Customer Focused Collaborative Demand Planning

by

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Submitted to the Engineering Systems Division in Partial Fulfillment of the Requirements for the Degree of

Master of Engineering in Logistics

at the

Massachusetts Institute of Technology

June 2008

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Abstract

Many firms worldwide have adopted the process of Sales & Operations Planning (S&OP) process where internal departments within a firm collaborate with each other to generate a demand forecast. In a collaborative demand planning process buyers and sellers collaborate with each other to generate a mutually agreed upon forecast which takes into account the needs and limitations of both buyers and sellers.

In this research we concentrate on finding out the value from both statistical and qualitative forecasts. We apply standard forecasting algorithms to generate a statistical forecast. We also generate a hybrid model that is a weighted technique using both a statistical and qualitative forecast. Then we evaluate the statistical, hybrid, and qualitative collaborative forecasts using an error analysis methodology. Finally we recommend an approach for forecasting a family of items based on our analysis and results. We also recommend changes to the existing process so that our recommendations on the forecasting approach can get seamlessly integrated into the overall process.

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Acknowledgements

There are many people I would like to acknowledge for their assistance and support throughout the pursuit of this research. Unfortunately, many will go unnamed here. For those who are not mentioned, please know that your words of encouragement made a difference.

First of all, I would like to express my sincere gratitude to Dr. Larry Lapide, my advisor, for all of his support and guidance throughout this endeavor. I would also like to thank Dr. Chris Caplice for his accessibility and support regardless of his busy schedule.

I would like to thank my sponsor Jonathan Melzar and all others from his team for help, support and availability, as well as the Demand Management Solutions Group.

I would like to thank my friends at MLOG particularly Prashant Nagpure for always lending a patient ear to my arguments. Finally, I would like to thank my wife Prachi Vimal. Without her support and encouragement this endeavor may not have been successful.

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Chapter 1: Introduction

This section describes the motivation of this research. The section goes on to explain the current process at HiTec Inc and a brief background of HiTec Inc and Wireless Inc.

1.1 Motivation

Collaborative planning has increasingly gained significance over the years with the strengthening of information infrastructures. Buyers and Suppliers can share their information such as capacity and demand so that they can plan their resources in a better way.

One important aspect of collaborative planning is Collaborative Planning Forecasting and Replenishment (CPFR). CPFR facilitates communication between a buyer and a supplier about the expected future demand and supply availability. Once the supplier has visibility of the future demand from the buyer, the supplier can plan better on raw materials procurement and save on costs related to uncertainty. CPFR model works even better when the customer is a large account and constant business transaction takes place between the buyer and the supplier. Collaboration helps the supplier to serve the customer better by knowing the future needs of the buyer.

Collaborative planning tries to solve the problem of stock outs of critical products and of excessive safety stock that shows on the balance sheet.

The scope of my thesis is to determine how the benefits of collaborative planning can be leveraged to reduce the lead time variability and to increase the probability of a product's availability when it is demanded.

The thesis looks at the current collaborative planning process between HiTec Inc and Wireless Inc, who is a strategically important customer of HiTec Inc. Wireless Inc is one of the biggest customer of HiTec Inc and HiTec Inc wants to explore whether there is any opportunity of improvement in the current collaborative planning and forecasting process. HiTec Inc wants to use the recommendations of this research to leverage their current service to the Wireless Inc and enhance the strategic alliance thus creating opportunities for further revenue and profits. It also wants to consider extending the recommendations of this research to other important customers.

1.2 Supply Chain Excellence

HiTec Inc today is a leader in supply chain management and logistics. HiTec Inc is the best examples of the virtual supply chain organization where all the logistic activities have been outsourced to 3PLs. There are various risks and benefits associated with being a virtual supply chain organization. HiTec Inc has been successful over the years because it was able to create a business model where the benefits of virtual supply chain outweighed the risks. One of the primary drivers of this model has been their focus on supply chain excellence (SCMx). SCMx is a state where the entire supply chain organization within HiTec Inc would deliver excellence in wherever they can establish their position as market leaders and innovators. HiTec Inc has identified some initiatives that would help them to get to a state of SCMx. Each business unit within the manufacturing organization in HiTec Inc has been following these initiatives and identifying new ones to achieve the desired goal. The scope of this thesis is limited towards studying a few of those initiatives followed by the collaborative planning business sub-unit within the demand planning business unit that sits under the supply chain organization of HiTec Inc.

1.3 Collaborative Planning Process

The intent of following a collaborative planning process was to provide excellent customer service in terms of timely order fulfillment to a select group of strategic clients. This process would protect the customer from supply variability due to unpredictable demand from other customers. The process would also ensure predictable and consistent delivery performance. The customer would be directly linked with HiTec Inc's supply chain which would help in quick response to the demand signal.

HiTec Inc would benefit from this process because a customer would be able to derive satisfaction due to improved delivery performance that would help in building strategic relationships. From the organizational point of view the collaborative planning process would help in the integration of sales & marketing, manufacturing and fulfillment, and enable them to work together to manage high revenue drivers.

1.4 AS-IS Process

As part of the current collaborative planning process, the team from the collaborative planning sub-unit interacts with the customer to generate a 120-day rolling forecasts for products each month. The 120-day rolling forecast is then broken into four months denoted by M+1, M+2, M+3, M+4 where M is the current month in which a forecast is generated. As the customer makes actual bookings, the booking numbers are deducted from the forecast numbers. At the end of the month if bookings are less than the forecasts, the quantity not used in the month does not get covered in the subsequent months but an updated forecast is generated each month to reflect the month to month changes.

Based on the 120-day rolling forecast, HiTec Inc makes a commitment for the availability of raw materials for the manufacturing of products. The supply reservations (SR) are calculated based on the standard product target and lead time. The SR for the current month expires if there are not sufficient days left to meet the target lead time. The expired SR does not get automatically rolled in the next month but has to be reflected as a change in forecast and a new SR has to be generated. SR information is updated weekly based on the information on available supply. The 120-day rolling forecast does not guarantee supply availability. Based on the forecast and supply of raw materials, demand is matched with supply and SR commitments are provided to the customer. Currently the demand and supply is matched manually and an automated process is not being used.

The marketing department also generates a quarterly forecast based on the bookings to generate expected revenues. The expected revenue is used as the basis for ordering raw materials for manufacturing.

One important role of the collaborative planning team is to make sure that the marketing forecast and the 120-day rolling forecast are aligned so that there is no mismatch between the manufacturing component orders and the customer forecast.

The success of the current process is measured by metrics such as forecast accuracy, delivery performance to target lead time and delivery performance to promise.

Chapter 2: Methods

To validate the collaborative planning process it is necessary to compare it with Collaborative Planning, Forecasting and Replenishment (CPFR) Model. We can apply the CPFR model in the current scenario to better understand the collaborative process.

It is also necessary to conduct research on the forecasting algorithms such as Moving Averages, Single Exponential Smoothing and Holt's Smoothing because these methods would be later used to analyze the current forecasting process and would also be used to generate a statistical forecast on a weekly basis.

2.1 Collaborative Planning Forecasting and Replenishment (CPFR)

CPFR is collaborative planning process which was conceptualized by the Voluntary Inter-industry Commerce Standards Association (VICS). VICS is an association of companies that defines processes which would help an organization in achieving seamless flow of products and information across their supply chain. CPFR is constituted by a VICS committee whose mission is to develop best practices for various collaborative planning scenarios. The processes include suppliers and retailers and helps in evolving an integrated planning approach.

Figure 1 below shows the VICS Framework CPFR. In the framework the consumer is placed at the center and is represented by a circle. The Retailer is represented by a concentric circle with a larger diameter compared to the consumer. The Retailer circle lists the activities to be performed by the retailer starting with Point of Sales (POS) forecasting with subsequent activities moving in clockwise direction. The concentric circle, outside the retailer circle, with arrows, depicts the collaborative activities that need to be undertaken. Finally the activities outside the biggest circle represent an aggregated planning approach recommended by the CPFR committee.

Figure 1: VICS CPFR Model (Source: VICS CPFR Committee)

Although the CPFR model was built keeping retail supply chains in mind, it can be extended to other supply chains as well where collaborative planning is integral part of the chain.

2.2 Forecasting

Forecasting is the stepping stone for Supply Chain Planning and Management. All the upstream planning decisions such as inventory planning, logistics planning and production planning depend on the forecast numbers. An accurate forecast is the key to reduce costs and achieve reductions in inventory levels. Although it's impossible to achieve 100% forecast accuracy, accuracy levels in the range of 90-100% are desirable. The forecast accuracy depends on the variability of the demand which essentially means that we can have more accurate forecasts for demand with less variability. Forecasts are much more accurate at the aggregate level. As the granularity, of the level at which we are generating a forecast, increases the accuracy decreases. Forecasts can be generated for both operational and strategic requirements. Operational forecasts are used in short term planning and execution and more often than not statistical time-series methods are used to produce operational forecasts. Operational forecasts are generated on a daily, weekly or monthly basis. Long term forecasts are produced for strategic reasons. For example if we want to know the impact of macroeconomic factors on our sales we look at the long term forecast which has a window of more than a year. Causal techniques are used to generate long term forecasts.

The scope of this work includes forecast generation on a monthly and weekly basis so we will only discuss operational forecasting. Besides aggregation, selection of an appropriate statistical model is also important for achieving better forecast accuracy. We have discussed a few Time-Series models that have widespread use in operational forecasting. The models evaluated or used for the purpose of the thesis are discussed in the subsequent sections. All the equations and expressions are adapted from Silver, Pyke and Peterson (1998).

2.2.1 The Simple Moving Average

The simple moving average is a smoothing procedure where an average of N periods is calculated in the current period and then in the next period the average is calculated over next N periods. In the next N periods the first period in the current period is removed and the $(N+1)^{th}$ period relative to the current period is included. The demand can be modeled as in equation 2.1:

$x_t = a + \varepsilon_t$ ------------ (2.1)

x_t = actual demand in period t.

a = level estimate

ε_t = random noise

The equation shows that the demand in period t can be represented as a level component which is a constant and a random noise (ε_t).

The N-period moving average ($\overline{x}_{t,N}$) is given by the equation:

$\overline{x}_{t,N} = (x_t + x_{t-1} + x_{t-2} + ... + x_{t-N+1}) / N$ ------------- (2.2)

In equation 2.2, x_t represents the actual demand. The level estimate in period t can be given by

$\hat{a}_t = \overline{x}_{t,N}$ ---------------- (2.3)

We can forecast the demand for period $t+k$ at the end of period t using the equation:

$\hat{x}_{t,t+k} = \hat{a}_t$ ------------ (2.4)

2.2.2 Simple Exponential Smoothing

A moving average procedure gives equal weights to each period for calculating the forecast. This procedure has limitations because the underlying demand model may be such that different weights might be required for each period. Simple exponential smoothing does exactly that, as follows:

The underlying demand model: $x_t = a + \varepsilon_t$ -------- (2.5)

Level Estimate: $\hat{a}_t = \alpha x_t + (1-\alpha)\hat{a}_{t-1}$ ----------- (2.6)

α is a smoothing constant and it can be approximated as α = 2/(N+1) -------- (2.7)

The initial estimate of a is found by considering the average of the first few periods of demand and the forecast model is the same as in equation 2.4

2.2.3 Holt's Method for Trend

In the previous discussions we assumed that a demand forecast has only a level component and does not have any trend. If our data is showing an increasing trend with time then we should apply a smoothing procedure that takes care of the trend in the underlying demand model, as follows:

The underlying demand model: $x_t = a + bt + \varepsilon_t$ ---------- (2.8)

The variable b represents the trend with respect to the time t.

The parameters a and b can be updated using the following equations:

$\hat{a}_t = \alpha x_t + (1-\alpha)(\hat{a}_{t-1} + \hat{b}_{t-1})$ ---------------------- (2.9)

$\hat{b}_t = \beta(\hat{a}_t - \hat{a}_{t-1}) + (1-\beta)\hat{b}_{t-1}$ --------------------- (2.10)

α and β are smoothing constants.

The initialization for level and trend components can be done using regression techniques and the forecasts are generated using the following equation.

$\hat{x}_{t,t+k} = \hat{a}_t + \hat{b}_t k$ ------------- (2.11)

$\hat{x}_{t,t+k}$ = forecast of the demand in time period t+k at the end of time period t.

$\hat{a}_t$ = estimate of level at the end of time of time period t.

$\hat{b}_t$ = estimate of trend at the end of time period t.

2.2.4 Damped Method for Trend Model

When the data has lot of random noise, it is very difficult to spot a trend. If the forecasting requirement is to project trend several periods ahead then the simple trend model does not give a clear picture because the trend may not be linear. The damped trend model is very useful for forecasting when history has a lot of noise and trend is not clear. This model is very similar to the Holt's model. An additional dampening parameter is introduced in the Holt's model to give us damped trend model, as follows:

$\hat{a}_t = \alpha x_t + (1-\alpha)(\hat{a}_{t-1} + \phi\hat{b}_{t-1})$ ----------------- (2.12)

$$\hat{b}_t = \beta(\hat{a}_t - \hat{a}_{t-1}) + (1-\beta)\phi\hat{b}_{t-1} \text{ ------------------- (2.13)}$$

where ϕ is a dampening parameter. When $\phi = 1$ then the above equations transforms to Holt's model.

Following is the forecasting model.

$$\hat{x}_{t,t+k} = \hat{a}_t + \sum_{i=1}^{k} \phi^i \hat{b}_t \text{ --------------------------- (2.14)}$$

If $0 < \phi < 1$ then the trend is damped and as k gets large, the forecast tends to a horizontal line. When $\phi > 1$, the trend becomes exponential.

2.2.5 Croston's Method for Intermittent Demand

Croston's method is used to generate forecasts for intermittent or erratic demand. When demand occurrences are infrequent then the exponential smoothing process does not produce the desired level forecast. In such cases the demand is modeled as two separate components.

The inter arrival time between non zero demand is the first component that is modeled as a random variable obeying a normal distribution. In any given period, the demand x_t can be modeled as,

$$x_t = y_t * z_t \text{ ----------------- (2.15)}$$

where, $y_t = 1$ if demand occurs otherwise $y_t = 0$ and z_t is the magnitude of the demand.

As mentioned above, the inter arrival time between demand can be modeled as a random variable. Let n be the time between consecutive non zero demands. Either a demand in a given period will occur or it will not occur. Thus, the event can be modeled as a Bernoulli's process with the probability of occurrence of non zero demand as *1/n.*

prob ($y_t = 1$) = *1/n* and prob ($y_t = 0$) = *(1 - 1/n)*

Croston (1972) proposed a framework for an updating procedure based on assumptions stated above.

If the demand is zero in a particular period then,

a) Demand estimates are not updated and

b) $\hat{n}_t = \hat{n}_{t-1}$ --------------- (2.16)

If the demand is non-zero in a particular period then,

a) $\hat{z}_t = \alpha z_t + (1-\alpha)\hat{z}_{t-1}$ ---------------------- (2.17)

b) $\hat{n}_t = \alpha n_t + (1-\alpha)\hat{n}_{t-1}$ ----------------------- (2.18)

Where,

n_t = number of periods since the last event of occurrence of non-zero demand.

$\hat{n}_t$ = estimated value of n at the end of period t.

$\hat{z}_t$ = estimate of the average size of demand at the end of period t.

α = smoothing constant.

Chapter 3: Data Analysis

We were provided with data of two product families, A & B. Each product family can be subdivided into product types and each product type can be further subdivided into Product Identities (PIDs). PIDs are at the lowest level in the product hierarchy. The requirement here is to analyze product level data for a fixed geography which is the world level. The time hierarchy is characterized by year, month and weeks. The data is provided in weekly buckets which can be aggregated into monthly and yearly buckets. Figure 2 shows the hierarchy for family A. Each product type can be further subdivided into PIDs. Product A has a total of 133 PIDs. Figure 3 shows the distribution of PIDs among each product type.

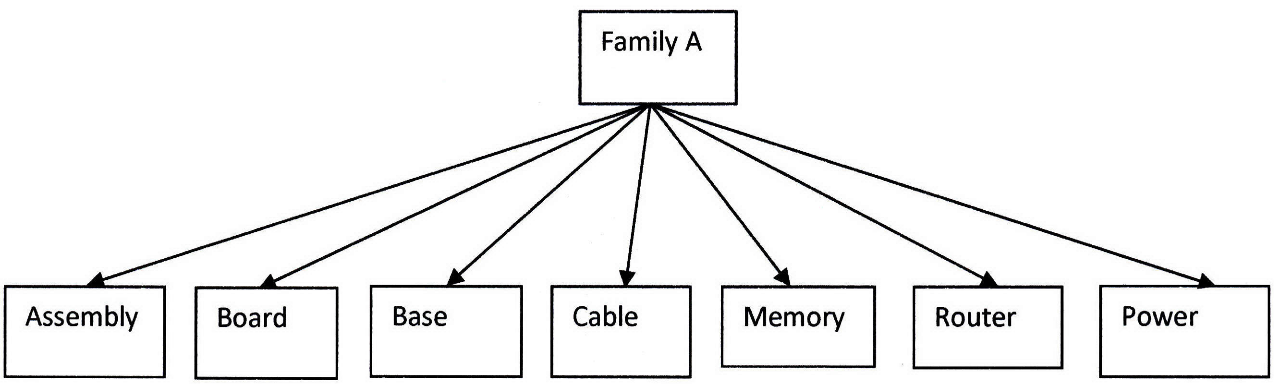

Figure 2: Family A Hierarchy

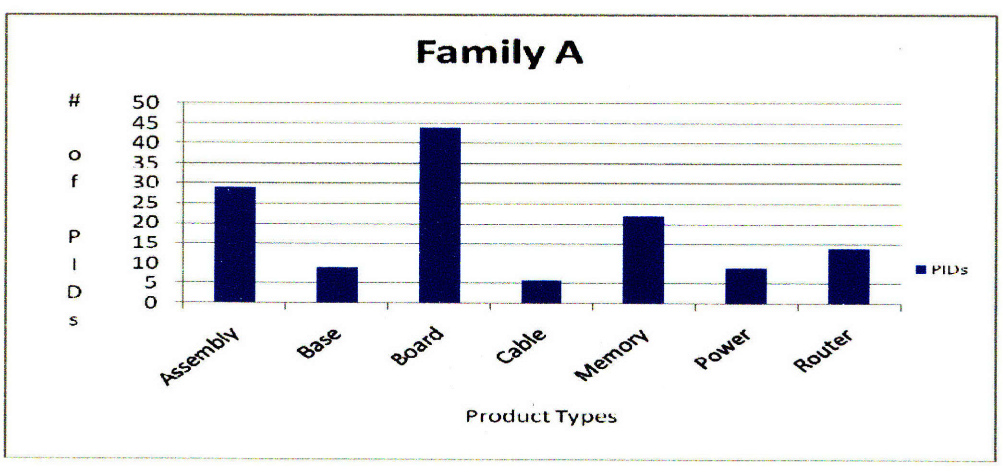

Figure 3: PID Distribution for Product Family A

Figure 4 shows the hierarchy for family B. Each product type can be further subdivided into PIDs. Product B has a total of 137 PIDs. Figure 5 shows the distribution of PIDs among each product type.

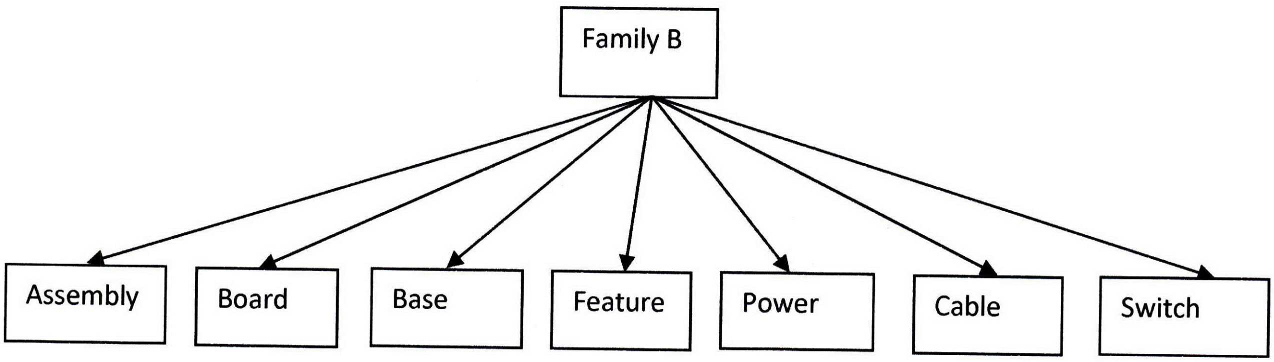

Figure 4: Family B Hierarchy

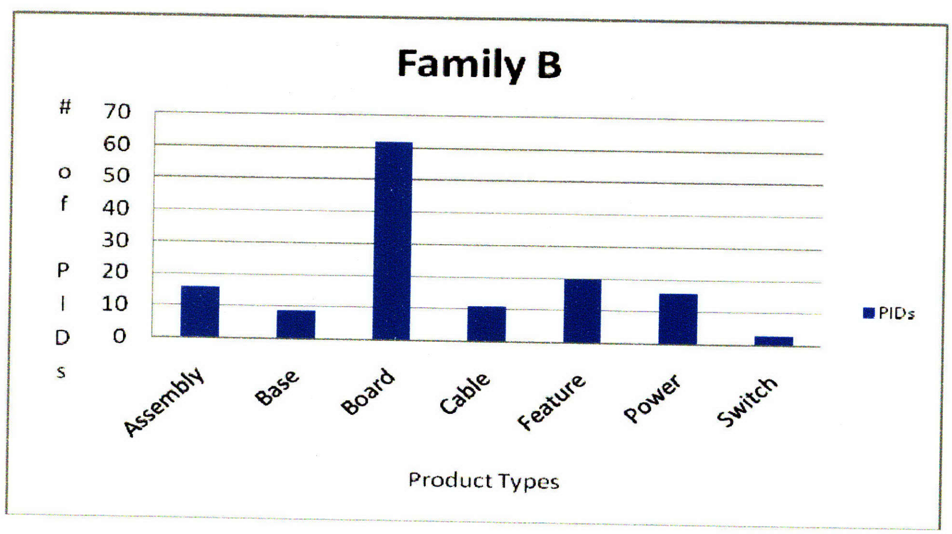

Figure 5: PID Distribution for Product Family B

The following subsections of this chapter present the data pattern of each product type under families A & B. Also, data patterns of some selected PIDs under each product type for family A

& B are also presented. Graphs, charting generated statistical forecast and history for the 19 week time period are also presented.

A Damped trend model was used to generate a forecast at product type level. If the product type has intermittent demand pattern then 20-period moving average technique was applied. Any product type or PID which had occurrence of events having zero demand for three consecutive period more than twice was deemed as type or PID having an intermittent demand pattern. Croston's method was not applied for intermittent demand pattern because the method assumes a normal distribution for non-zero demand occurrences. For almost all the types or PIDs this assumption was not satisfied because of the limited availability of data and a large number of occurrences of non-zero demand; thus Croston's method was found unsuitable for our purpose. Smoothing parameters, Holt's alpha and beta and dampening constants for the damped trend model and Root Mean Square Error (RMSE) of each forecast is also tabulated in sections below.

Brown (1963) showed that for given values of parameter α the Holt's alpha and beta parameter can be estimated using the following formula.

$$\alpha_{HW} = [1-(1-\alpha)^2] \dots\dots\dots\dots\dots\dots\dots\dots \text{(3.1)}$$

$$\beta_{HW} = \frac{\alpha^2}{1-(1-\alpha)^2} \dots\dots\dots\dots\dots\dots\dots\dots \text{(3.2)}$$

3.1 Analysis of Product A family

This section presents the analysis of data for different product types and their associated PIDs.

3.1.1 Analysis of Product Type – Assembly & Board

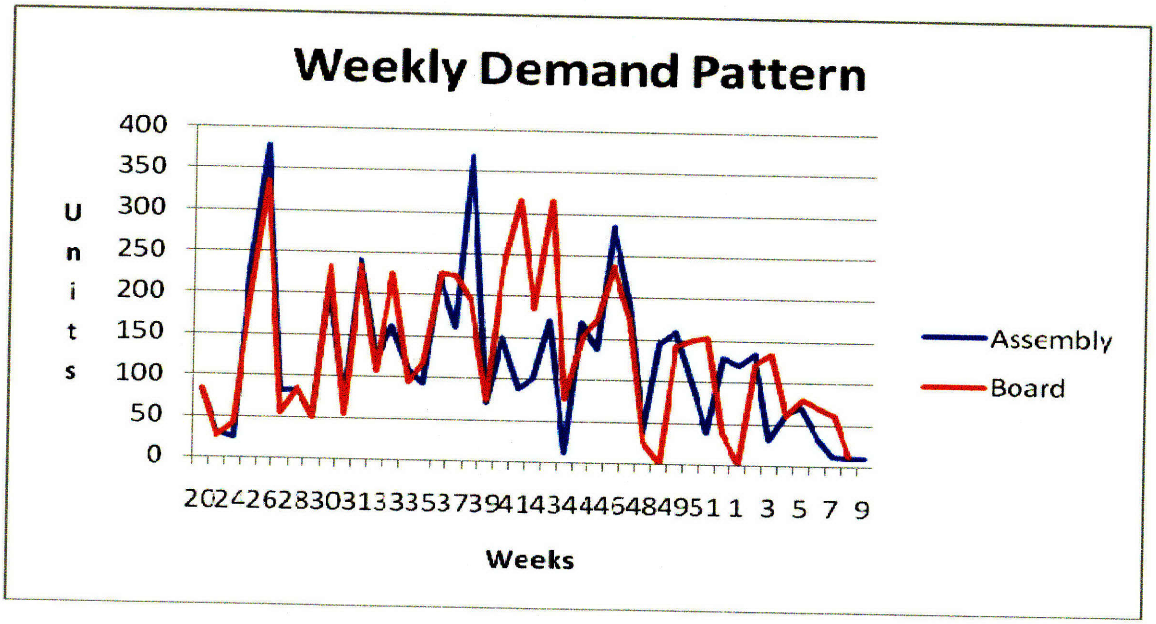

Figure 6: Weekly Demand Pattern for Assembly & Board

Figure 6 shows the demand pattern for the Assembly and Board product types. The pattern has a lot of noise and visual analysis does not reveal a trend. Seasonality is also ruled out because the product characteristics are not seasonal. The damped trend model is applicable to this type of pattern because the trend does not follow a fixed pattern.

Figure 7 below shows the plot of forecast against the history for Assembly and Board. The application of Holt's method would have produced a negative forecast thus the damped trend model had a better applicability for both Assembly and Board.

Table 1 shows the parameter values, Coefficient of Variation (COV) of the forecast and the root mean square error for Assembly & Board.

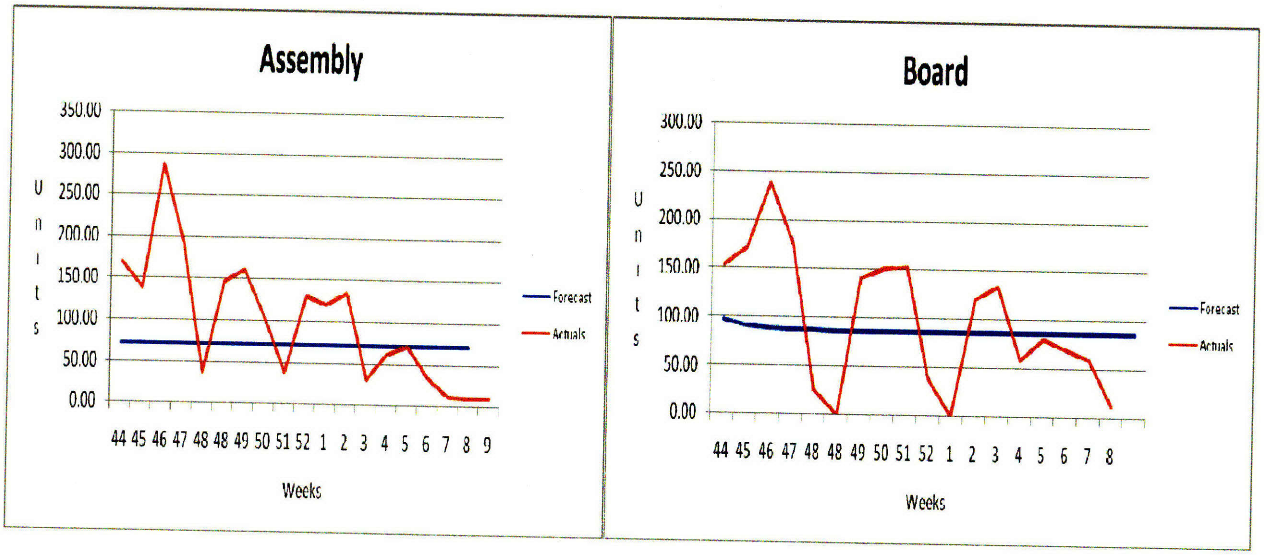

Figure 7: Forecast vs Actuals for Assembly & Board

	alpha (α_{HW})	beta (β_{HW})	phi (ϕ)	RMSE	COV
Assembly	0.51	0.177	0.3	78.971	111.35%
Board	0.75	0.33	0.5	68.129	79.13%

Table 1: Parameter List for Assembly & Board

3.1.1.1 Analysis of PIDs for Product Type – Assembly

Out of 29 PIDs under Product Type Assembly, six exhibited continuous demand while the rest exhibited intermittent demand. The Damped trend model was applied to those PIDs that exhibited continuous demand while 20-period moving average was applied to PIDs that exhibited intermittent demand. Figure 8 below shows the weekly demand pattern for continuous PIDs.

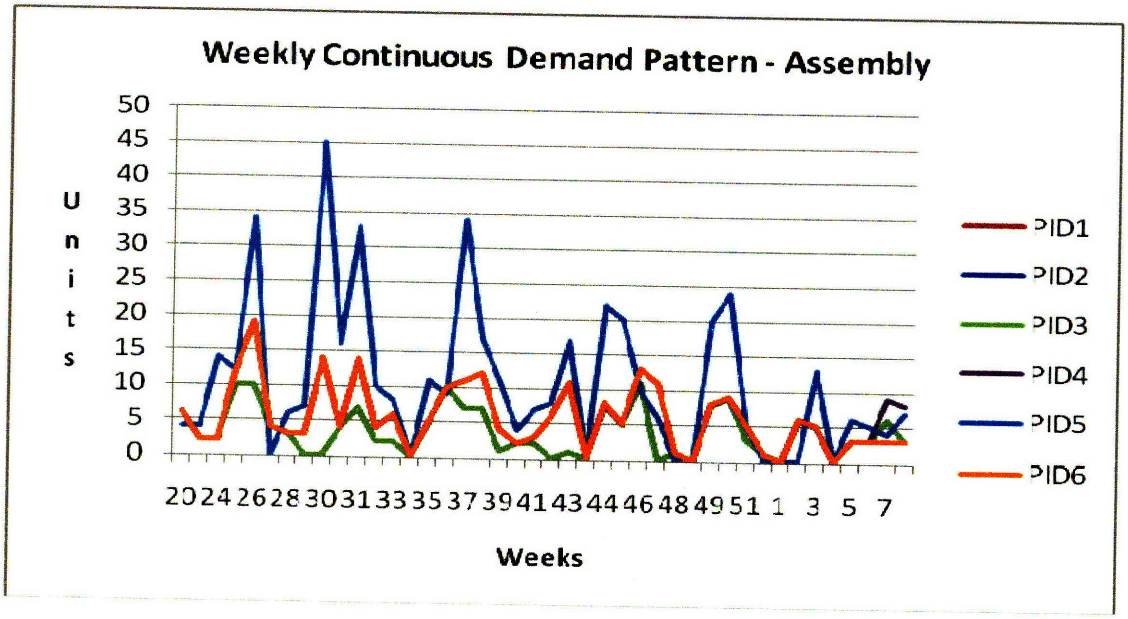

Figure 8: Weekly demand pattern for PIDs of Assembly with continuous demand

Figure 9 shows the weekly demand pattern for some of the PIDs with intermittent demand.

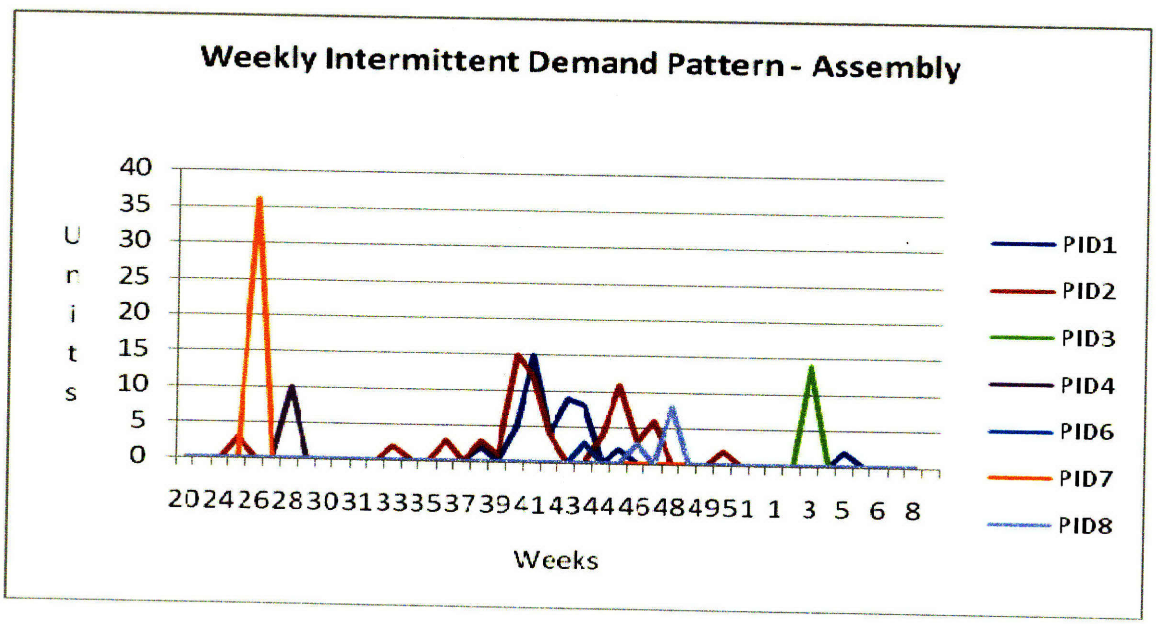

Figure 9: Weekly demand pattern for selected PIDs of Assembly with intermittent demand

3.1.1.2 Analysis of PIDs for Product Type – Board

Out of 62 PIDs under product type Board, five exhibited continuous demand while the rest exhibited intermittent demand. Damped trend model was applied to those PIDs that exhibited continuous demand while 20-period moving average was applied to PIDs that exhibited intermittent demand. Figure 10 below shows the weekly demand pattern for continuous PIDs, and Figure 11 shows the weekly demand pattern for some of the PIDs with intermittent demand.

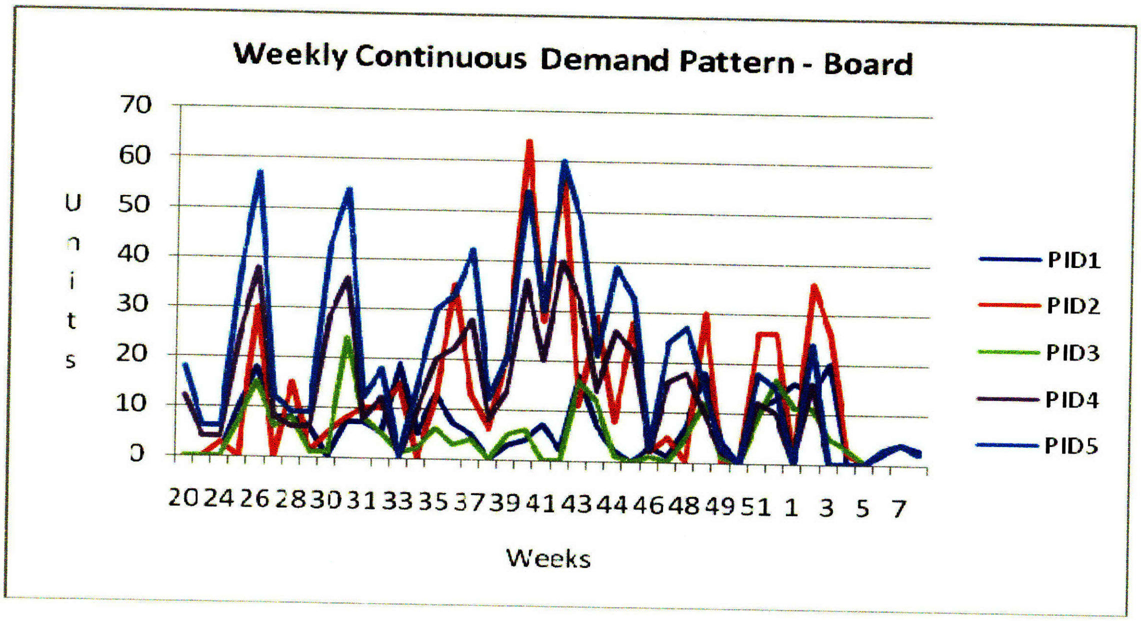

Figure 10: Weekly demand pattern for PIDs of Board with continuous demand

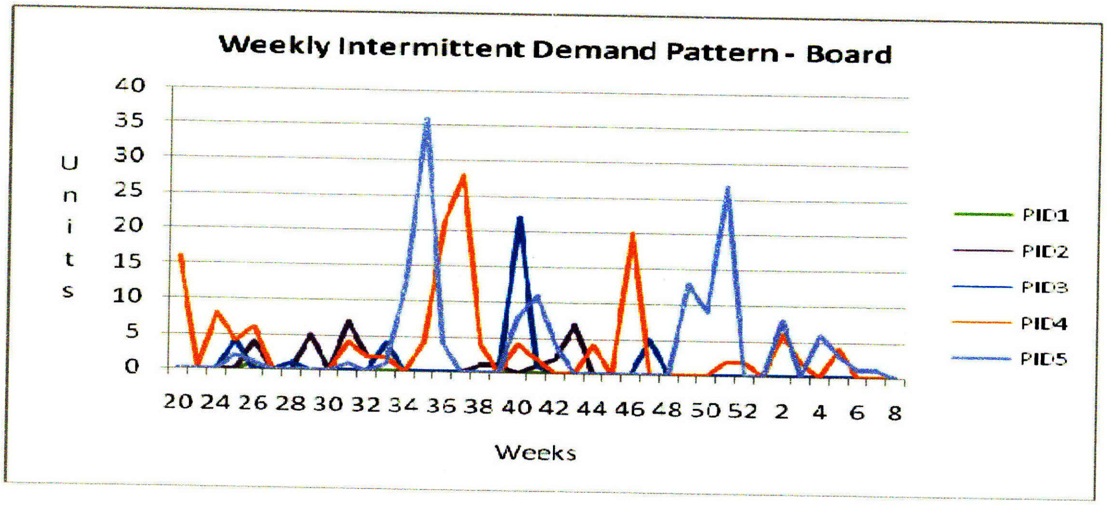

Figure 11: Weekly Demand Pattern for selected PIDs of Board with Intermittent Demand

3.1.2 Analysis of Product Type – Base & Cable

Figure 12 below shows the demand pattern for the Base and Cable product types. As in the case of Assembly and Board the demand pattern of Base and Cable is suitable for applicability of a damped trend model. Figure 13 below shows the plot of forecast against the history for Base and Cable. The application of Holt's method would have produced a negative forecast as it did in the case of assembly thus damped trend model was applied to the demand pattern of Base and Cable.

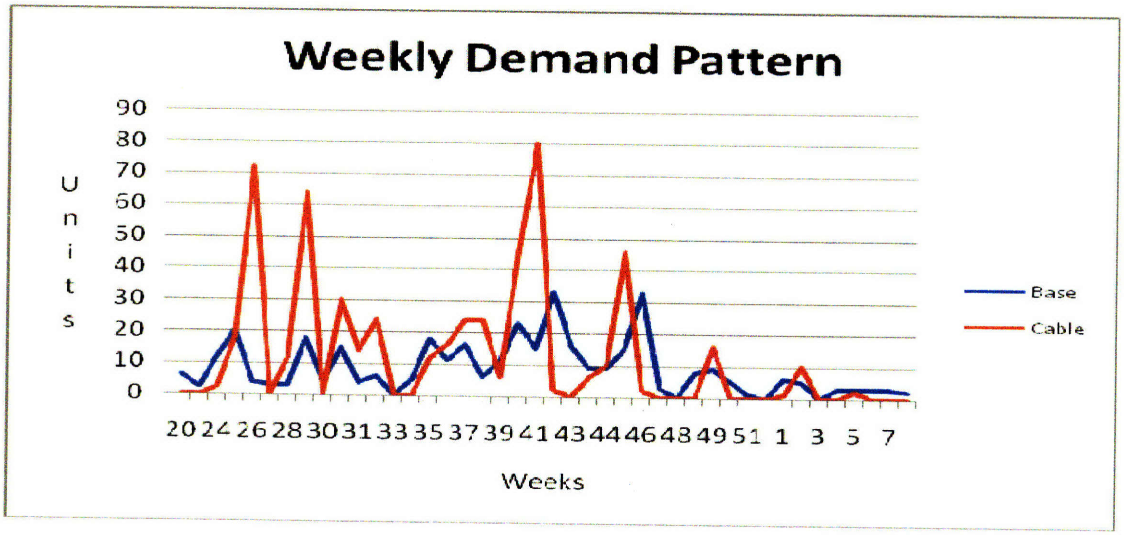

Figure 12: Weekly Demand Pattern for Base & Cable

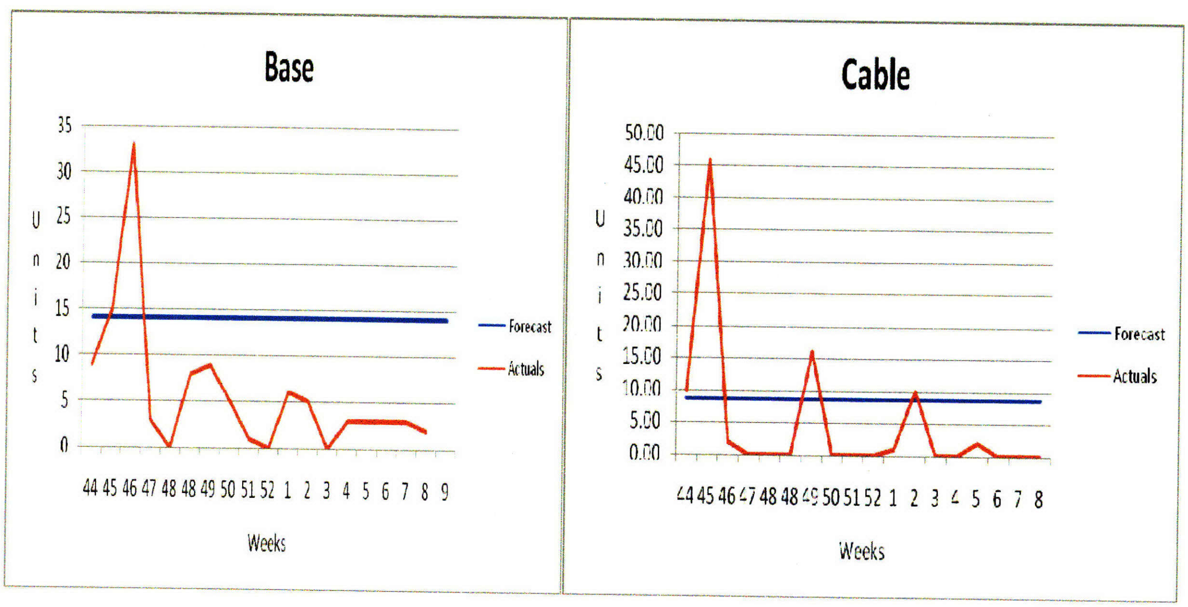

Figure 13: Forecast vs Actuals for Base & Cable

	alpha (α_{HW})	beta (β_{HW})	phi (ϕ)	RMSE	COV
Base	0.51	0.177	0.3	11.077	78.55%
Cable	0.51	0.17	0.3	11.574	134.88%

Table 2: Parameter List for Base & Cable

Table 2 shows the parameter values, COV of the forecast and the root mean square error.

3.1.2.1 Analysis of PIDs for Product Type – Base

Product type Base has 9 PIDs and all these PIDs exhibited intermittent demand. A 20-period moving average technique was applied to all the PIDs.

Figure 14 shows the weekly demand pattern for some of the PIDs belonging to Base.

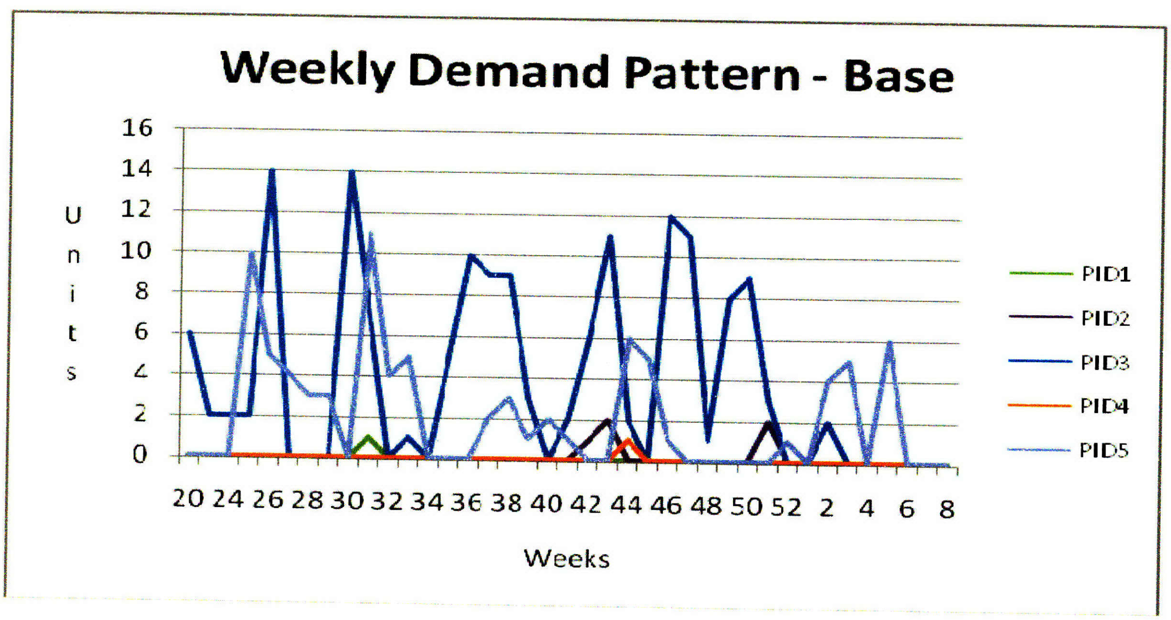

Figure 14: Weekly Demand Pattern for selected PIDs of Base with Intermittent Demand

3.1.2.2 Analysis of PIDs for Product Type – Cable

Product type Cable has 6 PIDs and all these PIDs exhibited intermittent demand. A 20-period moving average technique was applied to all the PIDs.

Figure 15 shows the weekly demand pattern for some of the PIDs belonging to Cable.

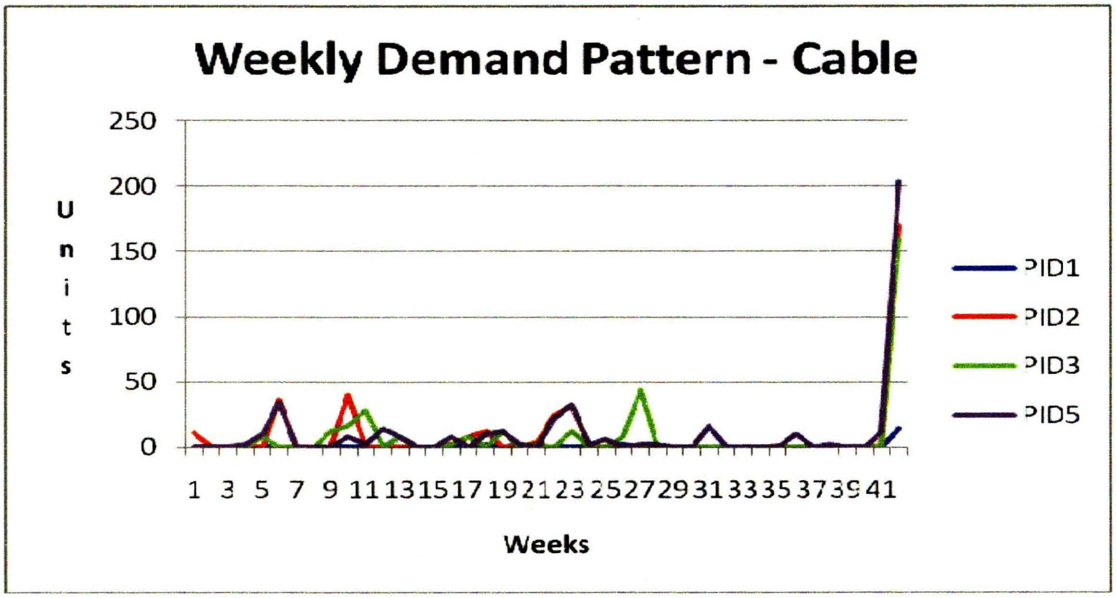

Figure 15: Weekly Demand Pattern for selected PIDs of Cable with Intermittent Demand

3.1.3 Analysis of Product Type – Memory & Router

Figure 16 below shows the demand pattern for the Memory and Router product types. As in the case of Assembly and Board the demand pattern of Memory and Router is suitable for applicability of a damped trend model. Figure 10 below shows the plot of forecast against the history for Memory and Router.

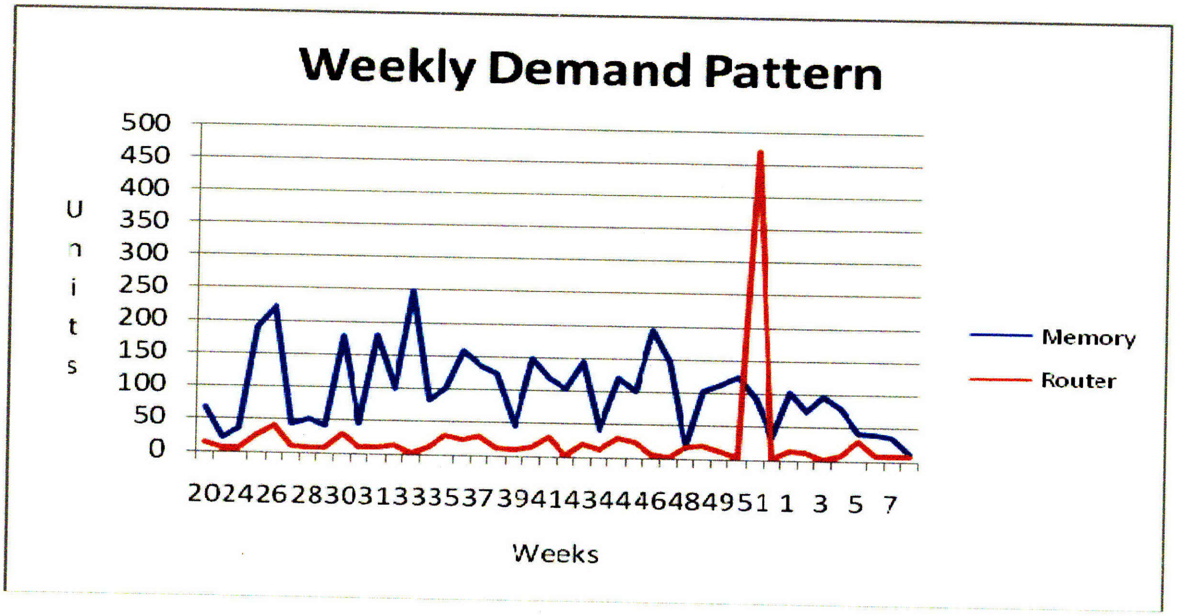

Figure 16: Weekly Demand Pattern for Memory & Router

Table 3 shows the parameter values, COV of the forecast and the root mean square error.

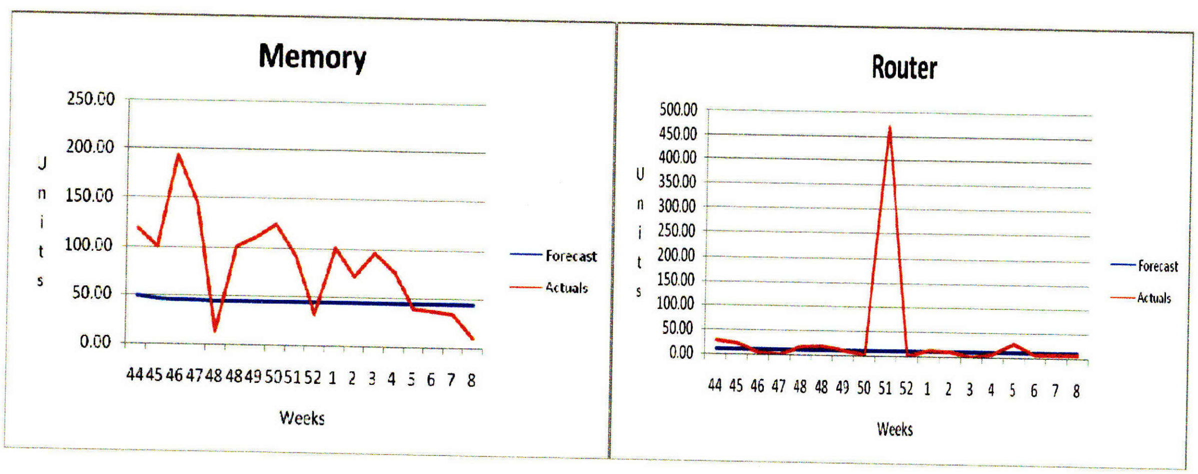

Figure 17: Forecast vs Actuals for Memory & Router

	alpha (α_{HW})	beta (β_{HW})	phi (ϕ)	RMSE	COV
Memory	0.75	0.33	0.5	60.835	136.51%
Router	0.51	0.17	0.8	8.559	82.57%

Table 3: Parameter List for Memory & Router

3.1.3.1 Analysis of PIDs for Product Type – Memory

Out of 22 PIDs under product type Memory, four exhibited continuous demand while the rest exhibited intermittent demand. A Damped trend model was applied to those PIDs that exhibited continuous demand while 20-period moving average was applied to PIDs that exhibited intermittent demand. Figure 18 below shows the weekly demand pattern for continuous PIDs.

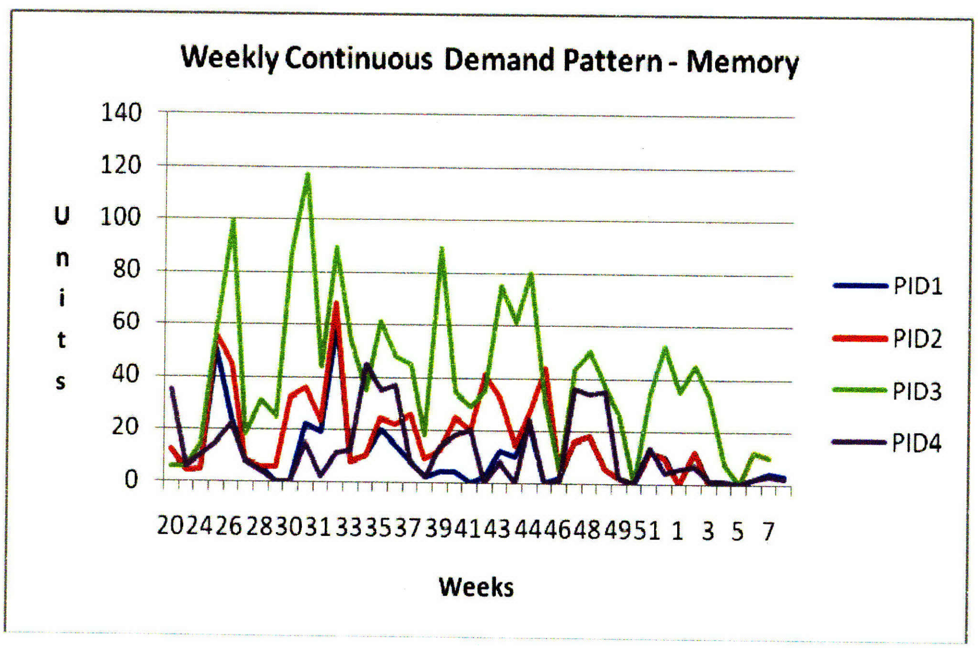

Figure 18: Weekly Demand Pattern for PIDs of Memory with Continuous Demand

Figure 19 shows the weekly demand pattern of some of the PIDs with intermittent demand

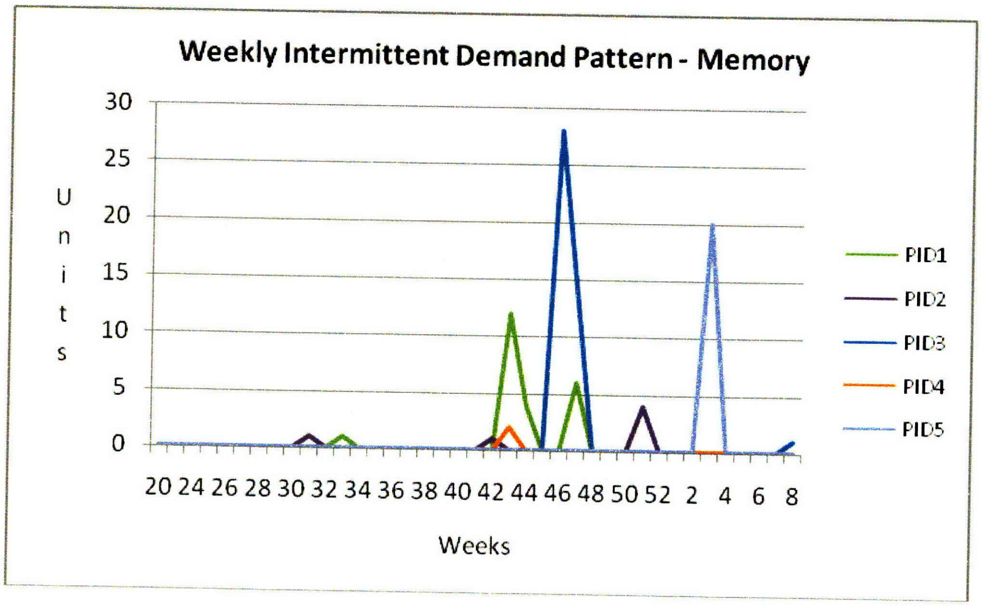

Figure 19: Weekly Demand Pattern for selected PIDs of Memory with Intermittent Demand

3.1.3.2 Analysis of PIDs for Product Type – Router

Out of 14 PIDs under product type Router, only one exhibited continuous demand while the rest exhibited intermittent demand. Damped trend model was applied to the PID that exhibited continuous demand while 20-period moving average was applied to PIDs that exhibited intermittent demand. Figure 20 below shows the weekly demand pattern for continuous PID

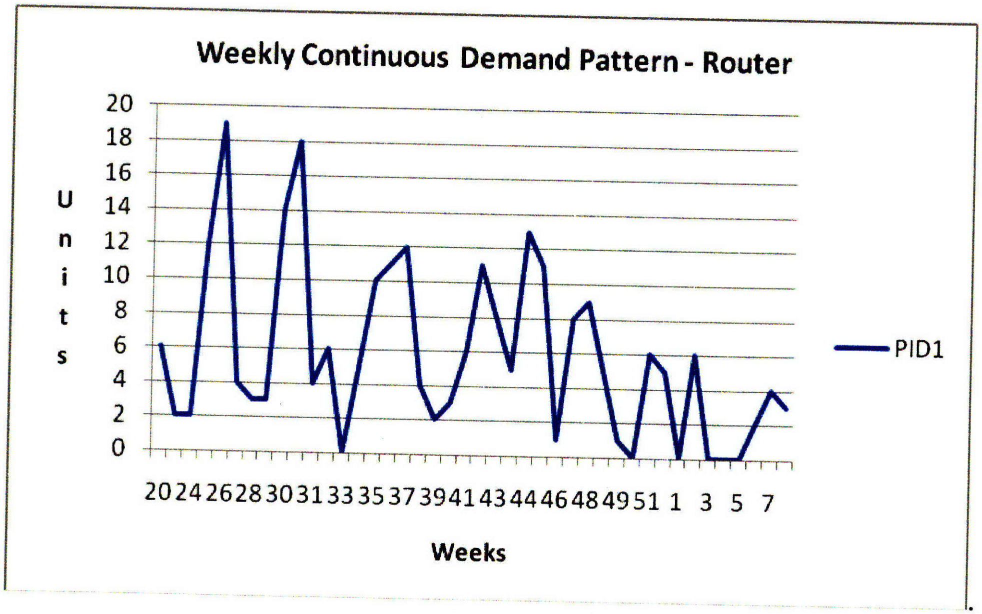

Figure 20: Weekly Demand Pattern of PIDs with Continuous Demand

Figure 21 shows weekly demand pattern for some of the PIDs exhibiting intermittent demand.

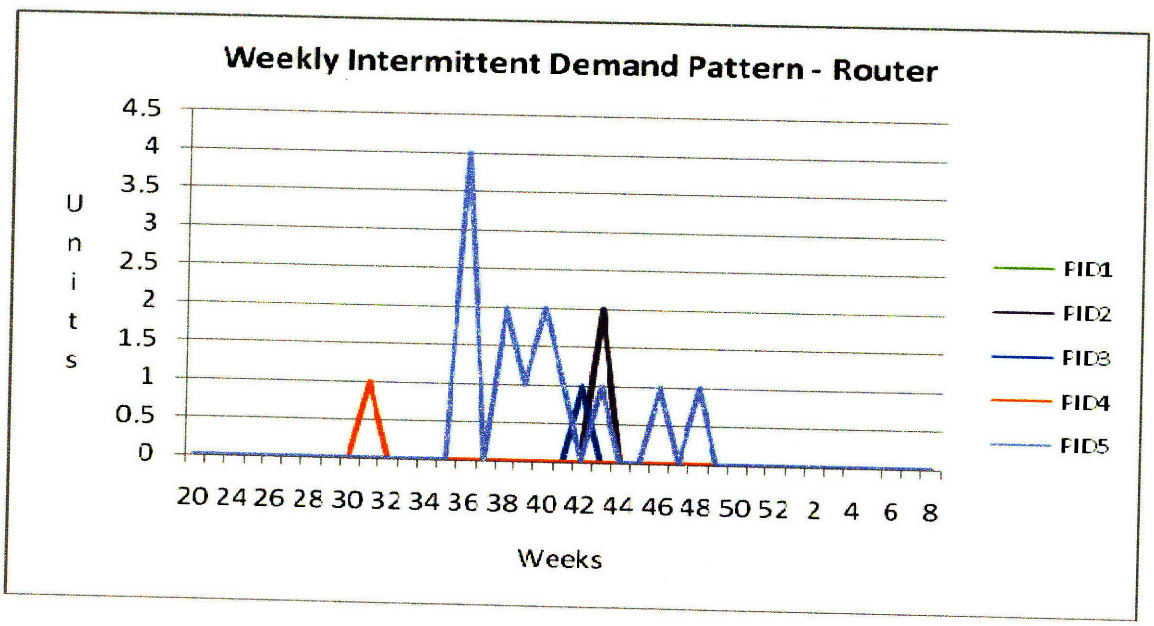

Figure 21: Weekly Demand Pattern for selected PIDs of Router with Intermittent Demand

3.1.4 Analysis of Product Type – Power

Figure 22 shows the weekly demand pattern for product type Power. It can be seen that this product type exhibits intermittent demand. Croston's method is a suitable model to apply to this kind of demand pattern but as discussed at the start of the section a 20-period moving average was applied to the Power type.

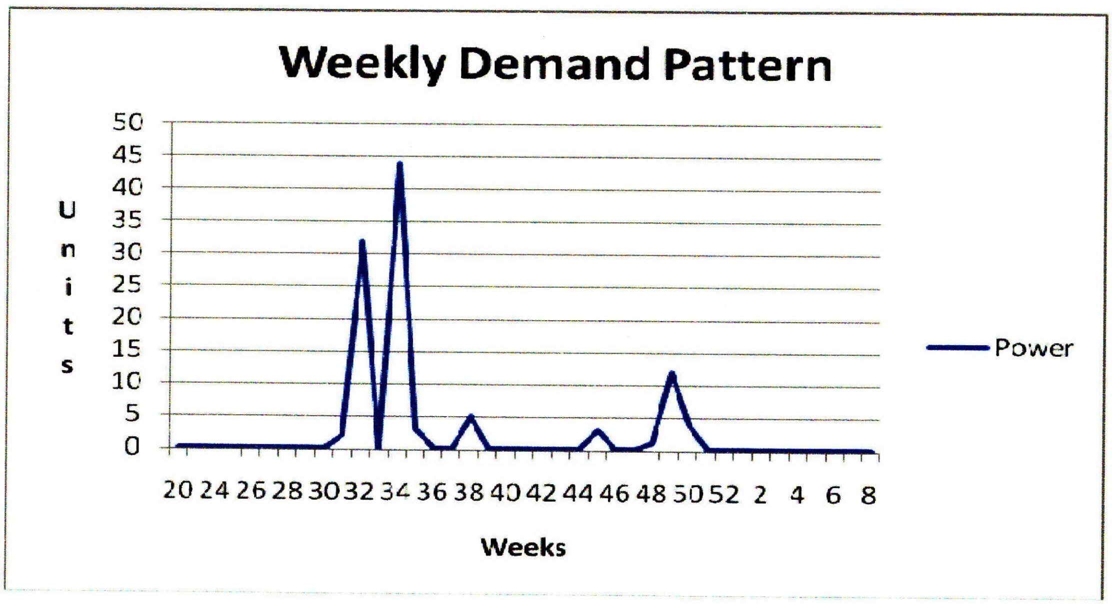

Figure 22: Weekly Demand Pattern for Power

Figure 23 shows the plot of forecast against history for Power. The important point here is the forecast would be level because we are using a moving average smoothing technique.

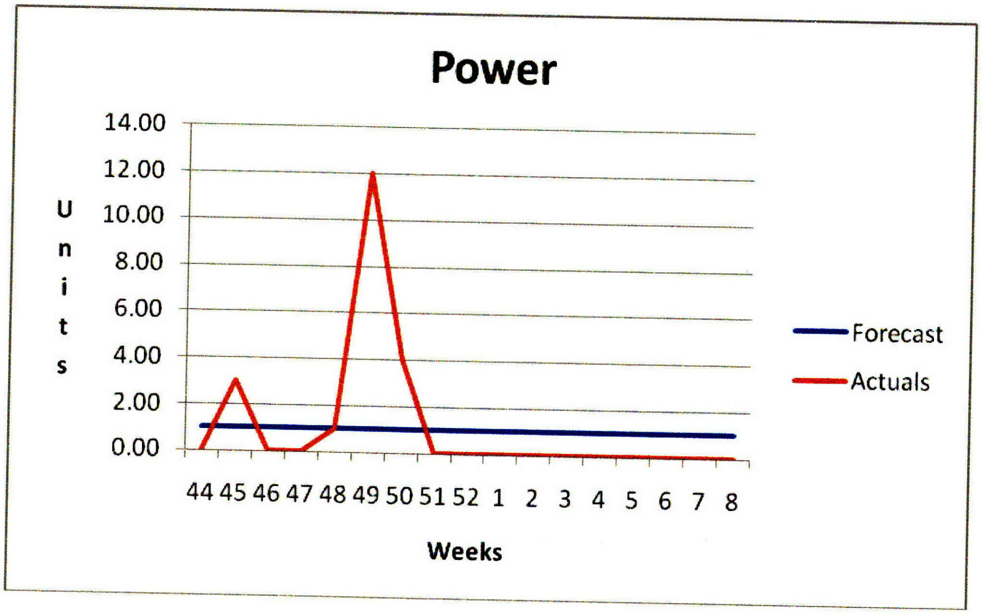

Figure 23: Forecast vs Actuals

3.1.3.1 Analysis of PIDs for Product Type – Power

Product type power has 9 PIDs and all these PIDs exhibited intermittent demand. A 20-period moving average technique was applied to all the PIDs. Figure 24 shows the weekly demand pattern for some of the PIDs belonging to power product type.

RMSE for power was 2.94 and COV was 294%.

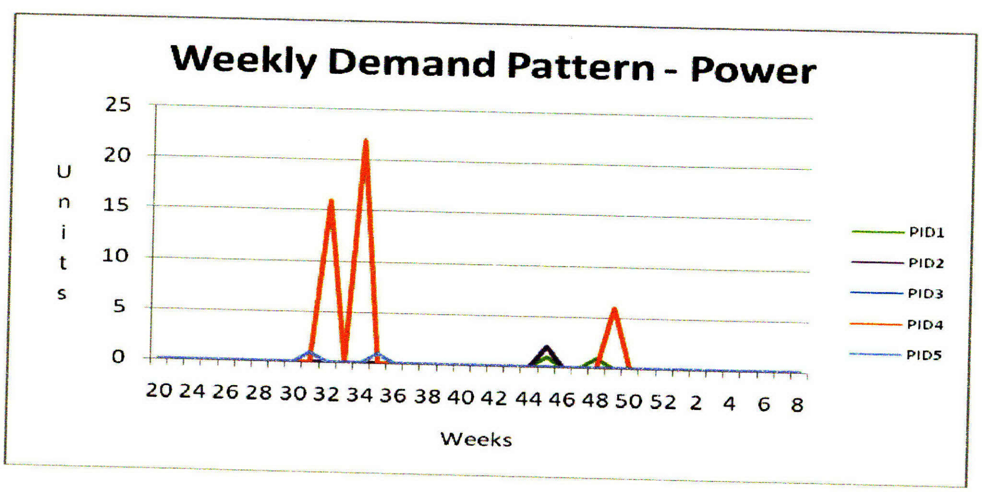

Figure 24: Weekly Demand Pattern of selected PIDs with Intermittent Demand

3.2 Analysis of Product B family

This section presents the analysis of data for different product types and their associated PIDs.

3.2.1 Analysis of Product Type – Assembly & Board

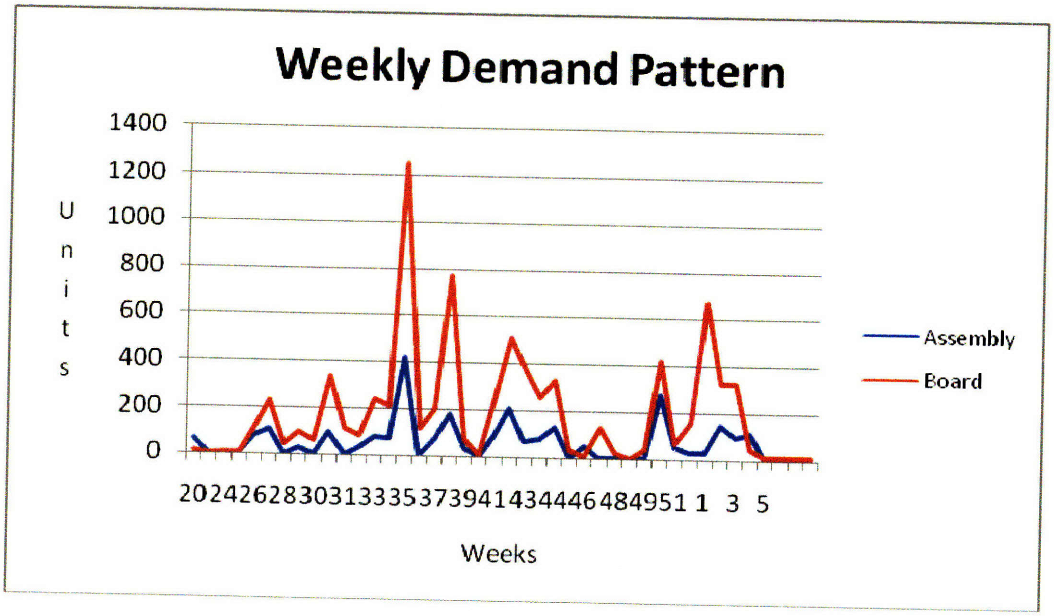

Figure 25: Weekly Demand Pattern for Assembly & Board

Figure 25 shows the demand pattern for the Assembly and Board product types. The pattern has a lot of noise and visual analysis does not reveal a trend. Seasonality is also ruled out because the product characteristics are not seasonal. Product type assembly exhibited characteristics that make the application of a moving average model suitable. Assembly type had two occurrences of patterns where three or more periods of zero demand was observed. Product type Board exhibited no such characteristic so a damped trend model was applied.

Figure 26 below shows the plot of forecast against the history for Assembly and Board. A 20-period moving average technique was applied to product type, assembly.

Table 4 shows the parameter values, COV of forecast and the root mean square error.

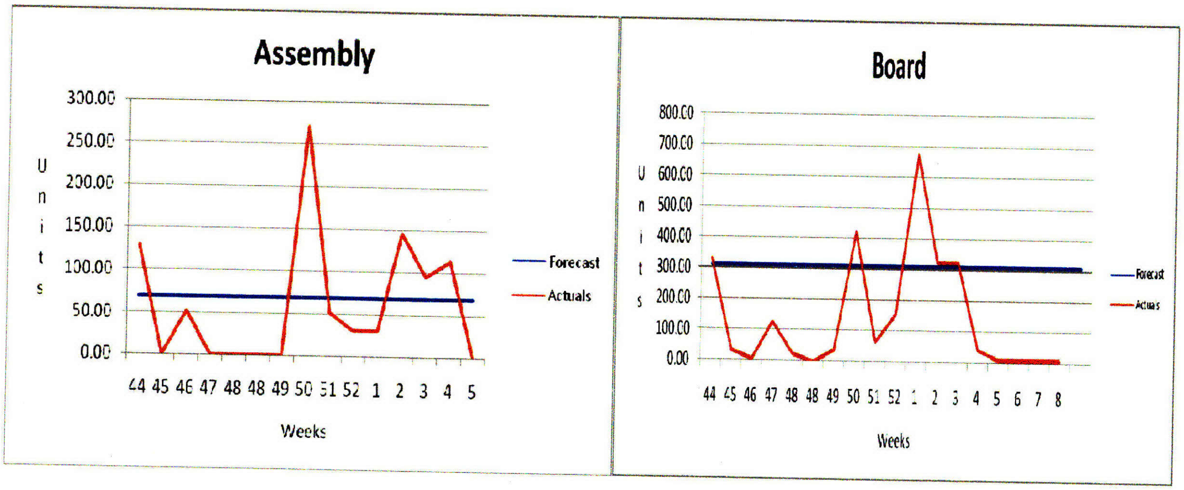

Figure 26: Forecast vs Actuals for Assembly and Board

	alpha (α_{HW})	beta (β_{HW})	phi (ϕ)	RMSE	COV
Assembly	0.51	0.18	0.3	72.85	107.05%
Board	0.51	0.18	0.4	250.9	2280.97%

Table 4: Parameter List for Assembly & Board

3.2.1.1 Analysis of PIDs for Product Type – Assembly

Product type Assembly has 16 PIDs and all these PIDs exhibited intermittent demand. A 20-period moving average technique was applied to all the PIDs. Figure 14 shows the weekly demand pattern for some of the PIDs belonging to Board.

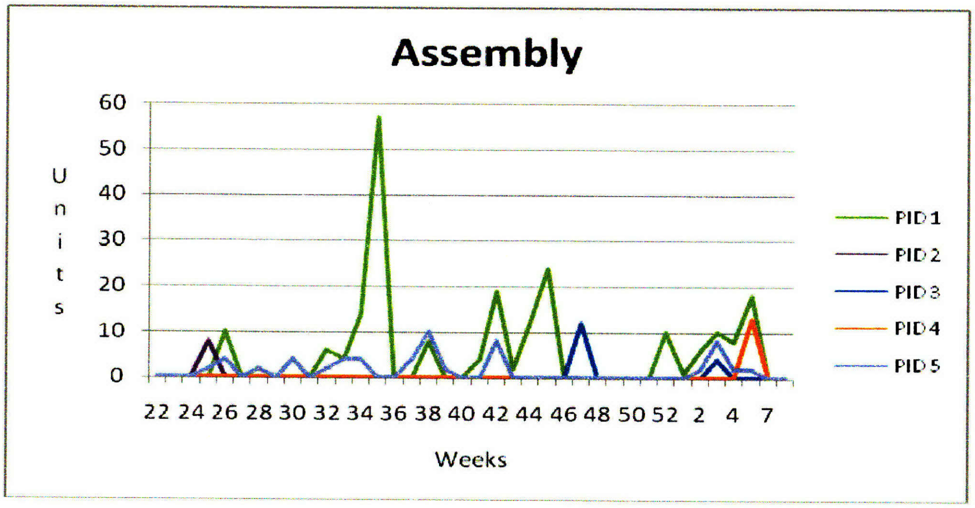

Figure 27: Weekly demand pattern for selected PIDs of Assembly

3.2.1.2 Analysis of PIDs for Product Type – Board

Product type Board has 62 PIDs and all these PIDs exhibited intermittent demand. A 20-period moving average technique was applied to all the PIDs. Figure 14 shows the weekly demand pattern for some of the PIDs belonging to Board.

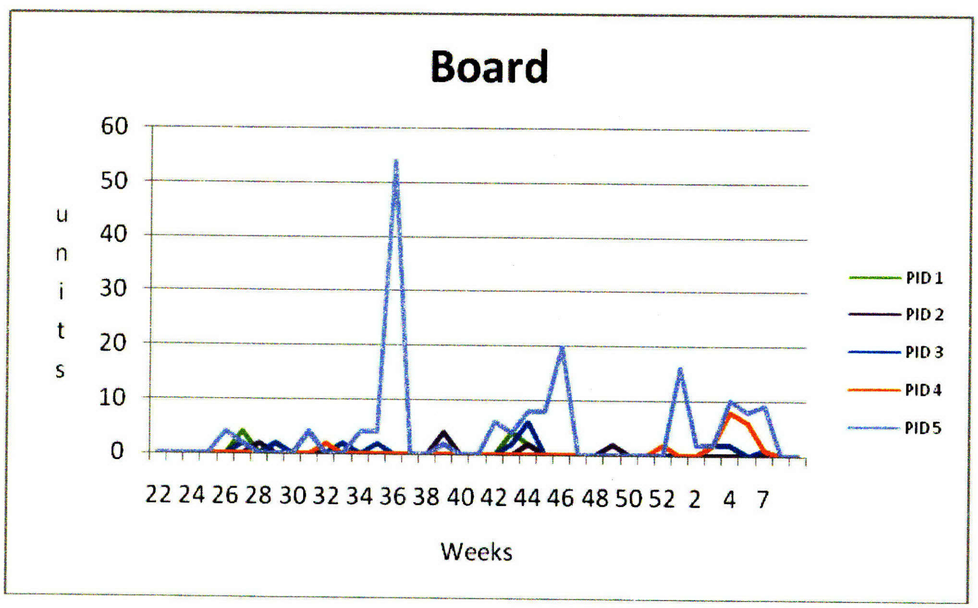

Figure 28: Weekly demand pattern for selected PIDs of Board

3.2.2 Analysis of Product Type – Base & Feature

Figure 29 shows the demand pattern for the Base and Feature product types. The pattern has a lot of noise and visual analysis does not reveal a trend. Seasonality is also ruled out because the product characteristics are not seasonal. Product type Base exhibited characteristics that make the application of moving average model. Base type had two occurrences of pattern where three or more periods of zero demand was observed. Product type Feature exhibited no such characteristic so a damped trend model was applied.

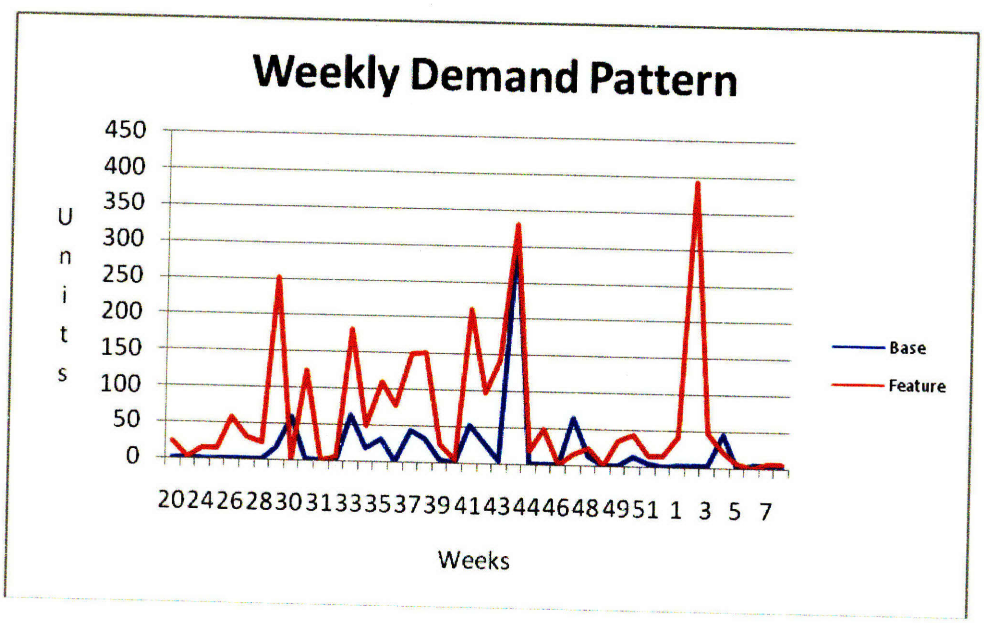

Figure 29: Weekly Demand Pattern for Base & Feature

Figure 30 below shows the plot of forecast against the history for Base and Feature. A 20-period moving average technique was applied to product type Base and a damped trend model was applied to product type Feature.

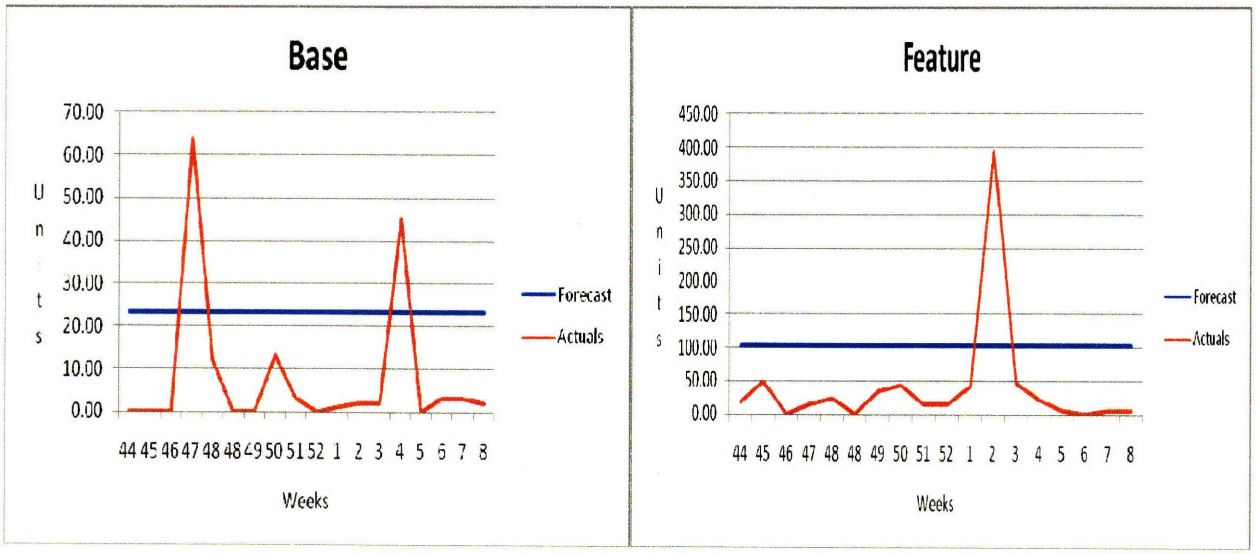

Figure 30: Forecast vs Actuals for Base & Feature

	alpha (α_{HW})	beta (β_{HW})	phi (ϕ)	RMSE	COV
Base	0.51	0.18	0.3	22.676	97.32%
Feature	0.0975	0.023	0.8	91.227	113.83%

Table 5: Parameter List for Base & Feature

Table 5 shows the parameter values, COV of forecast and the root mean square error.

3.2.2.1 Analysis of PIDs for Product Type – Base

Product type Base has 9 PIDs and all these PIDs exhibited intermittent demand. A 20-period moving average technique was applied to all the PIDs.

Figure 31 shows the weekly demand pattern for some of the PIDs belonging to Base.

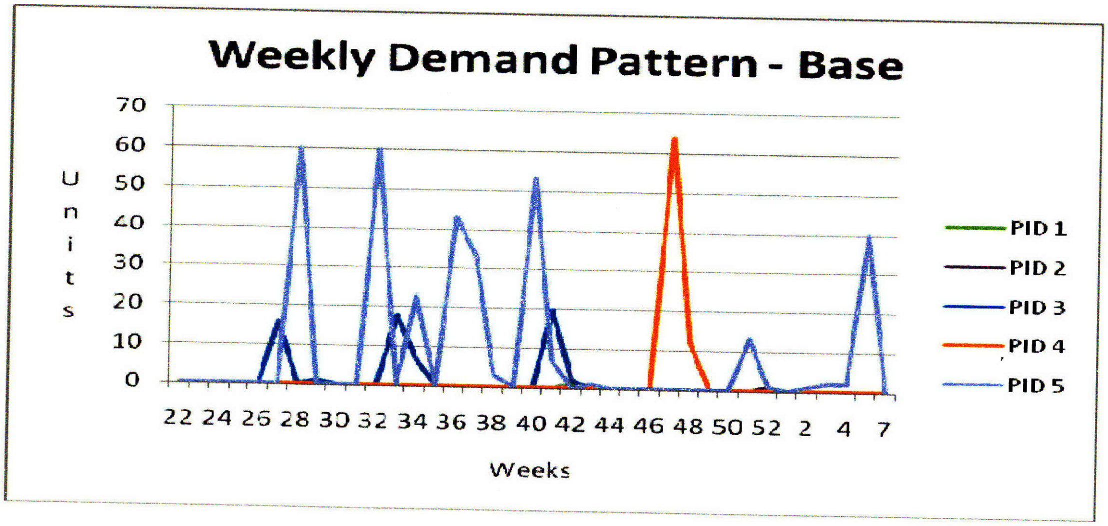

Figure 31: Weekly Demand Pattern for selected PID of Base

3.2.2.2 Analysis of PIDs for Product Type – Feature

Product type feature has 20 PIDs and all these PIDs exhibited intermittent demand. A 20-period moving average technique was applied to all the PIDs.

Figure 32 shows the weekly demand pattern for some of the PIDs belonging to Feature.

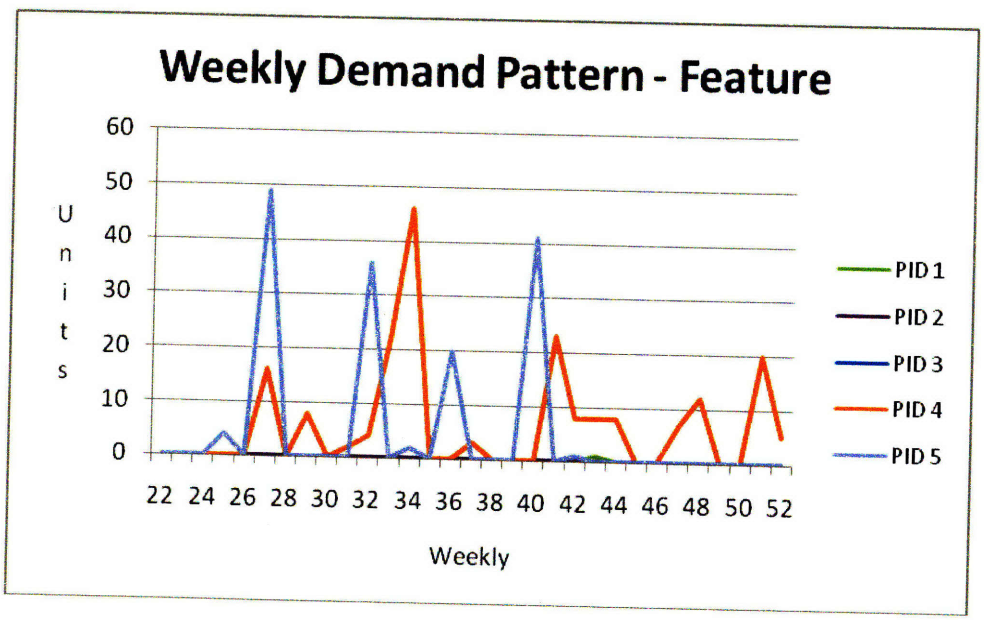

Figure 32: Weekly Demand Pattern for selected PIDs of Feature

3.2.3 Analysis of Product Type – Power & Cable

Figure 33 shows the demand pattern for the Cable and Power product type. Product type Power exhibited characteristics that make the application of moving average model. Power type had two occurrences of pattern where three or more periods of zero demand was observed. Product type Cable exhibited no such characteristic so a damped trend model was applied.

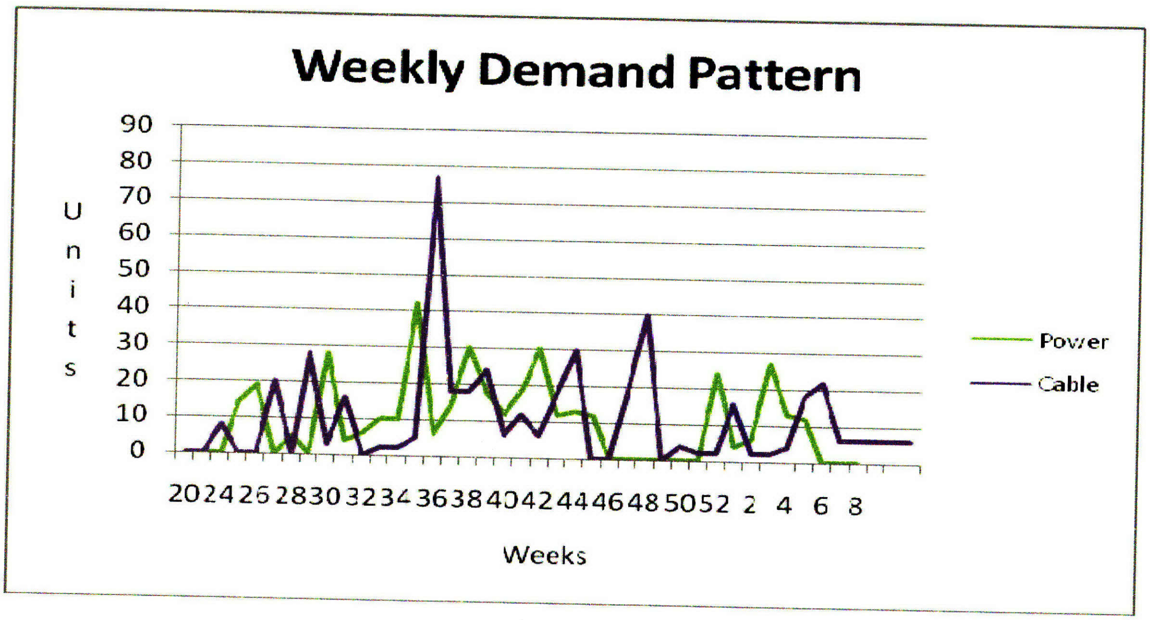

Figure 33: Weekly Demand Pattern for Power & Cable

Figure 34 shows the plot of the forecasts against the actuals.

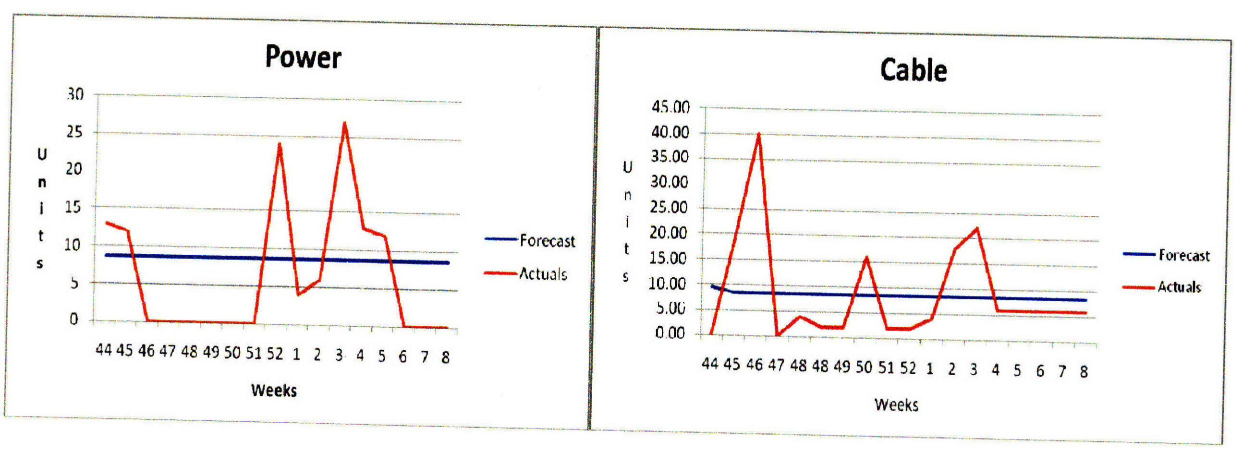

Figure 34: Forecast vs Actuals for Power and Cable

	alpha (α_{HW})	beta (β_{HW})	phi (ϕ)	RMSE	COV
Power	0	0	0	8.85	102.89%
Cable	0.5	0.18	0.3	9.216	118.36%

Table 6: Parameter List for Power & Cable

Table 6 shows the parameter values, COV of the forecast and the root mean square error.

3.2.3.1 Analysis of PIDs for Product Type – Power

Product type Power has 16 PIDs and all these PIDs exhibited intermittent demand. A 20-period moving average technique was applied to all the PIDs.

Figure 35 below shows the weekly demand pattern for some of the PIDs.

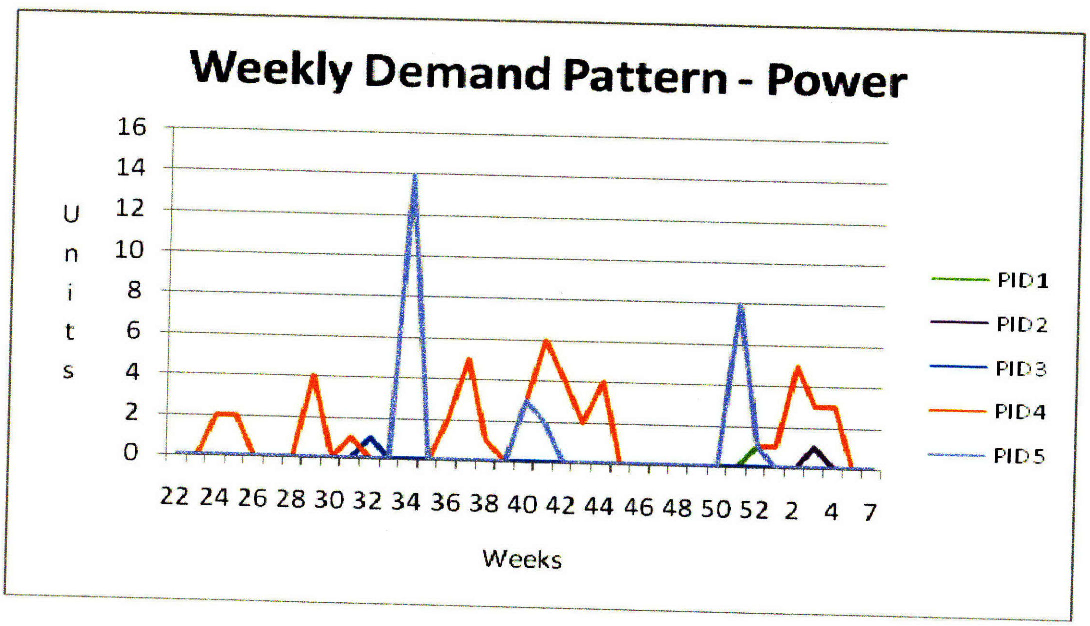

Figure 35: Weekly Demand Pattern for Selected PIDs of Power

3.2.3.2 Analysis of PIDs for Product Type – Cable

Product type Cable has 11 PIDs and all these PIDs exhibited intermittent demand. A 20-period moving average technique was applied to all the PIDs.

Figure 36 shows weekly demand pattern for some of the PIDs exhibiting intermittent demand.

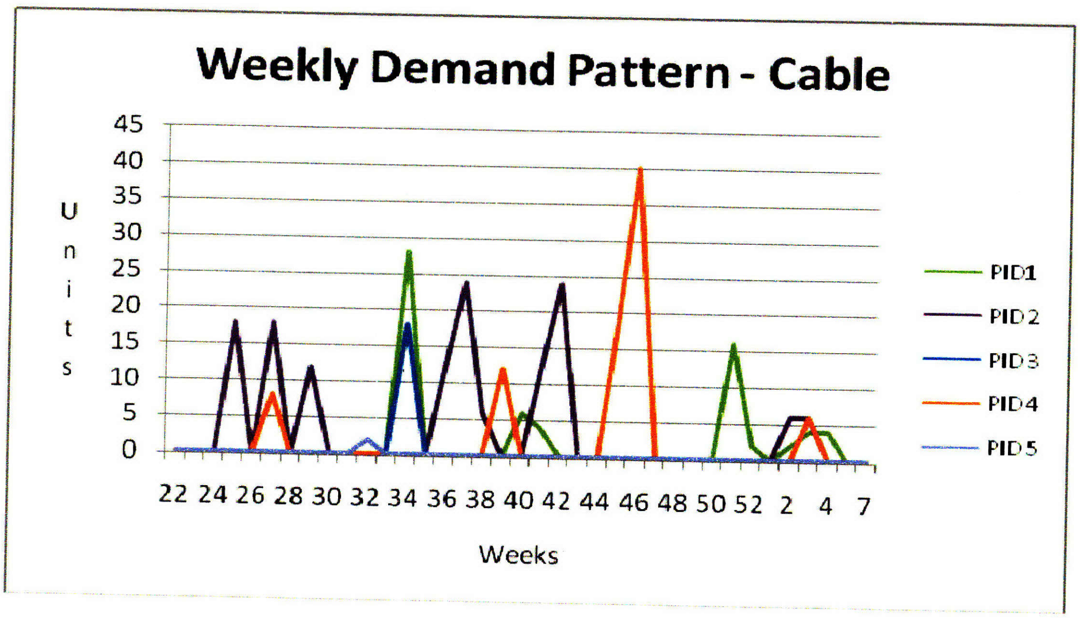

Figure 36: Weekly Demand Pattern of selected PIDs of Cable

3.2.3 Analysis of Product Type – Switch

Figure 38 shows the demand pattern for the Switch product type. Product type Switch exhibited characteristics that make the application of moving average model. Switch type had two occurrences of pattern where three or more periods of zero demand was observed.

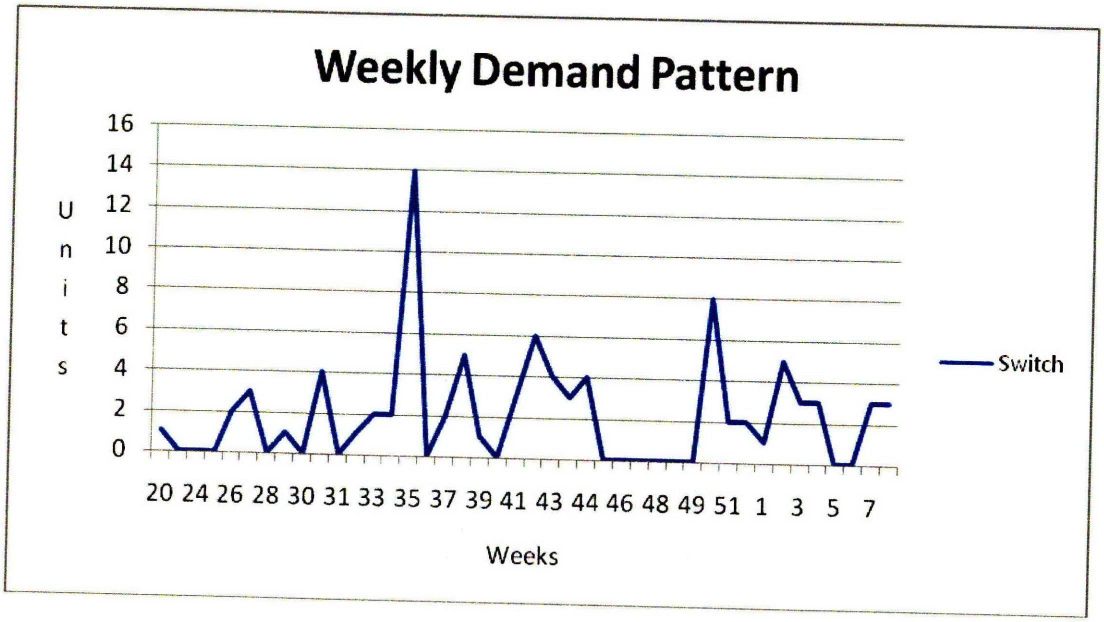

Figure 37: Weekly Demand Pattern for Switch

RMSE for switch was 2.055 and the COV was 93.39%.

Chapter 4: Analysis of Statistical Results

This section compares the forecast generated at the product family level with the forecast generated at the PID level and aggregated up to the product type level, called the Bottom up Forecast (BUF). The comparison is done for both the Product A and Product B family. Insights if any are also derived from the generated forecasts. If the forecast at type level is better than the BUF, than the BUF is corrected by adjusting the proportions at the PID level such that the corrected BUF numbers are exactly equal to the forecast generated at type level. If the BUF is better than the forecast at type level, then the type forecast is replaced by the aggregated BUF. The metric of performance here is Root Mean Square Error (RMSE). The forecast with lower RMSE is considered to be better. Finally, a hybrid model is proposed that takes statistical forecasts, BUF and Type, into consideration and comes up with a joint weighted forecast. The objective is to come up with a statistical model whose statistical numbers are superior to both statistical forecasts. The formula for the hybrid model is based on the α that gives the lowest RMSE, and is as follows:

Hybrid Forecast = α*Type Forecast + (1- α)*BUF

4.1 Forecast Analysis of Product Family A

As discussed in the data analysis section, product family A has 7 product types. Each product type can be further sub-divided into PIDs. The PID level is the lowest level in the product hierarchy.

4.1.1 Forecast Analysis of Product Type – Assembly

Assembly has 29 PIDs with most of the PIDs having intermittent demand. Table 7 below shows the mean absolute deviation (MAD) for aggregate forecast and BUF from week 44 of 2007 to week 9 of 2008. Table 8 below shows the RMSE for BUF, type level and hybrid.

Weeks	**Type**	**BUF**	**Hybrid**	**Weeks**	**Type**	**BUF**	**Hybrid**
44	97.704	9.67	97.70	1	49.109	8.20	49.11
45	66.987	8.50	66.99	2	63.109	8.14	63.11
46	215.072	8.46	215.07	3	39.891	8.07	39.89
47	122.098	8.45	122.10	4	8.891	8.01	8.89
48	33.895	8.40	33.89	5	0.109	7.94	0.11
49	75.108	8.35	75.11	6	36.891	7.87	36.89
50	89.108	8.30	89.11	7	59.891	7.80	59.89
51	32.109	8.24	32.11	8	60.891	7.76	60.89
52	32.891	8.19	32.89	9	60.891	7.76	60.89

Table 7: MAD of different forecasts for Assembly

	BUF	Type	Hybrid
RMSE	80.301	78.971	78.971 ($\alpha = 1$)

Table 8: RMSE of different forecasts for Assembly

From Table 8 it is clear that the type level forecast is accurate than BUF because type level forecast has slightly lower RMSE. Also, if we compare bucket by bucket we can see that the type level MADs are much better than BUF MADs.

Since type level forecast was better than BUF, the BUF forecast was adjusted by changing the PID level proportions such that the aggregate of PID forecast numbers were exactly equal to the type level forecast numbers for each weekly bucket.

4.1.2 Forecast Analysis of Product Type – Base

Base has 29 PIDs with all of the PIDs having intermittent demand. Table 9 below shows the MADs for aggregate forecast and BUF from week 44 of 2007 to week 10 of 2008. Table 9 below shows the RMSE for BUF and type level forecast.

Weeks	Type	BUF	Hybrid	Weeks	Type	BUF	Hybrid
44	5.14	0.80	0.80	1	8.10	3.80	3.80
45	0.89	5.20	5.20	2	9.10	4.80	4.80
46	18.90	23.20	23.20	3	14.10	9.80	9.80
47	11.10	6.80	6.80	4	11.10	6.80	6.80
48	14.10	9.80	9.80	5	11.10	6.80	6.80
49	6.10	1.80	1.80	6	11.10	6.80	6.80
50	5.10	0.80	0.80	7	11.10	6.80	6.80
51	9.10	4.80	4.80	8	12.10	7.80	7.80
52	13.10	8.80	8.80	9	14.10	9.80	9.80

Table 9: MAD of different forecasts for Base

	BUF	Type	Hybrid
RMSE	8.53	11.07	8.53($\alpha = 0$)

Table 10: RMSE of different forecasts for Base

From Table 10 it is clear that BUF is a better forecast than type level forecast. From Table 9 we can see that for most of the weekly buckets BUF MADs are much closer to history than type level MADs. Only for weekly buckets 45 and 3type level MADs have a better performance than BUF MADs. Thus in this case we do not adjust the BUF.

4.1.3 Forecast Analysis of Product Type – Memory

Memory has 22 PIDs with most of the PIDs having intermittent demand. Table 11 below shows the MADs for aggregate forecast and BUF from week 44 of 2007 to week 9 of 2008. Table 12 below shows the RMSE for BUF and type level forecast.

Weeks	Type	BUF	Hybrid	Weeks	Type	BUF	Hybrid
44	69.86	6.38	34.14	1	57.00	11.60	18.39
45	53.43	12.60	16.27	2	28.00	40.60	10.61
46	148.72	81.40	110.83	3	52.01	16.60	13.39
47	100.36	32.40	62.11	4	33.01	35.60	5.61
48	31.31	99.60	69.75	5	4.99	73.60	43.61
49	56.85	11.60	18.32	6	6.99	75.60	45.61
50	66.93	1.60	28.36	7	9.99	78.60	48.61
51	79.97	11.40	41.38	8	33.99	102.60	72.60
52	47.99	20.60	9.39	9	57.00	11.60	18.39

Table 11: MAD of different forecasts for Memory

	BUF	Type	Hybrid
RMSE	55.85	60.835	47.27($\alpha = 0.44$)

Table 12: RMSE of different forecasts for Memory

From Table 12 it is clear that Hybrid is a better forecast than both BUF and Type forecast. In this scenario we will have to make an adjustment to the BUF forecast so that BUF forecast exactly matches the Hybrid forecast number at the aggregate level.

4.1.4 Forecast Analysis of Product Type – Router

Router has 14 PIDs and all the PIDs have intermittent demand. Table 13 below shows the MADs for Type forecast and BUF from week 44 of 2007 to week 9 of 2008. Table 14 below shows the RMSE for BUF and Type forecast.

Weeks	Type	BUF	Hybrid	Weeks	Type	BUF	Hybrid
44	1.00	15.91	15.91	1	1.82	0.08	0.08
45	16.84	9.92	9.92	2	0.16	2.08	2.08
46	11.06	8.08	8.08	3	10.14	12.08	12.08
47	6.77	12.08	12.08	4	4.13	6.08	6.08
48	10.63	3.92	3.92	5	17.88	15.92	15.92
49	5.48	5.92	5.92	6	4.11	6.08	6.08
50	7.57	2.08	2.08	7	4.10	6.08	6.08
51	0.35	10.08	10.08	8	4.09	6.08	6.08
52	8.30	459.92	459.92	9	1.82	0.08	0.08

Table 13: MAD of different forecasts for Router

	BUF	Type	Hybrid
RMSE	108.766	109.171	108.766($\alpha = 0$)

Table 14: RMSE of different forecasts Router

From Table 14 it is clear that BUF is a marginally better forecast than type level forecast. MADs for type level forecast are higher than MADs for BUF for some of the week while for other weeks MADs for BUF are higher. There is no clear pattern visible here. Thus in this case too we don't adjust the type level forecast although the average error for BUF is better.

4.1.5 Forecast Analysis of Product Type – Board

Router has 44 PIDs with most of the PIDs having intermittent demand. Table 13 below shows the MADs for aggregate forecast and BUF from week 44 of 2007 to week 9 of 2008. Table 14 below shows the RMSE for BUF and type level forecast.

Weeks	Type	BUF	Hybrid	Weeks	Type	BUF	Hybrid
44	56.32	17.30	56.32	1	86.26	17.30	86.26
45	80.04	1.11	80.04	2	34.75	1.11	34.75
46	149.89	68.31	149.89	3	48.75	68.31	48.75
47	88.32	5.41	88.32	4	27.25	5.41	27.25
48	61.96	145.54	61.96	5	6.25	145.54	6.25
49	86.61	170.51	86.61	6	16.25	170.51	16.25
50	55.57	28.50	55.57	7	26.25	28.50	26.25
51	64.66	19.49	64.66	8	74.25	19.49	74.25
52	67.71	16.49	67.71	9	86.25	16.49	86.25

Table 15: MAD of different forecasts for Board

	BUF	Type	Hybrid
RMSE	98.549	68.129	68.129($\alpha = 1$)

Table 16: RMSE of different forecasts for Board

From Table 16 it is clear that Type level forecast is better than BUF. From Table 16 it is also clear that type level MADs are better as we go down further in the forecast horizon. For the first few weeks BUF MADs are better but as we go down further type level MADs become better.

Since type level RMSE is significantly better than the BUF RMSE, we adjust the BUF by following a top down approach in which the adjustment is based on the proportions.

4.1.6 Forecast Analysis of Product Type – Cable

Cable has 6 PIDs and all the PIDs have intermittent demand. Table 17 below shows the MADs for aggregate forecast and BUF from week 44 of 2007 to week 9 of 2008. Table 18 below shows the RMSE for BUF and type level forecast.

Weeks	Type	BUF	Hybrid	Weeks	Type	BUF	Hybrid
44	1.36	1.09	1.36	1	7.58	10.09	7.58
45	37.41	34.91	37.41	2	1.42	1.09	1.42
46	6.58	9.09	6.58	3	8.58	11.09	8.58
47	8.58	11.09	8.58	4	8.58	11.09	8.58
48	8.58	11.09	8.58	5	6.58	9.09	6.58
49	8.58	11.09	8.58	6	8.58	11.09	8.58
50	7.42	4.91	7.42	7	8.58	11.09	8.58
51	8.58	11.09	8.58	8	8.58	11.09	8.58
52	8.58	11.09	8.58	9	8.58	11.09	8.58

Table 17: MAD of different forecasts for Cable

	BUF	Type	Hybrid
RMSE	12.34	11.57	11.57($\alpha = 1$)

Table 18: RMSE of different forecasts for Cable

From Table 18 it is clear that Type level forecast is better than BUF. From Table 17 it is clear that type level MADs are better as we go down further in the forecast horizon. For the first few weeks BUF MADs are better but as we go down further type level MADs become better. Since type level RMSE is significantly better than the BUF RMSE, we adjust the BUF by following a top down approach in which the adjustment is based on the proportions.

4.1.7 Forecast Analysis of Product Type – Power

Cable has 9 PIDs and all the PIDs have intermittent demand. Demand at type level is also aggregate so a 20-month moving average technique was adopted for forecasting. Table 19 below shows the MADs for aggregate forecast and BUF from week 44 of 2007 to week 9 of 2008. Table 20 below shows the RMSE for BUF and type level forecast.

Weeks	Type	BUF	Hybrid	Weeks	Type	BUF	Hybrid
44	1	1	1	1	1	1	1
45	2	2	2	2	1	1	1
46	1	1	1	3	1	1	1
47	1	1	1	4	1	1	1
48	0	0	0	5	1	1	1
49	11	11	11	6	1	1	1
50	3	3	3	7	1	1	1
51	1	1	1	8	1	1	1
52	1	1	1	9	1	1	1

Table 19: MAD of Different Forecasts for Power

	BUF	Type	Hybrid
RMSE	2.94	2.94	2.94($\alpha = 1$)

Table 20: RMSE of different forecasts for Power

From the tables above it can be seen that both type level and BUF for product type Power are identical hence we do not adjust any forecast in this case.

4.2 Forecast Analysis of Product Family B

As discussed in the data analysis section, product family A has 7 product types. Each product type can be further sub-divided into PIDs. The PID level is the lowest level in the product hierarchy.

4.2.1 Forecast Analysis of Product Type – Assembly

Assembly has 16 PIDs and all the PIDs have intermittent demand. Table 21 below shows the MADs for aggregate forecast and BUF from week 44 of 2007 to week 9 of 2008.

Weeks	Type	BUF	Hybrid	Weeks	Type	BUF	Hybrid
44	68.05	10.95	10.95	1	68.05	38.05	38.05
45	68.05	59.95	59.95	2	68.05	77.95	77.95
46	68.05	68.05	68.05	3	68.05	26.95	26.95
47	68.05	16.05	16.05	4	68.05	45.95	45.95
48	68.05	68.05	68.05	5	68.05	67.05	67.05
49	68.05	68.05	68.05	6	68.05	67.050	67.050
50	68.05	68.05	68.05	7	68.05	67.050	67.050
51	68.05	68.05	68.05	8	68.05	67.050	67.050
52	68.05	202.95	202.95	9	68.05	67.050	67.050

Table 21: MAD of different forecasts for Assembly

Table 22 below shows the RMSE for BUF and type level forecast.

	BUF	Type	Hybrid
RMSE	72.746	72.848	72.746($\alpha = 0$)

Table 22: RMSE of different forecasts for Assembly

From Table 22 it is clear that both BUF and type level forecasts are identical. MADs for type level forecasts are higher than MADs for BUF for some of the weeks while for other weeks MADs for BUF are higher. There is no clear pattern visible here.

4.2.2 Forecast Analysis of Product Type – Base

Base has 9 PIDs and all the PIDs have intermittent demand. Table 23 below shows the MADs for aggregate forecast and BUF from week 44 of 2007 to week 9 of 2008. Table 24 below shows the RMSE for BUF and type level forecast.

Weeks	Type	BUF	Hybrid	Weeks	Type	BUF	Hybrid
44	23.300	26.85	23.300	1	22.300	25.85	22.300
45	23.300	26.85	23.300	2	21.300	24.85	21.300
46	23.300	26.85	23.300	3	21.300	24.85	21.300
47	40.700	37.15	40.700	4	21.700	18.15	21.700
48	11.300	14.85	11.300	5	23.300	26.85	23.300
49	23.300	26.85	23.300	6	20.300	23.85	20.300
50	23.300	26.85	23.300	7	20.300	23.85	20.300
51	10.300	13.85	10.300	8	22.300	24.85	22.300
52	20.300	23.85	20.300	9	21.300	25.85	21.300

Table 23: MAD of different forecasts for Base

	BUF	Type	Hybrid
RMSE	25.16	22.676	22.676(α = 1)

Table 24: RMSE of different forecasts for Base

From Table 24 it is clear that type level forecast is a better forecast than BUF. MADs for type level forecast are consistently better than MADs for BUF for all the weeks. Thus we adjust the BUF by adjusting the proportions at the PID level such that BUF numbers are exactly equal to type level forecast numbers.

4.2.3 Forecast Analysis of Product Type – Switch

Switch has 3 PIDs and all the PIDs have intermittent demand. Table 25 below shows the MADs for aggregate forecast and BUF from week 44 of 2007 to week 9 of 2008. Table 26 below shows the RMSE for BUF and type level forecast.

Weeks	Type	BUF	Hybrid	Weeks	Type	BUF	Hybrid
44	2.111	0.10	2.111	1	1.250	3.10	1.250
45	1.765	4.10	1.765	2	2.571	0.90	2.571
46	1.875	4.10	1.875	3	1.000	1.10	1.000
47	2.000	4.10	2.000	4	1.200	1.10	1.200
48	2.143	4.10	2.143	5	1.500	4.10	1.500
49	2.308	4.10	2.308	6	2.000	4.10	2.000
50	2.500	4.10	2.500	7	0.000	1.10	0.000
51	5.273	3.90	5.273	8	0.000	1.10	0.000
52	0.200	2.10	0.200	9	1.250	3.10	1.250

Table 25: MAD of different forecasts for Switch

	BUF	Type	Hybrid
RMSE	3.107	2.055	2.055($\alpha = 1$)

Table 26: RMSE of different forecasts for Switch

From Table 26 it is clear that type level forecast is a better forecast than BUF. MADs for type level forecast are consistently better than MADs for BUF for all the weeks except weeks 44, 51 and 3. Thus we adjust the BUF by adjusting the proportions at the PID level such that BUF numbers are exactly equal to type level forecast numbers.

4.2.4 Forecast Analysis of Product Type – Feature

Feature has 20 PIDs and all the PIDs have intermittent demand. Table 27 below shows the MADs for aggregate forecast and BUF from week 44 of 2007 to week 9 of 2008. Table 28 below shows the RMSE for BUF and type level forecast.

Weeks	Type	BUF	Hybrid	Weeks	Type	BUF	Hybrid
44	83.870	56.70	56.70	1	60.412	32.70	32.70
45	53.991	26.70	26.70	2	291.575	319.30	319.30
46	102.088	74.70	74.70	3	56.435	28.70	28.70
47	87.166	59.70	59.70	4	81.443	53.70	53.70
48	78.228	50.70	50.70	5	97.450	69.70	69.70
49	102.278	74.70	74.70	6	102.456	74.70	74.70
50	67.318	39.70	39.70	7	96.460	68.70	68.70
51	58.350	30.70	30.70	8	96.463	68.70	68.70
52	88.375	60.70	60.70	9	60.412	32.70	32.70

Table 27: MAD of different forecasts for Feature

	BUF	Type	Hybrid
RMSE	108.435	116.447	108.435($\alpha = 0$)

Table 28: RMSE of different forecasts for Feature

From table 28 it is clear that BUF is better than Type level forecast. From table 27 it is clear that BUF MADs are consistently better than type level MADs for all weeks. Thus we replace the type level forecast with BUF.

4.2.5 Forecast Analysis of Product Type – Board

Board has 62 PIDs and all the PIDs have intermittent demand. Table 27 below shows the MADs for aggregate forecast and BUF from week 44 of 2007 to week 9 of 2008. Table 28 below shows the RMSE for BUF and type level forecast.

Weeks	Type	BUF	Hybrid	Weeks	Type	BUF	Hybrid
44	19.429	130.95	130.95	1	365.032	475.95	475.95
45	273.209	162.05	162.05	2	15.032	125.95	125.95
46	303.064	192.05	192.05	3	13.032	123.95	123.95
47	181.006	70.05	70.05	4	263.968	153.05	153.05
48	284.983	174.05	174.05	5	296.968	186.05	186.05
49	308.974	198.05	198.05	6	296.968	186.05	186.05
50	270.970	160.05	160.05	7	296.968	186.05	186.05
51	110.031	220.95	220.95	8	296.968	186.05	186.05
52	242.968	132.05	132.05	9	308.968	198.05	198.05

Table 29: MAD of different forecasts for Board

	BUF	Type	Hybrid
RMSE	192.942	250.907	192.942($\alpha = 0$)

Table 30: RMSE of different forecasts for Board

From Table 30 it is clear that BUF is better than Type level forecast. From table 29 it is clear that MADs for type level forecast are higher than MADs for BUF for some of the week while for other weeks MADs for BUF are higher. There is no clear pattern visible here. Thus in this case too we don't adjust the type level forecast although the average error for BUF is better.

4.2.6 Forecast Analysis of Product Type – Cable

Cable has 11 PIDs and all the PIDs have intermittent demand. Table 31 below shows the MADs for aggregate forecast and BUF from week 44 of 2007 to week 9 of 2008. Table 32 below shows the RMSE for BUF and type level forecast.

Weeks	Type	BUF	Hybrid	Weeks	Type	BUF	Hybrid
44	9.550	10.05	10.05	1	4.474	6.05	6.05
45	10.526	8.95	8.95	2	9.526	7.95	7.95
46	31.526	29.95	29.95	3	13.526	11.95	11.95
47	8.474	10.05	10.05	4	2.474	4.05	4.05
48	4.474	6.05	6.05	5	2.474	4.05	4.05
49	6.474	8.05	8.05	6	2.474	4.05	4.05
50	6.474	8.05	8.05	7	2.474	4.05	4.05
51	7.526	5.95	5.95	8	2.474	4.05	4.05
52	6.474	8.05	8.05	9	4.474	6.05	6.05

Table 31: MAD of different forecasts for Cable

	BUF	Type	Hybrid
RMSE	10.1	10.1	10.1($\alpha = 0$)

Table 32: RMSE of different forecasts for Cable

From Table 32 it is clear that RMSE for each of the three types of forecasts is identical. From Table 31 it is clear that MADs for type level forecast are higher than MADs for BUF for some of the weeks, while for other weeks MADs for BUF are higher. Since the statistical forecast numbers of each of the three are equal we do not make any adjustments to BUF.

4.2.7 Forecast Analysis of Product Type – Power

Power has 16 PIDs and all the PIDs have intermittent demand. Table 33 below shows the MADs for aggregate forecast and BUF from week 44 of 2007 to week 9 of 2008. Table 34 below shows the RMSE for BUF and type level forecast.

Weeks	Type	BUF	Hybrid	Weeks	Type	BUF	Hybrid
44	4.4	3.8	4.4	1	4.6	5.2	4.6
45	3.4	2.8	3.4	2	2.6	3.2	2.6
46	8.6	9.2	8.6	3	18.4	17.8	18.4
47	8.6	9.2	8.6	4	4.4	3.8	4.4
48	8.6	9.2	8.6	5	3.4	2.8	3.4
49	8.6	9.2	8.6	6	8.6	9.2	8.6
50	8.6	9.2	8.6	7	8.6	9.2	8.6
51	8.6	9.2	8.6	8	8.6	9.2	8.6
52	15.4	14.8	15.4	9	4.6	5.2	4.6

Table 33: MAD of Different Forecasts for Power

	BUF	Type	Hybrid
RMSE	9.01	8.85	8.85($\alpha = 1$)

Table 34: RMSE of different forecasts for Power

From Table 34 it is clear that type level forecast is a marginally better forecast than BUF. From Table 33 it is clear that MADs for type level forecast are higher than MADs for BUF for some of the week while for other weeks MADs for BUF are higher. There is no clear pattern visible here.

Thus in this case too we don't adjust the type level forecast although the average error for BUF is better.

4.3 Summary of Results

In the two sections presented in this chapter we did a detailed analysis of the forecasts generated for both Families A & B. In this section we present a brief summary of the results obtained in the preceding sections. Table 35 tabulates the RMSE for BUF, Type and Hybrid forecast for family A and the most accurate forecast among the three forecasts is shown in bold. Figure 38 shows the comparison between the three forecasts on a bar chart.

Product Type	Type	BUF	Hybrid
Assembly	**78.971**	80.301	Same as Type
Base	11.07	**8.53**	Same as BUF
Memory	60.835	55.85	**47.27**
Router	109.171	**108.766**	Same as BUF
Board	**68.129**	98.549	Same as Type
Cable	**11.57**	12.34	Same as Type
Power	2.94	2.94	Same as BUF/Type

Table 35: RMSE of Type, BUF and Hybrid for Family A Types.

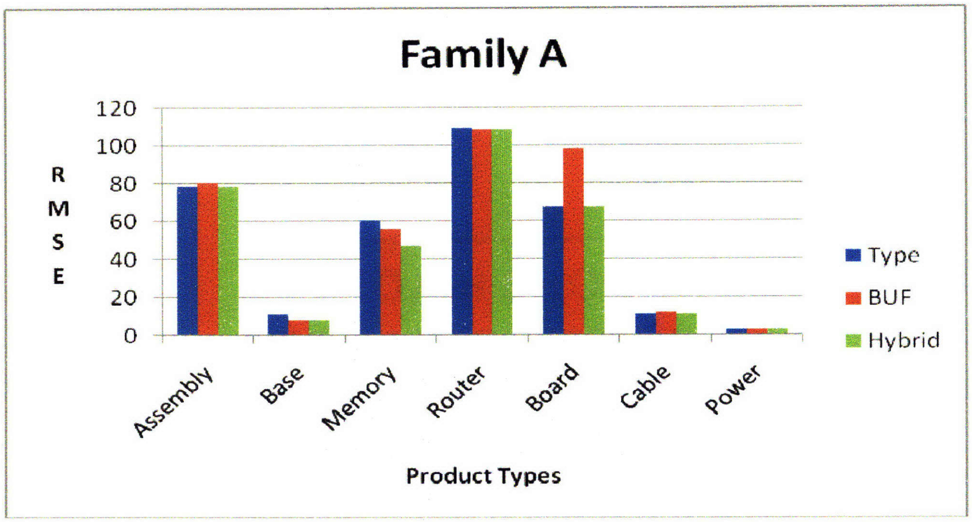

Figure 38: Type, BUF and Hybrid RMSE for Family A

Table 36 tabulates the RMSE for BUF, Type and Hybrid forecast for family B and the most accurate forecast among the three forecasts is shown in bold. Figure 39 shows the comparison between the three forecasts on a bar chart.

Product Type	Type	BUF	Hybrid
Assembly	72.848	**72.746**	Same as BUF
Base	**22.676**	25.16	Same as Type
Switch	**2.055**	3.107	Same as Type
Feature	116.447	**108.435**	Same as BUF
Board	250.907	**192.942**	Same as BUF
Cable	10.1	10.1	Same as BUF/Type
Power	**8.85**	9.01	Same as Type

Table 36: RMSE of Type, BUF and Hybrid for Family B Types.

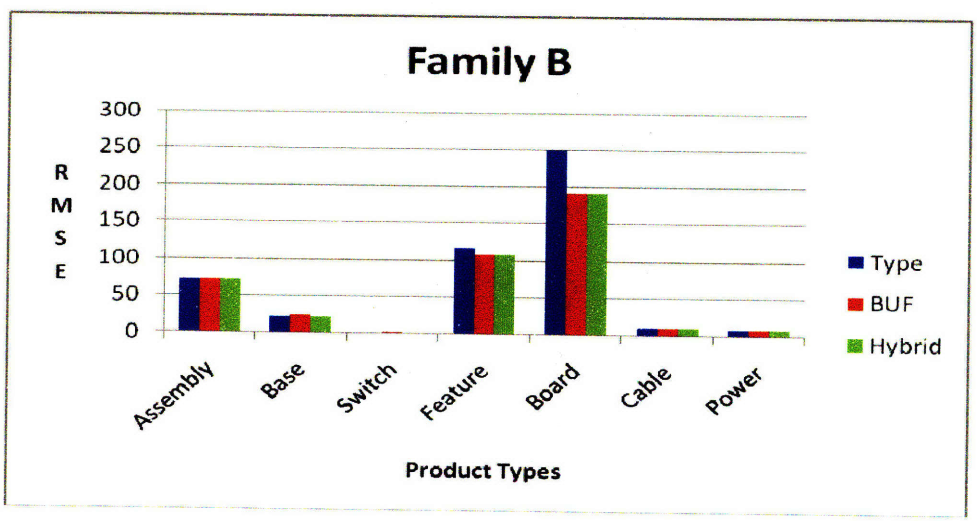

Figure 39: Type, BUF and Hybrid RMSE for Family B

From Tables 35 and 36 and Figures 38 and 39 we can see that there is no clear winner among BUF or Type. Also, the statistical Hybrid was either equal to the Type forecast or the BUF forecast for all types of both Families A & B except for Memory type for family A where the statistical Hybrid was different than both BUF and Type and was the best forecast among the three statistical forecasts.

Chapter 5: Comparison between Statistical & Qualitative Forecast

The data from qualitative forecasts (QF) includes only a few PIDs from Product A and Product B families. To make the comparison rational we compare the BUF, which can be either adjusted BUF or the true BUF, with the QF for only those PIDs whose QF data we have. This chapter contains two sections. The first section presents the comparison between BUF and QF. RMSE for both BUF and QF is calculated. A qualitative-quantitative hybrid model is also presented, termed HF, which is calculated as follows:

Hybrid Forecast (HF) = α*BUF + (1-α)*QF

Where α is the assigned weight that gives the lowest RMSE and $0 <= \alpha <= 1$

Qualitative forecast numbers are in monthly buckets so we aggregate the BUF from weekly buckets so that the comparison is rational.

5.1 Analysis of Product Family A

The QF for product family A contained 19 PIDs and 16 of the 19 PIDs belonged to product type Board. The forecast was in monthly buckets for the month of November '07, December '07 and January '07. The BUF was aggregated to monthly buckets from the weeks falling in the months of November '07, December '07 and January '07.

Table 37 below lists the RMSE for BUF, QF and HF. The lowest RMSE is in bold signifying that the forecast with lowest RMSE is the best among the three types of forecasts. A bar graph, Figure 40, is also listed below that charts the performance of BUF, QF and HF.

PID	Type	QF RMSE	BUF RMSE	HF RMSE
12000/16-AC4	Router	**2.52**	5.92	2.52 ($\alpha = 0$)
12000/16-DC	Router	9.33	**7.39**	7.39 ($\alpha = 1$)
12416/320	Assembly	15.64	11.76	**11.31** ($\alpha = 0.77$)
12000-SIP-601	Board	36.18	**11.43**	11.43 ($\alpha = 1$)
1X10GE-LR-SC	Board	46.74	**7.87**	7.87 ($\alpha = 1$)
4GE-SFP-LC	Board	339.89	65.39	**26.48** ($\alpha = 0.93$)
4OC12X/ATM-IR-SC	Board	1.15	3.11	**0.90** ($\alpha = 0.20$)
4OC12X/POS-I-SC-B	Board	**2.52**	4.36	2.52 ($\alpha = 0$)
4OC3X/ATM-IR-SC	Board	4.24	**1.00**	1.00 ($\alpha = 1$)
4OC3X/POS-IR-LC-B	Board	6.27	0.00	0.00 ($\alpha = 1$)
4OC48E/POS-SR-SC	Board	0.00	0.00	0.00 ($\alpha = 0$)
CHOC12/DS1-IR-SC	Board	**18.63**	21.24	18.63 ($\alpha = 0$)
CHOC48/DS3-SR-SC	Board	**10.25**	12.38	10.25 ($\alpha = 0$)
GSR16/320-CSC	Board	32.54	24.32	**24.09** ($\alpha = 0.87$)
GSR16/320-SFC	Board	48.58	37.22	**36.72** ($\alpha = 0.84$)
OC192E/POS-SR-SC	Board	28.91	**25.42**	25.42 ($\alpha = 1$)
OC48X/POS-SR-SC	Board	**6.48**	10.53	6.48 ($\alpha = 0$)
PRP-2	Board	**17.00**	21.66	17.00 ($\alpha = 0$)
PRP-2/R	Board	22.65	**9.55**	9.55 ($\alpha = 1$)

Table 37: RMSE of QF, BUF and HF for Family A PIDs.

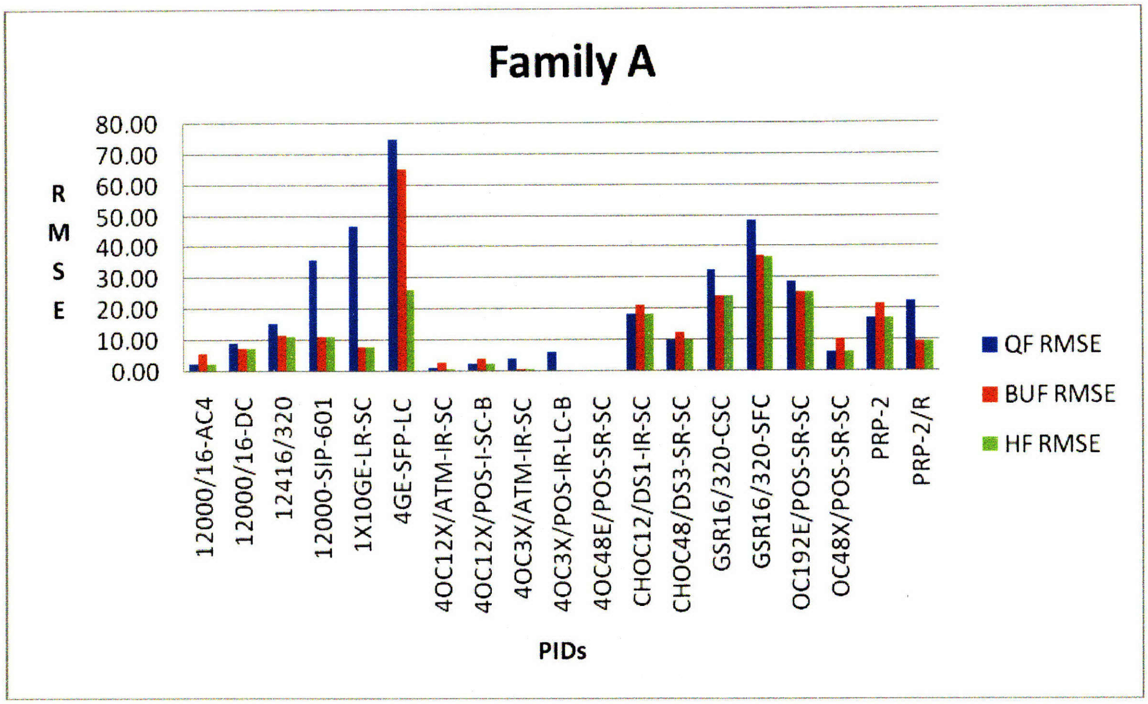

Figure 40: QF, BUF and HF RMSE for Family A

From Table 37 and Figure 40, it is clear that there seems to be no clear winner among HF, BUF, and QF. The best forecast among QF, HF and BUF is PID dependent.

5.2 Analysis of Product Family B

The QF for product family B contained 20 PIDs and 19 of the 20 PIDs belonged to product type Board. The forecast was in monthly buckets for the month of November '07, December '07 and January '07. The BUF was aggregated to monthly buckets from the weeks falling in the months of November '07, December '07 and January '07. Table 38 below lists the RMSE for BUF, QF and HF. The lowest RMSE is in bold signifying that the forecast with lowest RMSE is the best among the three types of forecasts.

PID	Type	QF RMSE	BUF RMSE	HF RMSE
MGX-AC2-2	Power	0.00	0.00	0.00 ($\alpha = 0$)
AXSM-16-155-XG	Board	2.31	2.04	**1.82** ($\alpha = 0.61$)
AXSM-16-T3E3-E	Board	2.89	2.61	**2.28** ($\alpha = 0.58$)
AXSM-8-622-XG	Board	19.69	**3.83**	3.83 ($\alpha = 1$)
BNC-3-T3E3	Board	48.91	**26.48**	26.48 ($\alpha = 1$)
MGX-2OC12POS	Board	4.62	4.71	**4.56** ($\alpha = 0.38$)
MGX-RPM-XF-512	Board	17.22	10.64	**10.40** ($\alpha = 0.86$)
MGX-SRME/B	Board	1.15	1.31	**1.01** ($\alpha = 0.40$)
MGX-T3E3-155	Board	2.31	2.29	**1.82** ($\alpha = 0.51$)
MGX-XF-UI/B	Board	25.36	**6.55**	6.55 ($\alpha = 1$)
MPSM-16-T1E1	Board	6.93	11.22	**5.46** ($\alpha = 0.30$)
MPSM-T3E3-155	Board	30.31	**5.57**	5.57 ($\alpha = 1$)
PXM1E-COMBO	Board	2.38	2.14	**1.66** ($\alpha = .56$)
PXM45/C	Board	5.29	7.06	**5.25** ($\alpha = 0.12$)
PXM-UI-S3/B	Board	6.00	7.92	**7.14** ($\alpha = 0.84$)
SMB-8-E3	Board	20.91	**15.65**	15.65 ($\alpha = 1$)
SMB-8-T3	Board	4.62	**3.67**	3.67 ($\alpha = 1$)
SMFIR-622-SFP	Board	285.12	**23.12**	23.12 ($\alpha = 1$)
SFP-4-622	Board	55.12	**41.87**	41.87 ($\alpha = 1$)
SFP-8-155	Board	5.16	4.02	**2.91** ($\alpha = 0.61$)

Table 38: RMSE of QF, BUF and HF for Family B PIDs.

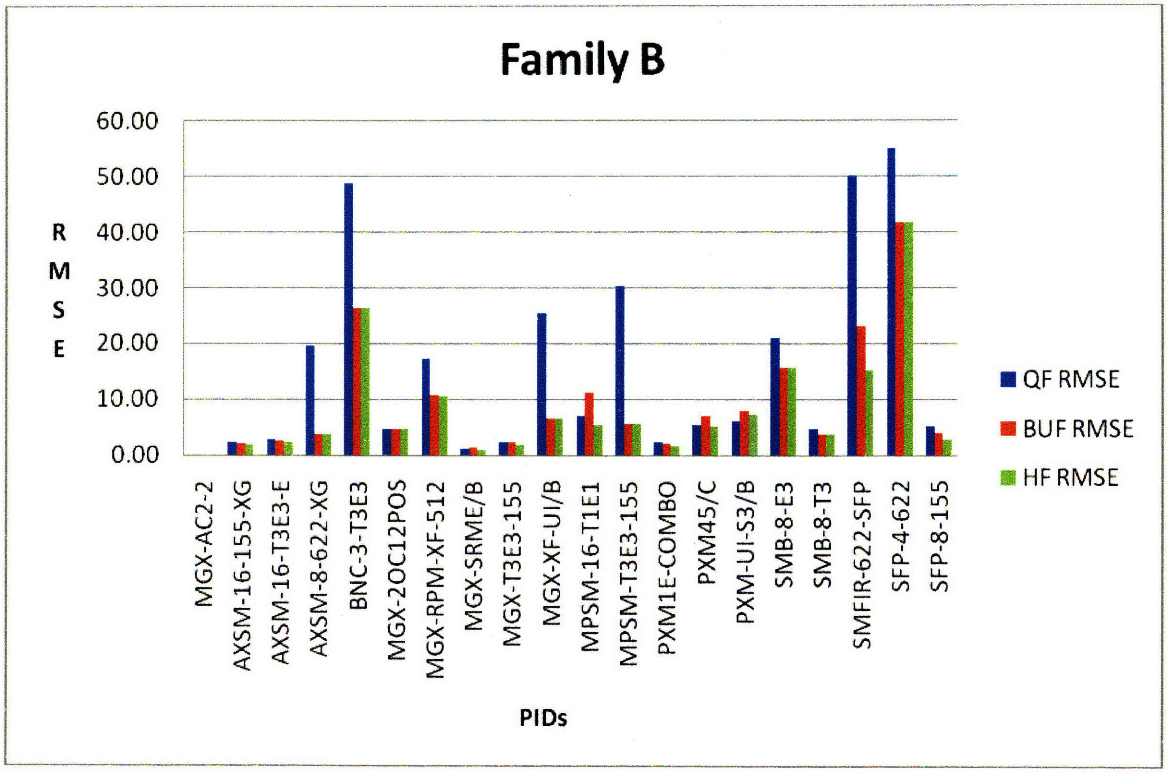

Figure 41: QF, BUF and HF RMSE for family B

A bar graph, Figure 41, is listed above that charts the performance of BUF, QF and HF.

From Table 38 and Figure 41, it seems clear that for all of the PIDs, BUF and HF are better than QF. Thus we conclude that QF should be replaced by either HF or BUF, but this is PID dependent.

Chapter 6: Recommendations & Future Research

The conclusion of Chapter 5 is that there is value to both the statistical and qualitative forecast because for a number of PIDs a forecast weighted by both QF and BUF, called HF, turned out to be superior then either QF or BUF. But to reap the benefits of HF we need to make changes to the current process to incorporate statistical and hybrid forecasting. Figures 42 and 43 below represent a flow chart of Systems A & B. System A generates a statistical forecast and tracks errors and smoothing parameters. It then feeds the best forecast among Type, BUF and Hybrid to System B. System B compares the best forecast among one obtained from System A, the QF and the HF. It then passes the best forecast obtained from the process to other systems for upstream planning.

To summarize our discussion we recommend the following:

- Develop a statistical forecasting system, called system A, which generates a statistical forecast both at the product type level and the PID level. Then generate a Hybrid forecast which is a forecast weighted by type and BUF. Then choose the best forecast among type, BUF and Hybrid forecast. If Hybrid or type forecast is better than the BUF then adjust the PID forecasts so that BUF forecasts are exactly equal to the best of the Hybrid or type forecast. Track errors over time. Periodically update the smoothing factors.
- Develop a composite forecasting system, called System B, which generates a quantitative-qualitative hybrid forecast. Then choose the most accurate forecast obtained from System A, called BUF (including adjusted BUF). Generate a Hybrid forecast (HF) which is a forecast weighted by the Qualitative forecast (QF) and BUF. Feed the most

accurate forecast to other systems for upstream planning. The weight, α, is periodically updated using an optimization technique.

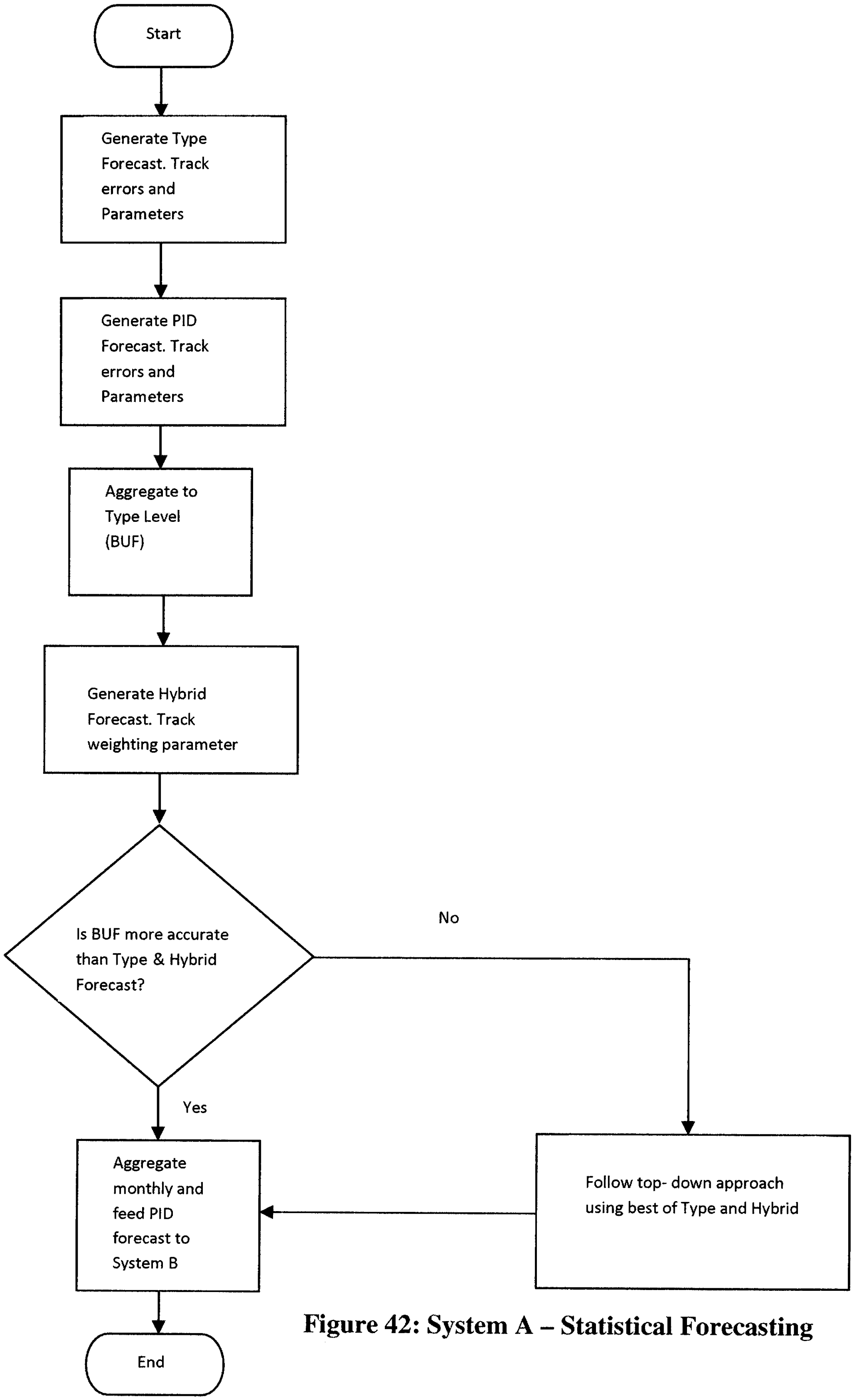

Figure 42: System A – Statistical Forecasting

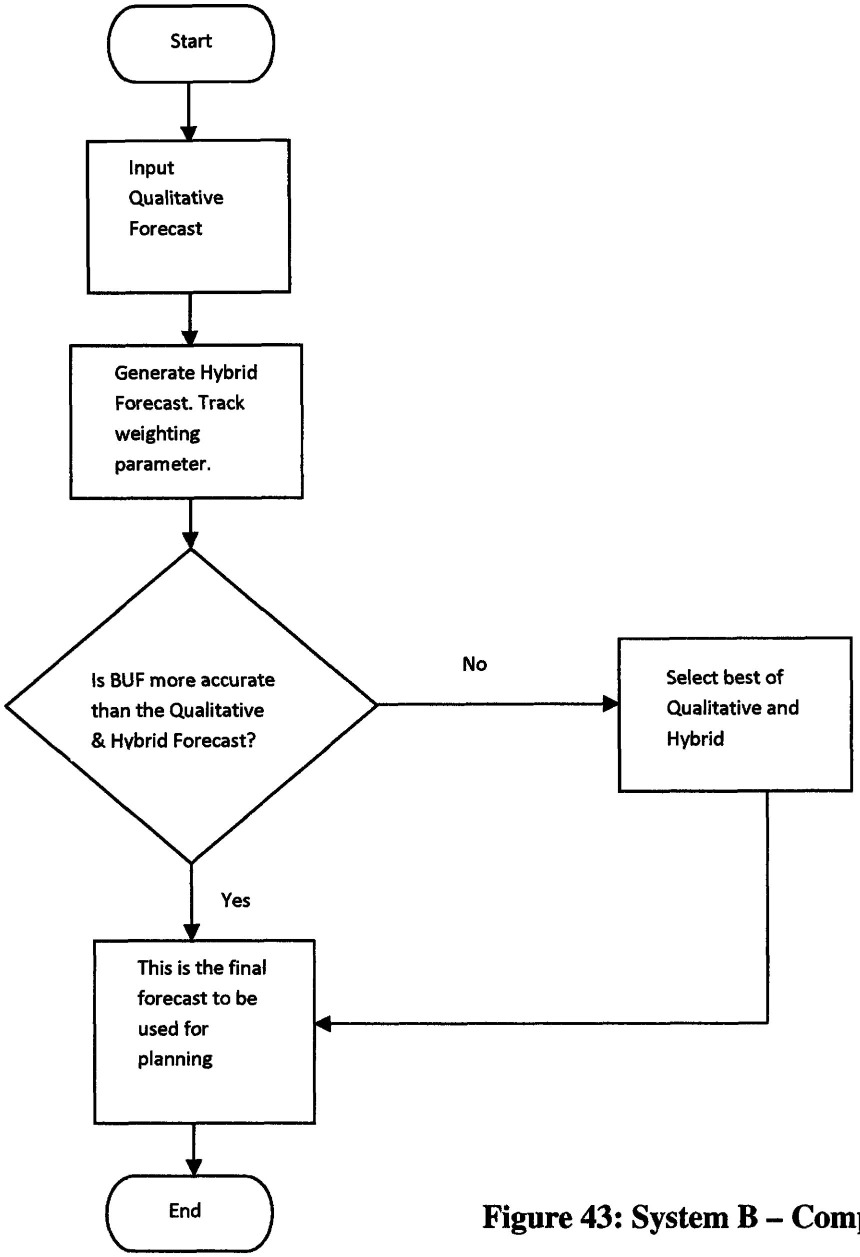

Figure 43: System B – Composite Forecasting

It's imperative to put a robust IT system in place to implement the recommendations.

For this project 42 weeks of data was provided. The results could have been more accurate if we had data spanning more than 100 weeks. We were not able to apply the Croston's method to intermittent demand because the non-zero data points did not follow a normal distribution. This situation may change if we use data for more than 100 weeks and the applicability of Croston's method may seem feasible. This situation might result in better forecasts. QF of very few PIDs was provided to us. Most of the PIDs, both from families A & B, belonged to the Board Product Type. If we can include more PIDs from other Product Types it would be helpful to study those product characteristics. We can summarize the future research as follows:

- The scope of this project can be expanded by using more data, typically data spanning more than 100 weeks.
- More PIDs from different product types other than Board should be included in the forecasting system. This would help in studying the product type characteristics which would be helpful for planning purposes.

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