journal of Advanced Manufacturing*, 25 (3), 377-384, 2005 a.

[24] Chung, S. H., Kang, H. Y., and Pearn, W.L., A service level model for the control wafers safety inventory problem. *The International Journal of Advanced Manufacturing*, 26, (5-6), 591-597, 2005 b.

[25] Covert, T. B. and Philip, G. S., An EOQ model with Weibull distribution deterioration. *IIE Transactions*, 5 (4), 323-326, 1973.

[26] Dantzig G. B., Linear programming under Uncertainty. *Management Science*, 1 (3-4), 197-206, 1955.

[27] Das, K., Roy, T. K. and Maiti, M., Multi-item inventory model with quantity-dependent inventory costs and demand-dependent unit cost under imprecise objective and restrictions: a geometric programming approach. *Production Planning and Control*, 11 (8), 781-788, 2000.

[28] Dixit, A. K. and Pindyck, R. S., *Investment under Uncertainty*, Princeton University

Press, 1994.

[29] Draper, N. R. and Cox, D. R., On distributions and their transformation to normality. *Journal of the Royal Statistical Society*, Series B, 31 (4), 472-476, 1969.

[30] Duran, S., Liu, T., Simchi-levi, D., and Swann, J. L., Optimal production and inventory policies of priority and price-differentiated customers. *IIE Transactions*, 39 (9), 845-861, 2007.

[31] Ferguson, A. and Dantzig, G. B., The allocation of aircraft to routes: An example of linear programming under uncertain demand. *Management Science*, 3 (1), 45-73, 1956.

[32] Foster, B., Meyersdorf, D., Padillo, J. M., and Brenner, R., Simulation of test wafer consumption in a semiconductor facility. *IEEE/SEMI Advanced Semiconductor Manufacturing Conference and Workshop*, 298-302, 1998..

[33] Ghare, P. M. and Scharader, G. H., A model for exponentially decaying inventory system. *International Journal of Production Research*, 21 (4), 449-460, 1963.

[34] Gumus, A. T. and Guneri, A. F., Multi-echelon inventory management in supply chains with uncertain demand and lead times: literature review from an operational research perspective. *Proceedings of International Mechanical Engineering*, 221 (B),

1553-1570, 2007

[35] Gupta, A. and Maranas, C. D., A two-stage modeling and solution framework for multisite midterm planning under demand uncertainty. *Industrial Engineering in Chemistry Research*, 39 (10), 3799-3813, 2000.

[36] Gupta, A., Maranas, C. D., McDonald, C. M., Mid-term supply chain planning under demand uncertainty: customer demand satisfaction and inventory management. *Computers & Chemical Engineering*, 24 (12), 2613-2621, 2000.

[37] Hahn, G. J. and Shapiro, S. S., *Statistical Models in Engineering*, Wiley, New York, 1967.

[38] Harris, F., How many parts to make at once, Factory. *The magazine of management*, 10 (2), 135-136, 1913.

[39] Hinkley, D. V., On power transformations to symmetry. *Biometrika*, 62 (1), 101-111, 1975.

[40] Hinkley, D. V., On quick choice of power transformation. Applied Statistics, 26 (1), 67-69, 1976.

[41] Hsu, A. and Bassok, Y., Random yield and random demand in a production system

with downward substitution. *Operations Research*, 47 (2), 277-290, 1999.

[42] Jana, R. K. and Biswal, M. P., Stochastic simulation-based genetic algorithm for chance constraint programming problems with continuous random variables. *International Journal of Computer Mathematics*, 81 (9), 1069-1076, 2004.

[43] Jana, R. K. and Biswal, M. P., Stochastic simulation based genetic algorithm for chance constraint programming problems with some discrete random variables. *International Journal of Computer Mathematics*, 81 (12), 1455-1463, 2004.

[44] Jarrow, A. R., and Rudd, A., *Option Pricing*, Irwin, 1983.

[45] Ji, C. L., Zhang, Y. Y., Wang, Y., and Xu, W. W., Application of chance-constrained programming to design centering, tolerance assignment, and tuning. *Proceedings of IEEE International Conference on Electronics, Circuits and Systems*, 2, 766-769, 2003.

[46] Johnson, N. L., Systems of frequency curves generated by methods of translation. *Biometrika*, 36 (12), 149-176, 1949.

[47] Kall, P., *Stochastic Linear Programming*, Springer Verlag, Berlin, 1976.

[48] Kar, S., Bhunia, A. K. and Maiti, M., Deterministic inventory model with two levels of storage, a linear trend in demand and a fixed time horizon. *Computer and Operation*

Research, 28 (13), 1315-1331, 2001.

[49] King, A., Stochastic programming problems: Examples from the literature. in Ermoliev, Y., and Wets, R. T.-B. (eds.) *Numerical Techniques for Stochastic Optimization*, Springer Verlag, Berlin, 543-567, 1988.

[50] Kumral, M., Genetic algorithms for optimization of a mine system under uncertainty. *Production Planning & Control*, 15 (1), 34-41, 2004.

[51] Leachman, R., Preliminary design and development of a corporate-level production system for the semiconductor industry. Working paper, Operations Research Center, University of California, Berkeley, CA.

[52] Leung, S. C., Wu, Y., and Lai, K. K., A stochastic programming approach for multi-site aggregate production planning. *Journal of the Operational Research Society*H, 57 (2), 123-132, 2006.

[53] Liou, C. S., Lin, T. K., Tu, B., and Chang, A., Capacity forecast model for control and dummy wafers. *IEEE/ISSM International Semiconductor Manufacturing Symposium*, 123-125, 2005.

[54] Mage, D. T., An explicit solution for SB parameters using four percentile points. *Technometrics*, 22 (2), 247-251, 1980.

[55] Manandhar, S. and Tarim, A., Scenario-based stochastic constraint programming. *International Joint Conference on Artificial Intelligence*, 257-262, 2003.

[56] Owen, D. B., The starship. *Communication in Statistics-Simulation and Computation*, 17 (2), 315-323, 1988.

[57] Özelkan, E. C., and Çakanyildirim, M., Resource downgrading. *European Journal of Operational Research*, 177 (1), 572-590, 2007.

[58] Pal, S., Goswami, A. and Chaudhuri, K. S., A Deterministic inventory model for deteriorating items with stock-dependent demand rate. *International Journal of production Economics*, 32 (3), 291-299, 1993.

[59] Petkov, S. B. and Maranas, C. D., Multi-period planning and scheduling of multiproduct batch planning under demand uncertainty. *Industrial Engineering in Chemistry Research*, 36 (11), 4864-4881, 1997.

[60] Platt, D. E., Robinson, L. W. and Freund, R. B., Tractable (Q, R) heuristic models for constrained service levels. *Management Science*, 43 (7), 951-965, 1997.

[61] Plackett, R., Reduction formula for multivariate normal integrals. *Biometrika*, 41, (3-4), 351-360, 1954.

[62] Popovich, S. B., Chilton, S. R., Kilgore, B., Implementation of a test wafer inventory

tracking system to increase efficiency in monitor wafer usage. *IEEE/SEMI Advanced Semiconductor Manufacturing Conference and Workshop*, 440-443, 1997.

[63] Prekopa, A., Numerical solution of probabilistic constrained programming models. in Ermoliev, Y., and Wets, R. T.-B. (editors.), *Numerical Techniques for Stochastic Optimization*, Springer Verlag, Berlin, 123-139, 1988.

[64] Pyzdek, T., Why normal distributions aren't [all that normal]. *Quality Engineering*, 7 (4), 767-777, 1995.

[65] Rao, U. S., Swaminathan, J. M., and Zhang, J., Multi-product inventory planning with downward substitution, stochastic demand and setup costs. *IIE Transactions*, 36 (1), 59-71, 2004.

[66] Shapiro, S. S. and Wilk, M. B., An analysis of variance test for normality. *Biometrika*, 52 (3-4), 591-611, 1965.

[67] Silva Filho, O. S. and Ventura, S. D., Optimal feedback control scheme helping managers to adjust aggregate industrial resources. *Control Engineering Practice*, 7 (4), 555-563, 1999.

[68] Silva Filho, O. S., An aggregate production planning model with demand under uncertainty. *Production Planning & Control*, 10 (8), 745-756, 1999.

[69] Slifker, J. F. and Shapiro, S. S., The Johnson system: selection and parameter estimation. *Technometrics*, 22 (2), 239-246, 1980.

[70] Subrahmanyam, S., Pekny, J. F., and Reklaitis, G. V., Design of batch chemical plants under market uncertainty. *Industrial Engineering Chemical Research*, 33 (11), 2688, 1994.

[71] Tukey, J. W., The comparative anatomy of transformations. *Annals of Mathematical Statistics*, 28 (3), 602-632, 1957.

[72] Wagner, H. and Whitin, T., Dynamic version of the economic lot size model. *Management Science*, 5 (1), 89-96, 1958.

[73] Watkins, D.W., McKinney, D. C., Lasdon, L.S., Nielsen, S. S., and Martin, Q. W., A scenario-based stochastic programming model for water supplies from the highland lakes. *International Transaction in Operation Research*, 7 (3), 211-230, 2000.

[74] Wets, R. J.-B., Solving Stochastic programs with simple recourse. *Stochastic*, 10 (3-4), 219-242, 1983.

[75] Wets, R. J.-B., Large-scale linear programming techniques in stochastic programming. *Numerical Techniques for Stochastic Optimization*, Ermoliev Y., Wets R. T.-B. (eds.). Springer Verlag, Berlin, 65-93, 1988.

[76] Wong, C. Y., and Hood, S. J., Impact of process monitoring in semiconductor manufacturing. IEEE/CPMT *International Electronics Manufacturing Technology Symposium*, 221-225, 1994.

[77] Wu, M. C., Chien, C. S., and K. S. Lu, Downgrading decision for control/dummy wafers in a fab, *The International Journal of Advanced Manufacturing*, 26 (5-6), 585-590, 2005.

[78] Wu, T. H., Huang, C. C., and Yang, Y. S., A tabu search approach for the deterministic and stochastic vehicle fleet mix and routing problem. *Journal of the Chinese Institute of Industrial Engineering*, 18 (2), 102-112, 2001.

[79] Yildirim, I., Tan, B., and Karaesmen, F., A multi-period stochastic production planning and sourcing problem with service level constraints. *Operation Research Spectrum*, 27 (2-3), 471-489, 2005.

[80] You, H. L., Jia, X. Z., Xu, L., and Cheng, G. B., Box-Cox transformation and characterization of microcircuit process equipment. *Research & Progress of SSE*, 25 (3), 398-402, 2005.

[81] Zhang, F., Roundy, R., Cakanyildirim, M., and Hun, W. T., Optimal capacity expansion for multi-product multi-machine manufacturing systems with stochastic

demand. *IIE Transactions*, 36 (1), 23-36, 2004.

[82] Zhu, M., Taylor, D. B., Sarin, S. C., and Kramer, R. A., Chance constrained programming models for risk-based economic and policy analysis of soil conservation. *Agricultural and Resource Economics Review*, 23 (1), 58-65, 1994.