

IMPROVING CUSTOMER SERVICE LEVEL THROUGH CENTRALIZED SUPPLY FLEXIBILITY

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SUBMITTED TO THE SLOAN SCHOOL OF MANAGEMENT AND THE ENGINEERING SYSTEMS DIVISION
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREES OF

MASTER OF BUSINESS ADMINISTRATION


AND

MASTER OF SCIENCE IN ENGINEERING SYSTEMS

IN CONJUNCTION WITH THE LEADERS FOR MANUFACTURING PROGRAM AT THE MASSACHUSETTS
INSTITUTE OF TECHNOLOGY JUNE 2006

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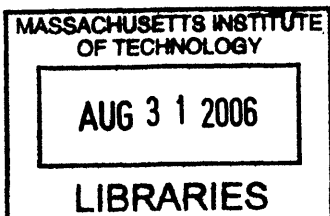
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Submitted to the Sloan School of Management and the Engineering Systems Division on May 15, 2006 in partial fulfillment of the requirements for the degrees of Master of Business Administration and Master of Science in Engineering Systems

ABSTRACT

This thesis explores a combined application of Supply Chain Management theory for centralized and decentralized distribution systems and Customer Relationship Management techniques in data mining to solve the challenges of supply allocations to individual customer entities at Intel Corporation.

The relatively long manufacturing lead time compared to order lead time restricts Intel's supply flexibility from responding to rapid order changes by each customer. As a result, the individual customer service level is sacrificed. Therefore, the objective of the research project is to improve customer service level by global optimization for all customers as opposed to the local optimization that each customer currently operates on. Over-ordering occurs in the local optimization system.

The proposed solution is to use a scientific and systematic methodology of data mining to guide operational strategies that will provide incentives to encourage customers to order more accurately with Intel. Through this exercise, the supplies can be virtually centralized at Intel instead of being committed out to each customer in a decentralized fashion. The hypothesis is that the new system with more accurate ordering from customers will result in increased supply flexibility and higher effective service level.

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ACKNOWLEDGEMENTS

I wish to acknowledge the Leaders for Manufacturing Program for its support. I am grateful for the opportunity to learn, contribute, and grow. My experience as an LFM at MIT and MIT Sloan has a profound impact on me and my perspective in the world at large. The knowledge and inspirations are truly invaluable.

I also wish to thank Intel Corporation for providing the resources and continuous support of the program. I have learned a great deal from working with my two supervisors, Dennis Arnow and Jennifer Rigoni. I also want to thank Tony Newlin and Adam King for sponsoring the project. And Benny Ma, who has been a tremendous help to my understanding of Intel's business processes, products, and organizations.

I also wish to thank my thesis advisors, Don Rosenfield and Roy Welsch. They have given me extremely attentive and responsive support in every aspect. This project will not be a success without all of their support and guidance.

To my fellow LFM classmates from class of 2006, thank you for providing such a wonderful and collaborative learning environment. I especially want to thank Becky Fearing for her unconditional friendship during one of the toughest times in my life.

Finally, to my dad, I will not be here without you.

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1. INTRODUCTION

This thesis is based on a six-month research internship at Intel Corporation. In the past, Intel has focused on technology innovation and has become successful in the microprocessor market.

Over time, Intel has grown its businesses significantly and diversified its product portfolio. The order fulfillment process has become more complex and demand variability between customers has also increased. Driven by technology innovation and increased competitive intensity, the “clockspeed” of the personal computer industry is turning ever faster than before [12], creating an imbalance of lead times between supply and demand. While manufacturing excellence initiatives to reduce cycle time and other process improvements are ongoing in order to alleviate this misalignment, Intel is currently constrained by those circumstances and seeks to find an efficient, fair way to serve its customers. Intel could improve service levels by increasing inventory, but the company would prefer to find a more cost effective approach. By managing supply effectively through improved order accuracy from customers, Intel hopes to deliver the right products at the right time, thereby better meeting its customers’ needs.

The main challenge of achieving an increase in service level that relates to the order accuracy mentioned above can be traced to the problem of over-ordering behaviors from the customers. Because there are no incentives for the customers to order accurately, especially when the needed quantity is less than the allowable allocation amount, there is a tendency on the part of the customers to request larger quantities than what are needed to buffer uncertainties and risks. They hold on to these allocated supplies for as long as they possibly can or until they are certain that they do not need those supplies.

This thesis will address this challenge through three main approaches: first, centralize excess supplies to improve customer service level; second, provide incentive schemes or offer supplier contracts to encourage accurate ordering; third, reduce system variability in terms of over-ordering to achieve improved supply flexibility. The discussion will be organized in the following structure:

Chapter 2, “Background and Context” gives an overview of the project motivation. It describes the company, products, and customers. After establishing the industry value chain and the organizational structure in which the project takes place, *Chapter 3, “Supply Chain Challenge”*, will describe the problem statement, the order fulfillment processes and the business policies that drive the customers’ behaviors as well as constrain the solution space. Moreover, the chapter explains the emergence of the proposed solution. *Chapter 4, “Building Centralized Customer Intelligence”* provides scientific methods supported by literature search on customer relationship management (CRM) and data mining techniques. The statistical analysis of patterns and performance measurement, and classification presents knowledge about customers’ behaviors. *Chapter 5, “Statistical Clustering – a Data Mining Task”* refines the classification by applying clustering techniques. Based on an analysis of historical customer behaviors, natural clustering suggests that four groups are most appropriate. *Chapter 6, “Recommended Operation Strategies”* then describes the strategic actions for implementation in the attempt to drive desired ordering behaviors. The benefits are explained in *Chapter 7, “Supply flexibility”*, which includes a model to illustrate the relationship between reduced over-ordering variability and increased supply flexibility. *Chapter 8, “Further Considerations”* will uncover the limitations of the analysis and suggest further analysis.

2. BACKGROUND AND CONTEXT

2.1. COMPANY PROFILE: INTEL CORPORATION

Intel Corporation, founded in 1968, currently employs 99,900 people worldwide. At the forefront of technological innovation in the semiconductor industry, Intel has accrued revenue totaling \$38.8B in 2005 with a net income of \$8.66B. Intel's corporate mission is to "Do a great job for our customers, employees and stockholders by being the preeminent building block supplier to the worldwide Internet economy¹." In January 2006, the company has re-branded itself and changed its tagline from "Intel Inside" to "Intel Leap Ahead." Prior to this re-branding, it also announced a new platform strategy and underwent one of the biggest organizational restructuring since inception. The new marketing and business strategy represents the most significant shifts of its kind in the company's thirty-seven years of history.

2.2. MICROPROCESSOR MARKETS AND PRODUCTS

As the world's largest chip maker, Intel is the number one market leader in microprocessors. Intel segments its microprocessor market into three major categories: PC desktop (DT), PC mobile (MB), and server (SVR). Each PC market is also segmented into "performance" and "value". For example, the brand name Pentium is under performance and the brand name Celeron is under value. In terms of trend, Centrino's success has fueled the increasing demand for Intel microprocessors and represents unanticipated strong growth in the mobile market. The temporary shortage of MB supplies has influenced customers' ordering

¹ www.intel.com

behaviors. In addition to CPUs, Intel also supplies chipsets, the complementary products to CPUs. Chipsets are monitored against CPU orders with an indicator called “attach-rate” with the ideal attach rate being 100%. The attach-rate that is associated with a customer is defined as the ratio of chipset quantity supplied over CPU quantity supplied to the particular customer. When the desired attach-rate cannot be supported by Intel, the customers will have to purchase the chipsets from third party vendor. This may pose a risk for the customers in terms of the availability and quality of the chipsets that are not supplied by Intel.

A recent surge in mobile demand results in capacity reprioritization for fulfilling higher margin products. This has resulted in an overall trend of decreasing attach-rate. There are two underlying factors to explain this trend. First, because the chipset capacity is constrained, Intel has made a calculated decision to make fewer desktop chipsets due to desktop CPUs having lower margins compared to mobile or server products. Consequently, the desktop attach rate is reduced and can potentially affect the CPU orders. Additionally, the mobile demand has grown at a rate that is faster than the shifts that can be made for changing the chipset production mix between desktop and mobile. Therefore, the chipset attach-rate for mobile is also suffered. The implication is that if the customers are not able to source enough chipsets from third party vendors to go with the CPUs, they may cancel the CPU orders. It is important to understand the factors that induce the cancellation of an order from a customer.

2.3. CUSTOMERS: MANUFACTURERS AND DISTRIBUTORS

Intel's core business is in selling microprocessors to the PC vendors such as Dell, HP, Lenovo, Gateway, other OEMs, and distributors. The PC industry has evolved tremendously during Intel's existence. It has started out with a couple of big players such as IBM and Compaq (now HP-Compaq) and has become a fragmented industry with many players competing on price. Globalization has become the keyword in describing the activities in this industry. The component manufacturing and assembly are taking place in all parts of the world with an outsized presence in Asia. The advantages for PC manufacturers to expand facilities to Asia include low labor costs, physical proximity to a large consumer market as well as to the contract manufacturers. The contract manufacturers in Asia have differentiated themselves by becoming more vertically integrated in order to offer faster lead time and more flexibility. When an industry whose product is being commoditized and is competing on cost leadership, these advantages become critical for a PC company's survival. Additionally, in the attempt to create more economies of scale and to gain more bargaining power over the suppliers, there is a recent trend for industry consolidation. Examples of mergers and acquisitions include Gateway and eMachines, HP and Compaq, Lenovo and IBM PC division.

Another interesting change in customer base is Intel's successful new business development with Apple. The "together at last" speech by Steve Jobs at the Apple's famous MacWorld Conference on June 6, 2005 suggests the excitement that this partnership has generated at both companies. Although at the present day, Apple does not have significant market share, one cannot ignore the long-term implication for Intel as a supplier in terms of additional obligations, resource allocation, and other commitments. Moreover, it is unknown at this

point how this new relationship will affect existing customer loyalty or Intel's relationship with customers such as Dell who currently exclusively uses Intel as the microprocessor supplier of choice.

Intel's customer base has differing business models which are reflected in their supply chain designs. Dell has designed its business with the "direct model" that replaces the traditional retail channel that many PC vendors still support. Dell uses online sales channel to take orders directly and has the ability to shape demand by responsive online promotions. The direct model increases visibility to end consumer demand. Dell is informed of its customer demand on a daily and sometimes even hourly basis. On the other hand, companies like HP and Gateway sell their PC products to retail channels such as BestBuy, Walmart, etc. and are one layer away in the chain from the end consumer. John Sterman's beer game from the theory of system dynamics [6] can provide insights to the effects and implications on ordering behaviors from the two different supply chain models. Sterman [6] explains that each additional link in the supply chain away from the end consumers adds time delay and variability in the demand signals. This phenomenon is referred as the "bullwhip effect" [6]. According to this theory, customers who have longer supply chain should exhibit ordering patterns that have higher variability, but it turns out that it is not necessarily the case. The results of the ordering patterns will be discussed in later chapters.

Because the PC industry has matured and stabilized, the actual demand from end consumers² at the aggregate is steady. However, among each PC maker, the demand can fluctuate

² End consumers are defined as the purchasers of personal computers

significantly. This variability can be attributed to the low switching costs for the end consumers since they can easily change from one brand of computer to another. Although Intel is capable of forecasting fairly accurately the aggregated market demand, it is less informed about the demand at each customer's³ level. Given the delay in the demand signals propagating from end consumers to PC manufacturers and the lack of incentives for the PC manufactures to order accurately, it is challenging for Intel to appropriately allocate its supplies to each PC manufacturer. The proposed solution is to centralize the supplies as much as possible and allow for maximum flexibility in responding to changes. One way to implement this solution is to give incentives to the customers to order accurately.

The proposed solution requires tremendous collaboration, trust, and understanding from the customers. Centralized supply flexibility is a global optimization. Ideally, it benefits all customers such that Intel can be more responsive to order changes. However, to the customers who can locally optimize their share of the supply allocation, it is a much more difficult message to convey. More importantly, it is extremely challenging to implement an incentive system that can motivate all customers equally. Customers have different business objectives that result in over-ordering and will respond to different types of incentives. For example, cost driven customers may care more about financial rewards, but market share driven customers may care more about securing supplies and are less sensitive to discounts. The customer behaviors are not necessarily consistent over time and they do not use the same ordering approaches towards different product segments and families. The observations of the patterns will be explained further in later chapters.

³ Customers are defined as the PC manufacturers

Intel's customer base is organized into multi-national companies (MNC), other original equipment manufacturers (OEM), and distributors (DISTI). DISTIs are also organized into four different regions. The analysis conducted per this research looks at the distributors at the regional level to depict the aggregated behaviors. Each region then is responsible for allocating the aggregated supplies to each distributor. According to this organization of the customer base, there will be thirteen customer entities (eight MNCs, one combined worldwide OEM, and four DISTIS) under study.

2.4. ORGANIZATION STRUCTURE

The project is co-sponsored by two organizations within the Customer Fulfillment Planning and Logistics Group (CPLG) which are Microprocessor Marketing and Business Planning (MMBP) and Supply Chain Transformation (SCT). As depicted in Figure 1, MMBP resides on the "demand" side and is responsible for forecasting the demand of all microprocessor units (roughly \$30B revenue) monthly and quarterly. MMBP also serves as the centralized operation that decides the supply allocation to each region and is organized by product groups. Additionally, MMBP also manages the weekly hotlist process that facilitates regular changes in orders. The forecasts are prepared by incorporating the demand numbers from four regional sales operations.

On the supply side, the fulfillment function carries out production planning for world wide manufacturing and logistics of delivering the products. SCT serves the interface, ensuring the best alignment. The motivation of the project mainly comes from the huge disparity of

lead times from both sides. Relatively long manufacturing lead time cannot respond fast enough to the short demand changing cycle (an estimated 13:1 ratio). The challenge of improving order accuracy is a major concern in both organizations, but the solution will impact MMBP the most. The access to both demand and supply sides is important for understanding the supply chain challenge.

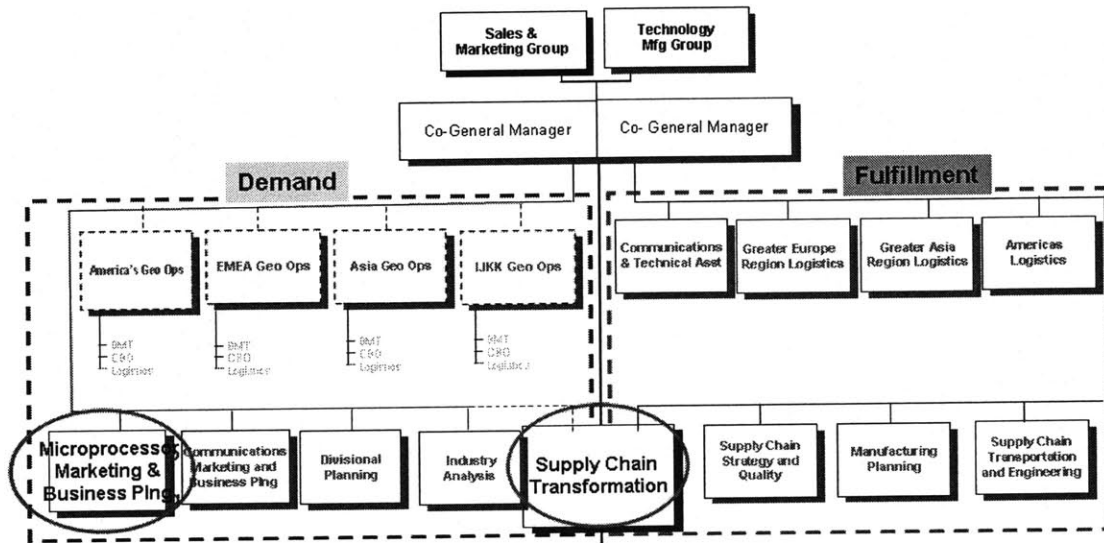


FIGURE 1. ORGANIZATION STRUCTURE FOR PROJECT

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3. SUPPLY CHAIN CHALLENGE

The project motivation comes from the fact there is no incentive for the customers to order accurately. Customers are allowed to cancel orders at the last minute. There has been a common belief in the organization that the customers tend to over order because of the three possible reasons; one, customers sometimes can be over-optimistic of the market condition or its expected performance, two, customers feel the need to buffer risks and demand uncertainties, and third, customers wish to tie up the supplies as competitive advantage assuming there are not enough for every player in the game of competing for market share.

This over-ordering phenomenon has implied risks for Intel, but most importantly, it impedes Intel's ability to provide optimal service level for all customers. Some customers will suffer a shortage not because there is not enough supply, but because supplies are committed incorrectly to over-ordering customers. Ideally, if manufacturing can respond to demand change, in the case of build-to-order, there will be no need to allocate supply in advance. However, because semiconductor manufacturing lead time is much longer than customer ordering lead time, Intel uses a build-to-stock system and utilizes a demand forecast performed quarterly to build chips. Any changes within the thirteen-week lead time will be negotiated by a separate process depending on supply availability at the time. The allocated supplies are referred to as "commits" and the commit processes will be explained later in chapter 4.

On the surface, one may argue that if the aggregate forecast thirteen weeks in advance is accurate, as long as Intel can reallocate the supplies easily and quickly, the financial impact from over-ordering should be minimal. However, sources of potential financial loss include the time value of money and cost of stock out [4]. From the time of supply commitment to cancellation, it can be as long as three months. Financially, money is worth more today than in the future. The earlier Intel can realize the sales, the better. On the revenue side, the publicized price has dropped during this time and Intel may have to sell it at a discount. Qualitatively, Intel risks damaging the relationship with customers served at a later time. Eventually, it can result in real demand lost to competitor. With those the implications, the author has focused on understanding the customer behaviors in terms of ordering patterns from 2003Q1 to 2005Q4 and studied the impact on supply flexibility. The value of improved service level can be derived from the study of the “Cost of Stock Out” [4] by taking the financial difference between current service level and the optimal service level. The improved flexibility will come from centralized supply allocation and transition from local optimization to global optimization in terms of the service levels. The current supply chain has the simplified architecture:

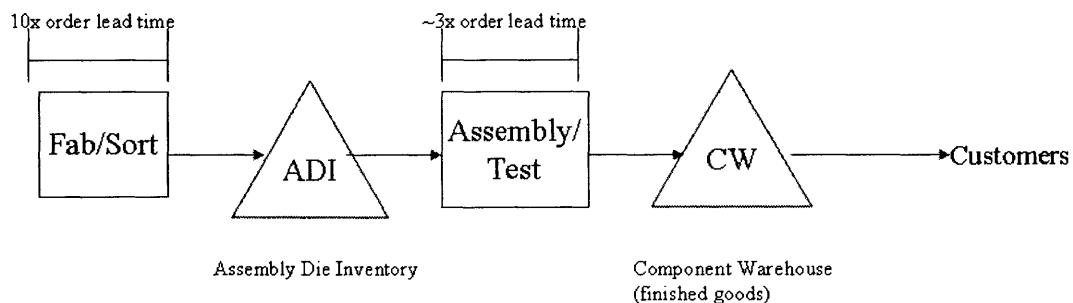


FIGURE 2. MANUFACTURING PROCESS AND SUPPLY CHAIN ARCHITECTURE

Because manufacturing lead time is much longer than the fluctuating demand cycle (changes daily, but managed weekly). Intel has to forecast demand in advance to create the “build plan”, which is a detailed schedule for factories around the world. The over-ordering can be attributed to customers being over-optimistic and buffering risks and demand uncertainties or the customers wishing to game the system to create competitive advantage. In the scenario where the total supply is limited, when a customer hoards the excess supplies, other customers will not be able to receive those supplies. In another words, if two PC vendors are going for the same retail deal, the one who can demonstrate supply commitment from Intel may potentially come ahead of the competition.

In addition, product transitions can also change the ordering dynamics. As Intel introduces new innovative products, it retires the old ones and helps the customers advance technologically. If Intel fails to deliver during product transition, it loses significant credibility and creates the perception of supply shortage. Once this has occurred, it enforces the vicious cycle of over-ordering.

3.1. BUSINESS DYNAMICS IS AN ENFORCING LOOP

The dynamics of the over-ordering situation creates what is known in the theory of system dynamics as a positive feedback loop, also referred as a reinforcing loop [6]. As the customers over order, it tightens up the supply availability and reduces flexibility to respond to changes in orders. Without increasing inventory, when flexibility decreases, service level

at the customer level will decrease even though the aggregate service level remains constant. The customers will respond with exaggerated order quantities to locally optimize their supply needs. This relationship is represented in Figure 3.

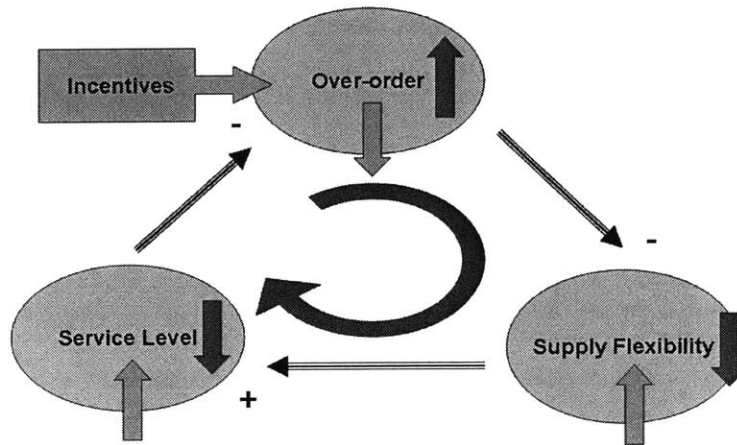


FIGURE 3. CAUSAL LOOP DIAGRAM FOR OVER-ORDER DYNAMICS

The goal of the customer behavior analysis for the research is to find methods to break up this reinforcing loop. Although the dynamics of the relationships are not changed, the directions of the effects are turned around. One way is to provide incentives. The incentives vary from customer to customer and differ from region to region. Providing incentives for profit sharing is considered, but the pricing scheme will have to be studied in detail and is not part of the project scope. Moreover, some customers are driven by discounts or rebates, but some care more about securing supplies than cheaper price. The solution space at the time of the project is narrowed into none-financial incentives to encourage accurate ordering. After talking to various customers, the author recommends a potential incentive of giving differentiated prioritization for supporting changes in orders based on past performance. The

next chapter will discuss the order fulfillment process at the operational level and what non-financial leverage Intel has to influence customer ordering behaviors.

3.2. THE ORDER FULFILLMENT PROCESSES AND BUSINESS POLICIES

Because Intel holds a very large share of the worldwide CPU market, it can utilize both bottom-up and top-down approaches to check and balance the demand numbers. Bottom-up consolidates demand numbers from all customers into a regional number (“GEO method”) and top-down rolls up numbers world wide by each customer (“Multi-National Companies (MNC) method”). The two methods help manage customers’ complex world wide operations. Intel breaks down its world wide sales operation into four regions, namely America (ASMO), Europe (EMEA), Asian Pacific (APAC), and Japan (IJKK). Each geographic operation has two main divisions, Customer Business Operation (CBO) and Business Management Team (BMT) that are critical to the customer orders. As depicted in Figure 4, CBO interacts with each customer account to obtain the regional customer demand and BMT is responsible for collaborating globally to validate the world wide demand by products. After BMT judges the demand numbers, it negotiates with MMBP for supply allocations. In addition, being sensitive to anti-trust issues, BMT serves as the “information keeper” between CBO and MMBP. It shields judgment from any biases. The structure is designed to also prevent favoritism.

The quarterly demand collection, judgment, and negotiation are driven by manufacturing lead time and financial reporting. This quarterly process is referred to as the Corporate Commit Process (CCP) and is managed by MMBP.

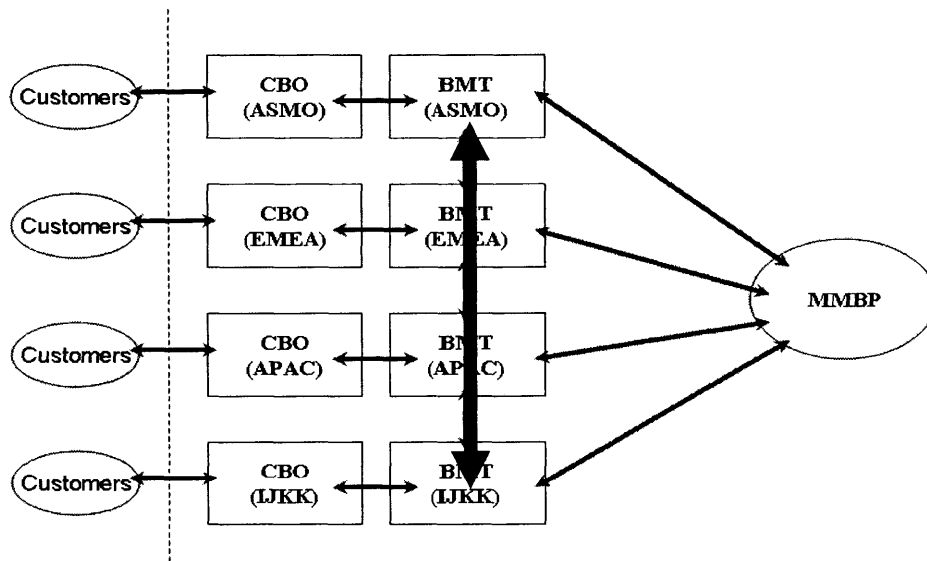


FIGURE 4. DEMAND FUNCTIONAL INTERACTIONS (EXTERNAL TO CPLG)

In parallel, MMBP also has a weekly process referred to as the “Hotlist” support that provides three options for changing orders: a) “upside”, which is a request for ordering additional quantity, b) “swap”, which is changing the order for the same quantity, but with a different product (sku), and c) “pull-in”, which is requesting earlier delivery date than scheduled. CCP facilitate orders thirteen weeks in advance and are outside of the manufacturing lead time. On the other hand, Hotlist facilitates the order changes within lead-time. Using first come first serve, Hotlist decides on granting the requests or not based on availability of the supply. Therefore, the time unit under analysis is based on weekly replenishment to capture the dynamics of the hotlist process.

3.3. PROCESS FLOW AND SUPPLY CHAIN CHARACTERISTICS

The outputs of the business processes relating the internal supply chain is presented in Figure 5. For the purpose of the customer performance analysis, the focus is on Judged Demand (JD), Backlog and Billing (B+B), and Commits from the point of wafer starts to customer delivery. JD is obtained through CCP described before and it includes demands by products. JD will govern the decisions on Assembly and Test (ATM) capacity, wafer starts, and ATM material purchasing. B+B is the combined result of CCP and Hotlist process. ATM will be forward looking the B+B numbers in the system weeks (4x order lead time) ahead to determine the production schedules.

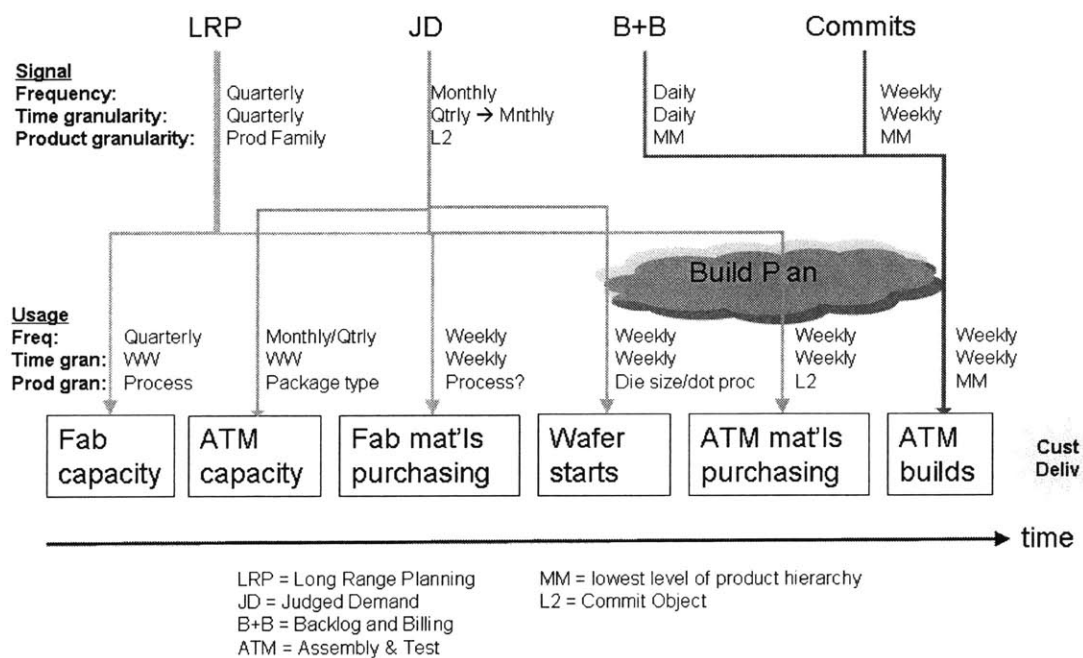


FIGURE 4. SUPPLY CHAIN CHARACTERISTICS

In the order fulfillment operation, JD incorporates customers “raw demand” and other economic factors and it contains the forecasts for the factories to plan the wafer starts. Once

JD is completed, factories do not change the build plan. Changes in orders do not influence what will be built. B+B and Commits will impact the ATM (Assembly & Test) production plan. However, this does not imply that Intel has the flexibility to respond to changes in five weeks because B+B and Commits reflect the negotiated results which are under the limitation of JD. The total demand and supply are stable, but product mix and allocation to customers may vary.

3.4. CANCELLATION AND RETURN POLICIES

In addition to processes, business policies play an essential role for driving customer behaviors. They govern the rules of the game. For Intel, ordering policy for cancellation is very flexible. Some customers can cancel at any time before products are shipped. Products cannot be returned except for defects. In an environment where customers have a choice between suppliers, it is important to benchmark the competitor's policies. Intel's competitor, Advanced Micro Devices (AMD), is rumored to permit product returns from customers. Intel is able to employ less competitive business policies because of the high perceived quality of its products and high switching cost for the customers to change to using AMD's microprocessors. To solve the over-ordering problem, Intel can potentially remove the cancellation policies and force customers to take all the orders placed. However, this is a dangerous move. Not only will this change be hard to implement, but it may also back fire as the risks are not fully understood and the customers' reactions are uncertain.

3.5. SOLUTION SPACE AND ITS IMPLICATIONS

The alternative solution to changing business policies for solving over-ordering problem is to provide incentives to the customers. The goal is to share accountability of the ordering inaccuracy with the customers. Although there are factors internal to Intel that can result in over-ordering, these factors are as difficult to trace as those that come from sources external to Intel. It is not the scope of the project to precisely distinguish the root causes of the over-ordering between Intel and its customers, but rather to infuse the win-win scenario by giving incentives to motivate customers to improve order accuracy. Meanwhile, there are two areas that Intel can focus on internally to prevent over-ordering.

First, one internal factor that contributes to over-ordering is the large supply variability [7] inherent to the semiconductor manufacturing businesses. Especially during new product transitions, the frequent synchronization between marketing and technology roadmaps is critical. When Intel introduces more advanced microprocessors to the customers and gradually retires older products, the customers rely on this timeline to manage their businesses. If the new products are not ready for shipment and it is too late for making substitutes, Intel will fail to deliver the promise and there can be a large cancellation on the bookings. This has happened once in the past within the time under this research study and it has fundamentally changed some customers' behaviors. It has not happened since the last occurrence and it will require continuity on delivering the promises.

Secondly, CBOs play the key roles in ordering behaviors. CBO represents the voice of Intel's customers and is pressured to achieve sales targets. Although being part of Intel, CBOs also strive for securing supplies for customers. With good intentions to help the

customers create localized supply flexibility and build in options for future supply decisions, CBOs who are knowledgeable about the processes will advise tactics to the customers on orders. These tactics can result in over-ordering, including ordering more than what the customers think they will need or ordering high-demand products to gain leverage in swapping later on. One improvement that can be made is increasing communications between MMBP and CBO. The organization goals need to be aligned in the best interests of the corporation. MMBP needs to be informed with field data and CBO needs to understand the benefits of order accuracy. As a company, it is also important for Intel to align the CBO's incentives to drive order accuracy.

In addition to managing inwardly, the efforts for managing outwardly will be described in the following chapters. Intel can utilize the customer intelligence in which this study offers to build an incentive system that is supported by scientific methods for measuring customer ordering performance. The approach hereafter reveals the underlying logic from data mining techniques and inventory theory.

4. BUILDING A CENTRALIZED SYSTEM FOR SUPPLY ALLOCATION

What makes the over-ordering problem that Intel is facing interesting is the fact that it confirms the two main supply chain challenges that Simchi-Levi has summarized [8]. First, the inherent uncertainty in the supply chain makes it impossible to forecast the exact demand. “Forecast is always wrong”. Secondly, local optimization impedes system wide strategy, also known as system optimization. In the case of over-ordering, Intel’s desire for customers’ commitment to orders with stable demand is directly in conflict with customers’ desire for order flexibility and responsiveness. This chapter is about applying supply chain management theories in combination with methods of customer relationship management to build a system that can provide informative decision making for the management as well as tactical fulfillment processes.

As depicted in Chapter 2 and 3, Intel has decentralized customer knowledge residing in its four regional sales operations and it manages the supplies centrally by MMBP. Being two organizations apart, MMBP has limited understanding of the customer behaviors. Here, the author proposes a ranking system that compares customers’ over-ordering behaviors using historical ordering data. This information can aid judgments for supply allocation decisions and provide a value proposition for giving incentives to encourage desired ordering behaviors.

4.1. CUSTOMER RELATIONSHIP MANAGEMENT

The ranking system is a form of customer intelligence, known as Customer Relationship Management (CRM). CRM is the emergence of database marketing and has evolved into a

continuous update of customer behaviors. The concept allows for a company to dynamically provide the best response to changing market conditions. Further considerations of using a CRM tool will be discussed in later chapters.

4.2. CUSTOMER ORDERING PATTERNS

Understanding customer ordering patterns is the first step in formulating a strategy to influence future ordering behaviors. The customer base is divided into individual multi-national companies (MNCs), aggregated other world wide original equipment manufacturers (OEMs), and regionally aggregated distributors (Geo Distis). The patterns of each customer entities for all products, DT, MB, and SVR will be analyzed separately. The ordering patterns are observed weekly in quarterly increments. Because bookings cannot be pushed across the quarter boundary, the quarter-end billing quantity is used as the actual demand for the quarter and it is being compared by the weekly backlog⁴-and-bill⁵ (BnB⁶) quantity. The following depicts the different types of ordering patterns:

⁴ Intel defines “backlog” as orders in the future that have not been fulfilled.

⁵ Intel defines “billings” as orders in the past that are fulfilled and customers are billed for

⁶ BnB is the “Backlog and Billing” = backlog + billing

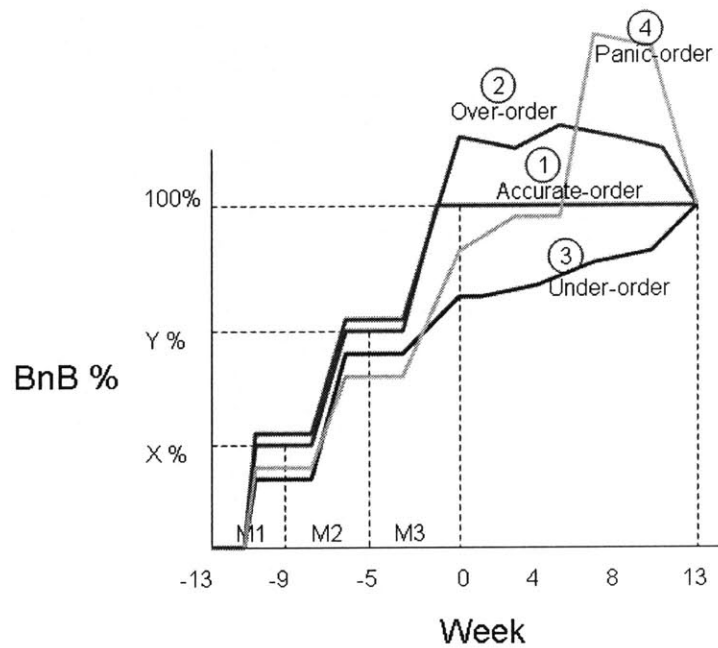


FIGURE 5. TYPES OF ORDERING PATTERNS

The horizontal axis represents the week and the vertical axis represents the percentage of BnB to final billing at the end of the quarter. The weekly BnB quantity is the sum of what is on order and what has been delivered. From week -13 to week 0, BnB consists entirely of what is on order (backlog). The customers start booking during week -13 and week 0 for products to be delivered between week 0 and week 13. From week 0 to week 13, some orders are shipped and customers are billed. Meanwhile, customers use the hotlist process (chapter 3) to request any changes to unfulfilled orders. The BnB amount begins to reflect demand fulfilled and expected future shipment. At week 13, BnB consists of the total billings, equal to the quarter-end shipped volume.

Using such pictorial methodology, the initial observations of the ordering patterns reveal that some customers can order accurately even thirteen weeks in advance and stay close to the final billing quantity (1). Although this may not account for swapping between products beneath the aggregation level of interest, the impact on supply flexibility is minor and overlooked for this analysis. The larger problem is when customers over-order throughout the quarter and cancel at the end (2). An interesting observation is the panic-ordering behavior (3). Some customers can request a large upside without taking it, introducing additional variability in the system. The under-ordering pattern (4) can be the systematic consequence of other customers over-ordering, resulting in lack of supply availability or it may be because of real under-estimate of supplies needed. It is difficult to determine the cause exclusively from the data or to quantify any negative impact on supply flexibility and therefore is omitted from the analysis.

4.3.RANKING SYSTEM

After getting an understanding of the ordering patterns, the next step is to develop a metric for customer performance measurement. It is critical that the metric is aligned with the goal of maximizing supply flexibility and can be explained in a transparent way to the customers in order to drive behaviors. As established previously, in measuring the customers' ordering accuracy, only over-ordering should be considered.

There are two parts of order inaccuracy. The first is the total amount over-ordered. Large amounts of over-ordering implies large amounts of supplies that are inaccurately allocated. The second is the variability of the weekly over-ordering. If the variance of the over-

ordering is high, it creates instability in the system and requires higher levels of safety stocks to maintain the same service level for all customers. In inventory theory, the safety stock is driven by the square root of sum square of the errors [10]. The hypothesis is that variability has added negative impact on system supply flexibility, which will be discussed in chapter 6. Figure 6 illustrates the two elements of over-ordering and the relative impact on supply flexibility. Scenario A has worse impact on supply flexibility than scenario B even though the total amount over-ordered is the same.

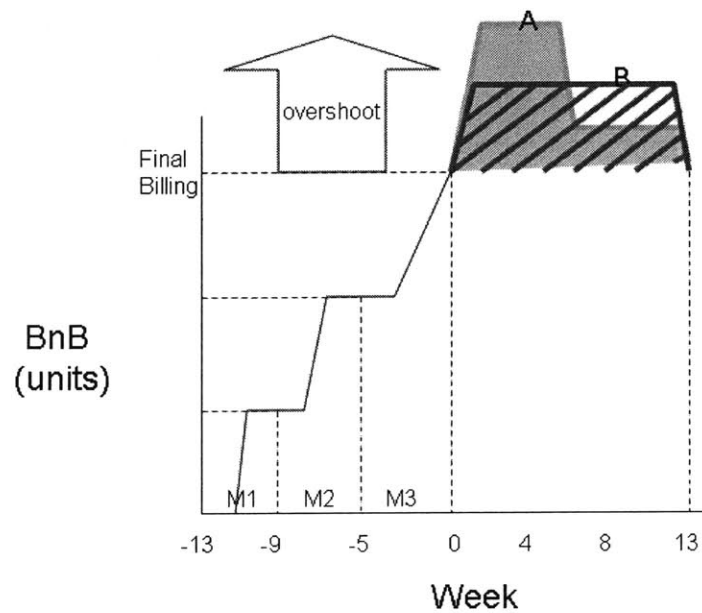


FIGURE 6. WEEKLY OVER SHOTS IN A QUARTER

To capture the impact from the two parts and quantify the relationship mathematically, a new variable is defined to measure the customers.

The “Quarter Over-Shoot (QOS)” is the square root of the sum-squared weekly over-order amount:

$$\text{Quarter Over Shoot (QOS)} = \sqrt{\sum_{i=0}^{i=13} (\text{WOS}_i)^2} \quad (\text{in units})$$

WOS_i (Week *i* Over Shoot) = BnB in Week *i* – Quarter-end Final Billing

Referring back to Figure 6, QOS will yield a larger number for scenario A than scenario B because over-ordering amounts are squared. Using QOS as a measurement of ordering performance for each product segment (DT, MB, and SVR) and product families, a relative ranking of the customer entities is generated for the last twelve quarters. Figure 7 depicts the ranking results from customers’ ordering performance on all products⁷. The x-axis represents time in units of quarters and y-axis is the amount of QOS calculated for each customer. The customer entities are masked to protect confidentiality and are represented by the letters. In each quarter, customers are ranked best to worst from bottom to top.

⁷ “All products” ordering performance uses the aggregated over-ordering amounts from all product segments. If the customers over-order desktop products, but under-order mobile products, no over-ordering amount will be recorded after the offsetting effects. However, a different level of aggregation can be applied using the same ranking methodology (see Appendix I)

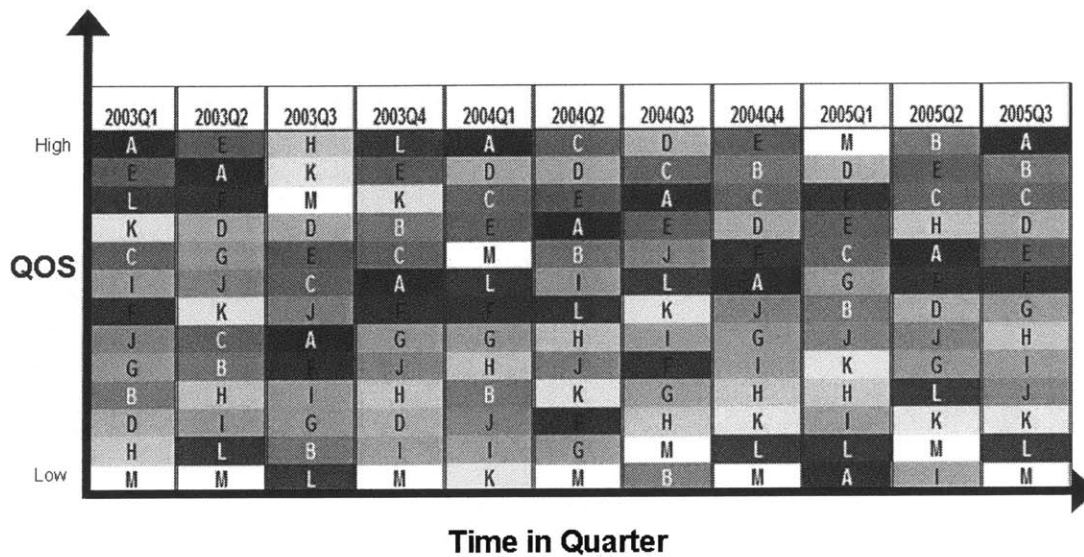


FIGURE 7. CUSTOMER OVER-ORDERING PERFORMANCE - ALL PRODUCTS

There are two weaknesses that lead to further refinement of this ranking methodology. The first is the observation of the rankings being highly variable over time. The magnitude of this variability of each customer's performance can be depicted in Appendix II. The second is that there are some insignificant QOS differences between the performances. Small differences in QOS may not be indicative of customers behaving good or bad. As a result, a clustering technique is employed to further refine the ranking system and suggest a fuzzier differentiation of the performances. The next chapter is devoted to the statistical method of clustering, which is a way to perform empirical classification.

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5. STATISTICAL CLUSTERING - A DATA MINING TASK

The history of database technology starts in the 1960's with data collection and database creation. In 1970's to early 1980's, it evolves into database management systems. The study of data mining is born in late 1980's and has been a continuous research topic to the present day. The clustering methods in the data mining field and knowledge discovery in databases (KDD) have gained increasing attention in various industries. Its applications span from stock market (trend prediction), consumer behaviors (purchase association), and genetics (human genome). The purpose of data mining is to extract knowledge from a large set of data. In the architecture of a typical data mining system, cluster analysis is considered to be part of the data mining engine [1].

Clustering is a discipline aimed at revealing groups of similar entities in data. The existing clustering algorithms can be broadly classified into partitioning and hierarchical [3]. Partitioned clustering determines the clusters based on an optimization of a particular criterion. The most commonly used is squared-error. The squared-error clustering method works well when the data set is large and has compact clouds of clusters that are fairly separated. In the case of QOS performance, the data set is not compactly clouded. Therefore, the Hierarchical clustering method is used. Hierarchical clustering utilizes an agglomerative algorithm, which starts with a disjoint set of clusters (each data point is a cluster of its own) and pairs of clusters then merged until the number of clusters reduces to one. The criterion for pairing is typically the distance measure between the two data points. This chapter will present the five common algorithms for calculating the distance measure and the rationale for selecting the Ward's algorithm.

5.1. HIERARCHICAL CLUSTERING ALGORITHMS

The key step in hierarchical clustering is calculating the “distance” between clusters. One popular statistical tool, JMP (www.jmpin.com), provides methods including average linkage, single linkage, complete linkage, centroid, and Ward.

a) Average Linkage

The average linkage method calculates the average distance between pairs of observations. It is slightly biased towards producing clusters with the same variance (Sokal and Michener 1958). The distance between cluster X and cluster Y is defined.

$$D_{XY} = \sum_{x \in C_X} \sum_{y \in C_Y} \frac{d(x_i, y_j)}{N_X * N_Y}$$

N_X = number of elements in Cluster X, C_X

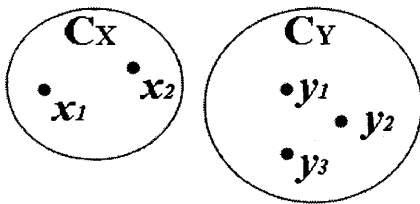
N_Y = number of elements in Cluster Y, C_Y

x_i and y_j represent the QOS quantities in each respective clusters.

$d(x_i, y_j)$ = squared Euclidean⁸ distance between x_i and y_j

⁸ The Euclidean distance between two points $P = (p_1, p_2, \dots, p_n)$ and $Q = (q_1, q_2, \dots, q_n)$, in Euclidean n -space, is defined as:

Example:



$$D_{XY} = [(x_1 - y_1)^2 + (x_1 - y_2)^2 + (x_1 - y_3)^2 + (x_2 - y_1)^2 + (x_2 - y_2)^2 + (x_2 - y_3)^2] / (2 \cdot 3)$$

b) Single Linkage

The single linkage method defines the distance between two clusters as the minimum distance between an element in one cluster and an element in the other. This method is originated by Florek et al. (1951a, 1951b) and then reinvented by McQuitty (1957) and Sneath (1957). It sacrifices performance in the recovery of compact clusters in return for the ability to detect elongated and irregular clusters. It is biased towards chopping off the tails of distributions before separating the main clusters (Hartigan 1981). The mathematical definition is as follows:

$$D_{XY} = \min \{d(x_i, y_j) : x_i \in C_X, y_j \in C_Y\}$$

c) Complete Linkage

The distance measure between two clusters in complete linkage is the maximum distance between elements in clusters. It is biased towards separating clusters with similar

$$\sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \dots + (p_n - q_n)^2} = \sqrt{\sum_{i=1}^n (p_i - q_i)^2}$$

diameters and can be severely distorted by outliers (Milligan 1980). The mathematical formula for complete linkage:

$$D_{XY} = \max \{d(x_i, y_j) : x_i \in C_X, y_j \in C_Y\}$$

d) Centroid

The distance measure in the Centroid method is defined as the squared Euclidean distance between the group averages (mean values of the elements) from the two clusters. The Centroid algorithm is more robust to outliers than most other hierarchical methods. However, it does not perform as well as Ward's method or average linkage (Milligan 1980). The mathematical formula for Centroid is defined as follows:

$$D_{XY} = d(\bar{x}, \bar{y})$$

Using the same example in Average linkage,

$$\bar{x} = (x_1 + x_2) / 2, \bar{y} = (y_1 + y_2 + y_3) / 3, \text{ and}$$

d is the squared Euclidean distance

e) Ward

Ward's distance is a weighted group average criterion. Ward's distance is maximized in Ward divisive clustering⁹ and minimized in Ward agglomerative clustering¹⁰. This

⁹ Divisive clustering is an approach to hierarchical clustering that works from top to bottom, by splitting a cluster in two distant parts, starting from the universal cluster containing all entities

¹⁰ Any method of hierarchical clustering that works bottom up, by merging two nearest clusters at each step

method tends to join clusters with a small number of observations and is strongly biased towards producing clusters with roughly the same number of observations. It is also very sensitive to outliers (Milligan 1980). The mathematical representation for Ward's distance is defined as following:

$$D_{XY} = \frac{N_X * N_Y}{N_X + N_Y} d(\bar{x}, \bar{y})$$

The use of Ward distance keeps the within cluster variance as small as possible at each of the agglomerative steps.

In selecting the appropriate algorithms available in the JMP tool, Ward algorithm is found to be most appropriate. The selection process starts with eliminating single linkage and complete linkage because they are the two extremes of ignoring the outliers and being completely sensitive to the outliers. In over-ordering performance, outliers are the ones that exhibit large QOS and should not be ignored. On the other hand, outliers represent the rare occasions of the poor performances and should not severely affect the clustering of the remaining customer entities. Next, Centroid is eliminated. Although Centriod is more robust to outliers than single and complete linkage methods, it does not perform as well compare to average linkage or Ward's, especially with small number of observations. Choosing between average and Ward is difficult because they both tend to produce clusters with similar variance. As mentioned in Chapter 4, variance drives the impact of supply flexibility. Therefore, this objective aligns with the metric for

measuring customer performance. However, Ward's method is slightly better for two reasons. The first is the stronger bias in producing clusters with the same variance. The second is the better performance when clustering smaller number of observations. The next section will present the clustering results.

5.2. HIERARCHICAL CLUSTERING USING JMP

The hierarchical steps through merging pairs of clusters whose means are the closest. A hierarchy of the clustering can be established. Using the statistical tool, JMP, hierarchical clustering is performed with Ward's algorithm and the distance measure of QOS values. An example of the output is shown in Figure 8 and Figure 9. Figure 8 shows the hierarchical sequence of the clustering and an "elbow plot" depicting each joint effort. The elbow plot graphs the distance that is bridged to join the clusters at each step and can be used to determine the appropriate number of clusters by looking for the natural break.

The appropriate number of clusters is not always obvious and it varies over time. The main consideration between too many clusters and too little clusters is whether or not the clusters are significantly apart. Although it is difficult to validate an exact, appropriate number of clusters, the first step is to narrow down the range of potential numbers using the elbow plot. Sometimes there is a natural break where the distance jumps up dramatically. In the case of MB product in 2005Q3 (Figure 8), either three or four clusters can be appropriate¹¹. For the past thirteen quarters among all three product segments, the natural break for the appropriate

¹¹ Judging the few appropriate number of clusters can be subjective and difficult to automate

number of clusters has been either three or four and there is no evidence that the number of clusters needs to exceed four. Therefore, four is chosen as the number of clusters.

In the example in Figure 8, one can obtain the resulting four clusters, C1, C2, C3, and C4 as follows:

C1: {A, B, M, F, J, C, G, L}

C2: {D}

C3: {E}

C4: {H, I, K}

Any number of clusters can be obtained by using the hierarchical tree in Figure 8 or the clustering history depicted in Figure 9. If clustering into three groups, customer E will be joined with the cluster consisting customers H, I, and K. Noticing that the clustering history in Figure 9 depicts that customer A, B, and M, essentially has the zero Ward distance to each other. In this particular case, these three customers all have QOS value of zero. This demonstrates the importance of introducing clustering techniques to the ranking system.

Product Segment=MB, Time (char)=05Q3
Hierarchical Clustering
Method = Ward

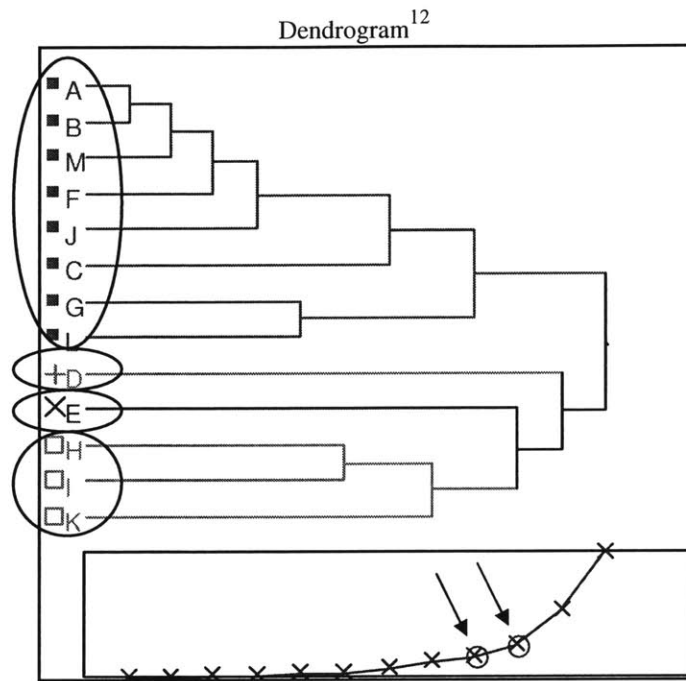


FIGURE 8. DENDROGRAM FROM JMP CLUSTERING EXAMPLE

Number of Clusters	Distance	Leader	Joiner
12	0.000000000	A	B
11	0.000000000	A	M
10	0.009737969	A	F
9	0.029282174	A	J
8	0.055892184	G	L
7	0.062834847	H	I
6	0.164369226	A	C
5	0.332494266	H	K
4	0.447793285	A	G
3	0.729058456	E	H
2	1.574363365	D	E
1	2.940023951	A	D

FIGURE 9. CLUSTERING HISTORY FROM JMP CLUSTERING EXAMPLE

¹² A dendrogram is a tree diagram frequently used to illustrate the arrangement of the clusters produced by a clustering algorithm

There are other soft issues relating to the ranking system such as the implementation challenges and transparency to the customers. The goal is to differentiate the behaviors sufficiently enough to guide the strategic responses without making the process too complex to explain internally or externally. It is important to measure the effectiveness of the ranking system for continuous improvements and to conduct experiments for learning customers' behaviors as they are dynamic.

Figure 10 reveals the result of clustering customer QOS performances on all products for the past 11 quarters. Customer groups are represented as class A, B, C, and D in the order from best performing to worst performing. The result still shows the high variability in the performance over time. Furthermore, there are very few customers (with the exception of 2005Q1) clustered into the worst performing group and many customers clustered into the best performing group. In another words, the supply flexibility is heavily strained by one or two customers and strained by the remaining customers in a cumulative effect. This finding is helpful in designing the operation strategies that will be discussed in the next chapter.

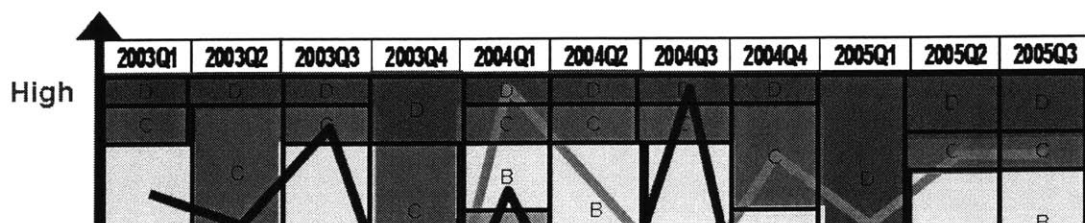


FIGURE 10. CLUSTERED RANKING FOR ALL PRODUCTS

6. OPERATION STRATEGIES

Chapter 4 suggests building a centralized supply allocation system using a customer performance ranking system and chapter 5 refines the ranking system using clustering techniques. This chapter focuses on the impact of financial savings through a higher service level and provides methods of operation strategies that can be implemented for encouraging more accurate customer ordering behaviors. As described in Chapter 5, there are four customer behavior classifications and each requires a different strategy.

Class A: Reward with support priority

Class A exemplifies the desired ordering behavior. Intel has leverage on customers by determining their hotlist priority. Currently the hotlist supplies are granted to requests in a “first come first serve” scheme. After implementing the classification schemes, Intel can differentiate its services according to customers’ historical performance¹³. The implication of Class A behavior is the high trust and confidence level between Intel and customers’ orders. Therefore, supplies should be made available to customers who demonstrate a high probability of turning bookings into actual billings.

Class B: Focused improvements on behavior control

Class B behavior can be described as customers consistently over-order a small amount. This consistency can be interpreted as an intentional risk buffering strategy from customers’ perspective or the initial allowable supplies amount given by Intel consistently exceeds customers’ actual demand. Both scenarios require further customized investigation to analyze

¹³ Historical performance is referred to as the most recent completed quarter

root cause. Although the supply flexibility impact is not severe from each customer, the additive effects still impede Intel's ability to respond to order changes. Therefore, hotlist support should be prioritized lower than Class A customers in order to encourage Class B customers to move towards being Class A.

Class C: Focused Improvements by Closer Supply Integration

With spikes of overshoots in the ordering patterns, dedicated investigations are needed since some problems may be caused internally by Intel through missed new product transition from factory or uncertainty in market conditions. The overshoot spikes imply "panicking" behaviors and closer integration can alleviate the impact of supply flexibility. Collaboration is critical as the customers may be under a more volatile market environment. Intel needs to know quicker and earlier the drivers behind the panics. Examples of supply chain integration include inventory co-management, shared information system, enhanced communication channels, or a combination of those schemes. Again, hotlist prioritization can be leveraged as incentives to encourage more accurate ordering. The priority level will only be higher than Class D, but not higher than Class B because Class C induces variability in the supply allocation system.

Class D: Enforced Judgment

Although not many customer entities belong to Class D, the large amount of supplies and high variability is detrimental to flexibility. The immediate improvement can be made through reducing the initial supply commitment as well as lowering hotlist priority level. How much to be reduced can be an experiment and should happen gradually. One key finding is that the Class

D customers behaviors are not always the same from quarter to quarter even without the interference of any incentive scheme.

The adjustment in allocation strategy is temporary and hopefully a short-term fix until all customers can exhibit Class A ordering behaviors with close to zero QOS. The impact of a drastic response is not well understood as the customers behaviors are complex. It is important to allow time to observe and analyze the results of change in operation strategies.

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7. SUPPLY FLEXIBILITY

Flexibility is about the ability to adapt or change. Ten or fifteen years ago, quality was much like flexibility today: vague and difficult to improve yet critical to competitiveness¹⁴. An article published by Harvard Business Review has alluded the statement to manufacturing flexibility, but the author believes it is even more important to have supply chain flexibility. Extending the factory flexibility analysis to supply chain flexibility in measuring the following four dimensions [9]:

- ❖ **Number of options:** number of tasks or products. Also called range. In the case of order fulfillment, there are three options for changing orders. Customers can request upside, swap, and pull-in.
- ❖ **Heterogeneity:** differences between tasks or products. The characteristics of CPUs can be broken down into die-constrained and non-die-constrained. Die-constraints include speed, cache size, front-side bus, voltage (MB only) and non-die-constraints are package, socket (DT only), and lead-free or not. Those factors are decided at different points in time. In figure 2, die-constraints are determined before the Fab/Sort process in and non-die-constraints can be determined just before the ATM process. For order changes within lead time, Intel has flexibility to a certain degree. Consequently, the difference in the scope of order changing options is that upside is more difficult to support than swap. Pull-in will depend on when the requests are received and how much time advancement is being requested. The earlier the request is made for a shorter pull-in, the higher the flexibility. However, the earlier the request, the higher uncertainty of the request.

¹⁴ Harvard Business Review “what really makes factories flexible?”, July-August, 2005

- ❖ **Changeover:** time, cost, and effort to changeover process or machine. Also called mobility. The more centralized the supplies are, the more flexibility there is to fulfill a different order change request. It allows for the pooling effect of available inventory.
- ❖ **Uniformity:** similarity of quality, costs, time, etc. This can imply a uniform customer service level. The higher variability among customers' over-ordering, the lower the uniformity is.

7.1. CUSTOMER SERVICE LEVEL

One of the most common and traditional ways of increasing service levels is to increase weeks of inventory (WOI), provided that the capacity of manufacturing as well as warehouses allow it. The tradeoff is the increase in inventory carrying cost. The relationship of inventory and service level can be depicted in Figure 17. A denotes to current state with service level X%. Increase in WOI can move A to B and result in a new service level that is greater than X%. The hypothesis is such that more accurate ordering can shift the curve rightward. Keeping the same inventory level, service level can be improved from X% to Y%.

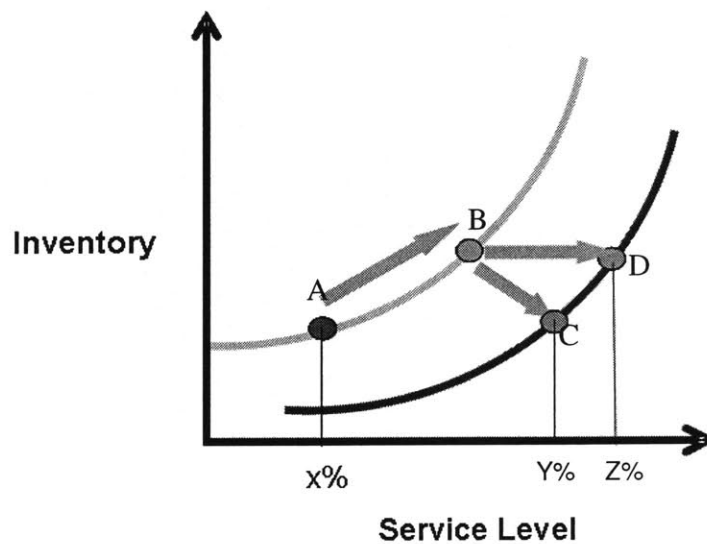


FIGURE 11. INVENTORY VS. SERVICE LEVEL

7.2. SERVICE LEVEL IMPACT OF OVER-ORDERING

There are two parts to the over-ordering problem that impedes supply flexibility and reduces the effective service level: one, the average amount over-ordering amount; two, the weekly variability of the over-ordering. The average over-ordering amounts reflect the average state of the supply flexibility. On the other hand, the weekly variability of the over-ordering reflects the volatility of supply flexibility. Although both factors reduce Intel's ability to reallocate the supplies in response to the changes in demand, the discussion here focuses on the quantitative impact of the weekly variability.

In supply chain management theory, when the centralized and decentralized systems have the same total safety stock, the service level provided by the centralized system is higher. The

magnitude of the increase in service level depends on the coefficient of variation and the correlation between demand from the different markets (Simchi-Levi, Kaminsky 2003). Here the different markets can be represented by the different customer entities. This idea is similar to “risk pooling”, which suggests that aggregating demand can reduce the variability in the system, hence allows for lower safety stock requirement to achieve the same service level. If safety stock level is kept the same, service level is increased. This analogy can be applied to a centralized supply allocation system. The difference is that Intel is also trying to influence at individual customer’s service level. In the case of Intel’s commitment to customers, customer’s ordering volatilities can offset each other. Existing allocation policy is decentralized and evidently, the effective service level is lower than expected service level according to the inventory policy.

7.3. MODEL SERVICE LEVEL IMPACT

The mathematical relationship between variability (σ) and service level can be described as the following:

$$\textit{Supply Buffer} = k (\textit{service level}) * \sigma$$

Supply Buffer represents the excess supply over total market demand. At the operating level, Intel refers this as the Left-To-Book (LTB). The time unit is as fine as daily. LTB equates to inventory level plus expected builds from factories and subtract the committed supplies. k is a function of service level in percentage and its value is distribution dependent. Assuming a normal distribution, k can be obtained using the standard normal z-table. σ is the variability

or standard deviation between the quarterly over-order quantities (QOS) from the customer entities in a given week.

To model the impact of reduced variability on service level, the supply buffer is kept constant. The inverse relationship implies that reduced variability will result in an increased service level: $\downarrow \sigma \Rightarrow \uparrow \text{service level}$

The current state has service level $SL1$, the resulting k value of $k1$, and variability of $\sigma1$. The new state has service level $SL2$, the resulting k value of $k2$, and variability of $\sigma2$. $k1 = k(SL1)$ and $k2 = k(SL2)$, which are distribution dependent. With fixed supply buffer, $k2$ can be derived as follows:

$$\text{Supply Buffer} = k1 * \sigma1 = k2 * \sigma2$$

$$\Rightarrow k2 = \frac{k1 * \sigma1}{\sigma2}, \text{ where } \sigma1 > \sigma2$$

Assuming normal distribution $SL2$ can be obtained by using an inverse of the standard normal cumulative distribution function in Excel:

$$\Rightarrow SL2 = \text{NORMSINV}(k2), \text{ where } SL2 > SL1$$

This service level improvement has the potential financial savings¹⁵ from not stocking out. According to the model (Sonnet, 2005), the estimated total savings of \$2.5M can be achieved through improvements from current service levels (SL1) to optimal service level of 98% (SL2). Based on the estimated current service levels for DT, MB, and SVR, the required percentage reduction in over-ordering variability for DT, MB, and SVR are 38%, 38%, and 20% respectively. The graphical representation can be illustrated below:

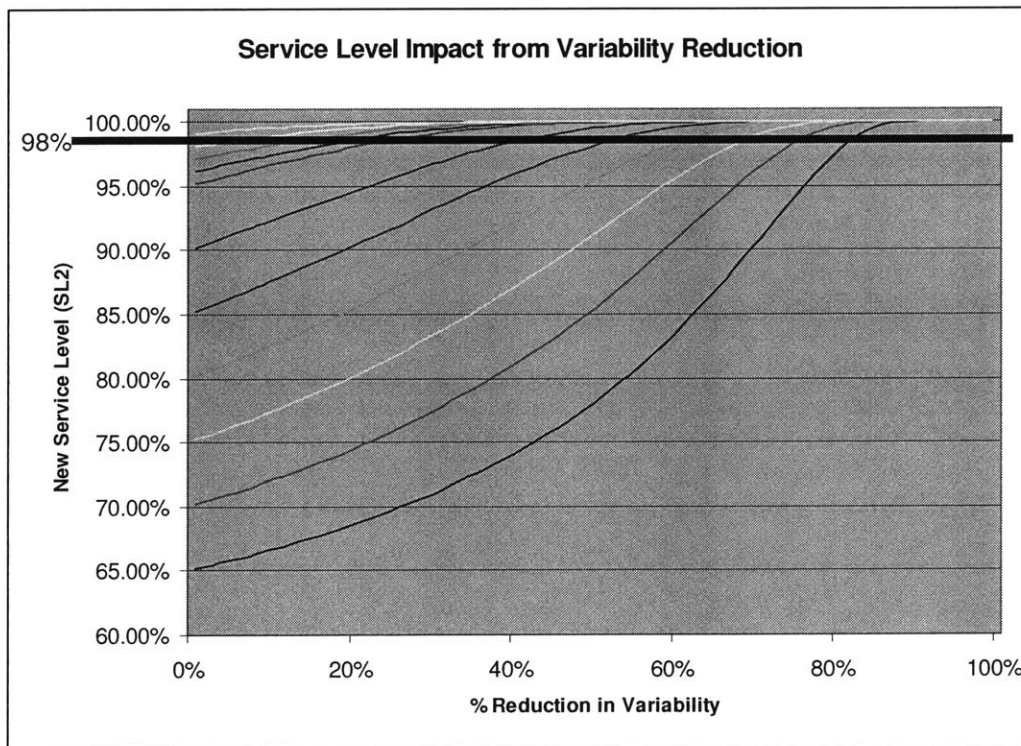


FIGURE 12. VARIABILITY REDUCTION AND SERVICE LEVEL IMPROVEMENTS

Once the percent reduction (P%) is obtained, the targeted weekly variability in units (σ_2) can be derived using initial variability (σ_1): $\sigma_2 = \sigma_1 * (1 - P\%)$

¹⁵ “Cost of Stock Out”, Claudia Sonnet (2005)

8. FURTHER CONSIDERATIONS

Customer behaviors are not static. The dynamics that influence ordering patterns are complex and changing. The analysis conducted here focuses on a high level framework in understanding some of the factors and implications of the over-ordering. The core metric in measuring customer performance involves the calculation of QOS, which is based on quarterly performance and for product segments (DT, MB, and SVR). However, similar analysis can be conducted for monthly performance or for product families. The optimal level of granularity in any dimension is not clear and selecting the appropriate slicing of the variable cube can vary depending on business processes or demand cycles.

Other limitations of the current analysis include:

- 1) The analysis does not address the under-ordering situation. The hypothesis is that if over-ordering can be corrected, the under-ordering phenomenon will disappear naturally in the condition of a perfectly accurate aggregated forecast.

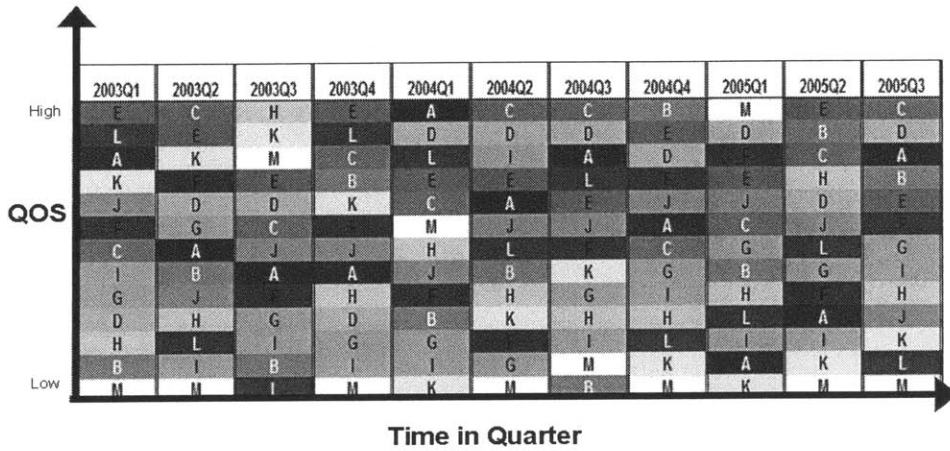
- 2) Using QOS as the simplified metric for measuring customer behaviors overlooks other important factors that can contribute to the over-ordering problem. The two major dependencies that can result in over-ordering are new product introduction and chipset attach rate. Moreover, QOS does not take into account customers' fundamental difference in business models. It makes no excuse for inherent delay and uncertainty for channels that have more links in the value chain.

- 3) The analysis overlooks potential difference in business policies (i.e. the return policy) for different customers based on order quantities or channels. Some customers may have higher buying power than others due to large volume and policies can be less stringent. This difference may have effects on customer behaviors certain ways that pure data cannot provide a comprehensive story.

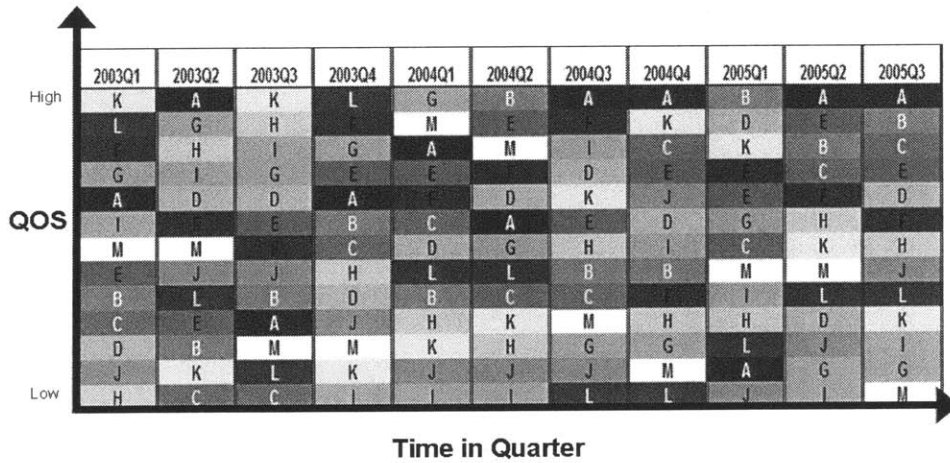
- 4) The relative ranking serves a temporary purpose until all customers become Class A behavior. The hotlist priorities are no longer valid when there are no differentiated ordering patterns, but the implication of all Class A customers is that the over-ordering problem has been fixed.

APPENDIX I. CUSTOMER RANKINGS OVER TIME BY PRODUCT SEGMENT

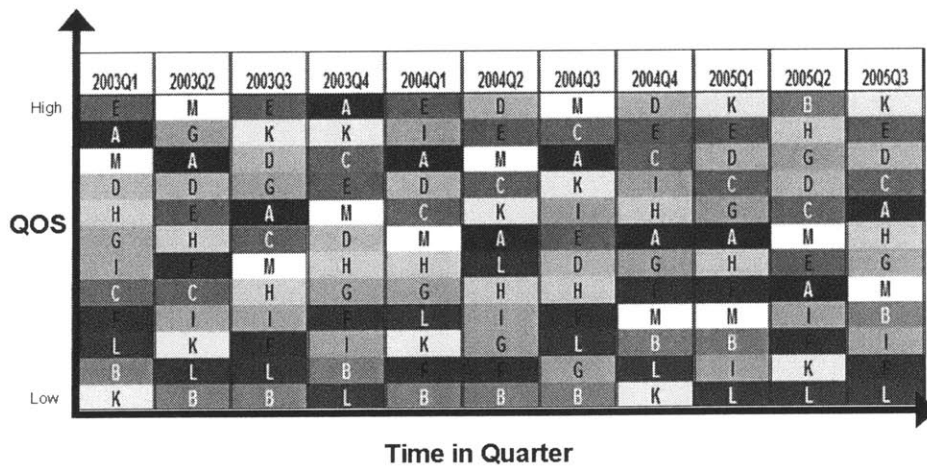
a. DT



b. MB

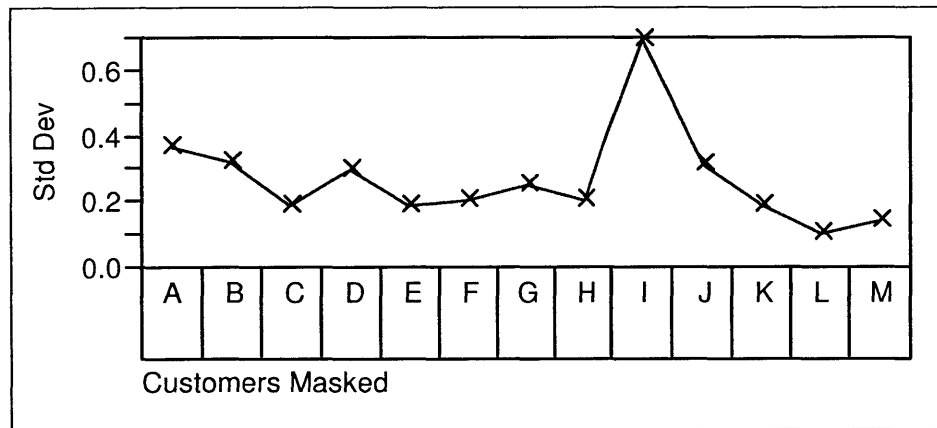
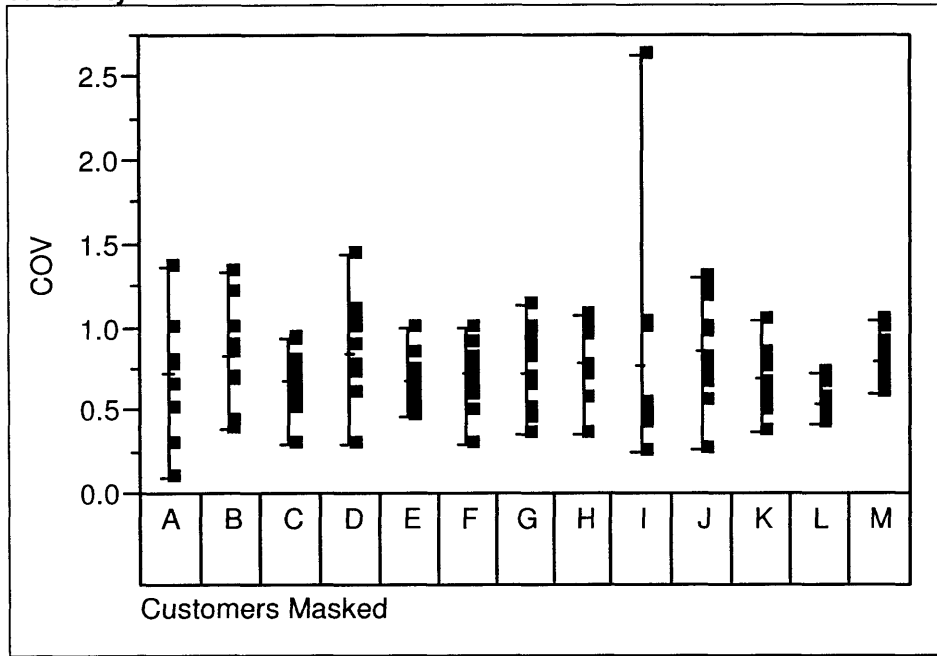


c. SVR

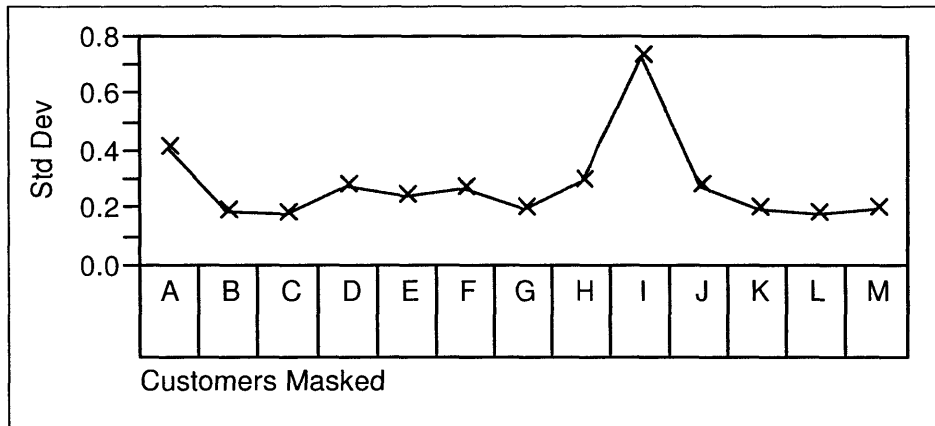


APPENDIX II. VARIABILITY OF QOS OVER TIME BY PRODUCT SEGMENT

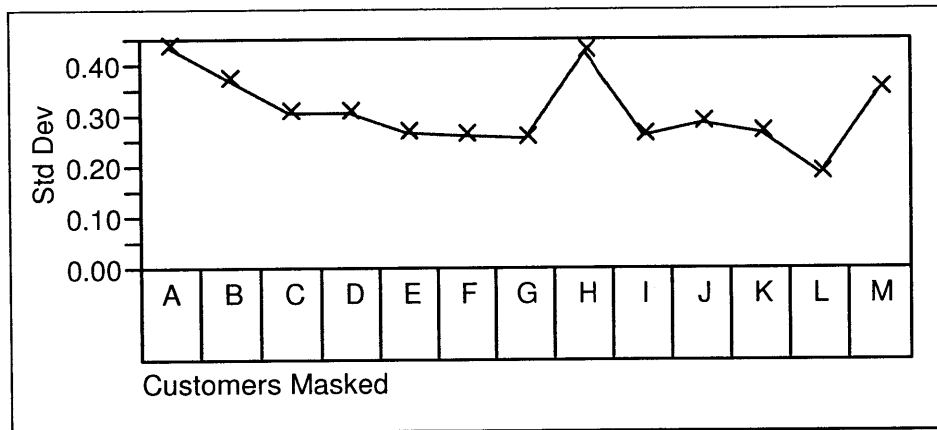
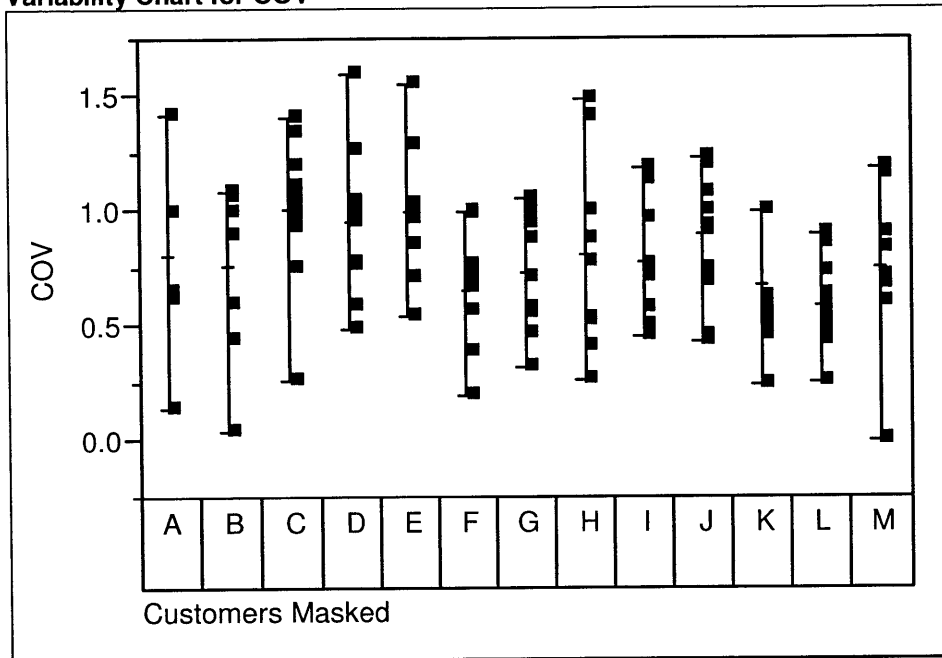
Product Segment=All
 Variability Gage
 Variability Chart for COV



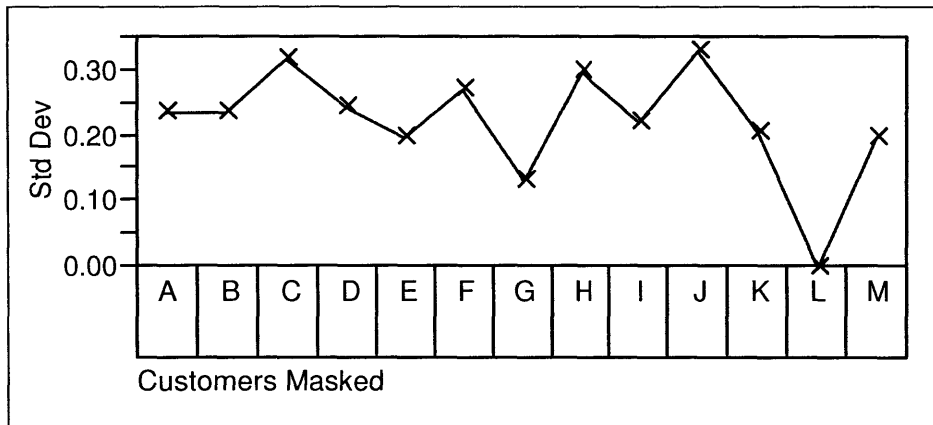
Product Segment=DT
 Variability Gage
 Variability Chart for COV



Product Segment=MB
 Variability Gage
 Variability Chart for COV



Product Segment=SvrWS
 Variability Gage
 Variability Chart for COV

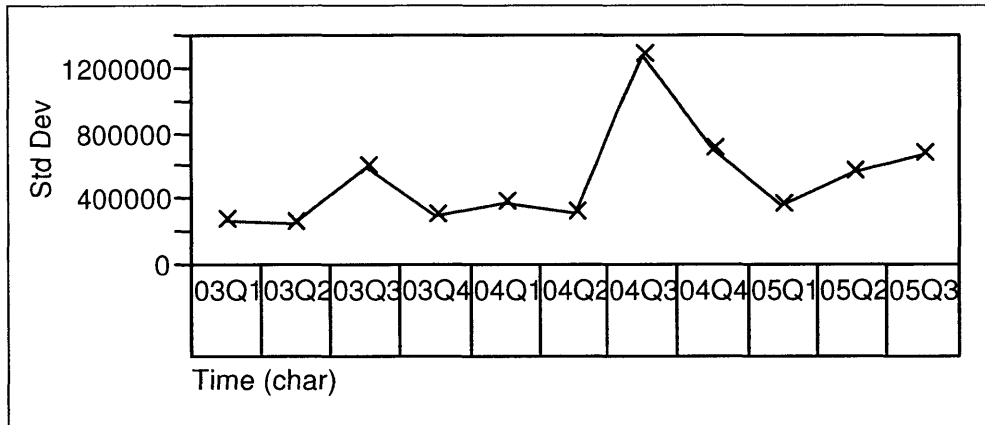
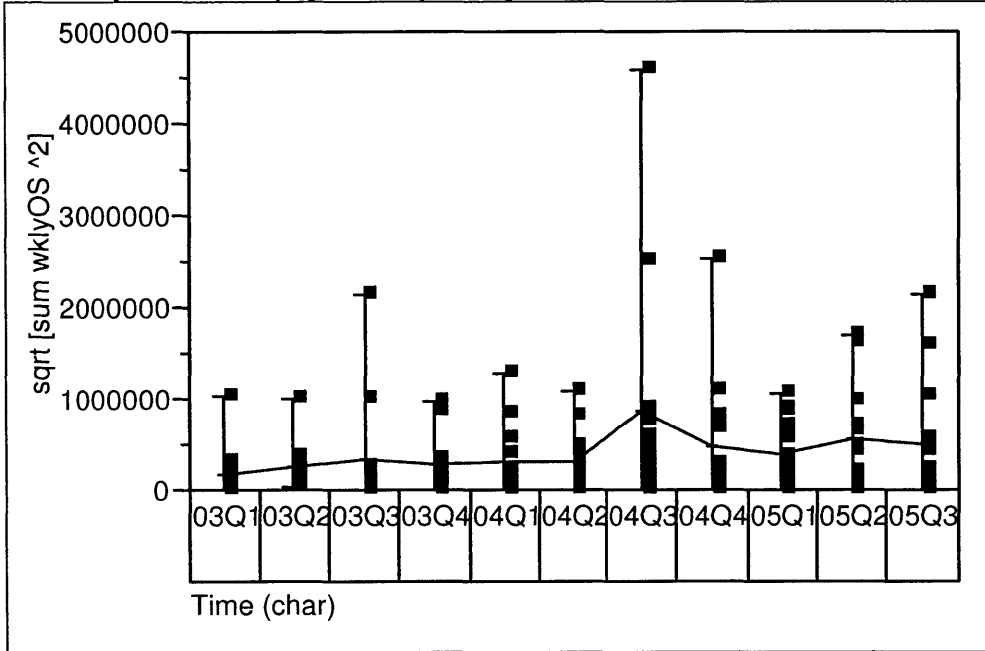


APPENDIX III. VARIABILITY OF QOS BETWEEN CUSTOMERS BY PRODUCT SEGMENT

Product Segment=All

Variability Gage

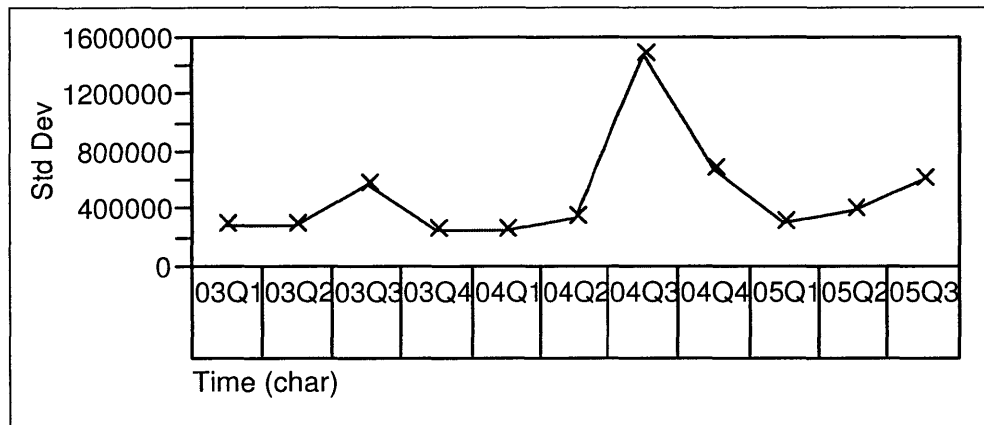
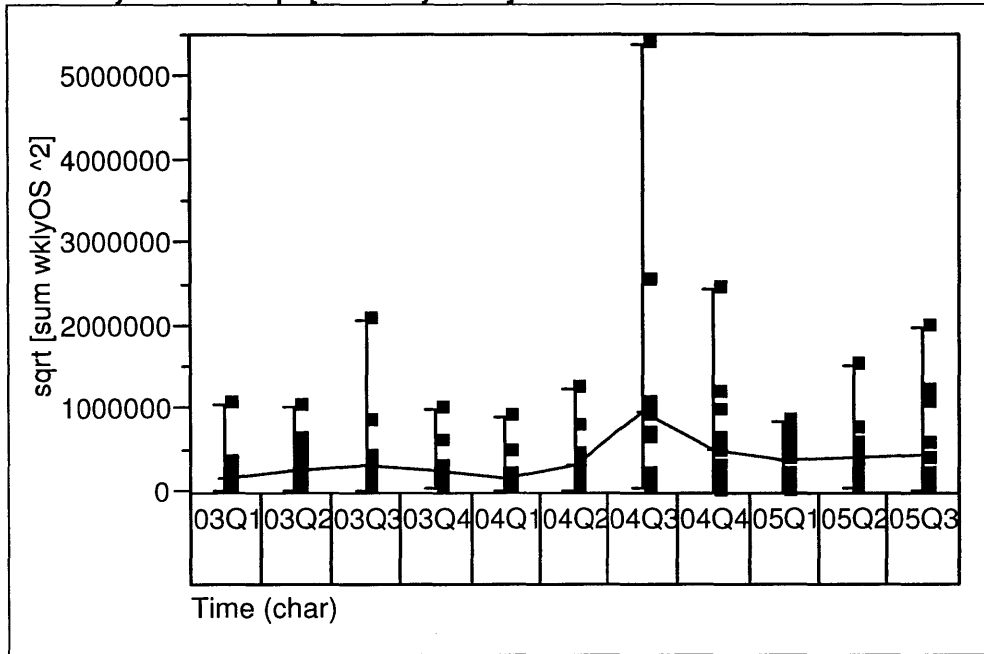
Variability Chart for $\text{sqrt}[\text{sum wklyOS}^2]$



Product Segment=DT

Variability Gage

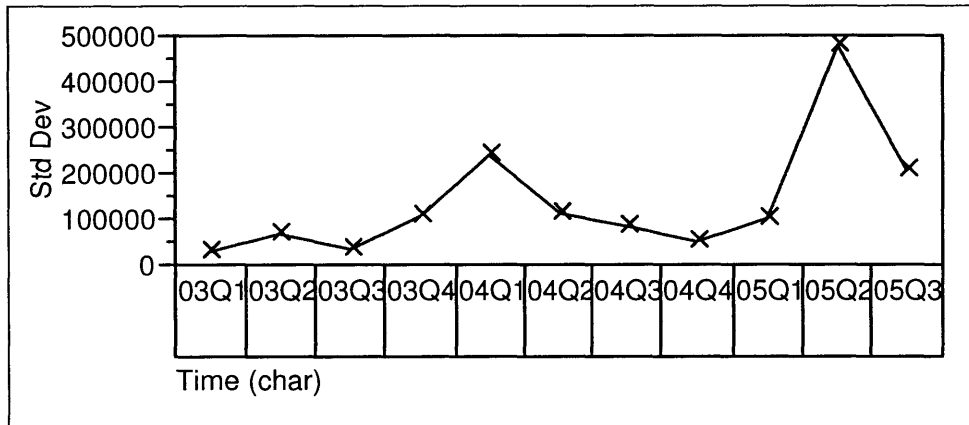
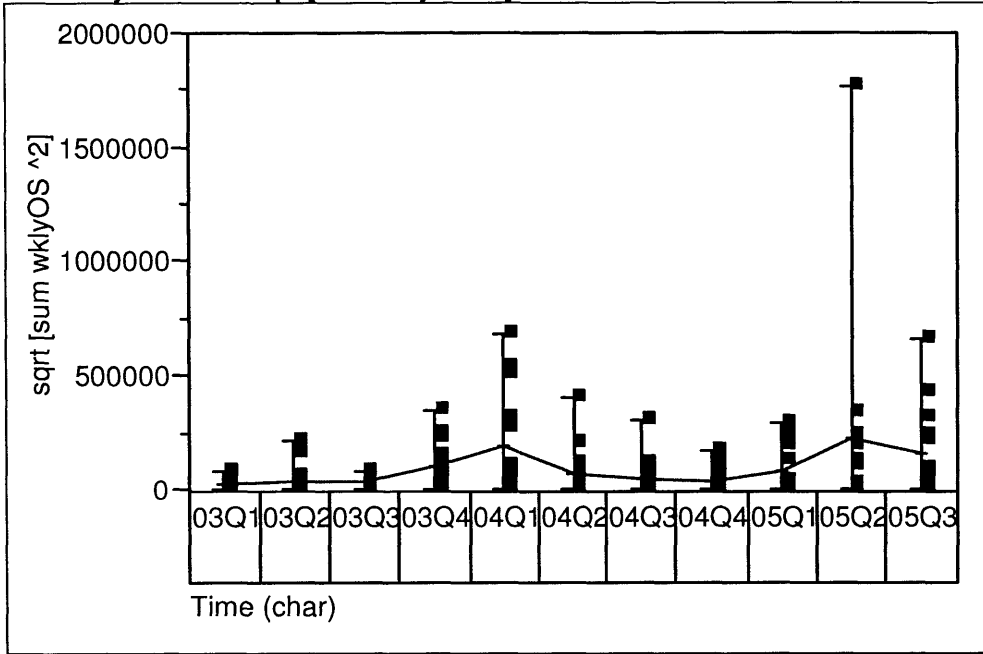
Variability Chart for sqrt [sum wklyOS ^2]



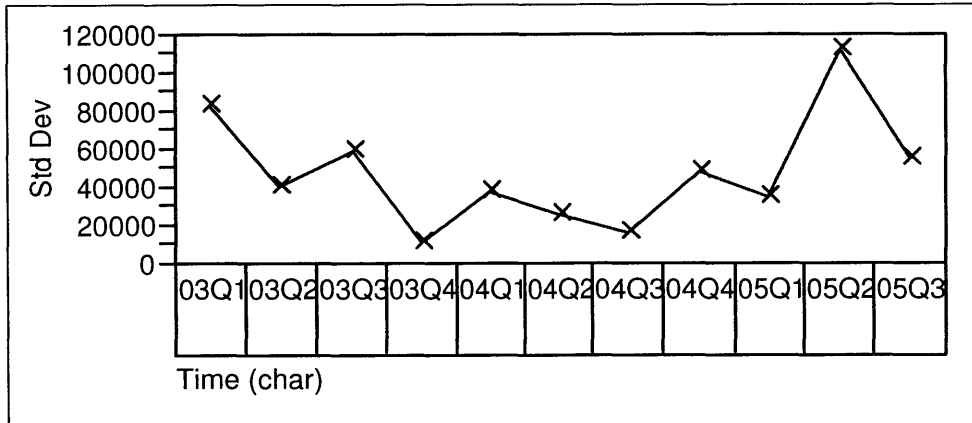
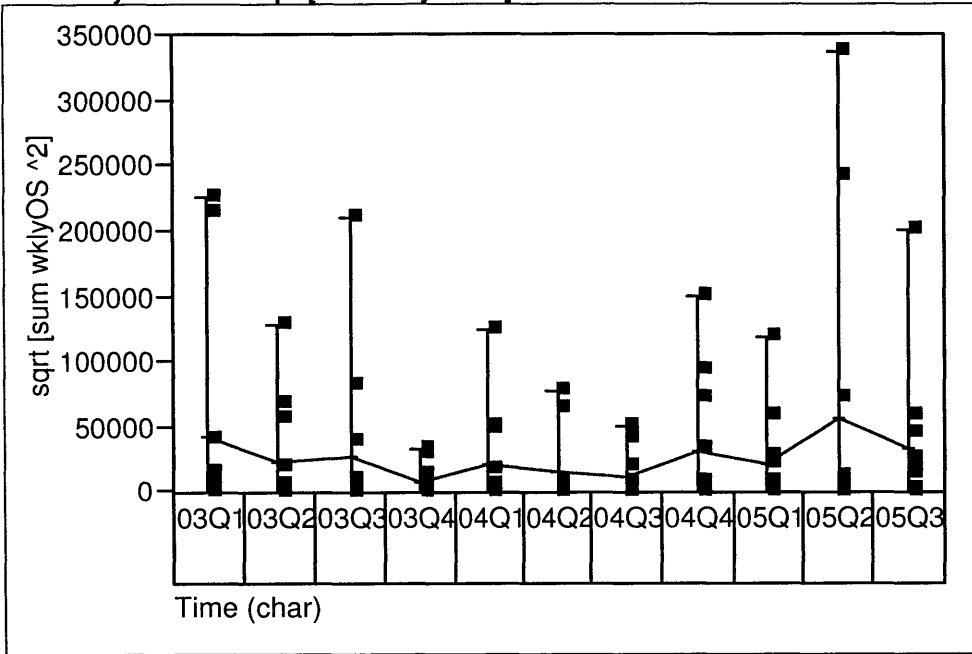
Product Segment=MB

Variability Gage

Variability Chart for sqrt [sum wklyOS ^2]

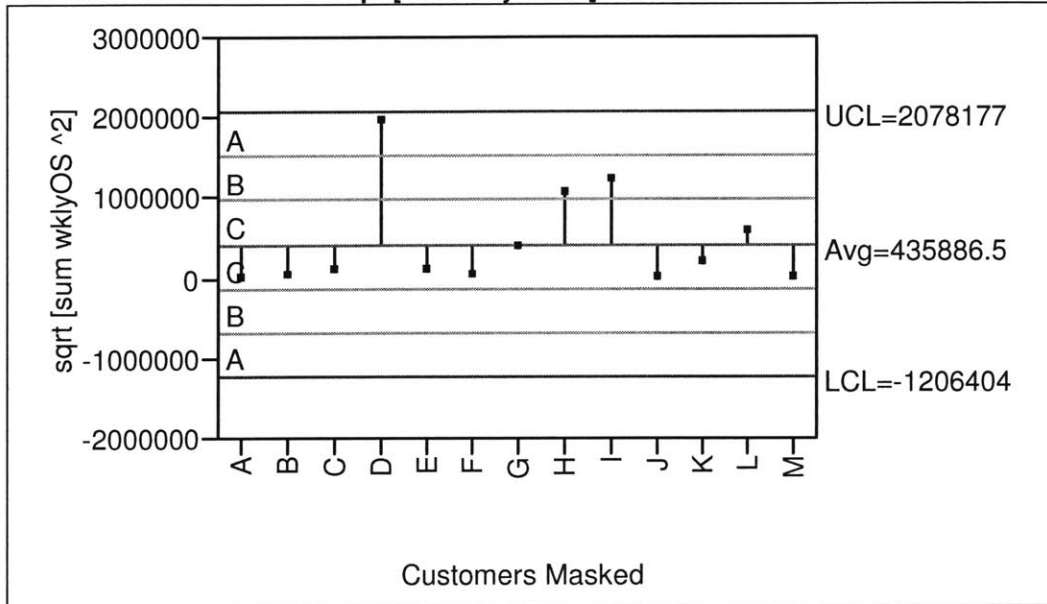


Product Segment=SvrWS
 Variability Gage
 Variability Chart for sqrt [sum wklyOS ^2]

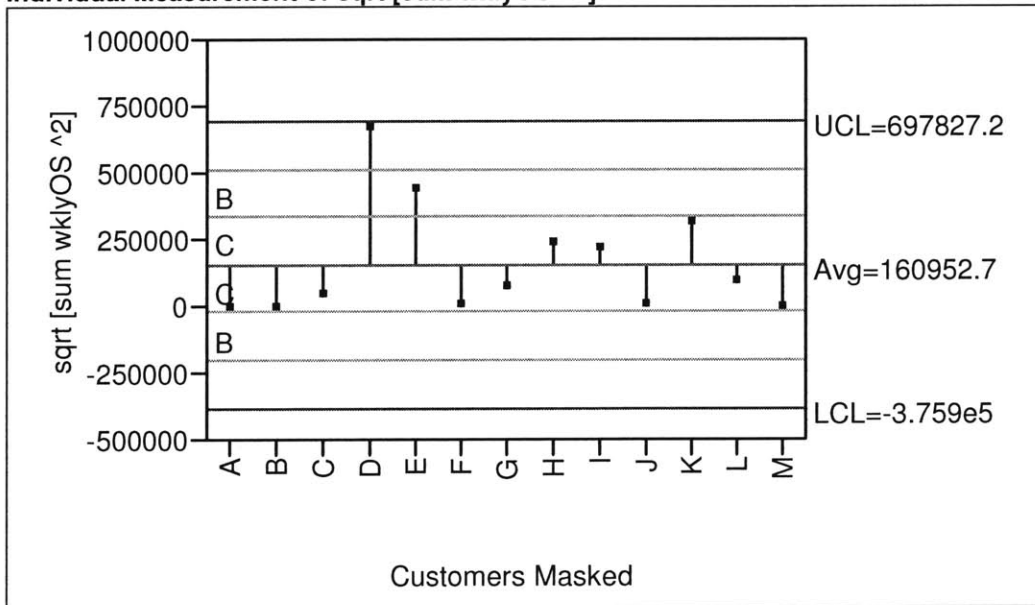


**APPENDIX IV. CONTROL CHART FOR QOS PERFORMANCE BY PRODUCT SEGMENT
(EXAMPLE: 2005Q3)**

**Product Segment=DT, Time (char)=05Q3
Control Chart
Individual Measurement of $\sqrt{\text{sum wklyOS}^2}$**



**Product Segment=MB, Time (char)=05Q3
Control Chart
Individual Measurement of $\sqrt{\text{sum wklyOS}^2}$**



Product Segment=SvrWS, Time (char)=05Q3
 Control Chart
 Individual Measurement of $\sqrt{\text{sum wklyOS}^2}$



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