Promotional Forecasting in the Grocery Retail Business

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Abstract

Predicting customer demand in the highly competitive grocery retail business has become extremely difficult, especially for promotional items. The difficulty in promotional forecasting has resulted from numerous internal and external factors that affect the demand patterns. It has also resulted from multiple levels of hierarchy that involve different groups in the organization as well as different methods and systems. Moreover, judgments from the forecasters are critical to the accuracy of the forecasts, while the value of tweaking the forecast results is yet to be determined. In this business, the forecasters generally have a high incentive to over-forecast in order to meet the corporate goal of maximizing customer satisfaction. The main objective of this thesis is to analyze the effectiveness of promotional forecasting, identify the factors contributing to forecast accuracy, and propose suggestions for improving forecasts. In light of this objective, we used WMPE and WMAPE as the measures of forecast accuracy, and conducted analysis of promotional forecast accuracy from different point of views. We also verified our results with regression analysis, which helped identify the significance of each forecasting attribute so as to support the promotion planning without compromising forecast accuracy. We suggest several approaches to improve forecast accuracy. First, to improve store forecasts, we recommend three models: the bias correction model, the adaptive bias correction model, and the regression model. Second, to improve replenishment forecasts, we propose a new model that combines the top-down and bottom-up approaches. Lastly, we suggest a framework for measuring accuracy that emphasizes the importance of comparing the accuracy of forecasts generated from systems and from judgments.

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1 Introduction

The Standard Industrial Classification defines grocery stores, code number SIC 541, as establishments primarily selling (1) a wide variety of canned or frozen foods such as vegetables, fruits, and soups; (2) dry groceries, such as tea, coffee, sugar, and crackers; and (3) other processed foods and non-edible grocery items. They are commonly known as supermarkets, food stores, convenient stores, and delicatessens (U.S. Census Bureau, 2000).

These food retailing establishments are part of one of the most competitive industries in the U.S (Cournoyer, 1980). In attempts to increase the market share, grocery retailers utilize a wide variety of marketing techniques. The grocery retail business is also known as an industry with a low profit margin. According to the Food Marketing Institute (FMI), the average net profit after taxes of the industry for 2004/2005 was only 1.16%. There are a few ways grocery retailers can differentiate themselves to achieve market share, one of which is by creating an effective supply chain, and to do that requires accurate forecasting. The literature is notably silent about using forecasting in the development of effective retail grocery supply chains, especially promotional forecasting which is the subject of this thesis.

As the number of consumer products has proliferated in grocery stores over the past several years, being able to predict the quantity of products consumers will buy has become extremely difficult. Overestimated forecasts lead to too much inventory in the stores, which ties up capital unnecessarily. On the other hand, inadequate inventory at the stores leads to stock-outs and dissatisfied customers. Taylor and Fawcett (2001) have conducted research on the on-shelf performance and have found that the advertised items have a stock-out percentage almost twice as high as the non-promoted items. The study by Emmelheinz and Emmelheinz (1991) shows that 39% of customers who do not find the items they look for go to another store for the items. Additionally, 21% delay the purchase, and some of these customers might go to other stores as well. Grocery retailers need to take control over their merchandising and supply chain operations by better predicting and shaping consumer demand. By being able to understand consumer demand better, they could forecast and leverage the demand signal to synchronize demand with their sources of supply. The importance of forecast accuracy cannot be overemphasized.

1.1 Thesis introduction

The main objective of this thesis is to analyze the effectiveness of promotional forecasting and identify the factors contributing to the forecast accuracy. With regards to the main objective, we also aim to identify the best approaches to improve the forecasting results by combining different forecasting methods at different levels of grocery retail supply chains, as well as the judgments from people responsible for the forecasts at each level. This thesis project is conducted in a partnership between MIT Center of Transportation and Logistics, and the ABC Supermarket[1], a leading midsized supermarket chain. The supply chain and forecasting operations of this company are described in Chapter 3. Although we work with only one company on the thesis, we expect to generalize the findings so that they can benefit other companies in this industry whose success relies on the accuracy of promotional forecasting.

[1] The name and some data used in this thesis are disguised to protect confidential information.

1.2 Grocery retail supply chain

Grocery retail supply chains consist of manufacturers, wholesalers, and retailers. Retailers may buy products directly from manufacturers, or may buy from wholesalers that purchase goods directly from manufacturers and distribute them to grocery stores. The flows of products in supply chain are illustrated in Figure 1.1. Products are usually delivered to the distribution centers of both wholesalers and retailers, and each individual store replenishes items from either the company-owned distribution centers or from the partner wholesalers' distribution centers. Occasionally, manufacturers might supply products directly to individual stores.

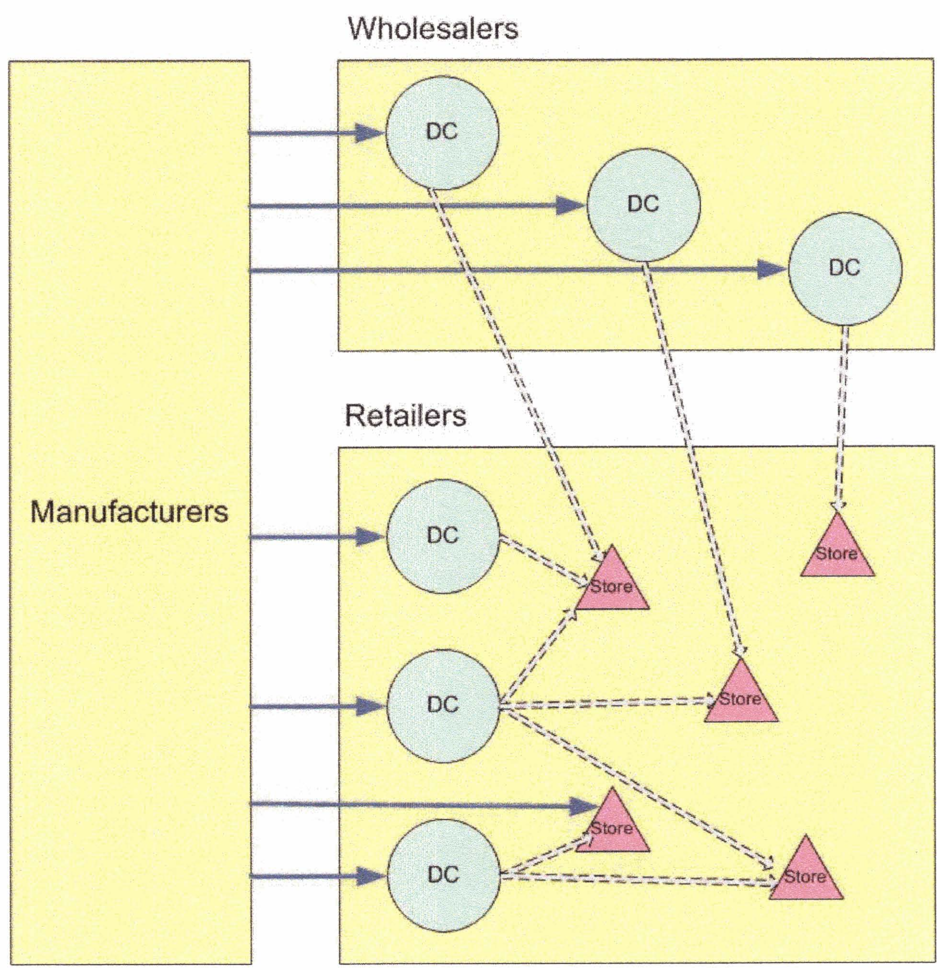


Figure 1.1: Simplified product movements in the grocery retail industry

The supply chain process starts at the grocery retailers who forecast the demand of each item for their stores throughout different time periods. Retailers may submit purchase orders to manufacturers to replenish the items into their own distribution centers, or inform wholesalers of the forecast amount to have them source and deliver the items to the retailers' stores. Based on the forecasts, each store maintains its own inventory by replenishing the items either from the company's distribution centers or from the wholesalers to local storage before placing them on the shelves. The items, when bought by customers, are checked out at the point-of-sale (POS) terminals, where the inventory levels of those items are adjusted. POS information increasingly receives attention from retailers because it does not only provide retailers with the necessary information to analyze the customers' demand, but also enables real-time operations of store inventory. According to Breskin (2004), some retailers begin to routinely feed POS data into demand-based planning, scheduling, and replenishment systems in order to boost sales and increase profit.

Several flows of goods and information exist among the three parties as well as among individual entities in the same party. For example, retailers submit the purchase order information to manufacturers to have the products delivered to their distribution centers. Similarly, each store also submits store orders to the distribution centers to have the items delivered to the store warehouses. When the customer purchases the items, POS sales data is recorded and usually shared with manufacturers and wholesalers so that they can plan the production and distribution accordingly. The goods and information flow described above is shown in Figure 1.2.

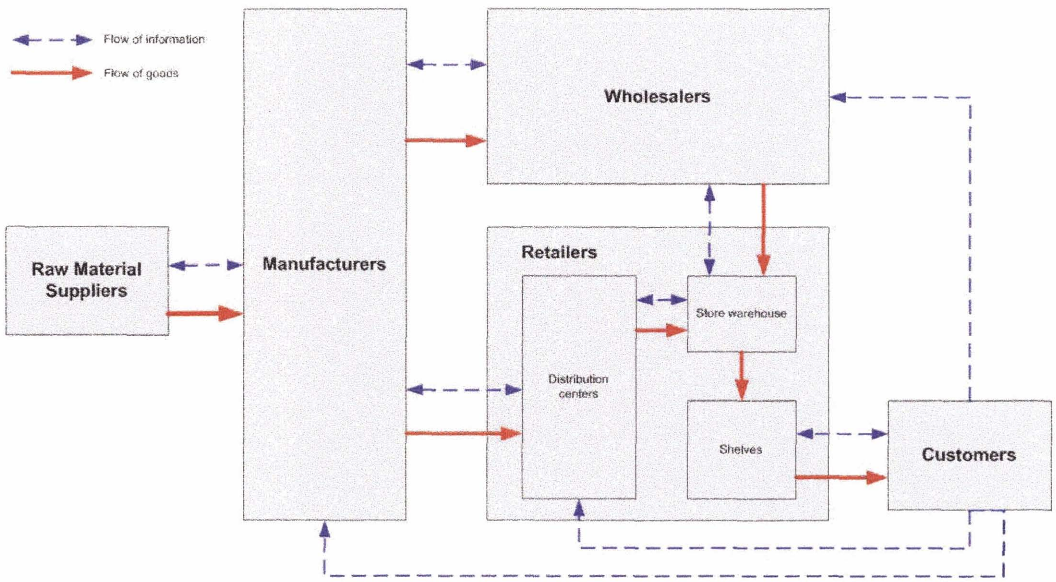


Figure 1.2: Flow of goods and information in the supply chain

Grocery retailers offer a broad range of products. Based on the information from FMI, the average number of items carried in a supermarket in 2004 is 45,000, which is more than double the figure it was ten years ago. Also, the scope of products that grocery retailers sell grows beyond food to toys, consumer electric products and other inedible products. As the number of items grows, the volume and complexity of information and product flows increase, making the replenishment and distribution processes of the grocery supply chain more complicated.

Because grocery retailing is driven mainly by promotions, demands of the products during the promotion periods are much more difficult to predict, resulting in inefficiency in the supply chain. The inability to predict demand of promotions results in either overstock or stock-outs. The impact of stock-outs is significant and the grocery retailers and manufacturers are working together to avoid or at least mitigate the impact of stock-outs. Forecasting is thus a key success factor in reducing the impact, as accurate forecasts help improve the efficiency of the supply chain by having the right amount of products produced and distributed to the stores at the right time.

Currently companies are moving toward amore collaborative approach to improve the efficiency in the grocery retail business. One approach that has gained popularity over the past years is the Collaborative Planning, Forecasting & Replenishment (CPFR®) which is the sharing of forecast and related business information among business partners in the supply chain to enable automatic product replenishment. CPFR enables buyers and sellers who have different views on the marketplace to create a single shared forecast that leads to higher forecasting accuracy than sophisticated algorithms.

1.3 Thesis outline

This chapter provided a brief introduction about our thesis. The rest of the thesis is organized as follows.

Chapter 2 provides the review of literature on forecasting in the grocery retail industry and forecasting information systems. The literature primarily discusses statistical and judgmental forecasting, promotional forecasting, and combining forecasts.

Chapter 3 illustrates grocery retailers' supply chain operations using the example of the ABC Supermarket's operations. Detailed process flows and information systems infrastructure are presented to depict how promotional forecasting is conducted within a firm.

Chapter 4 describes the characteristics of forecasts in the grocery retail business and how they impact promotional forecasting. Also, the objectives of forecasting at different levels of grocery retail supply chain and the challenges of forecasting in this industry are discussed.

Chapter 5 describes the methodology of this thesis. The first section covers the detailed framework of how the analysis was conducted. The following sections describe the scope and detail of the data used in this analysis and how it was structured. We then describe the methods and formulas that we designed to measure the forecasting accuracy.

Chapter 6 describes the details of the analysis. The results of forecasting accuracy analysis are presented in different aspects, from different levels of aggregation, forecasting attributes, time and forecasting methods.

Chapter 7 provides several suggestions to improve forecasts in the grocery retail industry. Several models of forecasts improvement are presented along with their benefits and limitations. The importance of measuring the forecast accuracy is emphasized and the measures and process that are appropriate for the grocery retail industry are recommended.

Finally, Chapter 8 summarizes the analysis and findings, identifies the contribution of the thesis, and suggests the areas for future research.

2 Literature Review

Forecasting is a critical step in the grocery retail supply chain as the forecasted quantity dictates the amount of goods flowing through the supply chains. In this chapter, we will discuss the research and studies done in the area of statistical and judgmental forecasting, promotional forecasting and combining forecasts. In addition, because forecasting is driven mainly by technology, we will also discuss the research in the area of forecasting information systems.

2.1 Forecasting in the grocery retail business

Statistical Forecasting vs. Judgmental Forecasting

Silver, Pyke and Peterson (1998) explains that forecasts are based on a combination of what has been observed in the past which is known as statistical forecasting, and the informed judgments about future events, which is known as judgmental forecasting. The statistical forecasting methods can be categorized into two broad models: causal forecasting and time series forecasting models. For time-series forecasting, Hanke and Wichern (2005) suggest that the most important aspect in selecting an appropriate forecasting model is to consider the different types of data patterns: horizontal, trend, seasonal and cyclical.

Regarding judgmental forecasts and judgmental adjustment of statistical forecasts, Makridakis (1986) suggests that forecasts generated using only judgments are not as accurate as those involving the judicious application of quantitative techniques because humans tend to be optimistic and underestimate future uncertainty. Sanders and Ritzman (2001) conclude from various studies that judgmental adjustment improves accuracy when forecasters possess domain knowledge but that it tends to introduce bias.

Promotional Forecasting

The literature related to promotional forecasting discusses primarily about the effect of promotions to market effectiveness. This includes the analysis of how past promotions can help predict the impact of future promotions. Cooper et al (1999) describes the method used for promotional planning. First he suggests that in order to analyze the effect of a promotion, the influence of promotion style, the influence of an item's promotion history, and the influence of a store's promotion history need to be analyzed. Leonard (2000) suggests that intervention analysis in an underlying time series can be used to determine how past promotions affected the historical sales and how proposed promotions may affect the future promotions. The challenge for this thesis that is not addressed by any literature is the approach to identify the significance of the impact each forecasting attribute has to the overall accuracy.

Combining forecasts

The combination of the results of two or more forecasting methods has been an area of research for the past twenty years. Clemen (1989) indicates that the primary conclusion of this line of research is that forecast accuracy can be substantially improved through the combination of multiple individual forecasts. Mahmoud (1989) argues that although the amount of research on combining forecasts is substantial, relatively little is known about when and how managers combine forecasts. Important managerial issues that require further study include managerial adjustment of quantitative forecasts, the use of expert systems in combining forecasts, and analyses of the costs of combining forecasts.

According to Armstrong (1989), research from over 200 studies demonstrates that combining forecasts produces consistent but modest gains in accuracy. However, this research does not define well the conditions under which combining is most effective nor how methods should be combined in each situation. Hibon and Evgeniou (2005) challenge the belief that combining forecasts improve accuracy relative to individual forecasts. Their results indicate that the advantage of combining forecasts is instead that it is less risky in practice to combine forecasts than to select an individual forecasting method. Silver, Pyke, and Peterson (1998) suggest that the best combination of procedures depends on the value of the measure of variability for each individual procedure as well as the correlation between the results of the procedures.

Along the same lines, Winkler and Clemen (2004) have investigated gains in accuracy using multiple experts and/or multiple methods. Adding experts and adding methods can both improve accuracy, with diminishing returns to extra experts or methods. The laboratory experiment conducted by Goodwin (2000) shows that during promotion periods, the use of integration between judgmental and statistical forecasts leads either to improvements over unaided judgment, or at worst, does not diminish the accuracy of the forecasts. Interestingly, the study done by Harvey and Harries (2003) shows that people responsible for integrating forecasts should not explicitly include their own forecasts among those they combine and should consider avoiding making their own forecasts altogether.

Regarding the combining methods, two studies by Agnew (1985) and Larréché and Moinpour (1983) suggest the use of median because it is less likely to be affected by the errors in the data. Clemen (1989) concludes that the simple average performs as well as more sophisticated statistical approaches. Part of our analysis is to further advance this work to determine optimal approaches for grocery retail businesses.

In order to find the general procedures for combining forecasts for each specific situation, Armstrong (1989) recommends that realistic simulations be used. He provides the example of determining the forecasting methods for the U.S. GNP. First, a variety of methods would be used to make two-year forecasts and they would then be compared with the actual outcomes. Methods will then be ranked by accuracy or by the extent to which the forecasts differ from one another. He also points out a several defects of realistic simulations; one of them is that if the situation changes, it will take some time until these changes are integrated into the system. Although there is some literature that discusses the realistic simulations, the literature has yet to address the combination of promotional, store-level and distribution center-level forecasts that exist in the grocery retail business.

2.2 Forecasting information systems

Technology is the key driver in business forecasting in the 21st century. Charles (2004) documents that during the past decade, data availability and quality have improved substantially along with the ability to store it. Jain (2003) argues that although the current technology has provided massive amounts of data, not enough efforts are being made to translate data into intelligence. Nevertheless, both agree that improving forecast accuracy will play a critical role in driving sales and profits as companies continue to harness the power of information to better serve their customers.

With the emergence of forecasting software and systems to support the forecasting tasks, Tyagi (2002) recommends that it is imperative that industries with high supply chain costs and thin margins to have efficient forecasting software. He provides characteristics of good forecasting software and emphasizes the importance of the ability to incorporate event and promotions management into forecasting. This includes the ability to analyze post events and promotions that provide feedback for future promotions.

According to Rosenblum (2005), many retailers believe that some tweaking of forecasting results will always be necessary, regardless of the quality of the math. In the study conducted by Aberdeen Group in 2005, 33% of 60 retailers participating in the study reported that they tweak the results that the forecasting systems generated. However, from the study the author concludes that best-in-class retailers should avoid tweaking the results as it leads to continued self-fulfilling prophecies of inadequate information and incorrect data. Another recommendation from the study is that companies should avoid having too many forecast engines that calculate planned sales differently based on different purposes of the application and different assumptions. Since the study was conducted in various retail segments, it is not clear if the recommendation also applies for the grocery retail business due to its unique forecasting attributes and assumptions.

3 Current Operations

This section illustrates the existing supply chain operations in the grocery retail industry using an example of the ABC Supermarket. Emphasis is given to the forecasting process flow and specifically promotional forecasting. Because supply chain operations are driven mainly by supporting information systems, we also describe the overall infrastructure of information systems deployed by ABC as part of its day-to-day supply chain operations. Finally, the challenges of forecasting faced by companies in the grocery retail industry including the ABC Supermarket are summarized.

3.1 ABC's supply chain operations overview

The ABC Supermarket is one of the leading midsized regional grocery retail chains with over 200 stores. The stores differ in their sizes, formats, items to carry, and customer demographics. In order to serve all the stores, ABC owns three distribution centers, one supplying perishable product, another supplying frozen and grocery food, and the other supplying health and beauty care products. We will refer to each distribution center as DC1, DC2 and DC3, respectively. Besides its own distribution centers, ABC also partners with a national distributor to supply the products to the stores that are not serviced directly by its own distribution centers.

ABC Store Support Center performs various centralized corporate functions including accounting, merchandising, procurement, supply chain, and information technology (see

Appendix A for the organization chart). Figure 3.1 shows the roles of different groups in the supply chain operations. The detail of each process is described below.

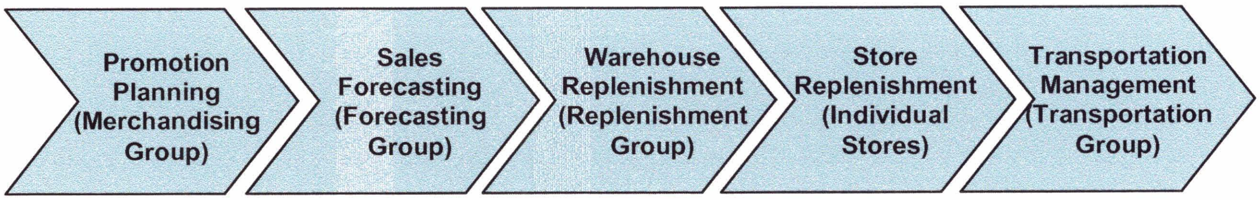


Figure 3.1: ABC's planning process

1) Promotion Planning

Designing the right weekly promotion is critical to ABC's profitability and success. Merchandisers deploy a sophisticated method that uses information such as offer type, pricing, circular layout and retail display to forecast the sales effect of a promotion and make decisions on promotional spending based on the projected uplift of the sales. Usually, promotion planning is done six to eight weeks in advance. The promotion week starts on Friday and ends on the following Thursday. Because incremental sales are only possible when products are available on the shelves, the merchandising team works closely with the supply chain group to ensure that the stores carry enough items to meet customers' demand during the promotion period.

Two important factors are taken into account when considering the promotion uplift:

- Cannibalization: The decrease in sales of related products when one product is promoted. As grocery retailers carry products from more than one producer for the same product type, the increase in sales of one brand comes at the expense of the other brands, and this effect needs to be taken into account when making promotion decisions. One example is the decrease in sales of orange juice A when orange juice B is on buy-one-get-one promotion.

- Halo effect: The increase in sales of other complementary items when a product is promoted. This includes the increased sales from the increased traffic resulted from promotions. For example, the sales of salsa sauce tend to be increased when chips are on sale.

The other factors that influence the magnitude of direct uplift include product type and subcategory, offer type, discount rate, store impact, display type, margin and vendor funding.

2) Sales Forecasting

There are two types of forecasting done at the ABC Supermarket: turn forecasting and promotional forecasting. Turn forecasting is the conventional forecasting that is conducted periodically to replenish the items that are not on promotions. Promotional forecasting is applied for promotional items determined by the merchandising group for the given promotion week. The chain promotional uplift from the merchandising team is passed to the forecasting team to forecast the detailed demand of each item at each individual store.

For both types of forecasting, ABC uses three-year historical sales data to analyze trend and seasonality patterns and forecast the future sales. The forecasting is done for each individual item at each store on the bottom-up basis – store to distribution center to chain. Although the forecasting is done by software systems, the final decision of whether to override the statistical forecasts proposed by the systems is made by the forecasters. In this thesis, we will focus only on promotional items.

3) Warehouse Replenishment

Based on the forecasts, the replenishment group reviews the aggregated distribution center-level forecasts, makes adjustment, optimizes the replenishment, and places purchase orders to vendors to replenish the items to the distribution centers. Again, although the replenishment group is given the aggregated forecast results from the systems, the final replenishment decisions are made based on the buyers' judgments.

4) Store replenishment

Individual ABC's retail stores review forecasting results provided by the central forecasting team and decide whether or not to adjust the original forecast. They then generate store orders and send to the distribution centers to replenish initial stocks four to six weeks ahead of the ad week. Between the time the initial order is placed and the promotion week, stores might place additional orders based on the projected demand. There is usually some discrepancy between the total order quantity from the stores and the order quantity that ABC places to manufacturers. If the distribution center replenishment quantity is greater than the store order quantity, there will be excess inventory for that item at the distribution centers. On the other hand, if the opposite is true, the distribution centers will not be able to supply the stores' demand, and the "scratch" quantity will appear in a report to be reviewed by the supply chain group.

5) Transportation Management (Inbound and Outbound Logistics)

Inbound logistics is defined as the transportation from suppliers to ABC's own distribution centers while outbound logistics covers the transportation from ABC's distribution centers to individual stores. ABC currently works with two contracted carriers and a number of third party carriers to provide the inbound and outbound transportation services based on purchase orders and store replenishment orders. The details of the inbound logistics of this partner can be found in the MLOG theses by Akkas and Archambault (2004). For the transportation planning purpose, ABC provides the carriers with the high-level demand forecasts so that the carriers can allocate enough transportation capacity to meet the peak demand during promotion weeks.

As each process is highly dependent on the others, collaborative effort between each group is necessary to maintain the efficiency in the supply chain. The overall goal of ABC's supply chain is not only to improve internal efficiency but also to maximize customer satisfaction and loyalty. It is very important for ABC to manage its supply chain effectively and efficiently so as to differentiate itself in product availability, quality, costs and ultimately customer satisfaction in the low-margin grocery retail business. Being able to deliver to customers the right merchandise at the right time and at a low cost is critical to every grocery retailer's success.

3.2 ABC's information system architecture

Like other grocery retail businesses, the ABC Supermarket is facing a several challenges such as dynamic market demands, intense competition, frequent business restructuring and talent attrition. To cope with these challenges, ABC has invested heavily on information technologies to maintain a competitive edge so as to empower its supply chain and achieve the best operation results. Various business systems in forecasting, replenishment, transportation and data management are linked together to accommodate the flow of goods and information. Figure 3.2 shows the current information systems architecture. The name of each system is disguised for anonymity.

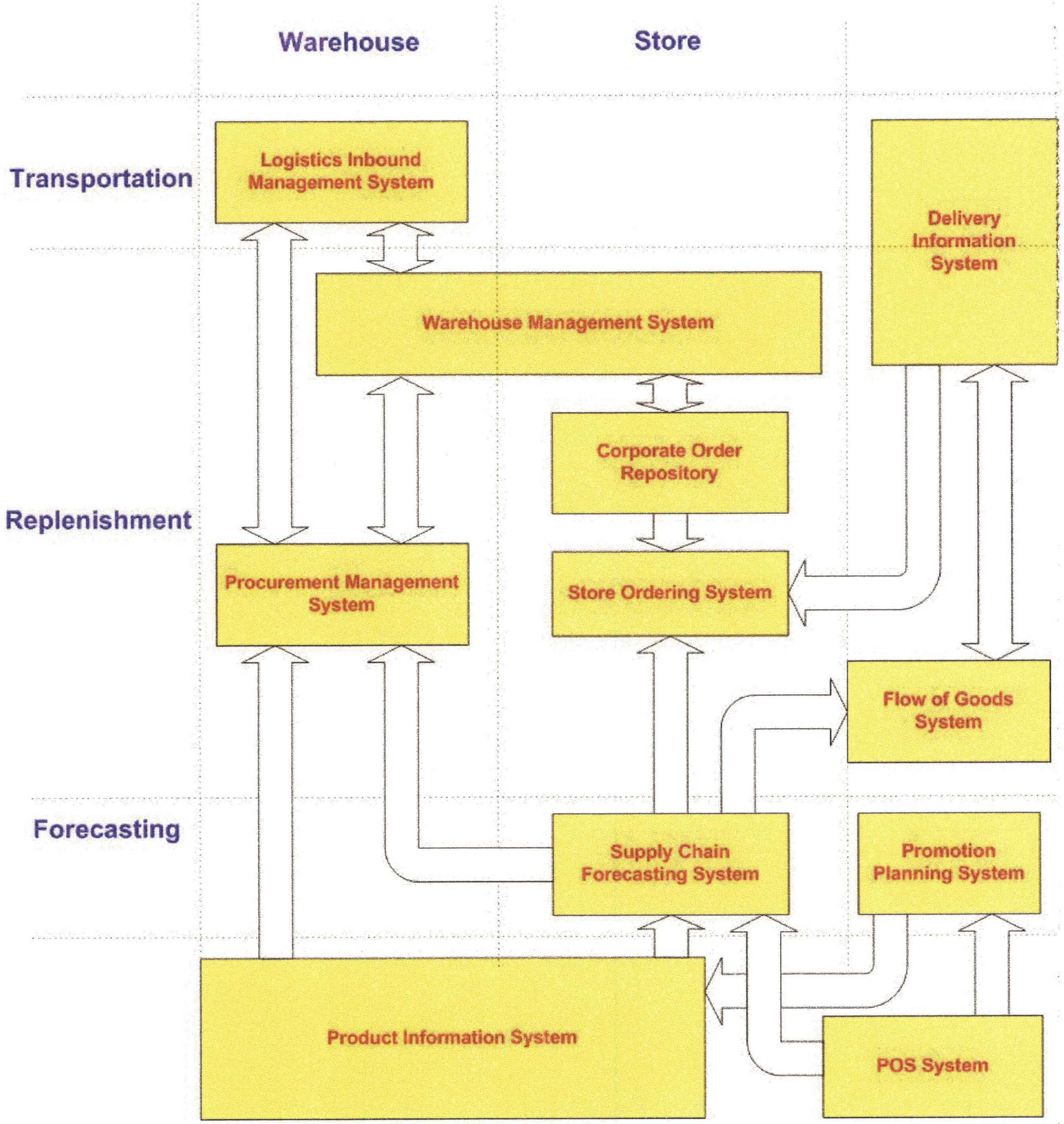


Figure 3.2: The current information systems architecture

The key components of ABC's information systems include:

- **Product Information System:** The Product Information System is the central system that stores item information such as item description, attributes, product groups, store information, and price. It functions as the master data repository for other systems.

- **Promotion Planning System (PPS)**: The Promotion Planning System is the promotion and advertising planning software that helps ABC predict chain-level sale revenues for promotional items using predefined uplift, halo and cannibalization effect based on the promotion attributes such as ad layout and offer type.

- **Supply Chain Forecasting System (SCFS):** The Supply Chain Forecasting System is the central forecasting system that uses historical demand data, seasonality and external factors to forecast weekly sales volume for all items in each store. It also provides aggregated forecasts to distribution centers for DC replenishment.

- **Flow of Goods System:** The Flow of Goods System helps manage the flow of information from various functions such as sales forecasts from supply chain group and the inventory movement from warehouses.

- **Procurement Management System:** The Procurement Management System is the system that facilitates the procurement process done by the replenishment group. Purchase orders are created based on aggregated forecasts from the Supply Chain Forecasting System and are submitted electronically to the suppliers by means of Electronic Data Interchange (EDI).

- **Warehouse Management System:** The Warehouse Management System facilitates the day-to-day inventory management as well as inventory optimization for each distribution center.

- **Store Ordering System:** The Store Ordering System is used by each individual store to place and track store orders from the distribution centers. ABC maintains two separate systems: one for perishable and the other for non-perishable products.

- **Corporate Order Repository:** The Corporate Order Repository is the central system that manages all the store orders and distributes them to the distribution centers and to the third-party wholesalers for store replenishment.

- **Logistics Inbound Management System:** The Logistics Inbound Management System is used by the transportation group to manage inbound transportation services from suppliers to the distribution centers.

- **Point-of-Sales (POS) System:** POS System keeps all the sales information from the check-out lanes of each individual store. This information helps ABC understand customer demand patterns which will lead to more effective promotion planning and more accurate supply chain forecasting.

The Product Information System and the Promotion Planning System are owned by the merchandising group while the Store Ordering System and POS System are owned by the marketing group. The rest of the systems are owned by the supply chain group.

These complex information systems provide an interconnected, collaborative platform for ABC's supply chain processes across all groups. However, due to the differences in underlying objectives, principles, assumptions, and use patterns, these systems occasionally generate results that are not synchronized, and sometimes even conflicting with each other. It is of great interests for ABC to reconcile these systems, especially between Supply Chain Forecasting System and Promotion Planning System that generate the forecasting results at two different levels to make the best out of its advanced technology. If the results of these two systems could be combined effectively, the company as a whole would greatly benefit from promotion effectiveness, forecast usability and resources allocation.

3.3 ABC's promotional forecasting process flow

The promotional forecasting process at the ABC Supermarket begins from the merchandising group. Based on the anticipated financial uplift from the incremental sales, current market trend, competitors' moves, sales season and future events, the merchandising group makes promotion decisions six to eight weeks ahead of the planned promotion week. Such decisions include the selection of promotional items, discount type, discount rate, ad layout and retail display. The promotion decisions are validated using the Promotion Planning System, which makes revenue projections of the promotions not only for the particular sales items, but also for the product groups as a whole. The Promotion Planning System results are further justified and adjusted by several merchandisers based on their experience and business knowledge.

Once promotional items are determined by the merchandising group, the promotion plans are sent to the Supply Chain Forecasting System. It is more sophisticated than the Promotion Planning System as it can handle demand trends, seasonality, promotions, events and other external demand factors. Four weeks ahead of the promotion week, the forecasting group executes the Supply Chain Forecasting System to forecast the units of sales for each item for each individual store. The results are then reviewed by the forecasters and are usually adjusted according to their domain knowledge. The adjusted forecasts are then aggregated as the combined forecasts for the distribution centers to make replenishment decisions.

After receiving distribution center forecasts, the replenishment team determines the optimal purchase quantities based on factors such as on-hand inventory, package constraints, shipment size constraints, warehouse capacities, supplier delivery schedules, and transportation lead times. All the purchase orders are processed in the Procurement Management System and are sent to the suppliers electronically.

Similarly, all stores are provided with the forecasts from the Supply Chain Forecasting System to assist their replenishment decisions. Based on the forecasts, on hand inventory, delivery lead times, delivery schedules, package and shipment constraints, individual stores place store replenishment orders to distribution centers using the Store Ordering System. All store orders are processed in the Corporate Order Repository System and are fulfilled by the corresponding distribution centers accordingly.

Figure 3.3 shows the collaborative promotional forecasting process flow. While the process is highly sequential, some activities occur concurrently and repetitively. For example, the merchandising team frequently makes late changes to promotion plans to respond to competitors' promotion plans, suppliers' production schedule changes, and sporadic events. The late changes bring great challenges to the forecasting and replenishment teams due to the high degree of integration between three groups. With long replenishment lead times, the replenishment team might not be able to respond to such changes timely, leading to over-stock due to unnecessary purchase or loss of sales due to insufficient stocks, both of which impact the bottom line of the company negatively.

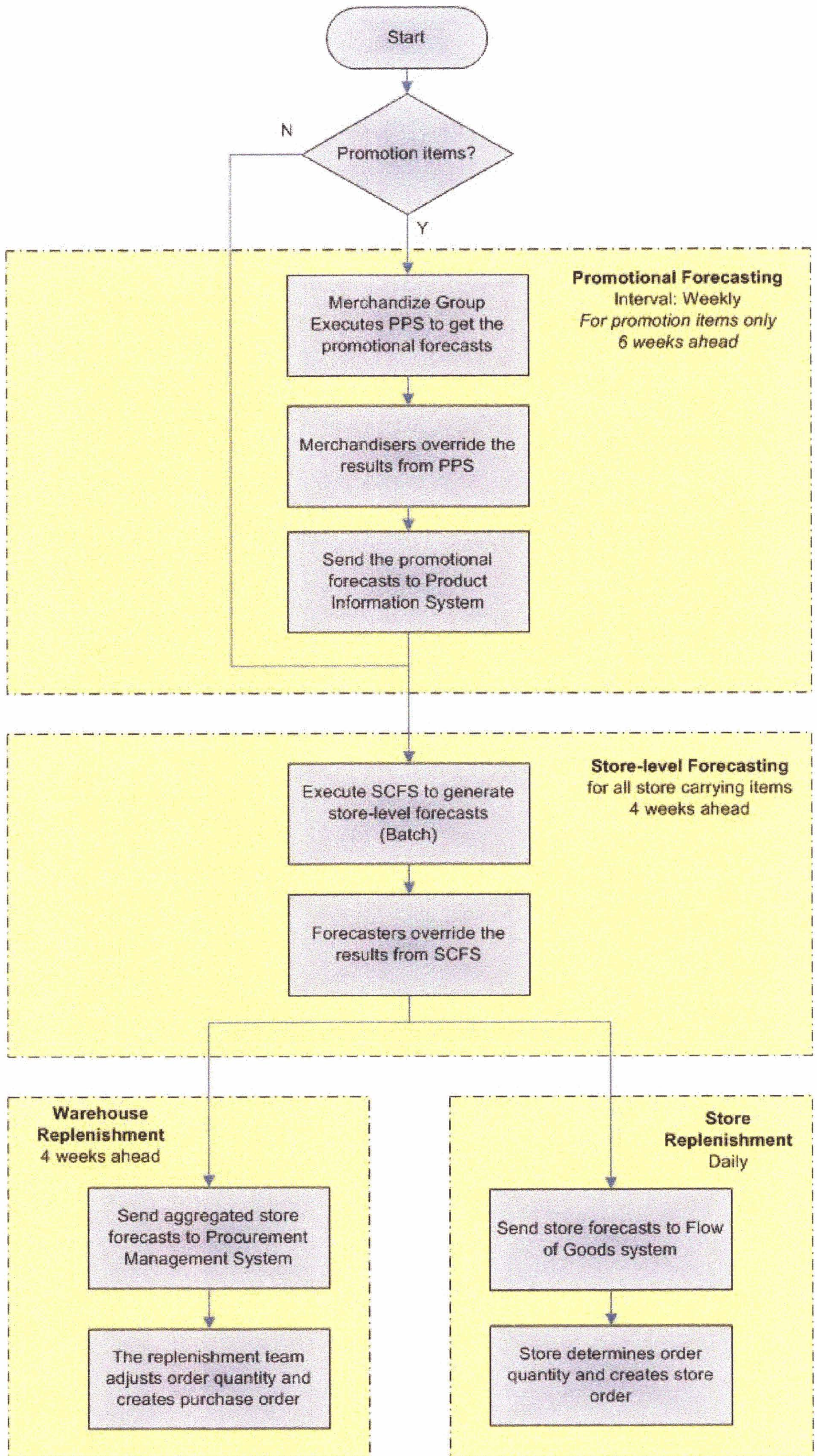


Figure 3.3: Promotional forecasting process flow

With the support of forecasting information systems, on one hand, ABC's forecasting is technologically advanced and capable of producing highly detailed forecast results. On the other hand, it is very sophisticated and may complicate business decisions. For example, usually forecasting systems apply sales uplifts with both seasonality and event information. If the two factors are correlated to each other, the uplift will be exaggerated.

Although the forecasting process and tools at ABC are considered one of the most advanced in the industry, they could be further improved in several ways. First, human judgment plays significant roles in the whole forecasting process, which is very subjective and tends to introduce bias and human dependency. Second, a systematic matrix of forecasting accuracy and promotion effectiveness should be established. By measuring the performance, ABC will be able to better understand its forecasting systems and make more informed decisions. It will also be able to allocate its resources to the most critical areas. Third, promotions must be planned in accordance with the business cycle. The current planning horizon of six weeks is a quite long and may not effectively capture market dynamics. A more integrated Sales & Operations Planning process may be able to help shorten the forecasting lead time. Lastly, the existence of two forecasting systems brings opportunities to combine forecasts. By comparing the two sets of results and determining a scientific way to utilize both data, ABC will be able to forecast the demand at each level more effectively and will be able to improve the efficiency of the whole supply chain operations.

4 Promotional Forecasting in the industry

4.1 Characteristics of the forecasts in the industry

As described in Chapter 1 and Chapter 3, the grocery retail business is unique in its structure, organization, supply chain network and the competition, all of which determine the characteristics of forecasts in this industry. First of all, because of the proliferation of SKUs and the number of customers that each store serves, the number of items on the shelves for each SKU can be very low for slow-moving products. Therefore, forecast accuracy measures that are used in other industries with high demand volume per SKU such as consumer product manufacturers and computer hardware manufacturers may not be applicable to measure the store-level forecasts of this industry. For example, mean absolute percent error (MAPE), which is the most popular measure used in the industries according to Kahn (1998), does not perform well when the demand values are low (Silver, Pyke & Peterson, 1998). Because MAPE is calculated by taking the average of the absolute percent error of each forecast, the high percent forecast error of low volume product is given the same weight as the forecast error with greater sale dollars. Also, because of the proliferation of the SKUs, the absolute measures such as root mean square error (RMSE) are not meaningful when comparing the accuracy across different products.

Moreover, because the corporate goal of almost all grocery retailers is to maximize customer satisfaction, they prefer holding extra inventory to risking stock-out. As described in the first chapter, the cost of under-forecast in this industry is high. According to Khan (2003), the inventory holding cost as a result of over-forecast is usually significantly lower than the cost of lost sales. This creates an incentive for grocery retailers to over-forecast the demand.

Because of broad range of products available in grocery retail stores, the demand pattern varies for each product even when the products are in the same product group and category, depending on the factors such as seasonality, rate of new product introduction, product life cycle, and availability of the products at the competitors' stores. Therefore, some products are more difficult to forecast than the others. Especially for the promotional forecasts, besides the regular attributes and historical sales data, a number of promotional attributes such as the offer type, page number and percent discount are also taken into account when predicting the demand. Some attributes are correlated to each other, resulting in higher forecasts than what they should be. Also, customers may react to the promotions differently for different products in patterns that are difficult to quantify.

Forecasting systems used by grocery retailers pose some other challenges to the companies in this industry. Similar to the ABC Supermarket, they usually have more than one forecasting system, each with different objectives, and even the same system may generate promotional forecasts multiple times until the promotion week approaches. Moreover, the algorithms used by the forecasting software are usually too complicated to be understood by the forecasters, and most of the time the forecasting methods are proprietary and not revealed by the software vendors.

Last but not least, because the forecasters play an important role in providing judgments to the forecasts generated by the systems, the tweaking of the forecasts can affect the accuracy both positively or negatively. The experience and familiarity with the products of the forecasters contribute a lot to the accuracy of the forecast results. Judgments tend to add bias and variations, and the impact of the judgments is difficult to quantity.

4.2 Forecast structures and objectives

Figure 4.1 shows the levels of forecasts and the groups that conduct and use the forecast results in the grocery retail business. The promotion decisions are made at the chain level by the merchandisers. Therefore, forecasting at this level is measured to assess the effectiveness of promotion plans. The distribution center replenishment and store replenishment are done by the replenishment group and supply chain group based on the store-level and distribution center-level forecasts. The purpose of forecasting at each level is different, so do the responsibilities and incentives of each group. Consequently the attributes, methods and systems used to generate forecasts at each level are all different. Table 4.1 summarizes the objectives of forecasting and the attributes of each forecasting level.

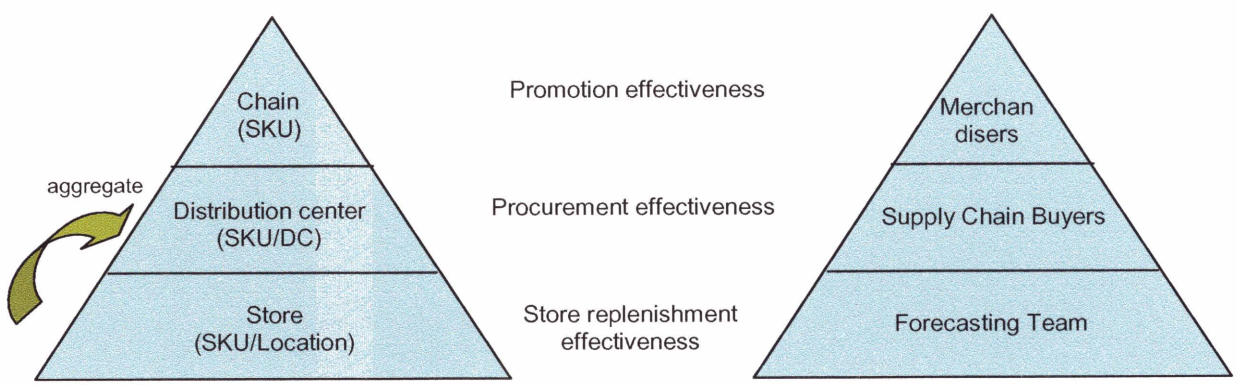


Figure 4.1: Forecasting levels in the grocery retail business

Table 4.1: Objectives and attributes of each forecasting level

Forecast levels	Objectives	Attributes
1. Chain-level forecast	Estimate the volume of products to be sold during the promotion period to make the promotion decisions and to plan the replenishment	Promotion attributes
2. Distribution center-level forecast	Establish the order quantity to optimize the inventory level at the distribution center while meeting the demand from the stores	Promotion attributes Turn and seasonality Store network Store-level forecasts
3. Store-level forecast	Estimate the demand for each item at each store as a basis for distribution center replenishment and store replenishment to maximize the shelf present.	Promotion attributes Historical point of sales data Turn and seasonality

4.3 Challenges of forecasting in this industry

Forecasting is a critical step dictating the number of products flowing through supply chain. In order to improve forecasts, grocery retailers need to understand their forecasting performance, and use this information to improve its forecasting processes and systems. To achieve this objective, they need to select the accuracy measures that can best reflect their forecasting performance. Also, they need to understand the impact of each forecasting attribute to the accuracy in order to fine-tune existing forecasting systems and make better informed forecasting judgments. In addition, as there are multiple levels of forecasts with different objectives, grocery retailers need to understand the performance of forecasts at each level, and determine the best way to leverage the forecasts done at different levels to improve the efficiency of the whole supply chain.

5 Methodology

To understand the operations and challenges faced by the grocery retail industry, we conducted fieldwork by visiting and interviewing key personnel in the supply chain and merchandising groups of the ABC Supermarket. Using this information as background, our primary methodology was data analysis and model simulation. This chapter describes the framework of our analysis, the scope and detail of the data, as well as the matrices we used to measure the forecast accuracy in the grocery retail industry.

5.1 Framework

For the data analysis, we collected the forecast and actual demand from the relevant forecasting systems of the ABC Supermarket. The error for each record was calculated and the distribution of forecast errors was analyzed. We removed some outliers but retained at least 95% of the data for our analysis so as to prevent our conclusion from being tainted by extreme variations. To understand the performance of current forecasts from different point of views, we structured accuracy measurement analysis such that each step revealed the effect of different characteristics on forecast accuracy. The analysis was structured into the following parts:

<u>Aggregation</u>

When the store forecasts are aggregated up to distribution center and chain level, the errors should be reduced by offsetting positive and negative errors. To understand the extent of such reduction, we aggregated store forecasts generated from the Supply Chain Forecasting System up to the distribution center and chain levels, and benchmarked the accuracy of both.

Attributes

This analysis was designed to help us understand the relationship between the attributes below and the forecast accuracy, as well as to understand the redundancy and effectiveness of the current forecasting process. The attributes that we used in the analysis are shown in Table 5.1.

Table 5.1: Groups for aggregated error measurement

Break by	Chain-level	DC -level	Store-level
Ad week	X	X	X
Holiday vs. non-holiday	X	X	X
Category	X	X	X
Product group	X	X	X
Product code	X	X	X
Offer type	X	X	X
Page number	X	X	X
Store ID			X
Distribution center ID			X

Promotional volume

We were interested in seeing if high volume and heavily promoted items are easier to forecast than others. With high volume items and/or frequent promotions, forecasters are more familiar with the demand uplift behavior and tend to make better forecast judgments about those items. To prove this statement, we grouped the products into A, B and C classes by the total actual sales throughout the analysis period and then measured the accuracy of the products by class.

Time

Generally, forecast errors increase as we forecast far into the future. To help us understand the effect of time on accuracy, we compared the distribution center-level forecasts, which are created four weeks ahead of the promotion week and sent to the replenishment team to create purchase orders for the suppliers, with the forecasts done two weeks ahead for the basis of store replenishment. During the two weeks, there are additional sets of historical sales data fed into the system and also additional information that can be used by forecasters to revise their predictions. Both the data and predictions help improve forecast accuracy. The analysis at this level was only limited to the forecasts of the distribution centers that are owned by the ABC Supermarket.

Different forecasting methods

At the chain level, the Promotion Planning System is used by the merchandising team to provide information to support promotion decisions. As described in Chapter 3, the assumptions, methods and attributes used by this system are different than those used by the Supply Chain Forecasting System. We attempt to identify the strengths and weaknesses of each system in order to identify the opportunity to blend the results from both systems for more accurate decision support.

Once we assessed the current performance and identify the impact of forecasting attributes to the forecast accuracy, we conducted regression analysis to verify the relationship between the different attributes and the forecast accuracy. Although we did not expect to find a strong correlation with R^2 higher than 50%, we targeted to at least rank the significance of the forecasting attributes to the forecasting accuracy.

With the results from the accuracy and the regression analysis, we built several models to experiment potential approaches to improve forecast accuracy. The first model that we built was to improve the forecast accuracy at the store level, as we believe that if the error store forecasts decreases slightly for each SKU at each store, the accuracy at the distribution center level will be improved significantly. The second model that we experimented is the blending of top-down and bottom-up forecasts at different levels. Currently the forecast at the distribution center level is aggregated up from the store forecasts, but we are interested in seeing if the chain forecasts could be leveraged to improve the accuracy.

5.2 Scope of data

In this study, we selected three categories of products: ice cream (806 SKUs), ice cream novelty (405 SKUs), and cereal (671 SKUs) for our analysis. The reason for choosing these product categories was that they are the products with frequent promotions throughout the year, making them good representatives for the study in promotional forecasting. Ice cream and ice cream novelties represent the products with seasonality pattern while cereal represents the product with stable demand. Also, according to ABC Supermarket, ice creams and novelties are the category with more frequent new product introductions than cereals, because customers' preferences on the flavors and packages change more rapidly. For each category, the products are further divided into groups which consist of items with similar characteristics. Each item contains product information such as item UPC (Universal Product Code), case UPC, case size, item size, item weight, manufacturer etc. The product hierarchy is shown in Figure 5.1.

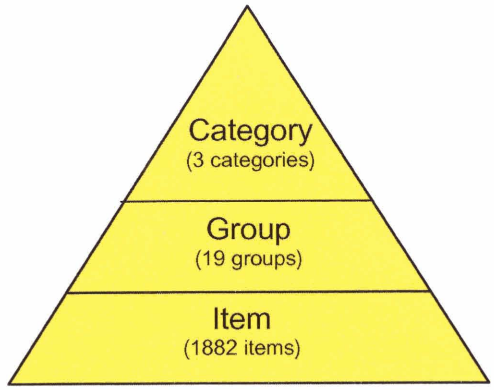


Figure 5.1: Product hierarchy

The data that we used for the analysis included the point-of-sales (POS) data and the forecasting data. As we focus our analysis on the promotional forecasting, we only consider the forecasting data of promotional items. The timeframe of the data is from September 2005 to February 2006 which covered three major holidays: Thanksgiving, Christmas, and New Year. All the stores were included in the analysis, but for certain analysis, we limited to the stores that were supplied by ABC owned distribution centers.

5.3 Forecasting data

We collected the data from three different systems: the Supply Chain Forecasting System, the Promotion Planning System and the Flow of Goods System.

Supply Chain Forecasting System

We extracted the store forecasts that were generated two weeks ahead of the promotion week from Supply Chain Forecasting System for each SKU at each store (SKU/Week/Store). For the six-month time period that we analyzed, there were a total of 113,861 records. We then analyzed the distribution of error and removed the outliers from the analysis. The number of records left was 112,100. The store forecasts were aggregated to distribution level

(SKU/Week/DC) that contains 1,658 records, and to chain level (SKU/Week) that contained 582 records. The relevant fields of data were: product code, product group, product category, ad week, store ID, DC ID, price, offer type, page number, forecast units, and actual units.

Promotion Planning System

The Promotion Planning System (PPS) generates the forecasts at the chain level for the merchandising team to support the promotion decisions approximately six to eight weeks ahead of the promotion week. For the same SKU that we extracted from the Supply Chain Forecasting System, there were a total of 499 records found in PPS. After analyzing the distribution of error, we removed the outliers which leave us 482 records for the analysis. The purpose of this system was different from the previous system as are the attributes and forecasting methods. Besides the forecasting attributes, PPS also takes into account the cannibalization and halo effect. Moreover, the system also calculates the profit uplift for the promotion in addition to the projected units to be sold. However, to benchmark the performance with the Supply Chain Forecasting System, we only considered the common attributes in the analysis.

Flow of Goods System

Four weeks ahead of the promotion week, the Supply Chain Forecasting System generates the store forecasts, aggregates them up to the distribution center level and sends the numbers to the Flow of Goods System for replenishment decisions in the distribution centers. We retrieved such aggregated data for our analysis as well. Note that the data we retrieved are only for ABC owned distribution centers.

5.4 Measure of accuracy

According to Makridakis, Wheelwright, and Mcgee (1983), the term "accuracy" that we refer to is called "goodness-of-fit", or how well the forecasting model is able to reproduce the data that are already known. We define the accuracy as the converse of error, which is the difference between actual and forecast quantity. To facilitate the comparison among different SKUs with different volume, we also calculated the error as a percentage. The summary of error definitions are shown below:

- Error = Actual – Forecast,
- Absolute error = |Actual – Forecast|,
- % Error = (Actual – Forecast)/Actual,
- Absolute % error = |Actual – Forecast|/Actual.

For the aggregated errors across a set of data, we selected the relative measures over the standard ones. Although the standard measures such as root mean square error (RMSE) are widely used robust measures, they do not facilitate comparison across different time series and different time intervals (Makridakis, Wheelwright & Mcgee, 1983) and different SKUs. Hence we use mean percentage error (MPE), which is suitable to determine the direction of error, i.e., whether it is over or under-forecast, and mean absolute percent error (MAPE), which is the most popular measure of variability used in the industry according to Kahn (1998).

However, MPE and MAPE are meaningful only when the volume is large. Due to the low volume per SKU nature of the grocery retail business, MPE and MAPE may not be the most appropriate measure, as the aggregate MPE and MAPE might be inflated by the items with low volume error but high percentage error. For example, when the forecast is 3 units and the actual demand is 1 unit, the percent error is 200%, which is equal to the situation where the forecast is 9,000 units and the demand turns out to be 3,000 units. In the first case, the impact of the error is very low while in the latter case, the cost of lost sales or stock-out could be enormous. We therefore designed the measures that maintain the advantages of MPE and MAPE while addressing their disadvantages, by taking the weighted average of the errors, with the forecast unit as the weight. By using the forecast unit to weigh the errors, it reduces the incentive to over-forecast as the mean percentage error will be amplified. We refer to our measures as WMPE and WMAPE, although they are different from the ones used in other literature such as those by Sivillo and Reilly (2004) and Cecere, Newmark and Hofman (2005).

The equations for the measures we use in the analysis are given below:

- *Mean Percentage Error (MPE):* $\text{MPE} = \frac{\sum_{m=1}^{n} \frac{e_m}{D_m}}{n}$,

- *Weighted Mean Percentage Error (WMPE):* $\text{WMPE} = \frac{\sum_{m=1}^{n} \frac{e_m}{D_m} \times F_m}{\sum_{m=1}^{n} F_m}$,

- *Mean Absolute Percentage Error (MAPE):* $\text{MAPE} = \frac{\sum_{m=1}^{n} \frac{|e_m|}{D_m}}{n}$,

- *Weighted Mean Absolute Percentage Error (WMAPE):* $\text{WMAPE} = \frac{\sum_{m=1}^{n} \frac{|e_m|}{D_m} \times F_m}{\sum_{m=1}^{n} F_m}$,

where D_m and F_m represent the actual demand and the demand forecast for item m respectively, and e_m represents the difference between actual and forecast demand, or D_m-F_m. To measure the variation of errors, we calculated the standard deviation of the absolute percent error (SDAPE) with the formula below:

$$SDAPE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2},$$

where $\bar{x}$ is the MPE of the forecasts.

Because the characteristics of the forecast data for each industry are different, it is important for the companies to select the right measures that best describe the performance of forecasts in their industry. We believe the weighted mean percent error (WMPE) and weighted mean absolute percent error (WMAPE) are suitable for the grocery retail business in that they not only reduce the impact of the high percent error of the low-volume forecasts but also help demonstrate the tendency to over-forecast in this industry.

6 Analysis and Results

The first step to understanding the behavior of a forecasting system is to analyze the accuracy of its results, which can be characterized by bias and variability. Bias measures the tendency to over or under-forecast of a forecasting system, and variability measures the magnitude of forecast errors. We use MPE as well as WMPE to measure bias, and MAPE, WMAPE and SDAPE to measure variability. A negative MPE or WMPE shows the tendency to over-forecast and a positive one shows the tendency to under-forecast. Similarly, a significant value of MAPE, WMAPE, or SDAPE shows that the system frequently produces large errors.

In Chapter 4 we described the incentive to over-forecast, and the difficulty of forecasting in the grocery retail industry. Strong evidence can be seen in the forecasts of ABC's forecasting systems, specifically in negative MPE and WMPE, and large MAPE, WMAPE and SDAPE. The following sections describe our analysis of the forecasts from ABC's forecasting systems from various point of views. The detail of the forecast accuracy analysis of the ABC Supermarket both in tabular and graphical formats can be found in Appendix B – Appendix G.

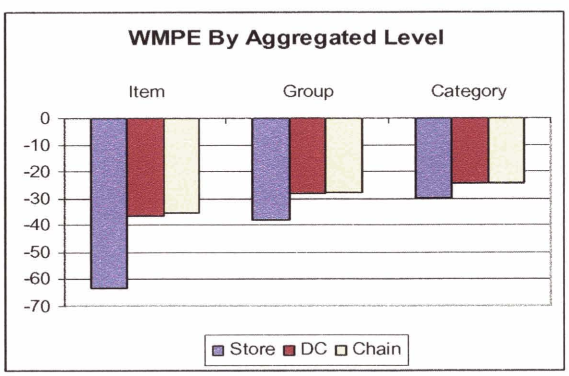
6.1 Analysis of forecast accuracy

6.1.1 Aggregation

As explained in Chapter 4, forecasts conducted at different echelons in the supply chain network have different forecasting objectives. It is important to investigate how forecasting systems perform at each echelon. Therefore, we aggregated the store-level forecasts up to distribution center (DC) level and further to chain level to compare the accuracy of the forecasts among these three levels. Additionally, because three categories (cereal, ice cream, and ice cream novelty) were included in our analysis and each category was further divided into groups, we also aggregated the item-level forecasts up to group level and further to category level. The accuracy measures of forecasts at each level are summarized in Table 6.1 and Figure 6.1.

Table 6.1: Forecast accuracy at each aggregated level

Level		COUNT	Bias		Variability		
			MPE (%)	WMPE (%)	MAPE (%)	WMAPE (%)	SDAPE (%)
Store-Week	Item	112100	-73.37	-63.40	93.94	74.85	134.76
	Group	28299	-54.55	-37.87	67.59	44.68	96.71
	Category	12063	-58.92	-29.78	69.23	35.15	101.68
DC-Week	Item	1658	-40.90	-36.59	49.84	43.35	58.86
	Group	383	-34.69	-28.25	39.66	31.49	41.11
	Category	148	-36.15	-24.53	40.07	27.95	39.57
Chain-Week	Item	582	-42.16	-35.67	49.92	41.87	55.13
	Group	142	-37.64	-27.85	41.62	30.70	42.42
	Category	61	-39.92	-24.30	42.87	27.57	41.70



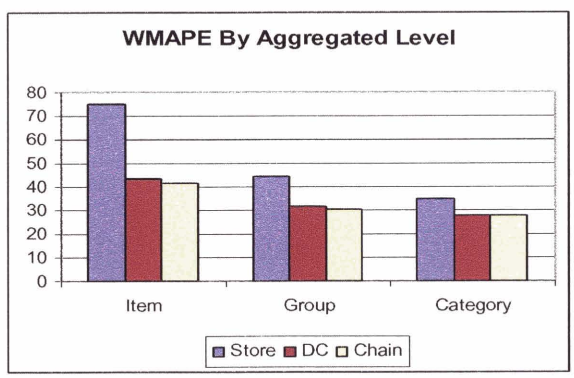


Figure 6.1: WMPE and WMAPE by aggregated levels

As shown above, the errors decrease when the forecasts are aggregated up. This matches our expectation as the positive errors from lower levels should be canceled out by the negative ones when pooled together. However, although the errors decrease significantly from store level to DC level (as well as from item level to group level), the errors between DC and chain levels (and between group and category levels) are very close. This implies that the direction of forecast errors at the chain and DC level is the same and hence the pooling effect at the top levels is not as significant as that at the store level.

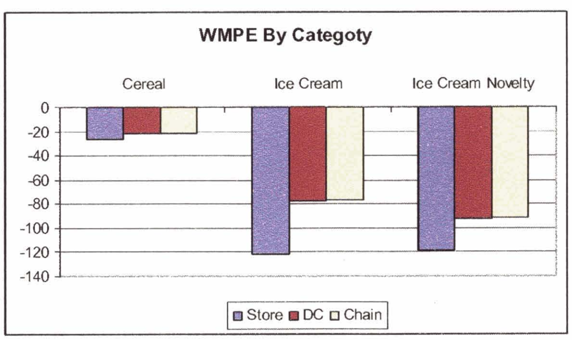
6.1.2 Product category

Since the three categories are very distinct in nature, it is interesting to see how the forecasting systems perform for each category. Cereals represent typical items with stable demands, while both ice creams and ice cream novelties represent items with seasonality demand with the coefficient of variation of the actual demand at 51%, 87% and 110% respectively. Table 6.2 and Figure 6.2 show that the forecasts for ice creams are worse than those for cereals, and the forecasts for ice cream novelties are even worse than those for ice creams. Our analysis shows that even with the promotions, seasonality is still an important factor shaping the demand for that particular period. The forecasting algorithms should incorporate seasonality as an integral part of the forecasting inputs. A technique of incorporating seasonality information into forecasting is described by Sivillo and Reilly (2004).

Moreover, according to the ABC Supermarket, ice cream and ice cream novelty are the product groups with more frequent new product introductions than cereal. New products are generally more difficult to forecast as there is no forecast history. Hence, the industry practice is to refer to existing products with other characteristics and make the best estimate. Although we believe that new product introduction also influence the high forecast errors of ice cream and ice cream novelty, we do not have enough information to conduct the analysis on its impact on promotional forecasts.

Table 6.2: Forecast accuracy by product category

Level	Category	COUNT	Bias		Variability		
			MPE (%)	WMPE (%)	MAPE (%)	WMAPE (%)	SDAPE (%)
Store-Week	Cereal	5425	-22.32	-25.87	30.55	31.23	31.10
	Ice Cream	2140	-87.68	-121.92	104.49	125.63	126.20
	IC Novelty	4498	-89.37	-118.30	99.12	124.14	125.27
DC-Week	Cereal	78	-18.77	-21.62	24.65	25.04	18.73
	Ice Cream	26	-57.73	-77.30	59.72	77.47	43.27
	IC Novelty	44	-54.21	-92.13	55.79	95.95	51.39
Chain-Week	Cereal	26	-19.79	-21.40	25.29	24.66	19.03
	Ice Cream	13	-56.46	-76.55	56.46	76.55	44.54
	IC Novelty	22	-53.95	-91.69	55.62	95.56	50.84



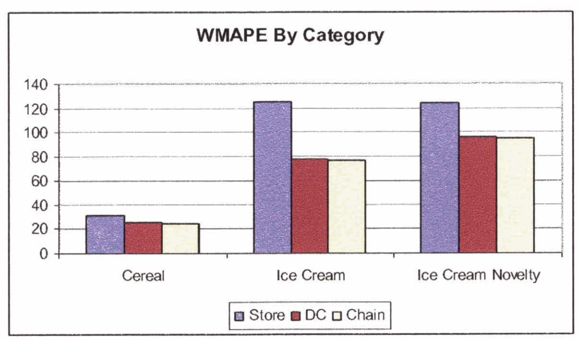


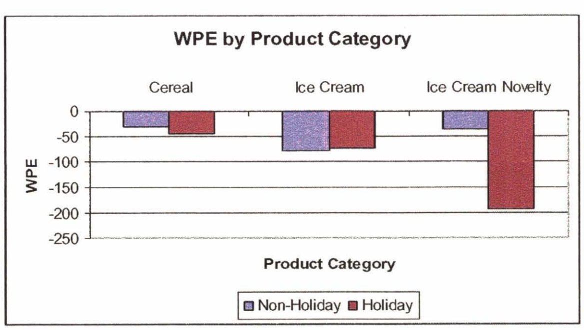
Figure 6.2: WMPE and WMAPE by product category

6.1.3 Holiday

Another factor that affects the accuracy is holiday. The time period that we selected covers three major holiday seasons: Thanksgiving, Christmas and New Year. We compared the DC-level forecasts aggregated by holiday weeks versus non-holiday weeks, and found that for cereals and ice cream novelties, the forecast accuracy during holiday periods is worse than that during non-holiday periods, but the result is opposite for ice creams (Table 6.3 and Figure 6.3). However, the holiday effects on cereals and ice creams are less prominent than that on ice cream novelties. Note that we selected the accuracy at the DC level to present in this section because DC-level forecasts are directly related to replenishment decisions and critical to the overall supply chain operations, but the patterns at all three levels are consistent.

Table 6.3: Holiday vs. non-holiday DC forecast accuracy by product category

Category	Holiday	COUNT	Bias		Variability		
			MPE (%)	WMPE (%)	MAPE (%)	WMAPE (%)	SDAPE (%)
Cereal	Regular	1101	-33.27	-31.49	44.83	38.93	58.71
	Holiday	381	-49.66	-45.52	54.03	49.26	56.39
Ice Cream	Regular	22	-62.30	-78.88	64.71	79.07	44.75
	Holiday	12	-38.53	-73.93	41.09	74.92	44.09
IC Novelty	Regular	98	-45.26	-34.67	48.66	45.14	39.70
	Holiday	44	-136.43	-192.87	136.43	192.87	57.50



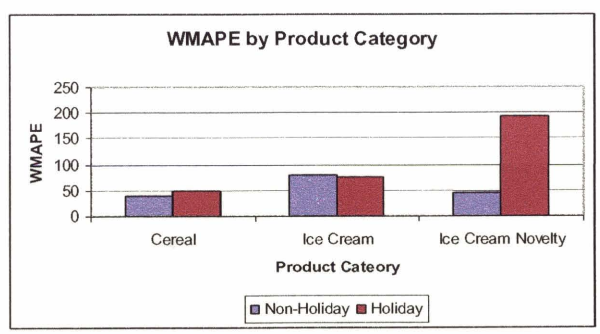


Figure 6.3: DC holiday vs. non-holiday WMPE and WMAPE by product category

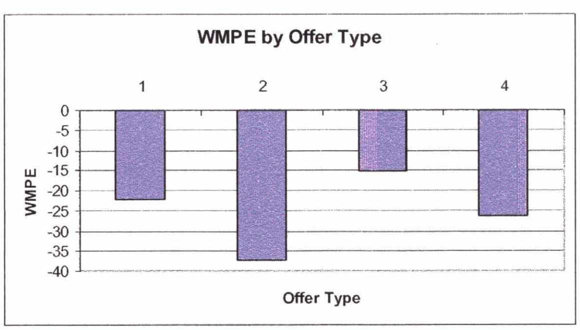
6.1.4 Promotion attributes

We also analyzed the accuracy by promotion attributes which include offer type and page number for aggregated forecasts at DC level. Offer type is the type of promotion offers, such as "Percent Off (offer type 1)", "Special Price (offer type 2)", "Amount Off (offer type 3)" and "Buy 1 Get 1 Free (offer type 4)". Page number is where the promotion offer is printed on the weekly circular. Such attributes are the integral parts of a promotion plan and have direct impact on the effectiveness of a promotion.

The forecast accuracy by different offer types at the DC level is shown in Table 6.4 and Figure 6.4. The data shows that, offer type 2 and 3, the most frequently used types by ABC, are the hardest to forecast among all the offer types.

Table 6.4: DC Forecast accuracy by offer type

Level	Offer Type	COUNT	Bias		Variability		
			MPE (%)	WMPE (%)	MAPE (%)	WMAPE (%)	SDAPE (%)
DC-Week	1	5	-73.76	-22.17	73.76	22.17	66.40
	2	1510	-43.69	-37.44	51.57	44.05	60.24
	3	114	-5.17	-15.30	28.68	35.61	32.32
	4	29	-30.82	-26.18	38.67	29.29	46.03



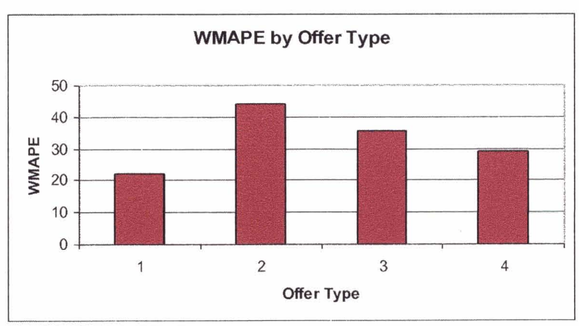
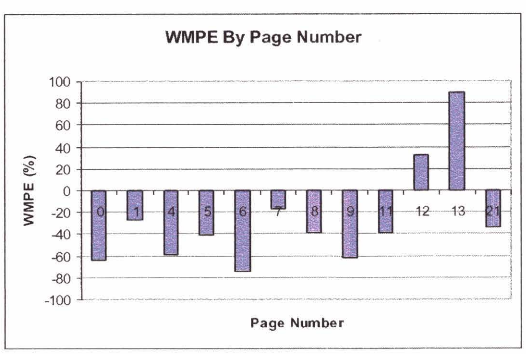


Figure 6.4: WMPE and WMAPE by offer type of DC forecasts

Table 6.5 and Figure 6.5 show the DC forecast accuracy by page numbers which demonstrates that the errors of the items placed on the front covers are among the highest. Interestingly, demands of products that are placed on certain pages in the middle of the circular are highly under-forecasted despite the typical over-forecast trend. The result shows that the forecasting system does take into account the page number factor to generate forecasts, but is incapable of making reliable interpretations.

Table 6.5: DC Forecast accuracy by page number

Page Number	COUNT	Bias		Variability		
		MPE(%)	WMPE(%)	MAPE(%)	WMAPE(%)	SDAPE
0	346	-47.36	-63.41	50.35	65.10	42.43
1	270	-15.07	-26.48	28.50	32.08	39.85
4	67	-63.51	-58.41	66.10	60.68	48.74
5	689	-41.92	-40.31	50.39	47.36	62.17
6	33	-65.91	-74.70	71.89	78.93	97.71
7	12	-31.42	-16.85	41.98	29.56	47.41
8	144	-49.04	-38.52	58.03	48.37	68.61
9	45	-94.29	-61.80	94.69	62.78	108.16
11	2	-40.03	-39.04	40.03	39.04	7.18
12	2	32.28	32.98	32.28	32.98	4.23
13	12	89.65	90.31	89.65	90.31	5.57
21	36	-39.61	-33.53	45.96	38.05	35.7



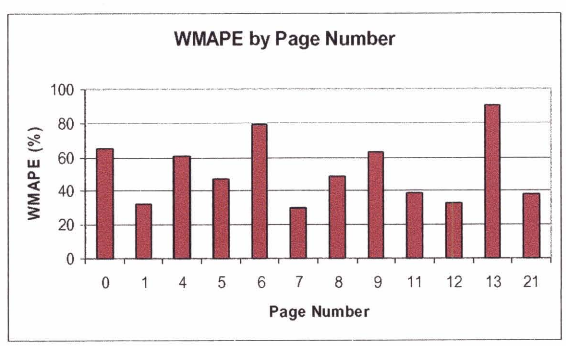


Figure 6.5: WMPE and WMAPE by page number of DC forecasts

6.1.5 ABC analysis

Besides attributes, we were also interested in the impact of promotional volume on the accuracy of the forecasts. If an item is heavily promoted, the forecasting system should have better information on the uplift effect, and be able to predict the demands more accurately. Also, if a promotion item accounts for high sales value, forecasters tend to spend more time making forecasting judgments for that product, and the accuracy should be better than that of another item with low sales and thus, less attention. We therefore conducted an ABC analysis by grouping all 177 items in our data set into class A, B and C based on the total actual selling units of the analysis period (Figure 6.6, Table 6.6). It is interesting to note that the ABC classification has no direct connection with page numbers and no evidence were found that cover page items are more likely to be classified as A items.

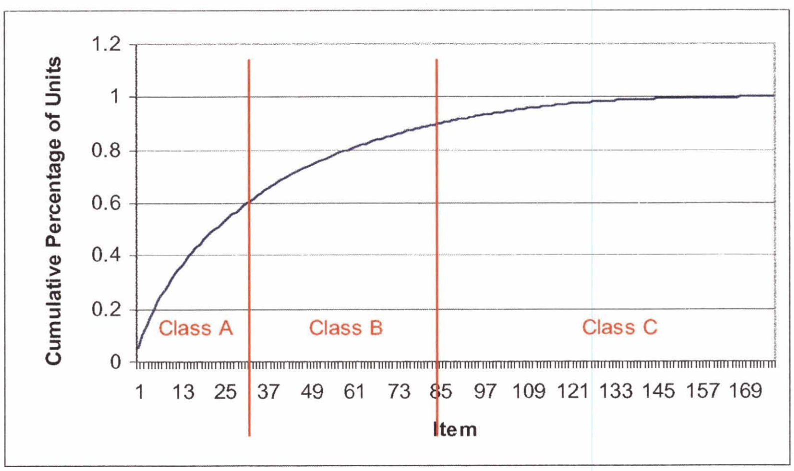


Figure 6.6: ABC classification of items

Table 6.6: ABC classification of promotional items

Class	# Items	Sales Units Percentage
A	32 (18%)	60%
B	52 (29%)	30%
C	93 (53%)	10%

Table 6.7 and Figure 6.7 summarize the forecast accuracy measures of the three classes. The results clearly show that the items that account for the majority of the sales have lower error than the ones with low sales. This implies that the forecasts for such products tend to be more accurate and effective and hence should be focused on for subsequent periods.

Table 6.7: Forecast accuracy by ABC classification

Level	Class	COUNT	Bias		Variability		
			MPE (%)	WMPE (%)	MAPE (%)	WMAPE (%)	SDAPE
Store-Week	A	27653	-26.29	-39.23	51.34	51.60	73.16
	B	34935	-63.84	-80.65	84.58	91.54	120.53
	C	49512	-100.52	-128.70	118.46	137.41	153.51
DC-Week	A	402	-12.98	-21.48	28.43	29.49	27.45
	B	517	-40.36	-49.40	49.59	55.32	59.14
	C	739	-56.47	-73.16	61.66	76.38	67.29
Chain-Week	A	134	-13.22	-20.78	27.62	28.11	26.78
	B	175	-41.51	-48.31	49.99	53.80	58.52
	C	273	-56.78	-71.64	60.82	74.54	59.76

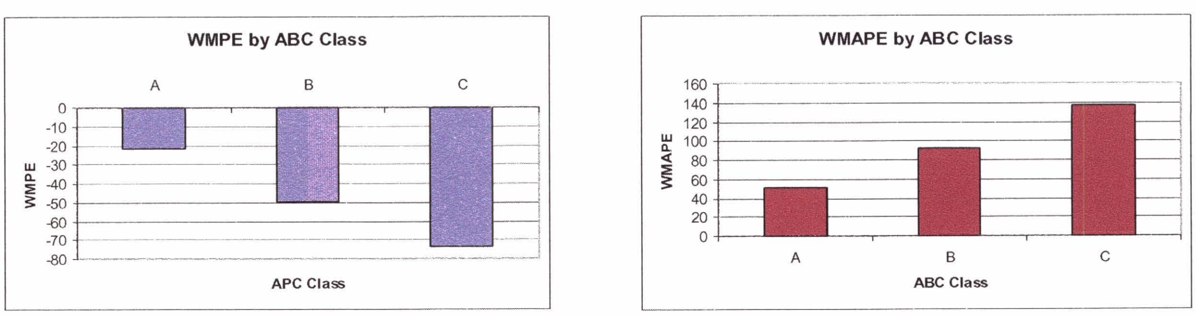


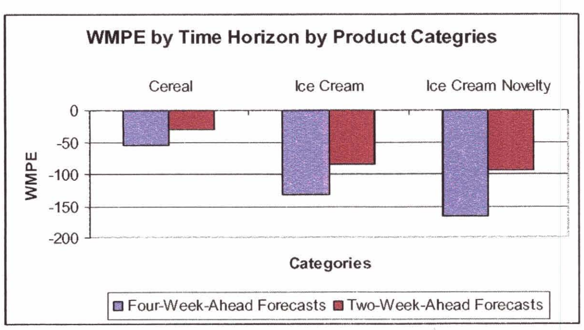
Figure 6.7: WMPE and WMAPE by ABC classification of DC forecasts

6.2 Analysis on time of forecasting

Generally, forecast errors increase as we forecast far into the future. To analyze such effect, we compared the DC-level forecast aggregation of four-week-ahead forecasts, which are sent to the replenishment team for purchase orders decisions, with the DC-level forecast aggregation of two-week-ahead forecasts that are sent to individual stores for store ordering decisions. The results (Table 6.8 and Figure 6.8) agree with our hypothesis, and can be explained in two ways. First, as the promotion week approaches, additional sales history data becomes available. Because it gets closer to the promotion week, sales data tends to be more accurate in reflecting the actual demand. Second, last-minute promotion plan changes which reflect suppliers, consumers and competitors' movement can be captured, leading to more accurate forecast results resulting in forecasts that are more accurate.

Table 6.8: DC Forecast accuracy by time of forecasting

Category	COUNT	Forecasts	Bias		Variability		
			MPE (%)	WMPE (%)	MAPE (%)	WMAPE (%)	SDAPE (%)
Cereal	494	4-week-ahead	-64.00	-55.52	69.48	59.13	75.43
		2-week-ahead	-35.83	-30.41	45.48	38.01	51.71
Ice Cream	17	4-week-ahead	-105.78	-131.22	105.78	131.22	67.27
		2-week-ahead	-56.61	-85.45	60.05	85.68	47.58
Ice Cream Novelty	71	4-week-ahead	-138.39	-166.21	139.37	169.09	130.80
		2-week-ahead	-73.69	-93.48	76.02	100.00	62.63



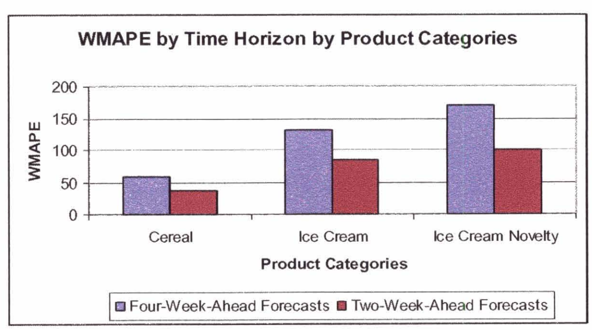


Figure 6.8: WMPE and WMAPE of two and four-week forecasts of DC forecasts

6.3 Comparison of different methods

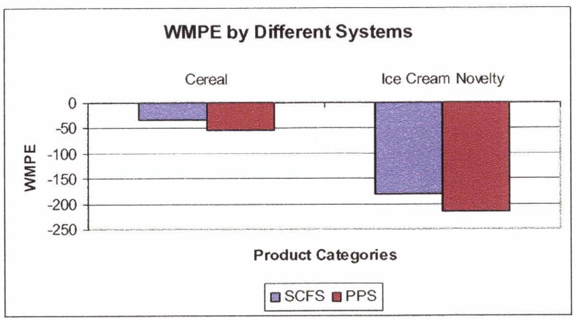
As stated in Chapter 3, in addition to the Supply Chain Forecasting System (SCFS) we studied above, there is another forecasting system deployed at ABC which we have referred to as The Promotion Planning System (PPS). This system is used by the merchandisers for promotion planning purposes. Unlike the Supply Chain Forecasting System that was designed to support replenishment decisions, PPS was designed to help evaluate the sales impact of a promotion. In other words, the two systems are designed with different underlying forecasting methods. It was interesting to compare the two systems and take advantage of any synergies if they existed. While SCFS does the forecasting for all items on the store level, PPS does the forecasting for promotional items only on the chain level.

We aggregated the store forecasts of SCFS up to the chain level and compared the results with the outputs of PPS. Table 6.9 and Figure 6.9 summarize the comparison[2]. More detailed results by product group are shown in Appendix F and Appendix G. We found that SCFS outperforms PPS in most situations, which can be explained in several ways. First, the algorithm of SCFS is much more sophisticated which makes it capable of performing advanced analysis. Second, SCFS is executed two to four weeks prior to the promotion event whereas PPS is executed six to eight weeks prior to the promotional event. Therefore, the shortened forecasting time helps reduce forecast errors. Third, the chain-level forecasts of SCFS are the results of store level aggregation, which the errors were reduced due to the pooling effects.

[2] We excluded ice cream from our analysis due to limitation of the data.

Table 6.9: Chain forecast accuracy comparison between SCFS and PPS

Category	COUNT	System	Bias		Variability		
			MPE (%)	WMPE (%)	MAPE (%)	WMAPE (%)	SDAPE (%)
Cereal	287	SCFS	-43.17	-32.18	51.27	38.01	58.96
		PPS	-72.94	-54.76	85.34	65.39	84.83
Ice Cream Novelty	15	SCFS	-125.06	-179.05	125.24	179.08	66.53
		PPS	-147.58	-215.46	149.21	215.70	93.89



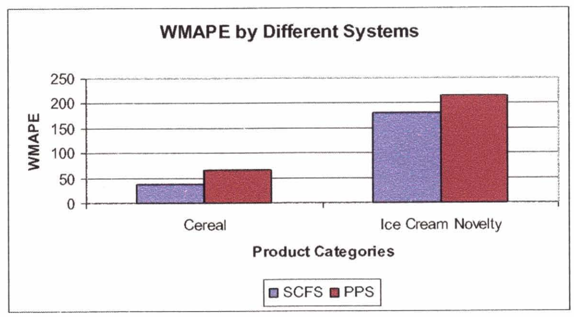


Figure 6.9: WMPE and WMAPE between SCFS and PPS at chain level

6.4 Regression analysis

Regression analysis is the most frequently used method to determine the relationship between a quantitative dependent variable Y (also called the outcome, response variable, or predicated variable), and a set of independent variables X_1, X_2, …, X_p (also referred to as input variables, control variables, or predicators). The assumption is that in the population of interest the following relationship holds:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \varepsilon,$$

where β_0, β_1, …, β_p are coefficients, and ε is the "noise," or the unexplained part. The data, which are a sample from a population, are then used to estimate the coefficients and variability of the noise. The approximate model can be written as follow:

$$\hat{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_p X_p .$$

The objectives behind fitting a model that relates a quantitative outcome with predicators include: (1) to understand the relationship between these factors, and (2) to predict outcomes of new cases. We used R^2_{adj}, which is a version of R^2 that has been adjusted for the number of predicators in the model, as an indicator of the goodness of fit. The closer R^2_{adj} is to 1, the stronger the relationship holds and the more likely the model can predict the outcome.

In our regression analysis, our goal is to understand the key factors that lead to forecast error, and the significance of each factor. As identified in the previous sections, we include category, holiday, page numbers[3] and offer types[4] as the candidates of predicators, and use the percentage error as the output variable. For comparison purpose, we conducted the analysis on both PPS data and chain level aggregates of SCFS data.

For PPS, The best fitted model we found is:

$$\hat{Y} = -11.1 - 59.1X_1 + 13.4X_2 - 117.4X_3 - 41.3X_4 - 220.4X_5 + 9.1X_6,$$

where the independent variables X_1, X_2, X_3, X_4, X_5, and X_6 denote Holiday, Cereal, Cover Page, Other Pages, Offer Type 2, and Offer Type 4 respectively.

For SCFS, The best fitted model we found is:

$$\hat{Y} = -110.1 - 37.7X_1 + 49.6X_2 - 21.5X_3 - 23.1X_4 + 55.6X_5 + 55.6X_6,$$

where the independent variables X_1, X_2, X_3, X_4, X_5, and X_6 denote Holiday, Cereal, Cover Page, Other Pages, Offer Type 2, and Offer Type 4 respectively.

[3] To reduce the number of page number variables, we decided to use front page, middle page, and back pages instead of individual page numbers as the input variables.
[4] The different offer type values are converted into a set of logic variables.

In general the models are weak for describing the correlation between the outcome variable and the predicators, as R^2_{adj} is very small (0.18 and 0.23 for SCFS and PPS respectively). This implies that other uncontrollable or unexplainable factors contributed significantly to the errors, and hence focusing merely on the specified factors will not be sufficient to improve the accuracy. However, it does offer some value in helping us understand the significance of different factors to forecast errors. According to the model, the most relevant factors by the order of significance are holiday, category, front page, and offer types. Category and offer type affect the accuracy in the positive direction, and holiday and front page the opposite direction. The finding is consistent for both PPS and SCFS. To reduce forecast errors, grocery retailers should understand the order of significance of the forecasting attributes in order to support the judgments of the forecasts.

7 Improving Forecasts

As described in Chapter 4, forecasting the demand in the grocery retail business is very difficult due to its high number of SKUs and relatively low volume of each SKU per store. Also, consumer preferences vary from location to location and tend to change very often without exact patterns. Especially when the products are on promotions, there are countless factors that need to be taken into account in predicting the demand. The results of accuracy measures from Chapter 6 prove this hypothesis; even for ABC Supermarket that is equipped with advanced forecasting software systems, the forecasting error is high and there is also a high tendency to over-forecast. This chapter will analyze the reasons for the high error rate as well as the strong bias and suggest approaches to improve forecasts in the grocery retail business: improvement at the store level, distribution center-level, and measuring forecasts.

7.1 Reasons for high forecast error and bias

By analyzing the results and interviewing key personnel at the ABC Supermarket, we summarize the reasons for high forecasting error and high bias as follow:

- *Collinearity of forecasting variables*

For promotional items, there are numerous promotional attributes such as page number that the item appears on the circular, offer type, and amount off as well as the historical time series sales data and seasonality patterns of the item. Therefore, the systems apply uplift for each variable on top of the others, resulting in overestimated demand. Measuring forecast accuracy and conducting regression analysis helped reveal the impact of multiple uplift and forecasters can benefit from this information to make necessary judgments when removing systematic bias.

- *The relationships between variables and demand uplifts are hard to quantify*

As shown in Chapter 6, demands influenced by each different value of the attributes have different level of the predictability which is difficult, if not impossible, to quantify. We observed a noticeable difference in forecast accuracy between different page numbers and offer types, but the results from the regression analysis did not reveal exact pattern of the relationship. According to the ABC Supermarket, the configuration of the systems is a one-time activity and is not constantly updated to reflect changes in consumer behavior. In addition, without constantly measuring current performance, the current configurations of the systems cannot be evaluated and improvements cannot be identified.

- *Some forecasting variables are omitted*

Although grocery retailers employ sophisticated forecasting software to assist with the forecasting process, it is not possible to take into account all relevant variables. According to Bunn and Salo (1996), the reasons why some variables need to be omitted from the forecasting model include: (1) they have insufficient data to be estimated (2) they are highly collinear with other variables in the model (3) they are purely judgmental and (4) they have not been important in the past. The experience of forecasters therefore contributes to higher forecast accuracy when those variables need to be taken into account. From the results of the ABC analysis in Chapter 6, items with frequent promotions that the forecasters are familiar with have higher forecast accuracy compared to items that are not on promotions very often. This result emphasizes the influence of the forecaster's experience to the accuracy. However, the learning process of forecasters cannot be effective without constant accuracy measurement that provides the information on the result of the judgments they make for the next forecasts.

- *Incentive to over-forecast*

As described in Chapter 4, the cost of lost sales for this industry is very high compared to the cost of holding extra inventory. The systems are thus designed to include some safety factor to the forecast. However, when forecasters make judgments to override the forecasts, they often add more items on top of that number, making the forecast even more inflated. From the analysis, only one-third of the store forecasts are underestimated, but the impact to the business is high and the forecasters prefer to avoid this situation whenever possible.

- *No measurement system*

Lack of the forecast measurement system apparently is the most important reason for the high forecasting error of grocery retailers. Because of the high volume of forecast data due to high number of SKUs and stores, many grocery retailers may not have the system in place that is capable of processing forecast data into meaningful accuracy measurements. Kahn (2003) conducts a benchmark on forecast error with the companies mainly in consumer product business. Although products in this industry are easier to forecast than those of the grocery retail industry due to lower number of SKUs, higher volumes, and fewer number of locations, only 45% of the 40 respondents reported that they measured the forecasting error. Without understanding the current forecast performance, grocery retailers cannot improve their forecasting process which is a critical step dictating the efficiency of its supply chain. Cecere, Newmark and Hofman (2005) provide a framework to measure forecast accuracy to drive the supply chain excellence, and they suggest that to improve the forecast accuracy, companies need to effectively model their channels, measure accuracy, benchmark performance, and generate use among internal and external customers.

7.2 Improving store forecasts

From the analysis of forecast accuracy of store forecasts compared to the aggregated distribution center- and chain-level forecasts in Chapter 6, we found that the accuracy improves as the forecasts are aggregated up because the positive and negative errors tend to offset with each other. Therefore, if the store forecasts can be improved just slightly, the accuracy at the distribution center level can be improved significantly. The forecasts at the distribution center are the ones sent to replenishment group to place purchase orders, thus if the forecasts at this level are more accurate, the efficiency of supply chain will be improved and the cost due to overstock or lost sales will be reduced.

Because the results of accuracy measure suggest that there is a strong systematic and judgmental over-forecasted bias, we see the opportunity that the bias can be removed. We therefore propose three models to improve forecasts at the store level and discuss the benefits and limitations of each model.

7.2.1 Model one: The bias correction model

The first approach is to use the average percent error from the past results to adjust the forecasts. According to the formula of percent error calculation, we can derive the de-biased forecasts as follows:

$$\varepsilon = \frac{\hat{A} - F}{\hat{A}},$$

$$\hat{A} = \left(\frac{1}{1-\varepsilon}\right) \times F ,$$

where ε is the WMPE of the past forecasts of that product, F is the forecast generated from the system, and Â is the expected actual demand. We will refer to the value of $\left(\frac{1}{1-\varepsilon}\right)$ as the "bias correction factor".

We partitioned the forecast data into the training set and the validation set at the proportion of approximately 50% and 50%. The correction factors were calculated from the training set, and were applied to the validation set to prevent the overfitting condition. We were interested in comparing the results of removing the bias using the correction factor calculated from the past forecasts with the same item, with the correction factor calculated by the forecasts of the whole product group. Although the correction factor for each product should better reflect the performance of each individual item, it tends to contain noise and can only be used for the products with historical forecast data. To test the hypothesis, we calculated the factor for each of 100 items and 11 groups in three product categories and compared the accuracy after removing the bias using two sets of factors.

<u>Simulation result</u>

We first de-biased the forecast of each item using the correction factor for the same product computed from the training data. We found that the overall accuracy improves dramatically when the bias is removed. Table 7.1 shows the accuracy measure of the de-biased forecasts compared to the original ones. From the result, WMPE improves from -83.27% to -22.27 % and WMAPE improves from 93.86% to 57.25%.

Table 7.1: The accuracy measurement of the original and the de-biased store forecasts using correction factor calculated from the same product code

Forecasts	WMPE (%)	WMAPE (%)
Original forecasts	-83.27	93.86
De-biased forecasts	-22.27	57.25

We also aggregated the forecasts up and measured the accuracy for the aggregated distribution center-level and chain-level forecasts. The results are shown in Table 7.2. With the improved store forecasts, the performance at distribution-center level improves significantly as expected. Therefore, if bias is removed first from the store forecasts before they are aggregated up to distribution-center level and sent to replenishment group to place purchase orders, the units of products ordered from the manufacturers will have less discrepancy compared to the units sold at the stores, creating the efficiency in the grocery retail supply chain, both at the distribution centers and at each individual store.

Table 7.2: The accuracy measurement of the DC-level forecasts aggregated from original and de-biased forecasts

Forecasts	WMPE (%)	WMAPE (%)
Original forecasts	-38.33	42.63
De-biased forecasts	4.67	27.88

As the characteristics of the products vary, the correction factors to remove the bias should be calculated for each item so that the correction factor best represents the data for that product. However, because calculating factors by item might not be practical, is impacted by noise and cannot be used for new items, we calculated factors by product group, and used the factor to remove bias from the new forecasts. It can be seen from Table 7.3 that the overall error is only slightly higher than when the factors are calculated by products, and for some product groups, the accuracy is even better. This is because the demand patterns for each product group do not vary much, and by calculating the factors by group, they are less likely to be impacted by meaningless noise (Table 7.4).

Table 7.3: The accuracy measurement of the original and the de-biased store forecasts using factors calculated by item vs. by product group

Forecasts	WMPE (%)	WMAPE (%)
Original forecasts	-83.27	93.86
De-biased forecasts using factor by product	-22.71	57.25
De-biased forecasts using factor by group	-25.24	60.15

Table 7.4: The accuracy measurement by group of the original and the de-biased store forecasts using factors calculated by item vs. by product group

Category	Group	Count	Original forecasts		De-biased forecasts using factor by item		De-biased forecasts using factor by group	
			WMPE (%)	WMAPE (%)	WMPE (%)	WMAPE (%)	WMPE (%)	WMAPE (%)
Ice cream	589	136	-126.85	135.03	-4.26	22.90	-38.16	52.90
	591	1062	-141.82	145.10	-32.93	56.33	-34.00	56.83
Novelty	590	2191	-236.24	241.33	-13.29	55.76	-59.46	92.67
	2038	600	-46.52	74.97	43.11	61.75	25.80	55.57
Cereal	668	194	-125.97	129.67	-14.10	55.97	-64.03	79.86
	674	3269	-79.73	88.39	8.31	42.44	-15.14	45.73
	676	1310	-120.43	131.38	-8.58	71.39	-33.54	73.53
	683	7893	-68.56	78.60	-29.26	57.56	-21.64	53.48
	685	16649	-72.53	84.94	-18.48	57.87	-19.04	56.80
	700	3525	-174.46	180.53	-52.49	78.04	-105.56	123.86
	2940	1664	-48.31	55.78	-18.42	39.77	-24.16	41.84

<u>Benefits and limitations of the model</u>

The greatest benefit of this model is that it is easy to implement and is intuitive to forecasters. Also, with the number of SKUs per store, this model does not require sophisticated information systems to handle. However, by using a single average percent error for every new observation, the benefit of the reduced error needs to be offset by the loss of accuracy for the forecasts that are already close to the demand. Also, because of the high standard deviation of errors, the average percent error that mitigates the extent of over-forecast for some items may result in the under-forecast for other items. Most importantly, the assumption for this model is that the performance of the forecasts fluctuates around the same mean, which might not always be the case due to the variation of customer demands and other external factors. As advised by Goodwin (2003), changes in the nature of the outcome-forecast relationship over time may mean that corrections based on biases which no longer apply are counter-productive.

7.2.2 Model two: The adaptive bias correction model

Because of the problem of changing customer demand patterns that may make the correction factors calculated using past results no longer apply, we see the opportunity for the grocery retailers to use the learning techniques to feed the past performance back to adjust the forecasts for the next promotion periods. Based on this model, the simple learning technique that we adopt is to adjust the factor with the new percent error every time the forecast is measured. Note that what we adapt is not the factor, but the percent error ε which is a component of the factor. This adaptive model can be written as:

$$\varepsilon_{n+1} = \varepsilon_n + \left[\alpha \times \frac{(A-F)}{A}\right].$$

The variable α is the weight which determines the extent to which the new error influence the value of the factor in the next observation. We select the value 0.1 for α, as the accumulative WMPE should weight more than the percent error of the current observation. Thus, our model could be written as:

$$\varepsilon_{n+1} = \varepsilon_n + \left[0.1 \times \frac{(A-F)}{A}\right],$$

$$Factor_n = \frac{1}{1-\varepsilon_n}.$$

We use this model to simulate the result of the forecast data of select SKUs. Like in the previous simulation, we calculated the factor from the training data set and applied it to the validation set. Instead of using a constant factor, we adapted it based on the model above. To measure the performance, we compared the WMPE and WMAPE of the model using constant factors and the one using adaptive factors.

Simulation result

The simulation result reveals that if the initial factor is a good representative of the new forecasts generated from the system, the model using constant factors performs better than the adaptive factor, as it is not polluted by noises of the new forecasts. However, if the initial factor is not a good representative, the adaptive factor helps bring the factor closer to the new weighted average of the new set of forecasts. Figure 7.1 represents the movement of factor of product A from the initial factor of around 0.33 to reflect the new data which is 0.67.

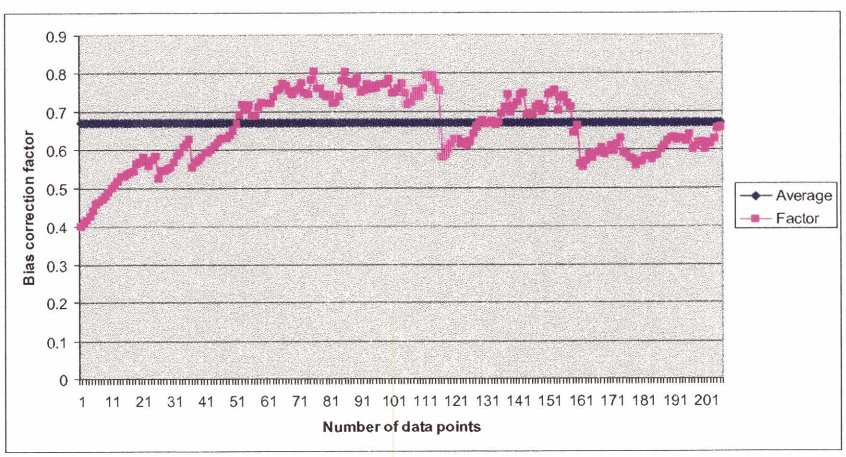


Figure 7.1: Changing pattern of correction factor for a cereal product using adaptive model

The sensitivity analysis of two product codes in cereal category is shown in Table 7.5 and 7.6. We can see that for product A, if the initial factor is 1.0, without adapting the factor, the aggregated WMPE is -48.48% while the adaptive model gradually changes the constant for every new observation and converges to the equilibrium where the error is close to zero, resulting in the WMPE after 207 observations at -5.25%.

Table 7.5: Sensitivity analysis of product code A (cereal)

Initial factor	Static		Adaptive	
	WMPE (%)	WMAPE (%)	WMPE (%)	WMAPE (%)
1.8	-165.40	165.84	-9.06	35.76
1.6	-139.26	140.00	-8.36	35.19
1.4	-108.91	110.22	-7.42	34.40
1.2	-78.59	81.08	-6.43	33.77
1.0	-48.38	55.00	-5.25	33.05
0.8	-18.57	36.05	-3.77	32.15
0.6	10.72	32.28	-1.80	31.81
0.4	40.83	46.08	1.33	32.63
0.2	70.10	70.26	8.58	34.02

Table 7.6: Sensitivity analysis of product code B (cereal)

Initial factor	Static		Adaptive	
	WMPE (%)	WMAPE (%)	WMPE (%)	WMAPE (%)
1.8	-344.27	346.60	-30.48	88.43
1.6	-302.54	305.90	-29.58	88.16
1.4	-250.95	256.50	-28.38	87.74
1.2	-199.73	211.25	-27.18	87.94
1.0	-149.41	173.48	-25.73	88.87
0.8	-98.93	144.65	-24.13	90.66
0.6	-49.70	126.29	-21.64	92.62
0.4	0.23	111.35	-18.10	97.58
0.2	49.45	101.17	-11.65	123.17

Benefits and limitations of the model

The adaptive model is more robust for the changing demand patterns of grocery retailers as it learns from new observations and changes the bias correction factor to fit the new demand trend. This provides the flexibility to the grocery retailers and helps reduce the effort of monitoring and checking the validity of the bias correction factor. However, there are some limitations to this model besides the ones described in the previous model. First, because the adjusted forecast is not defined when the percent error is 100%, this model cannot be used for the under-forecasted items because as the model adapts itself and the error reaches the value of 100%, the adjusted forecast will go to infinity. Moreover, although it is capable of adjusting the factor to the new demand trend, it is polluted by the noise of each data point. If this model is implemented, the factor should be adapted once per ad week, not for every new data point.

7.2.3 Model three: The regression model

A bias correction model that is suggested by many studies such as Goodwin and Lawton (2003) and Shaffer (1998) is the linear regression model that predicts the demand based on the original forecasts:

$$\hat{A} = \hat{\alpha} + \hat{\beta}F + \hat{\gamma}H$$

where F represents the original forecast, H represents the holiday flag and $\hat{\alpha}$, $\hat{\beta}$ and $\hat{\gamma}$ represent the regression coefficients. Without bias, the value of $\hat{\alpha}$ and $\hat{\beta}$ should be 0 and 1 respectively. The expected actual, $\hat{A}$, represents the recommended adjusted forecast that exclude the systematic bias from the original forecasts. The reason that the holiday factor is included in the regression model is that it is a significant attribute that impacts the level of accuracy based on the analysis in Chapter 6.

We tested the model on select products under the cereal group. First, we randomly partitioned the forecast data into the training set and the validation set in the proportion of approximately 50% and 50%. For each one of the three select products, Product C, D and E, the coefficients of the regression according to the model above were determined and the regression equations were formed. The expected actual demand for each data point is calculated according to the product's regression equation using the validation data. To measure the performance, WMPE and WMAPE of each product is measured and compared with the WMPE and WMAPE of the original forecasts.

Simulation result

We obtained the regression equation of Product A and B as follow:

Product C: $\hat{A} = 9.49 + 0.59F - 9.66H$

Product D: $\hat{A} = 5.76 + 0.47F - 2.36H$

Product E: $\hat{A} = 21.35 + 0.79F - 20.31H$

The simulation result of Product C and D is shown in Table 7.7. We can see that the revised forecasts generated from the regression model perform better than the original forecasts. For Product C, the WMPE decreases from -157.61% to -106.55% and WMAPE decreases from 181.28 % to 154.58%. The same trend applies for Product D. However, for product E, the accuracy decreases using the regression model. The result emphasizes that in general, the accuracy improves when using this model to remove the bias, but not for every product.

Table 7.7: Simulation results of regression model of select products

Product	Original forecasts		Revised forecasts from regression models	
	WMPE (%)	WMAPE (%)	WMPE (%)	WMAPE (%)
Product C	-157.61	181.28	-106.55	154.58
Product D	-59.47	66.07	-5.62	41.64
Product E	-35.66	50.39	-59.02	67.67

Benefits and limitations of the model

Once the regression model is identified, it is easy to calculate the adjusted forecast that yields significant improvements. There is also no limitation on the zero nominator like in the previous two models. However, the regression model needs to be identified per product which can be a time-consuming process for grocery retailers with large number of SKUs to handle. Also, the regression model needs to be revised every time new observation is available, which is not practical to do in practice. The other issue of this model is that it is less intuitive to the forecasters compared to the first model. The forecasters need coefficients in order to calculate the expected forecast, as opposed to bias correction factor that is more meaningful.

7.2.4 Summary of store forecasts improvement

Because the improvements of store forecasts can potentially improve the efficiency of the whole supply chain, we recommend that grocery retailers improve store forecasts by removing the bias using the WMPE of the past results as the factor to de-bias the forecasts. However, because the demand pattern of each product changes over time, constant factors might not be valid for the next observations. Therefore, an adaptive factor can be employed to add flexibility into the forecast adjustment process.

These models work in theory while in practice there can be some implementation issues. First of all, the accuracy of forecasts in grocery retail business varies significantly according to many internal and external factors. Therefore it is not appropriate to adjust the bias using a single representative value that works well for some forecasts but not for the others. Goodwin and Lawton (2003) suggests that although the approach such as unbiasedness test can be applied to determine when to correct the forecasts, it is unlikely to work in practical context and the policy of always correcting forecast is preferable. Also, the better accuracy of forecasts must be offset by increased costs and efforts in measuring and improving forecasts. Because of the high number of SKUs, it is difficult to manage the improvement of all the products without a robust measurement and forecasting system that the companies can monitor the performance of the forecast before and after override and use the result as the learning input for the forecasting improvement. The use of adaptive forecasting using mathematical methods and learning techniques such as Bayesian Adaptive Control and Neural Networks is discussed in Roseboom (2005).

7.3 Improving replenishment forecasts

As replenishment plays a critical role in the supply chain operation, improving the forecasts at the DC level is very important for enhancing overall supply chain performance. We propose the following three-step approach to improve DC-level forecasts (Figure 7.2):

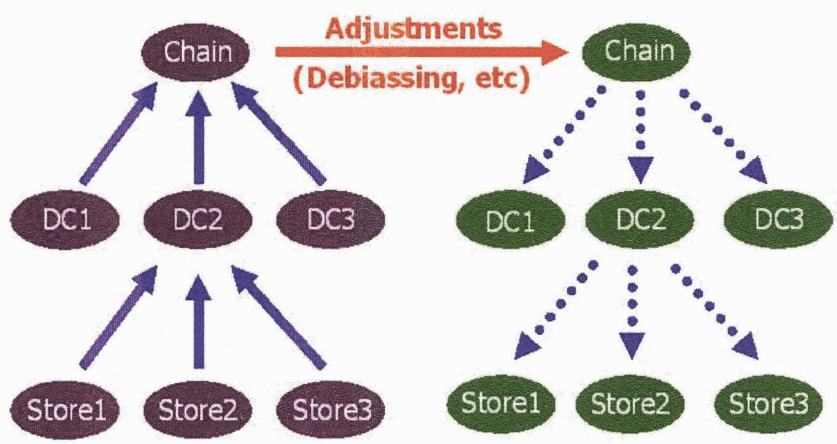


Figure 7.2: A three-step approach to improve forecasts

(1) Aggregate store-level forecasts up to DC level and further to chain level. The noise of forecasts at lower levels are thus removed.

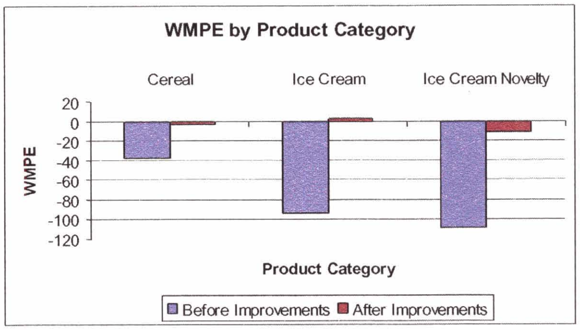
(2) Make improvements on the relatively accurate chain-level forecasts. Such improvements include removing bias, reducing variability, factoring in external factors, and incorporating experts' judgments.

(3) Allocate the adjusted chain-level forecasts down to DC level and further to store level if needed, by the same allocation portion as in the original data.

We experimented with this approach on ABC's SCFS data. The improvement we performed on step two was to remove the chain-level bias using the method explained in section 7.2. The data was partitioned into two disjoint sets: a training set for determining the bias correction factor, and a validation set for testing the approach. The bias correction factors were calculated for each product group, and applied to all items in the same group. The results of our experiments (Table 7.8) were superior: the adjusted forecasts were significantly better than the current ones for all categories at all levels, especially at the DC level (Figure 7.3). More detailed data of the results are shown in Appendix H.

Table 7.8: Forecast accuracy before and after the improvement

Category	Group	Level	WMPE (%)	WMAPE (%)	SDAPE (%)
Ice Cream	Chain	Before	-92.75	92.75	46.51
		After	3.16	23.43	16.01
	DC	Before	-93.42	93.42	46.20
		After	2.80	23.44	15.22
	Store	Before	-143.89	147.22	168.03
		After	-22.90	53.10	80.86
Ice Cream Novelty	Chain	Before	-107.62	116.06	65.46
		After	-10.80	44.25	23.22
	DC	Before	-108.51	117.47	64.31
		After	-11.28	44.41	23.94
	Store	Before	-201.51	210.67	304.19
		After	-61.50	95.03	155.97
Cereal	Chain	Before	-35.91	41.28	60.13
		After	-2.09	28.02	36.80
	DC	Before	-37.14	43.27	62.04
		After	-3.09	29.03	39.00
	Store	Before	-87.37	98.67	410.84
		After	-42.00	70.56	320.43



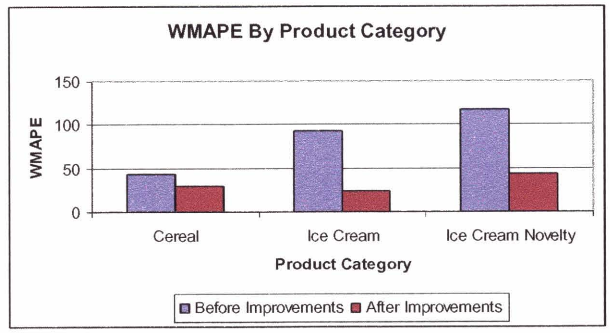


Figure 7.3: WMPE and WMAPE of DC-level forecasts before and after the improvement

A second possibility is to combine the PPS forecasts with the aggregated SCFS forecasts at the chain level. In general this is a good opportunity to improve forecasts, as proven by many studies. However, in ABC Supermarket's case, since SCFS outperforms PPS in most situations, the combination tends to lead to forecasts with less accuracy. Out of 117 items, the accuracy of only 47 items improved. However, for the ones that the accuracy improved, the result was impressive; for one of the products in this experiment, the MPE went down from -322.06% to -109.98%. Although the combination of forecasts from two systems did not always lead to forecast improvement for the ABC Supermarket, this approach can be applied for blending forecast results from other systems at different levels in other situations.

In summary, the objectives and benefits of improving store forecasts described in section 7.2 are different from the three-step approach discussed in this section. Also, the results might vary depending on the variability of the data and the number of stores of each particular grocery retailer. Therefore, the decisions on the approach a grocery retailer should take depend on which forecasting level it needs to focus the improvement effort on, as well as the readiness of supporting information systems to perform the improvement tasks.

7.4 Improving accuracy measuring systems

From our experiment, there is no easy method to fix the forecast with such a high variation level as in the grocery retail business. However, our experiment has shown that the improvement in forecasting is impossible without constantly measuring forecasts. Therefore, in this section we will suggest the framework and methods to measure the forecasts of the grocery retail business so that the performance of current forecasts can be fed back to refine the forecasting systems and process.

7.4.1 Measurement process

Not only do grocery retailers need to measure forecast accuracy, they need to have a structured measurement process in place to ensure that measurement results are meaningful and can be used to compare multiple forecasts as well as to revise the system configurations and forecasting process. One of the biggest problems for companies across all industries, including the ABC Supermarket, is that the original forecasts from statistical models are not recorded in the systems and thus they cannot be compared with the forecasts overridden by forecasters or management. According to the study conducted by Cecere, Newmark and Hofman (2005), leading companies measure the impact of overrides on forecast accuracy and balance their impact with forecast performance. Therefore, it is crucial for companies to measure the accuracy of both original forecasts and judgmental forecasts so that the sources of errors could be identified and the systems and processes can be refined accordingly. At each level of forecasting (chain, distribution center, and store), we suggest the model as illustrated in Figure 7.2.

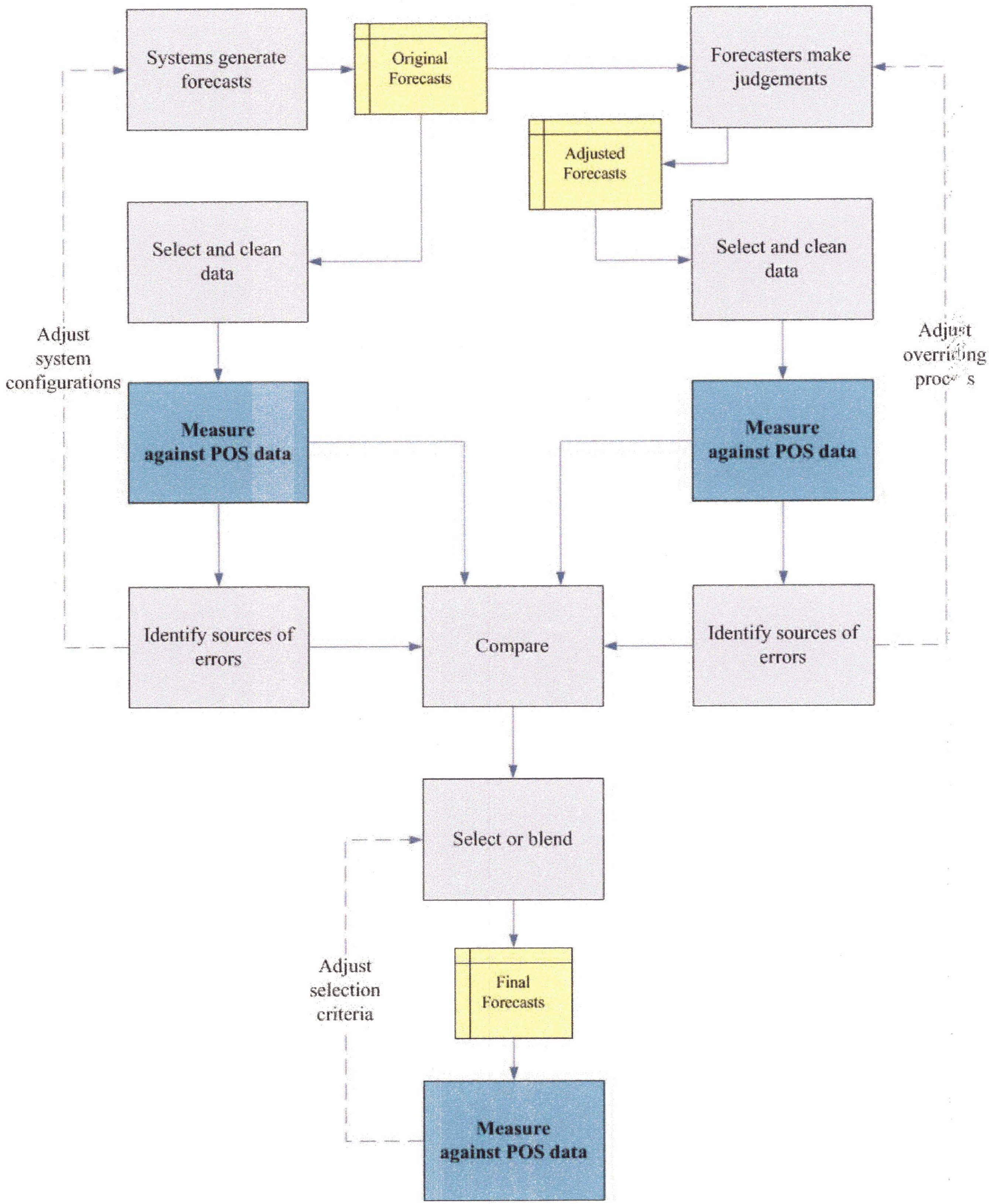


Figure 7.4: Recommended forecast measurement process

7.4.2 Measurement level

It is important that the forecasts are measured separately at each level because the objectives of the forecasts are different. Unless we understand the forecasts at each level, we cannot understand the impact to the supply chain and operations. For example, the forecasts measured at the DC level indicate the effectiveness of replenishment process whereas the forecasts measured at store indicate both the effectiveness of store replenishment and customer service level.

From the product structure perspective, the forecasts should be measured according to the hierarchy. In the case of ABC Supermarket, the forecasts should be measured for each item, group and category so that the performance of each group and category can be compared and the improvement effort can be focused at the right products.

Another dimension that grocery retailers can measure the accuracy is by geography. Customer preferences can vary largely depending on demographic differences. Therefore, grocery chains that operate in regional or national scope need to understand local requirements and adjust forecasts based on the specific preferences. We have measured the accuracy of ABC and have found that the accuracy varies greatly from one store to the other even for the same item. We did not have enough information to conduct the analysis further but we believe that the demographic attributes of that store influence the demand pattern for each store.

7.4.3 Measures of accuracy

As mentioned in Chapter 5, we have proposed WMPE and WMAPE which are more suitable for the characteristics of forecast data in the grocery retail business than the original MPE and MAPE. Again, the benefits of these two measures are that the impact of high percent error of low volume item is mitigated and that it alleviates the incentive to over-forecast as the higher the forecast number is, the higher impact that data point will be.

It is important for companies to choose the measures that best reflect the forecasting performance and do not introduce bias to the future forecasts. As suggested by Kahn (1998), the choice of the denominator of measures such as MPE and MAPE can introduce bias. For example, if forecast unit is used as the denominator, it encourages over-forecasting because the larger forecast reduces reported forecast value. On the other hand, the use of actual unit as the denominator encourages under-forecasting. Therefore, it is important that companies choose the measure formulas that suit their history and policies.

The duration of the data to measure is another decision companies have to make. For grocery retailers, it is important to measure the performance by ad week for promotional items so that the effectiveness of promotional forecasting can be identified. For turn forecasting, the accuracy of each product needs to be measured at least once a month so that the impact of wrong forecasts can be captured and correct before it affects customer satisfaction.

8 Summary and Conclusion

In this thesis, we analyzed effectiveness and performance of promotional forecasting as well as the factors contributing to accuracy. We also suggested several models to improve the forecasts accuracy. This chapter summarizes the analysis and the key findings. Also, the areas for future research are suggested.

8.1 Summary of analysis and findings

By surveying literature, conducting fieldwork, and studying the supply chain and forecasting process of a grocery retailer, we have found that promotional forecasting in the low-margin and highly competitive grocery retail business has been extremely difficult. The difficulty in promotional forecasting has resulted from numerous internal and external factors that affect the demand patterns. It also results from multiple levels of hierarchy that involve different groups in the organization as well as different methods and systems. Moreover, judgments from forecasters are critical to the accuracy, but the value of tweaking the forecast results is not easy to identify due to the lack of measurement systems. The current operations of the ABC Supermarket described in Chapter 3 illustrate all of these issues. With high numbers of SKUs and high costs of lost sales, the grocery retailer industry tends to over-forecast demands at all levels. Also, with the unique characteristics of the grocery retail business, forecasting practices used in other industries might not be applicable to it.

We believe that measuring forecasts is the best starting point for grocery retailers to understand their performance and refine the processes and systems in accordance to the measurement results as in an old saying, "what cannot be measured cannot be improved". Therefore, first we conducted an analysis to measure promotional forecast accuracy from different aspects: levels of aggregation, product characteristics, promotional attributes, different time of forecasting, and different forecasting systems. We propose WMPE and WMAPE as the measures of forecast accuracy in the grocery retail business because they have several characteristics that can better reflect the performance of forecasts than the other conventional measures do.

The results from our analysis show that forecasts are more accurate as they are aggregated up from store to DC to chain as well as from item to product group to product category as expected. This justifies the effort to improve store forecasts in order to increase effectiveness of the whole supply chain. For the analysis on product category, we found that for ice creams and ice cream novelties, both with seasonal demand and frequent new product introductions, the forecasts are significantly less accurate than those of cereals, which represent products with constant demands and longer product life cycles. The analysis of holiday versus non-holiday periods also suggests that in general errors are higher for the items promoted during holiday periods. For the impact of promotional attributes on accuracy, we found that the accuracy of forecasts for different offer types varies, and ad layout attributes do affect the forecast accuracy, but the exact effects are hard to capture by forecasting systems.

Interestingly, when ABC analysis was conducted to test the impact of promotional volume on the forecast accuracy, we found that with more experience and familiarity of the products, systems and forecasters are able to predict the demand significantly better. In order to achieve improved forecast accuracy while minimizing the efforts of forecasts, the products should be classified into several classes based on sales value which is known as ABC classification. The products that generate high sales to companies or known as class A products should be reviewed extensively by forecasters in order to ensure the highest accuracy possible. Class B products should be managed by exception, or only when there are circumstances that cannot be managed by forecasting systems. For the rest of the products that generate low sales to the companies, they should be fully automated by the systems. By applying ABC classification in the grocery retail business, forecasters can prioritize their efforts based on the value of time spent perfecting the forecasts to the profitability of the company.

We also compared the forecasts generated four weeks ahead with the forecasts generated two weeks ahead on the same set of data, and found that the forecasts conducted two weeks ahead are more accurate. This result suggests the possibility of improving forecast accuracy by shifting the forecasting process for products with short replenishment lead time to a point closer to the promotion week. As for different methods, we found that although in general the forecasting results from the supply chain group are more accurate, sometime the insight and experience of merchandising team could be leveraged to achieve even better results.

We also conducted regression analysis to verify the significance of different attributes to the accuracy. Although we could not find an exact relationship between the attributes and the accuracy, the result of stepwise regression shows that some attributes such as holiday, product category and front page are more significant than the others. This could provide some insights to grocery retailers on how to plan the promotions without compromising forecast accuracy.

We have suggested several ways to improve forecasts. First, according to the results of the analysis, we see the opportunity to improve store forecasts so that the forecasts at higher forecasting levels can be substantially improved when they are aggregated up. We have proposed three models: the bias correction, the adaptive bias correction, and the regression model. The advantages and disadvantages of each are discussed in Chapter 7. Also, we have conducted an experiment on the combination of bottom-up and top-down approaches to improve forecasts, which was proven very effective on both chain- and distribution center-level forecasts. However, the practical use of these models in grocery retailers is yet to be studied. The cost of improving forecasts should be justified by the benefits grocery retailers would earn.

We believe that the key element of success in forecasting is measuring the accuracy and revising the systems and processes according to the current forecasting performance. Thus, we have suggested a framework for measuring accuracy that emphasizes the importance of comparing the accuracy of forecasts generated from systems and from judgments. It is important to note that forecasts from the systems and by judgments should be recorded and analyzed separately so that the sources of forecast errors and the value of forecasters' judgments could be better identified.

8.2 Suggestions for future research

Besides measuring forecasts, we see the opportunity to improve the forecasting process for promotional items. If the process is reengineered so that the forecasting time horizon is postponed closer to the ad week, the systems and forecasters should be able to forecast the demand more accurately. Moreover, the algorithms to remove the bias can be improved further, although we believe that identifying the sources of bias and eliminating them should be more sustainable in the long run.

In this study, we initially planned to identify the value of judgmental forecasts but because original forecasts from the ABC Supermarket's computer systems are overridden by judgmental forecasts, we did not have enough information to conduct this analysis. Judgmental forecasting is the area with substantial amount of research. Nevertheless the impact of judgment of forecasters to the forecast accuracy in the grocery retail business is yet to be identified.

Furthermore, as flexibility in the supply chain is important for grocery retailers in order to respond to changes in promotion planning, benefits and implications of adopting collaborative approaches such as CPFR® in promotional forecasting and replenishment should be studied further so that different parties within and across organizations can rely on the same forecasts to synchronize efforts and deliver better supply chain performance.

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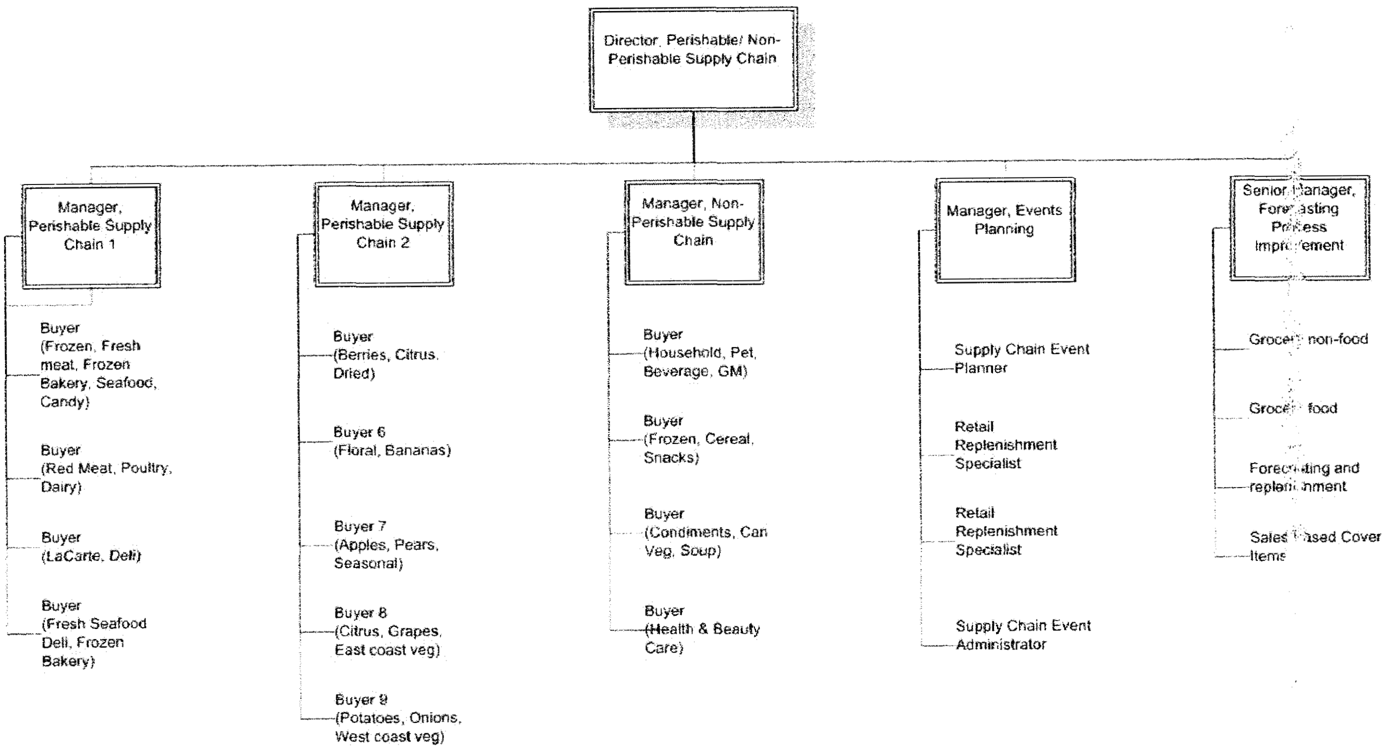
Appendix A

Organization chart of the ABC Supermarket's supply chain group



Appendix B

Results of forecast accuracy analysis – Aggregation (Tables)

1. Category

WMPE (%)

Category	Chain	DC	Store
Ice Cream	-76.55	-77.30	-121.92
IC Novelty	-91.69	-92.13	-118.30
Cereal	-21.40	-21.62	-25.87

WMAPE (%)

Category	Chain	DC	Store
Ice Cream	76.55	77.47	125.63
IC Novelty	95.56	95.95	124.14
Cereal	24.66	25.04	31.23

2. Group

WMPE (%)

Cate gory	Group	Chain	DC	Store
I.C.	589	-8.16	-10.11	-180.21
I.C.	591	-80.22	-80.95	-128.89
Nov.	590	-116.57	-117.37	-178.53
Nov.	2038	-46.58	-47.39	-106.93
Cer.	668	-30.46	-31.16	-78.47
Cer.	674	-43.75	-44.68	-76.17
Cer.	676	-57.58	-60.33	-111.41
Cer.	683	-26.48	-27.16	-48.76
Cer.	685	-32.21	-33.15	-58.72
Cer.	700	-51.30	-52.54	-81.17
Cer.	2940	-22.72	-23.47	-42.56

WMAPE (%)

Cate gory	Group	Chain	DC	Store
I.C.	589	8.73	17.04	188.92
I.C.	591	80.22	80.95	132.60
Nov.	590	117.68	118.98	184.73
Nov.	2038	67.07	67.73	123.30
Cer.	668	39.06	39.71	90.39
Cer.	674	49.54	51.11	87.05
Cer.	676	57.85	61.48	119.83
Cer.	683	34.27	35.40	61.37
Cer.	685	38.21	39.90	70.44
Cer.	700	56.83	58.08	90.44
Cer.	2940	26.84	27.87	53.24

3. Holiday

WMPE (%)

Holiday	Chain	DC	Store
Non-Holiday	-30.93	-31.82	-56.86
Holiday	-57.42	-58.52	-93.46

WMAPE (%)

Holiday	Chain	DC	Store
Non-Holiday	37.81	39.30	69.14
Holiday	60.56	61.93	101.08

4. Week

WMPE (%)

Week	Chain	DC	Store
09/02/05	7.28	7.01	-9.09
09/09/05	-14.27	-16.45	-41.07
09/16/05	-32.25	-33.87	-59.04
09/23/05	-80.92	-82.07	-115.56
09/30/05	-25.08	-25.80	-56.21
10/07/05	-18.26	-18.62	-35.69
10/14/05	7.50	7.37	-9.97
10/21/05	-45.61	-47.03	-72.69
10/28/05	-62.14	-63.55	-106.75
11/04/05	-50.02	-51.00	-81.01
11/11/05	-40.41	-41.43	-69.05
11/18/05	-87.92	-89.56	-141.73
11/25/05	-36.27	-37.07	-57.88
12/02/05	-48.21	-48.65	-71.38
12/09/05	-22.69	-23.14	-52.10
12/16/05	-82.08	-83.11	-133.11
12/23/05	-107.64	-110.56	-172.30
12/30/05	-24.18	-24.53	-45.28
01/06/06	-10.03	-10.41	-37.65
01/13/06	-45.76	-47.41	-78.99
01/20/06	-12.82	-13.02	-27.20
01/27/06	-18.15	-18.67	-40.24
02/03/06	-8.22	-8.74	-31.11
02/10/06	-33.47	-33.95	-50.78
02/17/06	-34.65	-35.95	-67.66
02/24/06	1.41	1.03	-30.21

WMAPE (%)

Week	Chain	DC	Store
09/02/05	23.75	24.15	41.15
09/09/05	24.30	29.75	58.72
09/16/05	39.41	42.46	72.73
09/23/05	81.87	82.99	119.91
09/30/05	34.95	35.63	71.81
10/07/05	24.43	25.00	47.20
10/14/05	22.99	23.04	41.53
10/21/05	48.09	49.49	79.87
10/28/05	65.08	67.20	115.42
11/04/05	52.46	53.42	88.39
11/11/05	40.63	41.73	74.17
11/18/05	89.07	90.79	146.95
11/25/05	36.27	37.08	62.37
12/02/05	48.83	49.50	77.29
12/09/05	27.68	28.33	65.24
12/16/05	95.07	96.10	147.94
12/23/05	107.64	111.09	175.78
12/30/05	26.98	28.49	56.41
01/06/06	23.67	24.66	58.42
01/13/06	47.62	50.13	89.03
01/20/06	23.40	23.73	42.03
01/27/06	22.69	24.16	53.34
02/03/06	19.47	20.94	49.84
02/10/06	35.21	36.37	56.60
02/17/06	35.74	37.24	75.41
02/24/06	21.37	22.25	56.93

5. Offer Type

WMPE (%)

Offer Type	Chain	DC	Store
1	-21.25	-22.17	-56.73
2	-36.52	-37.44	-63.86
3	-14.30	-15.30	-67.50
4	-25.06	-26.18	-46.41

WMAPE (%)

Offer Type	Chain	DC	Store
1	21.25	22.17	69.27
2	42.55	44.05	75.10
3	34.76	35.61	91.68
4	28.01	29.29	55.65

6. Page Number

WMPE (%)

Page No.	Chain	DC	Store
0	-62.04	-63.41	-132.55
1	-25.83	-26.48	-44.88
4	-56.09	-58.41	-108.66
5	-39.38	-40.31	-67.72
6	-73.14	-74.70	-101.61
7	-14.06	-16.85	-47.80
8	-37.28	-38.52	-74.31
9	-58.79	-61.80	-111.25
11	-38.68	-39.04	-65.08
12	33.23	32.98	1.46
13	90.80	90.31	81.37
21	-33.10	-33.52	-56.32

WMAPE (%)

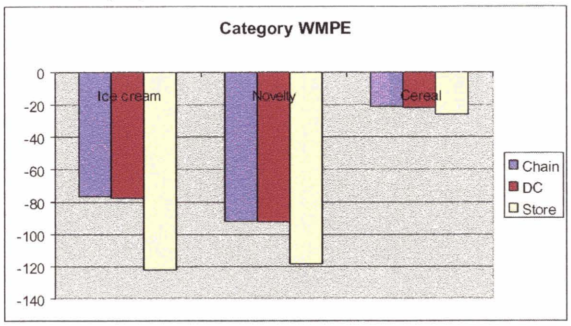
Page No.	Chain	DC	Store
0	63.28	65.10	140.99
1	30.93	32.08	54.59
4	57.68	60.68	116.44
5	45.91	47.36	79.92
6	77.46	78.93	109.79
7	17.11	29.56	65.26
8	47.08	48.37	88.74
9	59.41	62.78	117.79
11	38.68	39.04	69.88
12	33.23	32.98	41.29
13	90.80	90.31	83.64
21	36.35	38.05	66.15

Appendix C

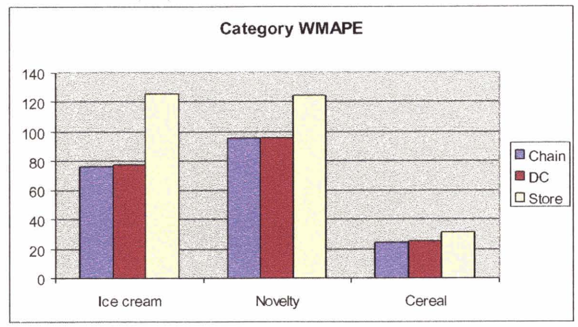
Results of forecast accuracy analysis – Aggregation (Graph)

1. Category

WMPE (%)

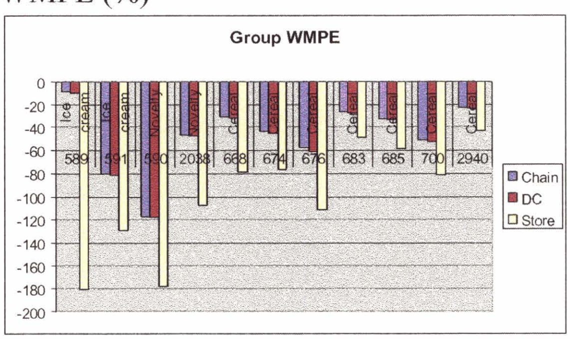


WMAPE (%)

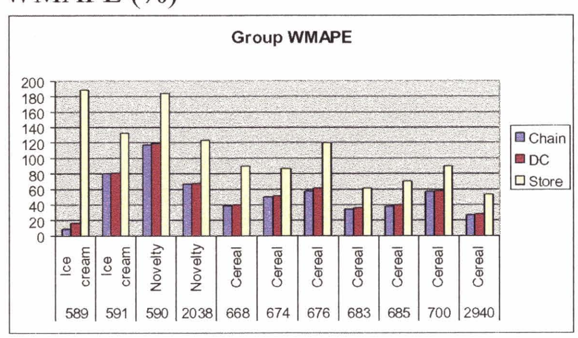


2. Group

WMPE (%)

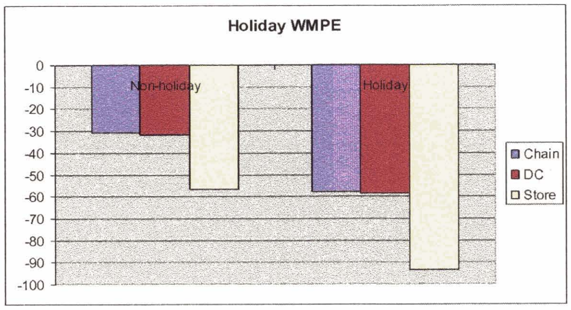


WMAPE (%)

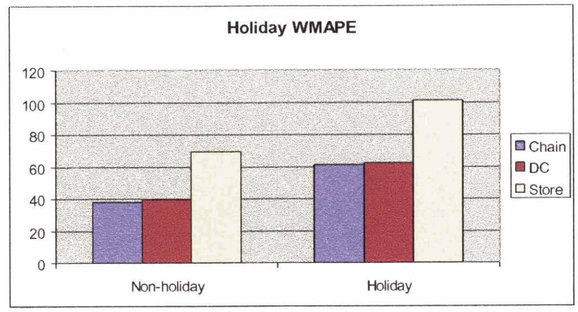


3. Holiday

WMPE (%)

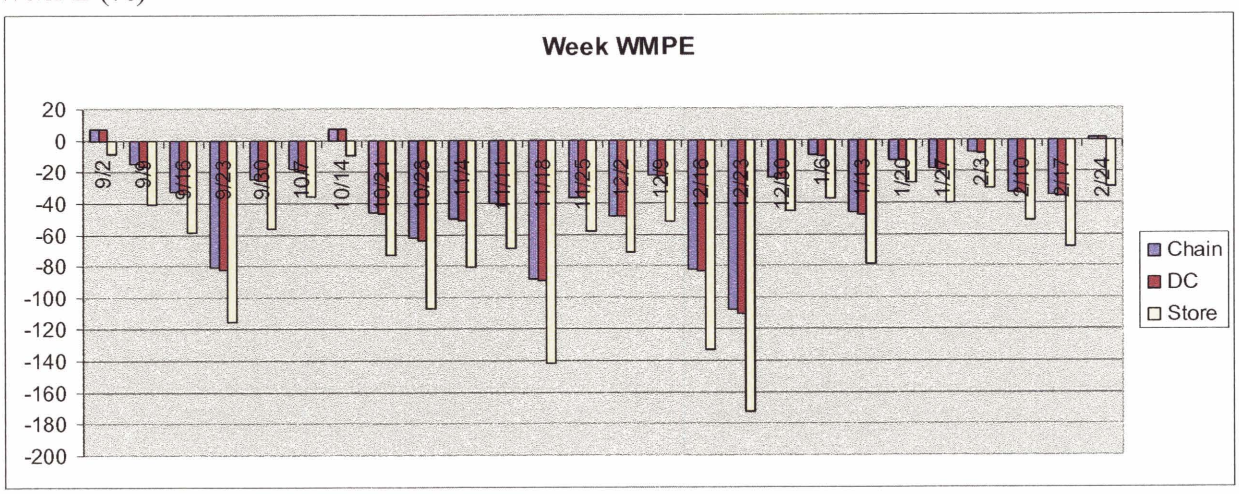


WMAPE (%)

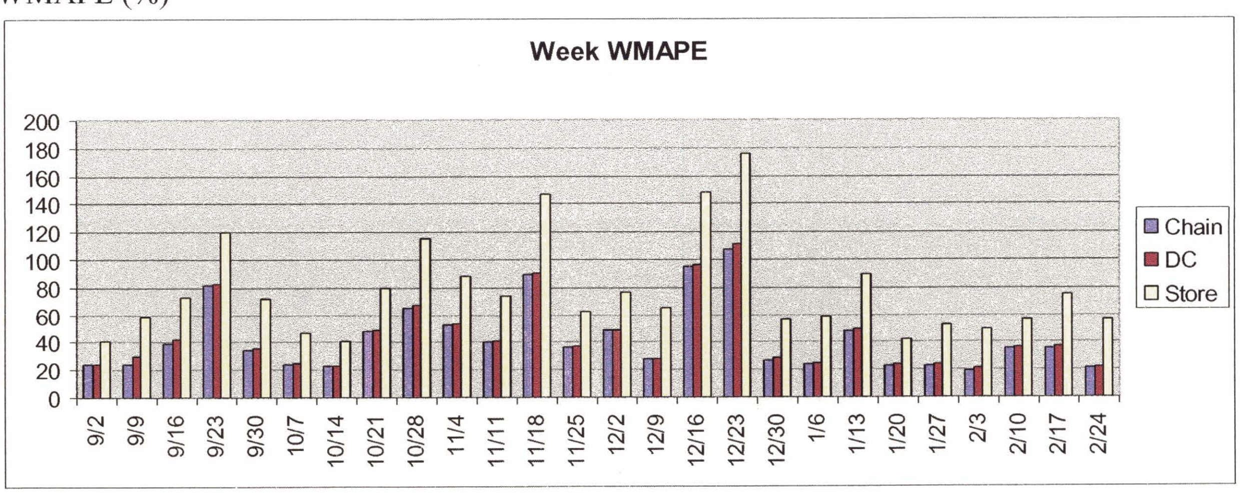


4. Week

WMPE (%)

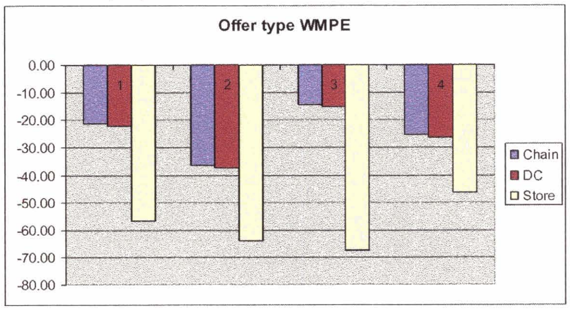


WMAPE (%)

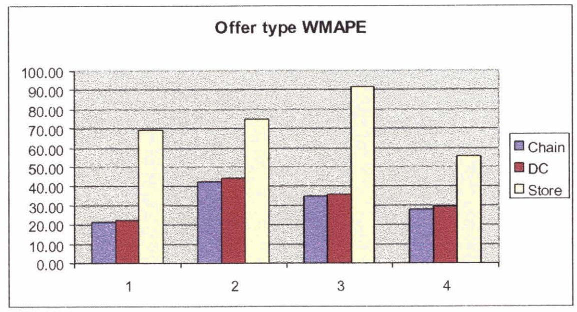


5. Offer Type

WMPE (%)

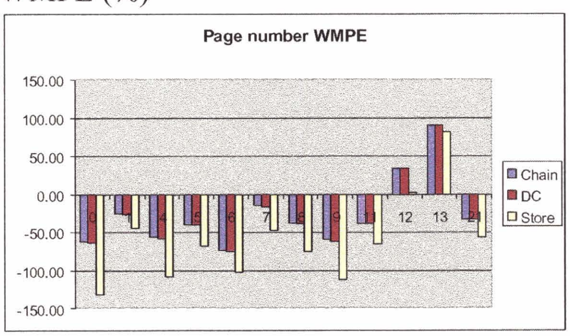


WMAPE (%)

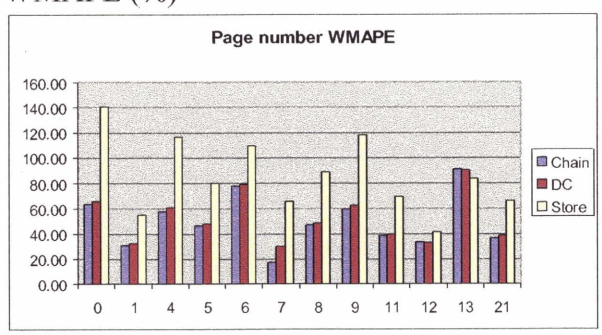


6. Page number

WMPE (%)



WMAPE (%)



Appendix D

Results of forecast accuracy analysis – Time (Tables)

1. Category

WMPE (%)

Category	4 wks	2 wks
Ice Cream	-131.22	-85.45
Ice Cream Novelty	-166.21	-93.48
Cereal	-55.52	-30.41

WMAPE (%)

Category	4 wks	2 wks
Ice Cream	131.22	85.68
Ice Cream Novelty	169.09	130.80
Cereal	59.13	38.01

2. Group

WMPE (%)

Category	Group	4 wks	2 wks
Ice Cream	589	-15.43	-47.19
Ice Cream	591	-89.17	-134.09
IC Novelty	590	-104.34	-153.09
IC Novelty	2038	-46.22	-97.17
Cereal	668	-38.04	-77.82
Cereal	674	-43.55	-79.23
Cereal	676	-58.00	-94.69
Cereal	683	-24.10	-47.36
Cereal	685	-30.05	-50.83
Cereal	700	-48.14	-64.25
Cereal	2940	-33.63	-44.03

WMAPE (%)

Category	Group	4 wks	2 wks
Ice Cream	589	47.19	21.93
Ice Cream	591	134.09	89.17
IC Novelty	590	153.13	107.47
IC Novelty	2038	110.97	64.78
Cereal	668	84.10	45.34
Cereal	674	81.62	49.73
Cereal	676	94.69	60.13
Cereal	683	52.69	32.45
Cereal	685	54.14	38.22
Cereal	700	66.61	53.38
Cereal	2940	45.45	37.53

3. Holiday

WMPE (%)

Holiday	4 wks	2 wks
Non-Holiday	-51.76	-28.85
Holiday	-80.81	-55.28

WMAPE (%)

Holiday	4 wks	2 wks
Non-Holiday	55.60	37.12
Holiday	83.28	58.77

4. Week

WMPE (%)

Week	4 wks	2 wks
09/02/05	-18.08	3.99
09/09/05	-18.08	-15.38
09/16/05	-42.10	-31.89
09/23/05	-102.61	-75.00
09/30/05	-49.53	-26.80
10/07/05	-48.44	-18.78
10/14/05	-23.82	6.04
10/21/05	-66.59	-46.86
10/28/05	-70.88	-55.71
11/04/05	-61.40	-46.66
11/11/05	-65.49	-35.48
11/18/05	-131.53	-83.73
11/25/05	-54.87	-33.00
12/02/05	-92.61	-56.21
12/09/05	-45.61	-22.58
12/16/05	-92.19	-61.67
12/23/05	-147.80	-134.95
12/30/05	-47.55	-25.99
01/06/06	-14.47	-7.14
01/13/06	-61.67	-30.82
01/20/06	-35.88	-11.66
01/27/06	-28.71	-20.32
02/03/06	-28.04	-10.20
02/10/06	-66.24	-28.43
02/17/06	-66.67	-37.21
02/24/06	-44.44	1.69

WMAPE (%)

Week	4 wks	2 wks
09/02/05	33.80	24.32
09/09/05	36.45	30.53
09/16/05	49.84	45.18
09/23/05	103.44	76.21
09/30/05	56.99	38.22
10/07/05	49.53	24.11
10/14/05	26.15	22.18
10/21/05	66.78	50.80
10/28/05	73.09	60.35
11/04/05	62.66	50.01
11/11/05	65.49	35.79
11/18/05	132.32	84.73
11/25/05	54.87	33.00
12/02/05	92.61	56.21
12/09/05	46.88	27.32
12/16/05	104.88	78.67
12/23/05	148.64	134.96
12/30/05	48.33	28.04
01/06/06	26.81	25.06
01/13/06	62.26	35.42
01/20/06	40.53	22.63
01/27/06	32.43	25.56
02/03/06	29.65	18.49
02/10/06	66.24	31.92
02/17/06	68.45	38.28
02/24/06	44.56	20.90

5. Offer Type

WMPE (%)

Offer Type	4 wks	2 wks
1	-28.82	-17.19
2	-58.15	-33.97
3	-14.14	-11.91
4	-50.86	-43.54

WMAPE (%)

Offer Type	4 wks	2 wks
1	28.82	17.19
2	61.50	41.25
3	33.64	32.62
4	52.62	45.93

6. Page Number

WMPE (%)

Page No.	4 wks	2 wks
0	-85.44	-67.25
1	-52.09	-21.51
4	-122.72	-85.43
5	-55.08	-37.03
6	-87.21	-65.94
7	-25.85	-9.25
8	-55.93	-33.17
9	-114.97	-67.30
11	-148.80	-48.41
12	23.65	28.04
13	-29.27	89.68
21	-54.64	-33.99

WMAPE (%)

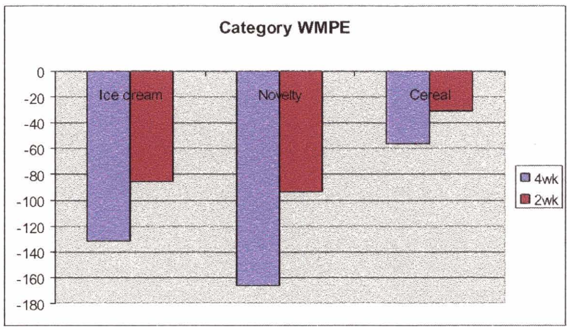
Page No.	4 wks	2 wks
0	86.83	68.43
1	55.57	27.90
4	122.72	89.57
5	58.73	44.60
6	90.26	71.12
7	31.53	30.99
8	63.24	44.33
9	114.97	69.24
11	148.80	48.41
12	23.65	28.04
13	30.85	89.68
21	55.85	37.04

Appendix E

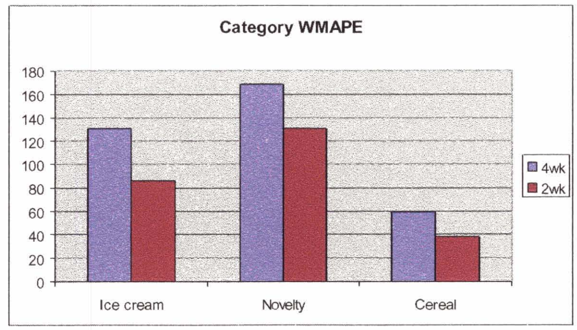
Results of forecast accuracy analysis – Time (Graphs)

1. Category

WMPE (%)

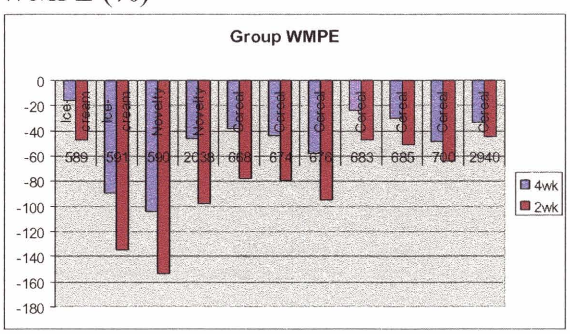


WMAPE (%)

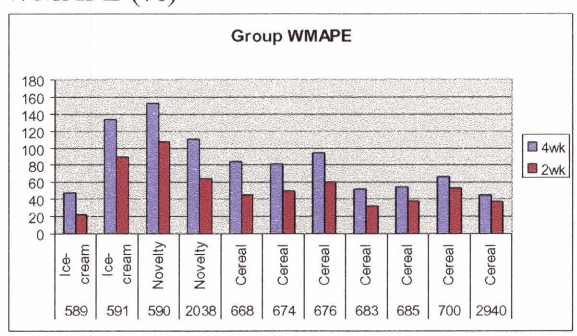


2. Group

WMPE (%)

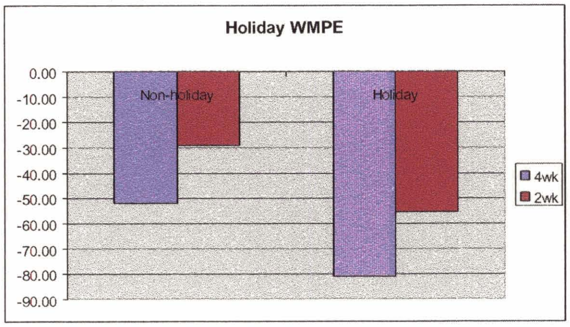


WMAPE (%)

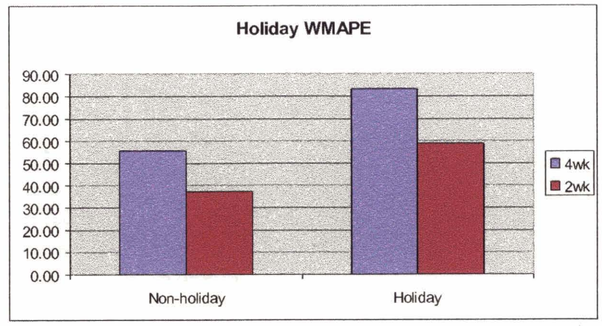


3. Holiday

WMPE (%)

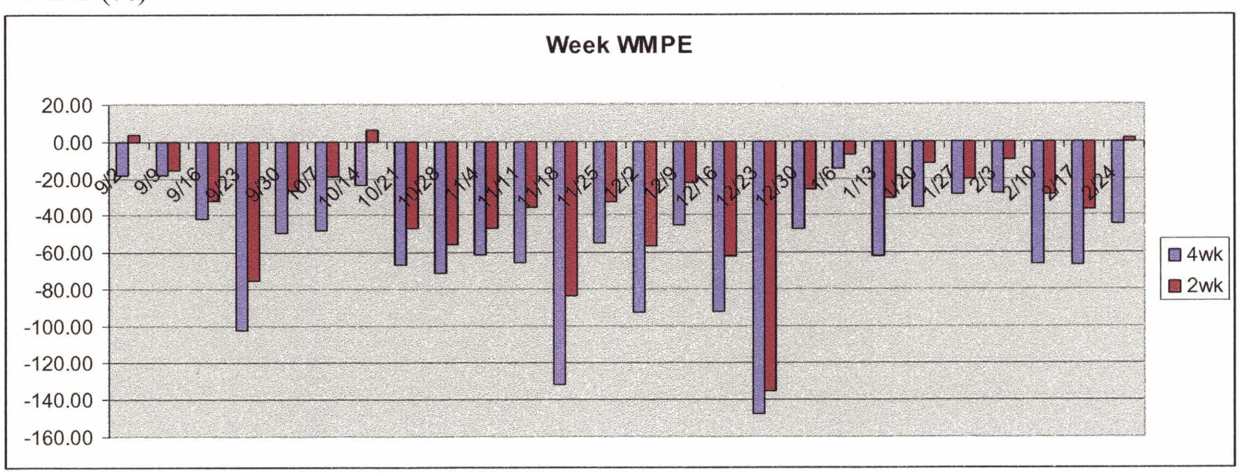


WMAPE (%)

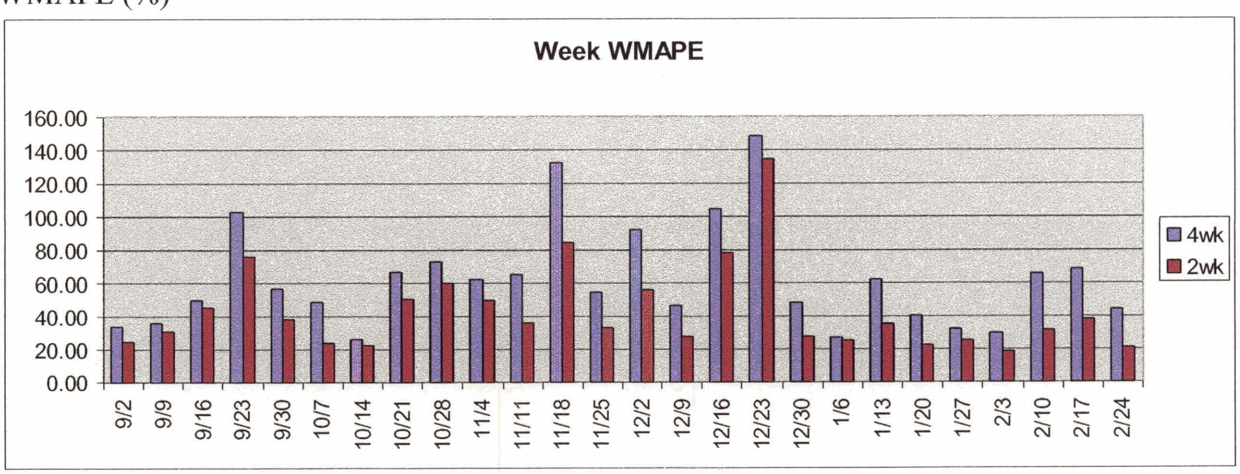


4. Week

WMPE (%)

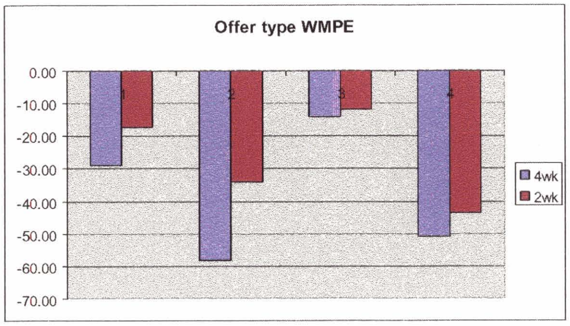


WMAPE (%)

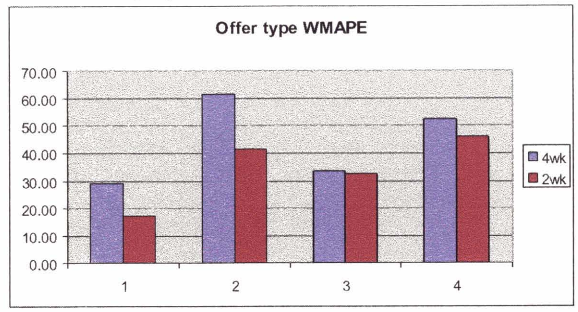


5. Offer Type

WMPE (%)

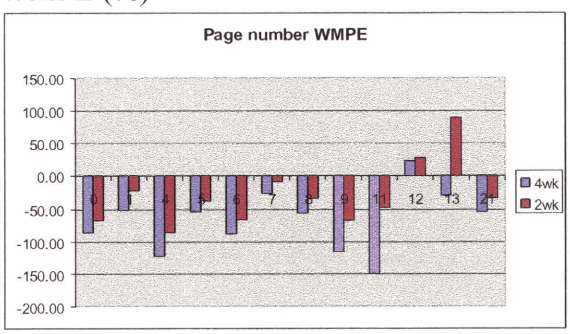


WMAPE (%)

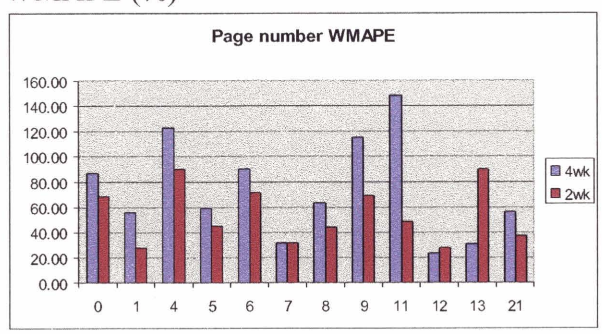


6. Page number

WMPE (%)



WMAPE (%)



Appendix F

Results of forecast accuracy analysis – Methods (Tables)

(Note: due to the limitation of data, the following tables only show the results of two categories: ice cream novelty and cereal.)

1. Category

WMPE (%)

Category	SCFS	PPS
IC Novelty	-179.05	-215.46
Cereal	-32.18	-54.76

WMAPE (%)

Category	SCFS	PPS
IC Novelty	179.08	215.70
Cereal	38.01	65.39

2. Group

WMPE (%)

Category	Group	SCFS	PPS
IC Novelty	590	-192.14	-235.82
IC Novelty	2038	-121.81	-111.61
Cereal	676	-68.83	-234.46
Cereal	683	-26.49	-43.22
Cereal	685	-31.95	-41.62
Cereal	700	-52.11	-71.84

WMAPE (%)

Category	Group	SCFS	PPS
IC Novelty	590	192.18	236.1
IC Novelty	2038	121.81	111.61
Cereal	676	68.94	234.46
Cereal	683	33.15	54.05
Cereal	685	37.93	53.85
Cereal	700	53.91	74.59

3. Holiday

WMPE (%)

Holiday	SCFS	PPS
Non-Holiday	-30.66	-53.28
Holiday	-44.51	-67.60

WMAPE (%)

Holiday	SCFS	PPS
Non-Holiday	37.07	64.95
Holiday	47.41	73.04

4. Week

WMPE (%)

Week	SCFS	PPS
09/02/05	8.75	9.27
09/09/05	-14.62	-23.76
09/16/05	-4.37	16.28
09/23/05	-77.99	-91.74
09/30/05	-26.42	-10.62
10/07/05	-19.78	-33.01
10/14/05	5.23	-51.43
10/21/05	-78.66	13.25
10/28/05	-55.07	-118.58
11/04/05	-55.82	-64.86
11/11/05	-37.95	-48.43
11/18/05	-78.93	-133.28
11/25/05	-35.85	-44.52
12/09/05	-21.34	-85.63
12/16/05	-55.84	-89.88
12/23/05	-145.65	-226.25
12/30/05	-25.45	-15.58
01/06/06	-17.70	-86.70
01/13/06	-23.11	-244.52
01/20/06	-20.83	-35.44
01/27/06	-18.50	-49.78
02/03/06	-2.96	-5.04
02/10/06	-32.94	-20.36
02/17/06	-54.51	-114.38
02/24/06	11.98	6.90

WMAPE (%)

Week	SCFS	PPS
09/02/05	17.72	25.71
09/09/05	24.36	38.79
09/16/05	13.87	18.36
09/23/05	79.37	94.98
09/30/05	37.11	43.57
10/07/05	30.44	41.51
10/14/05	36.77	58.41
10/21/05	78.66	18.28
10/28/05	57.97	122.72
11/04/05	57.46	68.24
11/11/05	37.95	51.58
11/18/05	79.25	133.28
11/25/05	35.85	52.20
12/09/05	26.30	87.29
12/16/05	73.18	91.82
12/23/05	145.65	226.25
12/30/05	26.10	25.41
01/06/06	24.36	114.78
01/13/06	23.36	244.52
01/20/06	27.55	35.44
01/27/06	23.49	55.96
02/03/06	19.57	17.14
02/10/06	34.65	34.23
02/17/06	54.51	114.38
02/24/06	14.68	44.71

5. Offer Type

WMPE (%)

Offer Type	SCFS	PPS
2	-50.91	-33.01

WMAPE (%)

Offer Type	SCFS	PPS
2	38.85	61.69

6. Page Number

WMPE (%)

Page No.	SCFS	PPS
0	-77.05	-206.34
1	-25.21	-49.90
4	-122.05	-156.55
5	-35.93	-47.45
6	-16.44	-7.69
7	0.09	-6.39
8	-43.84	-75.61
9	-96.30	-162.19
13	90.80	-42.38
21	-33.80	-21.79

WMAPE (%)

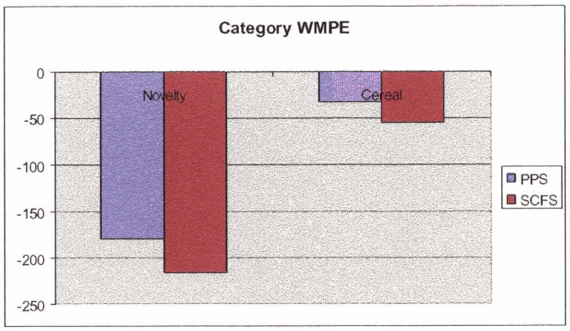
Page No.	SCFS	PPS
0	78.17	206.39
1	28.75	59.15
4	122.05	156.55
5	42.59	61.75
6	30.80	22.23
7	2.23	25.84
8	53.36	77.19
9	96.30	162.19
13	90.80	51.64
21	33.97	25.76

Appendix G

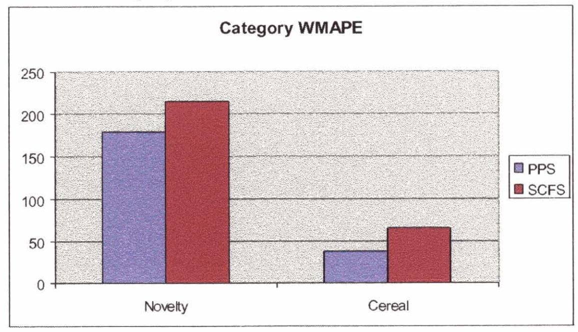
Results of forecast accuracy analysis – Methods (Graphs)

1. Category

WMPE (%)

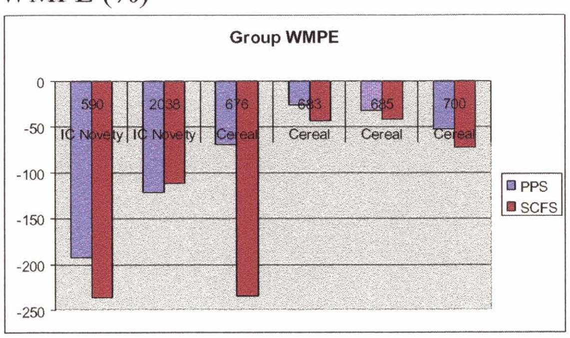


WMAPE (%)

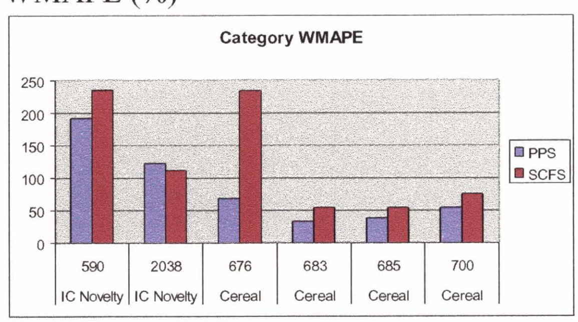


2. Group

WMPE (%)

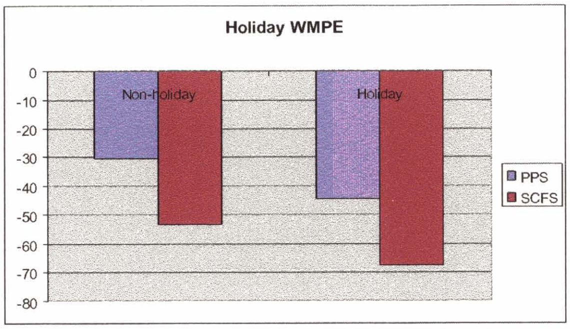


WMAPE (%)

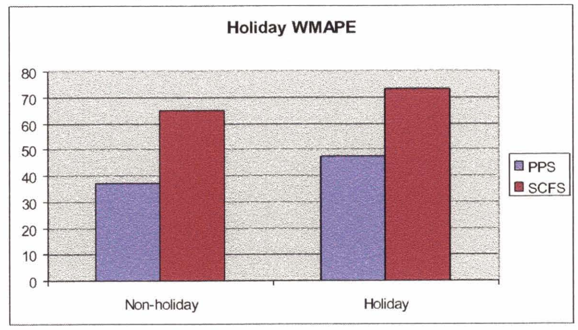


3. Holiday

WMPE (%)

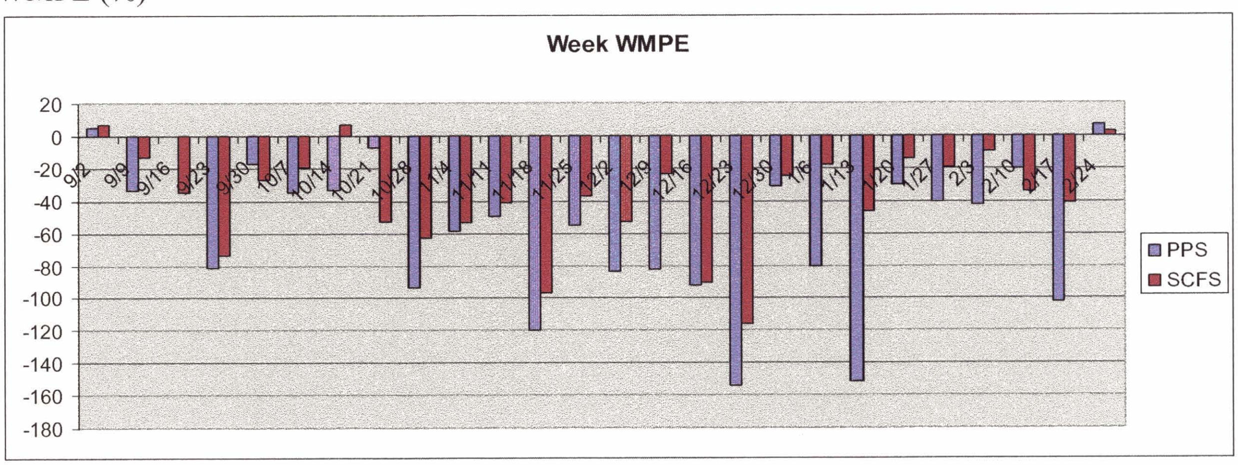


WMAPE (%)

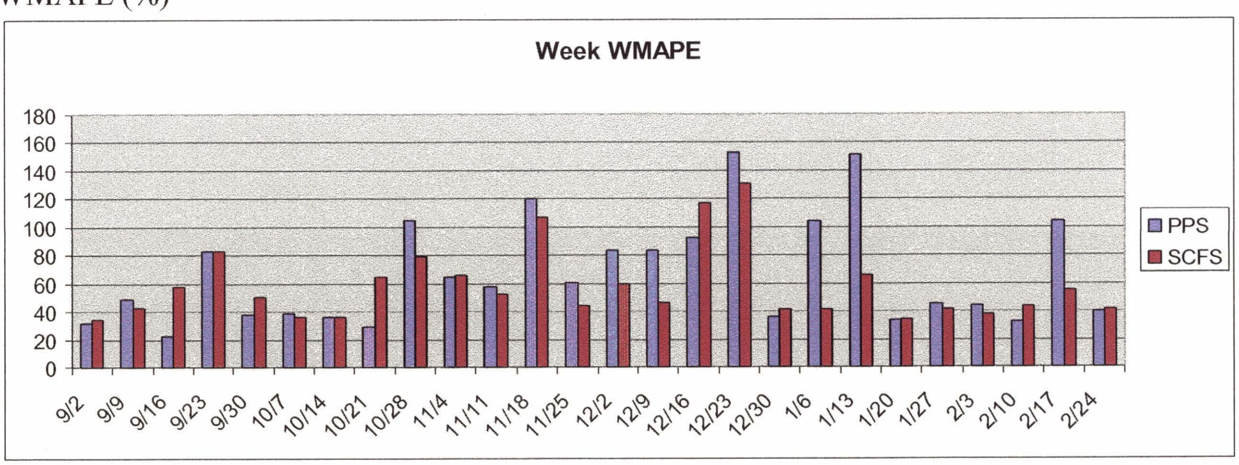


4. Week

WMPE (%)



WMAPE (%)

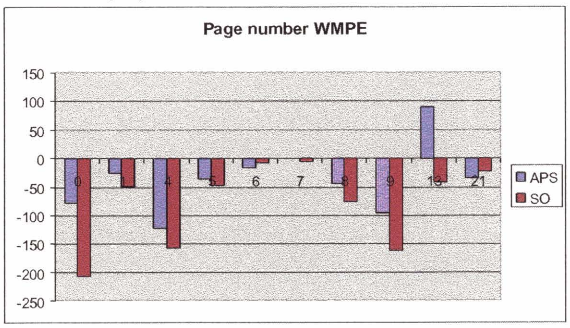


5. Offer Type

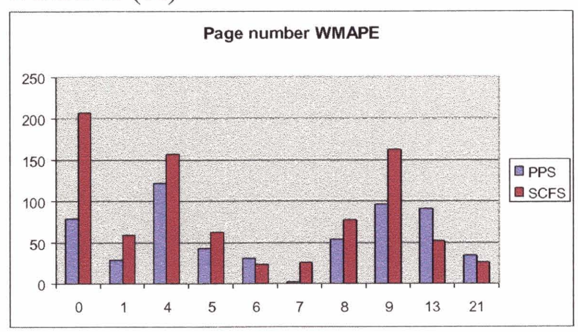
N/A

6. Page number

WMPE (%)



WMAPE (%)



Appendix H

Detailed results of the 3-step replenishment forecast improvement

(1) Aggregate the forecasts bottom-up from store level to DC level to chain level

Category	Group	Level	Count	MPE (%)	WMPE (%)	MAPE (%)	WMAPE (%)	SDAPE (%)
Ice Cream	589	Store	210	-45.73	-185.83	80.30	194.00	101.67
		DC	2	-69.83	-69.74	69.83	69.74	23.63
		Chain	1	-68.10	-68.10	68.10	68.10	N/A
	591	Store	1260	-107.38	-143.48	115.15	146.77	176.22
		DC	12	-91.03	-93.65	91.03	93.65	49.00
		Chain	6	-89.78	-92.98	89.78	92.98	50.15
Ice Cream Novelty	590	Store	4830	-142.08	-245.04	151.01	249.42	329.71
		DC	46	-94.93	-138.76	97.16	139.75	69.08
		Chain	23	-95.49	-137.79	95.72	137.98	71.53
	2038	Store	1680	-138.30	-82.93	150.40	105.09	214.62
		DC	16	-74.67	-26.10	82.74	56.76	48.38
		Chain	8	-72.19	-25.44	80.50	56.35	45.66
Cereal	668	Store	210	-109.25	-128.36	115.75	132.07	177.82
		DC	3	-59.20	-57.07	59.20	57.07	5.36
		Chain	1	-56.99	-56.99	56.99	56.99	N/A
	674	Store	3990	-77.44	-93.55	96.67	102.21	211.15
		DC	57	-36.89	-49.90	43.10	52.90	41.44
		Chain	19	-35.04	-48.88	40.42	50.66	39.74
	676	Store	5040	-111.33	-130.93	123.83	139.06	276.68
		DC	72	-65.58	-58.78	67.17	59.95	55.56
		Chain	24	-68.30	-56.85	68.54	57.23	52.20
	683	Store	12180	-85.56	-69.20	104.56	80.96	483.91
		DC	174	-39.31	-30.02	49.40	37.05	78.69
		Chain	58	-40.82	-29.27	49.91	35.80	79.99
	685	Store	22680	-79.98	-76.83	102.94	89.84	342.16
		DC	324	-33.22	-32.64	45.22	40.18	49.50
		Chain	108	-32.98	-31.62	44.00	38.02	47.61
	700	Store	5670	-118.62	-167.45	129.36	172.96	383.54
		DC	81	-68.37	-77.44	70.86	79.16	72.98
		Chain	27	-71.67	-75.43	74.07	77.18	73.09
	2940	Store	2520	-150.07	-144.65	163.12	153.03	869.00
		DC	36	-38.31	-36.30	41.66	38.18	75.17
		Chain	12	-35.53	-31.57	37.76	33.11	50.55

(2) Apply a product group specific bias correction factor to each item forecast in the group:

Category	Group	Bias Correction Factor	Comparison	MPE (%)	WMPE (%)	MAPE (%)	WMAPE (%)	SDAPE (%)
Ice Cream	589	0.813	Before	-68.10	-68.10	68.10	68.10	-68.10
			After	-36.21	-36.21	36.21	36.21	N/A
	591	0.498	Before	-89.78	-92.98	89.78	92.98	50.15
			After	5.41	3.77	18.41	23.23	15.91
Ice Cream Novelty	590	0.529	Before	-95.49	-137.79	95.72	137.98	71.53
			After	-3.39	-25.76	29.96	48.02	22.78
	2038	0.595	Before	-72.19	-25.44	80.50	56.35	45.66
			After	-2.28	25.49	23.16	35.10	25.31
Cereal	668	0.980	Before	-56.99	-56.99	56.99	56.99	N/A
			After	-54.02	-54.02	54.02	54.02	N/A
	674	0.794	Before	-35.04	-48.88	40.42	50.66	39.74
			After	-7.13	-18.10	28.58	30.65	21.31
	676	0.592	Before	-68.30	-56.85	68.54	57.23	52.20
			After	0.12	6.92	26.09	24.34	16.19
	683	0.775	Before	-40.82	-29.27	49.91	35.80	79.99
			After	-8.88	0.05	35.47	24.74	55.91
	685	0.714	Before	-32.98	-31.62	44.00	38.02	47.61
			After	5.19	6.16	31.49	28.70	24.79
	700	0.719	Before	-71.67	-75.43	74.07	77.18	73.09
			After	-23.35	-26.05	38.60	40.86	44.32
	2940	0.943	Before	-35.53	-31.57	37.76	33.11	50.55
			After	-28.02	-24.28	32.93	27.74	45.97

(3) Allocate the adjusted chain level forecasts down to DC level and further to store level, using the same allocation portion as in the original data:

Category	Group	Level	Count	MPE (%)	WMPE (%)	MAPE (%)	WMAPE (%)	SDAPE (%)
Ice Cream	589	Chain	1	-36.21	-36.21	36.21	36.21	N/A
		DC	2	-37.68	-37.68	37.68	37.68	20.14
		Store	210	-38.65	-148.05	73.41	158.01	85.93
	591	Chain	6	5.41	3.77	18.41	23.23	15.91
		DC	12	4.80	3.44	19.96	23.21	13.71
		Store	1260	-10.18	-20.67	46.75	51.23	79.38
Ice Cream Novelty	590	Chain	23	-3.39	-25.76	29.96	48.02	22.78
		DC	46	-3.10	-26.28	30.01	47.99	23.39
		Store	4830	-38.90	-82.92	69.72	107.04	166.75
	2038	Chain	8	-2.28	25.49	23.16	35.10	25.31
		DC	16	-3.75	25.09	24.72	35.71	25.81
		Store	1680	-46.48	-9.60	79.58	65.92	119.43
Cereal	668	Chain	1	-54.02	-54.02	54.02	54.02	
		DC	3	-56.24	-54.10	56.24	54.10	5.38
		Store	210	-109.20	-128.27	115.70	131.98	177.83
	674	Chain	19	-7.13	-18.10	28.58	30.65	21.31
		DC	57	-8.60	-18.92	29.86	31.73	23.82
		Store	3990	-41.70	-53.59	73.48	71.05	163.71
	676	Chain	24	0.12	6.92	26.09	24.34	16.19
		DC	72	1.73	5.77	28.75	24.93	18.14
		Store	5040	-33.87	-37.62	69.75	70.24	158.42
	683	Chain	58	-8.88	0.05	35.47	24.74	55.91
		DC	174	-7.71	-0.53	35.83	25.60	54.85
		Store	12180	-44.37	-30.84	79.97	59.27	371.74
	685	Chain	108	5.19	6.16	31.49	28.70	24.79
		DC	324	5.01	5.43	32.36	29.18	26.48
		Store	22680	-29.97	-26.23	73.81	61.20	240.88
	700	Chain	27	-23.35	-26.05	38.60	40.86	44.32
		DC	81	-20.97	-27.49	37.78	42.18	43.95
		Store	5670	-58.69	-92.21	84.49	111.74	271.75
	2940	Chain	12	-28.02	-24.28	32.93	27.74	45.97
		DC	36	-30.66	-28.75	36.67	32.30	69.80
		Store	2520	-136.49	-131.11	152.33	142.00	820.57

The DC-level forecast improvement after applying three-step approach

Category	Group	Comparison	MPE (%)	WMPE (%)	MAPE (%)	WMAPE (%)	SDAPE (%)
Ice Cream	589	Before	-69.83	-69.74	69.83	69.74	23.63
		After	-37.68	-37.68	37.68	37.68	20.14
	591	Before	-91.03	-93.65	91.03	93.65	49.00
		After	4.80	3.44	19.96	23.21	13.71
Ice Cream Novelty	590	Before	-94.93	-138.76	97.16	139.75	69.08
		After	-3.10	-26.28	30.01	47.99	23.39
	2038	Before	-74.67	-26.10	82.74	56.76	48.38
		After	-3.75	25.09	24.72	35.71	25.81
Cereal	668	Before	-59.20	-57.07	59.20	57.07	5.36
		After	-56.24	-54.10	56.24	54.10	5.38
	674	Before	-36.89	-49.90	43.10	52.90	41.44
		After	-8.60	-18.92	29.86	31.73	23.82
	676	Before	-65.58	-58.78	67.17	59.95	55.56
		After	1.73	5.77	28.75	24.93	18.14
	683	Before	-39.31	-30.02	49.40	37.05	78.69
		After	-7.71	-0.53	35.83	25.60	54.85
	685	Before	-33.22	-32.64	45.22	40.18	49.50
		After	5.01	5.43	32.36	29.18	26.48
	700	Before	-68.37	-77.44	70.86	79.16	72.98
		After	-20.97	-27.49	37.78	42.18	43.95
	2940	Before	-38.31	-36.30	41.66	38.18	75.17
		After	-30.66	-28.75	36.67	32.30	69.80