APPLICATION OF MODERN PRINCIPLES TO DEMAND FORECASTING

FOR ELECTRONICS, DOMESTIC APPLIANCES AND ACCESSORIES

A thesis submitted in partial fulfillment

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By

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I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY Gregory Daniel Noble ENTITLED Application of Modern Principles to Demand Forecasting for Electronics, Domestic Appliances and Accessories BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Master of Science in Engineering

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Abstract

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Royal Philips is a large scale producer of consumer electronics, personal appliances, lighting, and healthcare appliances. Demand data from 12 Business Units (BU) of Royal Philips was examined in the study; four business units from each of three divisions: DAP, PA, and CE. From the data supplied, different forecast techniques were evaluated to determine which procedure produces the highest quality forecasts. Three forecasting techniques were evaluated using the provided data. The three forecasting techniques evaluated are the exponential smoothing forecasting method, the exponential smoothing with a linear trend forecasting method, and the Winters forecasting method.

The Visual Basic for Applications (VBA) language was used to implement the functionality of the exponential smoothing, exponential smoothing with linear trend, and the winters forecasting methods forecasting models into Microsoft Excel for this study. Additionally, VBA was used to compute the Mean Absolute Error, which was used to compare each of the models. Overall, the exponential smoothing with a linear trend forecasting method is the best forecasting model for the examined business units. The exponential smoothing with a linear trend model should be used in most cases where the coefficient of variance of the demand data is small. The exponential smoothing model should be used in most cases where the coefficient of variance is of the demand data is large. The Winters method forecasting models had much higher variability in the resulting forecasts of the examined business units. This higher variability may have been due to the complexity in the estimation of the model parameters. Thus, the Winters method, while good in theory, isn't necessarily the best choice for forecasting in practice with the examined business units and similar products.

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1. Introduction

Royal Philips is a large scale producer of consumer electronics, personal appliances, lighting, and healthcare appliances. A list of 12 Business Units (BU) was specified by Royal Philips to be examined in the study; four business units from each of three divisions: Domestic Appliances (DAP), Personal Appliances (PA), and Consumer Electronics CE. From the data supplied, different forecast techniques are to be evaluated to determine if the is a way to systematically produce high quality forecasts.

In this project, the future demand is being forecasted for each of the 12 business units. Forecasting supports the decision made by the manufacturer of the number of units of the product to produce; thus, it is important to accurately forecast the demand of these 12 business units in order for the manufacturer to produce the correct amount of product. If the manufacturer produces more product than the actual demand, then money is lost due to product that was produced but not sold. If the manufacturer produces less than the actual demand, then money is lost due to lost sales. Thus, an accurate product forecast can help eliminate costs due to overproducing or under producing.

Three time series forecasting techniques are evaluated using the provided data. A time series forecasting model is used when there is a need to predict a numerical parameter for which past results are good indicators of future behavior, but where a sufficient cause-and-effect relationship is not available for model construction (Hopp, 2001). The three time series forecasting techniques evaluated are the exponential smoothing forecasting method, the exponential smoothing with a linear trend forecasting method, and Winters forecasting method. The purpose of time series forecasting within this application is to predict the future product sales from the 12 BU's that were provided by Royal Philips in order to evaluate each of the forecasting methods based upon their accuracy in predicting the product sales. A flow chart showing how the forecasting methods are used to produce the desired results is shown in Figure 1.

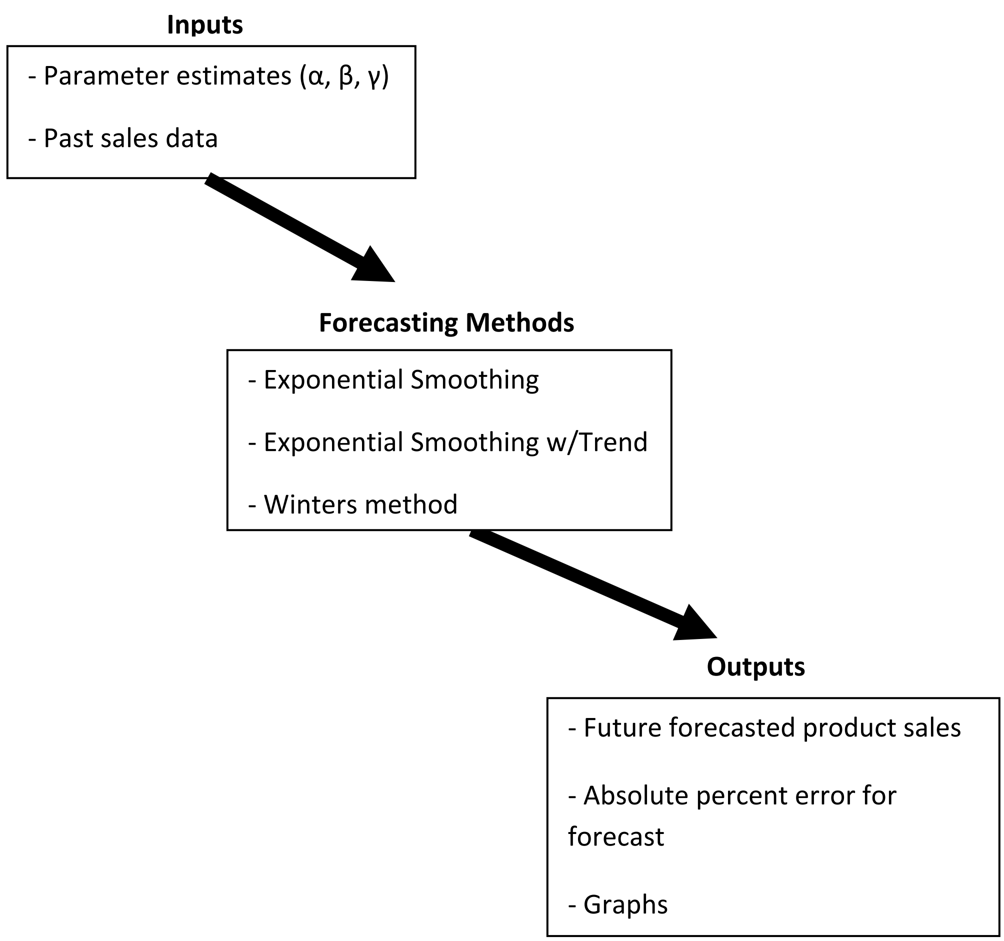


Figure 1: Flow chart of forecasting process using Microsoft Excel.

In this application, the Visual Basic for Applications (VBA) language was used to implement the functionality of the exponential smoothing, exponential smoothing with linear trend, and the Winters method forecasting models into Microsoft Excel for this study. Each of the forecasting methods was coded in this language in order to operate on data located in Microsoft Excel worksheets. This allows for the forecast parameters to be easily customized for each forecast, as well as custom graphing of the results. This also allows the generation of forecasts to be made in a quick manner as opposed to more manual methods for generating forecasts. An example of the use of Microsoft Excel to create a graph describing the absolute percent error in a forecast for one of the BU's is shown in Figure 2.

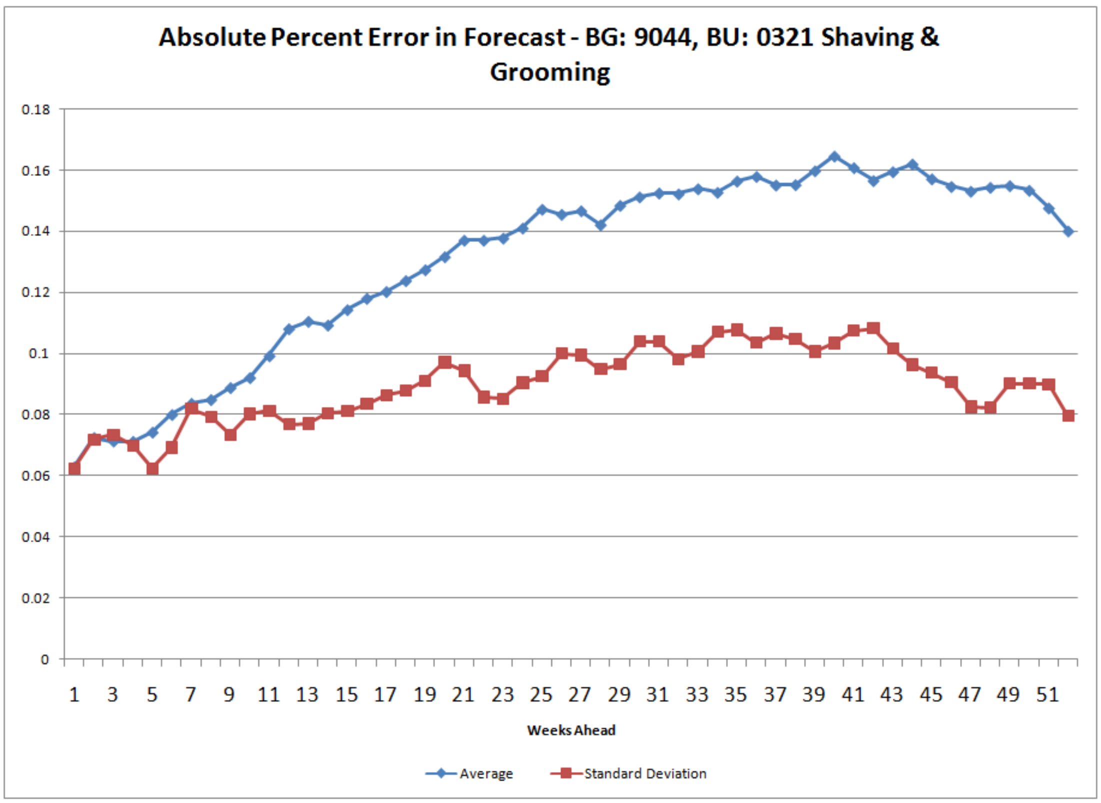


Figure 2: Example absolute error chart as would be displayed in business unit report.

The coefficient of variance was calculated from the original de-season data from each business unit. The de-seasoned data is the sales data with the seasonality factored out of the data. A flow chart explaining the de-seasoning of data and the other steps taken in calculating the forecasts can be seen in Figure 3.

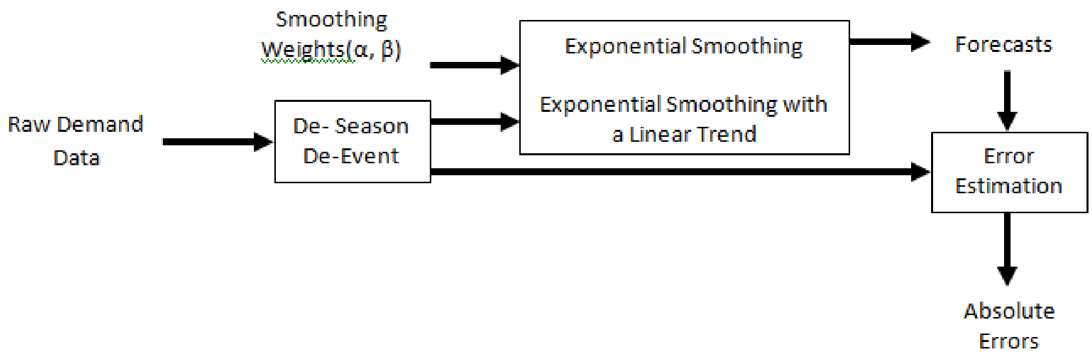


Figure 3: Flow chart of forecasting using exponential smoothing and exponential smoothing with a linear trend

The coefficient of variance, defined as the ratio of the standard deviation to the mean, is used to scale the variance of the data in order for making more effective comparisons. Through the coefficient of variance a scalable comparison of the variance of each of the evaluated business units can be made. The relationship between the coefficient of variance and the best average absolute error (average of absolute error from first 13 weeks and first 26 weeks) is shown in Figure 4. The average of absolute error from 13 weeks of forecasts and 26 weeks of forecasts is used to calculate the best average absolute error because there is equal interest in the forecasts of 13 and 26 weeks from the current time period.

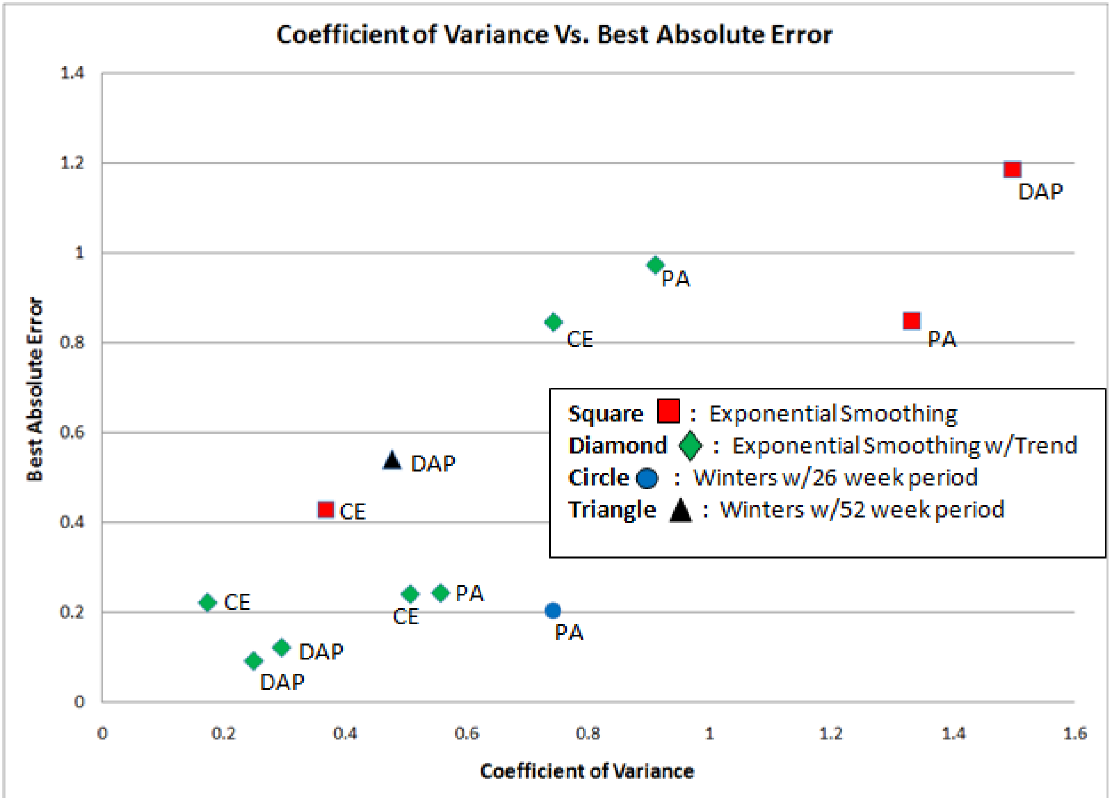


Figure 4: Coefficient of Variance vs. Best Absolute Error.

It appears from Figure 4 that there is relationship between the coefficient of variance and the best absolute error. As the coefficient of variance increases the best absolute error increases. Thus, a business unit with a higher coefficient of variance of the de-seasoned data will, in general, have more error in the forecast.

Overall, the exponential smoothing with a linear trend forecasting method is the best forecasting model for the examined business units. The exponential smoothing with a linear trend model should be used in most cases. An exception is cases where the smoothed trend model parameter is large; in which case, the exponential smoothing model should be used. When the smoothed trend parameter is large, forecasts for into the future were inaccurate. The Winters method forecasting models had much variability in the resulting forecasts of the examined business units due to complexity in the estimation of the model parameters. Thus, the Winters method, while good in theory, isn't necessarily the best choice for forecasting in practice with the examined business units and similar products.

Chapter 2 summarizes a review of literature on this topic, which includes examples of forecasting in practice and a modern perspective on forecasting. Chapter 3 explains the three forecasting techniques that were used to make product forecasts. The three forecasting techniques are the exponential smoothing forecasting technique, the exponential smoothing with a linear trend forecasting technique, and the Winters method for seasonality forecasting technique. Chapter 4 explains how JMP IN and VBA were used in this project and Chapter 5 gives the results, analyzes the results and examines conclusions.

2. Literature Review

It is important to understand how product forecasting has been previously used. In this chapter several examples of forecasting are given in order to demonstrate the process of product forecasting and show product forecasting as it is used in different scenarios. Additionally, product modern views on forecasting have led to the derivations of many principles as rules for forecasting. Many of these principles and rules for forecasting are explained in this chapter.

Examples of Forecasting in Practice

There are many examples of forecasting methods in practice. In [Fisher, 1994] forecasting is used to adequately estimate future sales at Sport Obermeyer Ltd., a fashion-ski-apparel business. Due to changing fashion trends and an increasing need to generate accurate forecasts, Sport Obermeyer Ltd. decides to adopt a new approach to forecasting called "accurate response." The approach incorporates two basic elements that many other forecasting systems lack. The first of these elements is that the approach takes into account the amount of missed sales opportunities. The second element is to distinguish between products for which demand is easily predictable from the products for which demand is more unpredictable. By including these elements in the forecasting method, the company gains the ability to use flexible manufacturing capacity and shorter cycle times more effectively. Through the implementation of the "accurate response" approach, Sport Obermeyer was able to almost entirely eliminate the cost of producing skiwear that customers don't want (overproduction) and the cost of not producing skiwear that customers do want (underproduction).

In [Burruss, 2003] a forecasting methodology, called the Product Life Cycle (PLC) forecasting method is proposed in order to more accurately forecast products with high uncertainty, a steep obsolescence curve, and a short life cycle. A short life cycle is usually a life cycle ranging from 9 to 18 months. The article describes three requirements for products to be adequately forecasted by this method within the electronic consumer products industry. They should have well-defined life cycle phases from introduction to maturity and then to end of life, a high demand spike during the introduction phase, followed by a gradual downward leveling-off during maturity, and a steep end-of-life (EOL) drop-off that is often caused by planned product rollovers.

A step-by-step overview of the Product Life Cycle forecasting method, as used by Hewlett-Packard, is described. The first step is to analyze historical data in order to generate a basic Product Life Cycle shape for the product family or group for which the forecast is to be created. The second step is to develop a template for seasonality and adjust the forecast model accordingly. The third step is to develop a template for scheduled price drops. The fourth step is to use the price drop template that was developed in step three to readjust the seasonally-adjusted forecasts. The fifth step is to develop a template that shows how shipments of the product are affected by special events. The sixth and final step is to apply the special events template to the forecast model, which should already be adjusted for seasonality and price drop.

The Product Life Cycle forecasting method has many benefits in forecasting. It gives forecasters the ability to track the impact of factors such as seasonality, price drops, and special events on sales, individually as well as collectively. It also improves the forecast accuracy for products with high uncertainty and a short life cycle. Hewlett-Packard estimates that the company is saving $15 million annually as a result of improvement in forecast accuracy due to the Product Life Cycle forecasting method.

Modern Perspective on Forecasting

In [Fildes, 2007] 149 surveys were collected from forecast practitioners from a wide range of industries in order to examine the use of judgment in forecasting and to investigate whether the company's forecasting procedures were consistent with the principles. The surveyed forecasters were responsible for forecasting a number of items from one item to 34 million items, with a median of 400 items. The survey showed that a majority of the forecasters forecasted on a monthly basis. Forecasting on a weekly basis was the second most common; however, there were more than double the amount of forecasters forecasting on a monthly basis than any other time frame.

The established principles for when to use judgment, as in the study, were as follows: Principle 1: Use quantitative rather than qualitative methods; Principle 2: Limit subjective adjustments of quantitative forecasts; Principle 3: Adjust for events expected in the future. The established principles for how to apply judgment, as in the study, were as follows: Principle 4: Ask experts to justify their forecasts in writing; Principle 5: Use structured procedures to integrate judgmental and quantitative methods. Principles on how to use judgment include: Principle 6: Combine forecasts from approaches that differ; and Principle 7: If combining forecasts, begin with equal weights. The established principles for how to assess the effectiveness of judgment were Principle 8: Compare past performance of various forecasting methods; and Principle 9: Seek feedback about forecasts. Principle 10 is to use error measures that adjust for scale in the data. Finally, Principal 11 is to use multiple measures of forecast accuracy.

The results from this study show that many organizations are falling short of good practice in forecasting. Many rely heavily on unstructured judgment and insufficiently on statistical methods and often blur forecasting with their decisions. Many organizations could improve forecast accuracy if they followed basic principles such as limiting judgmental adjustments of quantitative forecasts, requiring managers to justify their adjustments in writing, and assessing the results of judgmental interventions.

[Saffo, 2007] explains that the difference between prediction and forecasting is that prediction is concerned with future certainty while forecasting looks at how hidden currents in the present, influence possible changes in direction. The primary goal of forecasting is to identify the full range of possibilities. Six rules are given for effective forecasting (Saffo).

Rule 1 is to define a cone of uncertainty. The cone of uncertainty is used to help the decision maker exercise strategic judgment. The most important factor with the cone of uncertainty is defining its breadth, which is a measure of overall uncertainty. When making the cone of uncertainty, a cone that is too narrow is worse than one that is too broad. At the start, defining a cone too broadly increases the capacity to generate hypotheses about outcomes and eventual responses. A cone that is too narrow can result in unwanted surprises. In order to create a cone of uncertainty, one must be able to adequately distinguish between the highly improbable outliers and wildly impossible outliers.

Rule 2 is to look for the S curve. Many important developments typically follow the S-curve shape of a power law: "Change starts slowly and incrementally, putters along quietly, and then suddenly explodes, eventually tapering off and even dropping back down." It is important to identify an S-curve pattern as it begins to emerge, well ahead of the inflection point.

Rule 3 is to embrace the things that don't fit. The entire portion of the S curve to the left of the inflection point is paved with indicators that are subtle pointers that when aggregated become powerful hints of things to come. The best way for forecasters to spot an emerging S curve is to become attuned to things that don't fit. Because of our dislike of uncertainty and our preoccupation with the present, we tend to ignore indicators that don't fit into familiar boxes.

Rule 4 is to hold strong opinions weakly. The author claims that one of the biggest mistakes a forecaster can make is to over rely on one piece of seemingly strong information because it happens to reinforce the conclusion he or she has already reached. In forecasting, lots of interlocking weak information is more trustworthy than a point or two of strong information.

Rule 5 is to look back twice as far as you look forward. When looking for parallels, always look back at least twice as far as you are looking forward. The hardest part of looking back is to know when history doesn't fit.

Rule 6 is to know when not to make a forecast. There are moments when forecasting is easy, and other moments when it is impossible. The cone of uncertainty is not static; it expands and contracts as the present events take place. Thus, there are moments of uncertainty when the cone broadens to a point at which the forecaster should refrain from making a forecast.

When forecasting, the amount of forecast error greatly affects the profitability of the product. Thus, being able to make forecasts with as little forecast error as possible is desired. [Jain,2008a] explains that there are three forecasting characteristics that indicate how much forecasting error a company can afford. These three characteristics are the cost of an error, the adjustment capability of a company, and industry benchmarks. The cost of forecasting error comes from two types of forecasting error; over-forecasting and under-forecasting. Over-forecasting error results in excess inventory which leads to discounts on the product in order to attempt to sell the excess inventory. The second type of forecasting error is under-forecasting. Under-forecasting results in lost sales and an increased production cost due to an increased production rate. It is very beneficial for a company to have the ability to adjust to an error quickly. The adjustment capability of a company and its products is dependent on the lead time. The shorter the lead time, the faster a company can adjust to forecast errors, thus allowing companies with shorter lead times the luxury of larger forecasting error. Industry benchmarks show a company how much error they can afford. By comparing forecasting errors with other companies in the industry, a company can determine if they are forecasting with the accuracy needed to stay competitive. This also allows the company to set goals for how much forecasting error is reasonable and where the company should aim to have their forecasting errors.

A result observed in this study was that when calculating forecast error, the error will be smaller when calculating the error for large groups of products (with larger total volume) rather than for a product by itself (with relatively small volume). In general, the larger the group that the error is being calculated for, the smaller the error will be in comparison to the forecasting error of the individual products. This is due to combining the total sales and associated forecasts for larger groups of products, which allows for the offset of over-forecasting by under-forecasting between different products. Furthermore, as expected, the study showed that forecasting error increases as the forecasting time horizon is increased.

The type of model used when forecasting has a significant influence on the forecast. There are many different forecasting models; thus it is important to match the right model with the dataset. [Jain, 2008b] explains that there are three types of forecasting models; time series (univariate), cause-and-effect, and judgmental. In time series modeling, past data is used in order to determine the best statistical fit. Time series models include: simple and moving averages, simple trend, exponential smoothing, decomposition, and Autoregressive Integrated Moving

Average (ARIMA). Cause-and-effect models are used when there is a cause (independent variable) and an effect (dependent variable). For example if the number of vehicle sales are dependent upon the amount of money spent on advertising then the cause is the amount of money spent on advertising and the effect is the number of vehicle sales. A cause-and-effect forecasting model is usually appropriate in scenarios where there is a strong relationship between the cause and effect variables. Cause-and-effect models include: regression, econometrics, and neural network. Judgment models are used when there is no historical data or if the data that exists is not applicable. This scenario comes into play when a forecast for new product is being prepared or in cases concerning the sale of fashion products (fashion products may follow different trends). Judgment models include: analog, Delphi, diffusion, Performance Evaluation Review Technique (PERT), survey, and scenario.

The study in [Jain, 2008b] reports that the most common type of forecasting model used in today's industry are time series models, which account for 61% of all forecasting models used. Time series models are followed by cause-and-effect models at 18% and judgment models at 15%. Five percent of the surveyed companies use custom "homegrown" models. Further analysis of the time series models show that averages/simple trend models account for 57% of the time series models used. This is followed by exponential smoothing at 29%, ARIMA at 7%, and decomposition at 6%.

3. Forecasting Techniques

In this chapter the exponential smoothing, exponential smoothing with a linear trend, and the Winters method for seasonality forecasting techniques are explained. It is important to explain these forecasting techniques in order to understand how their usage affects the forecast results. Additionally, the differences between the techniques can be seen through the formulation of the techniques and through the examples provided with each technique.

Exponential Smoothing Forecasting Technique

Three different forecasting techniques were used for forecasting in this study. The first is the exponential smoothing forecasting technique. The exponential smoothing technique (Hopp, 2001) uses the computation of a smoothed estimate in order to generate forecasts. The calculations of the smoothed estimate and forecast are defined as:

$$\mathrm{F}(t) = \alpha \mathrm{A}(t) + (1 - \alpha)\mathrm{F}(t - 1)$$

$$\mathrm{f}(t + \tau) = \mathrm{F}(t) \qquad \tau = 1, 2, \ldots$$

where F(t) = the smoothed estimate at time t

α = a smoothing constant ranging from 0 to 1 that is chosen by the user

A(t) = the actual demand in time period t

f($t + \tau$) = the forecast for τ periods ahead of t

τ = the number of forecast periods ahead of the current time period

The exponential smoothing technique is based on a model that assumes that there is a trend of zero over the course of the time periods. Instead, the technique relies solely on the weighted average of the data, which is controlled by the user declared value of α. When α is lower, the model will be more stable but yet less responsive to recent changes in the demand. When α is larger, the model will be less stable due to more responsiveness to recent changes in the demand, which leads to forecasts that track the latest demand closely and could lead to extremely large or small forecasts.

The exponential smoothing technique has a clear disadvantage to other forecasting techniques in that it does not explicitly take into account trends in the demand. Because there is no trend included in the model of demand, the exponential smoothing technique will tend to underestimate the future demand for products that have an increasing trend and overestimate the future demand for products that have a decreasing demand.

Week	Demand	Forecasts f(t + 1)		
t	A(t)	α = 0.1	α = 0.5	α = 0.9
1	5	--	--	--
2	7	5.2	6	6.8
3	9	7.2	8	8.8
4	13	9.4	11	12.6
5	10	12.7	11.5	10.3
6	16	10.6	13	15.4
7	21	16.5	18.5	20.5
8	27	21.6	24	26.4
9	30	27.3	28.5	29.7
10	36	30.6	33	35.4
11	43	36.7	39.5	42.3
12	50	43.7	46.5	49.3
13	60	51	55	59
14	51	59.1	55.5	51.9
15	74	53.3	62.5	71.7
16	85	75.1	79.5	83.9
17	96	86.1	90.5	94.9
18	108	97.2	102	106.8
19	120	109.2	114	118.8
20	135			
Total of Absolute Differences:		231.5	195.5	160.7

Figure 5: Exponential smoothing for one week ahead with α = 0.1, α = 0.5, and α = 0.9

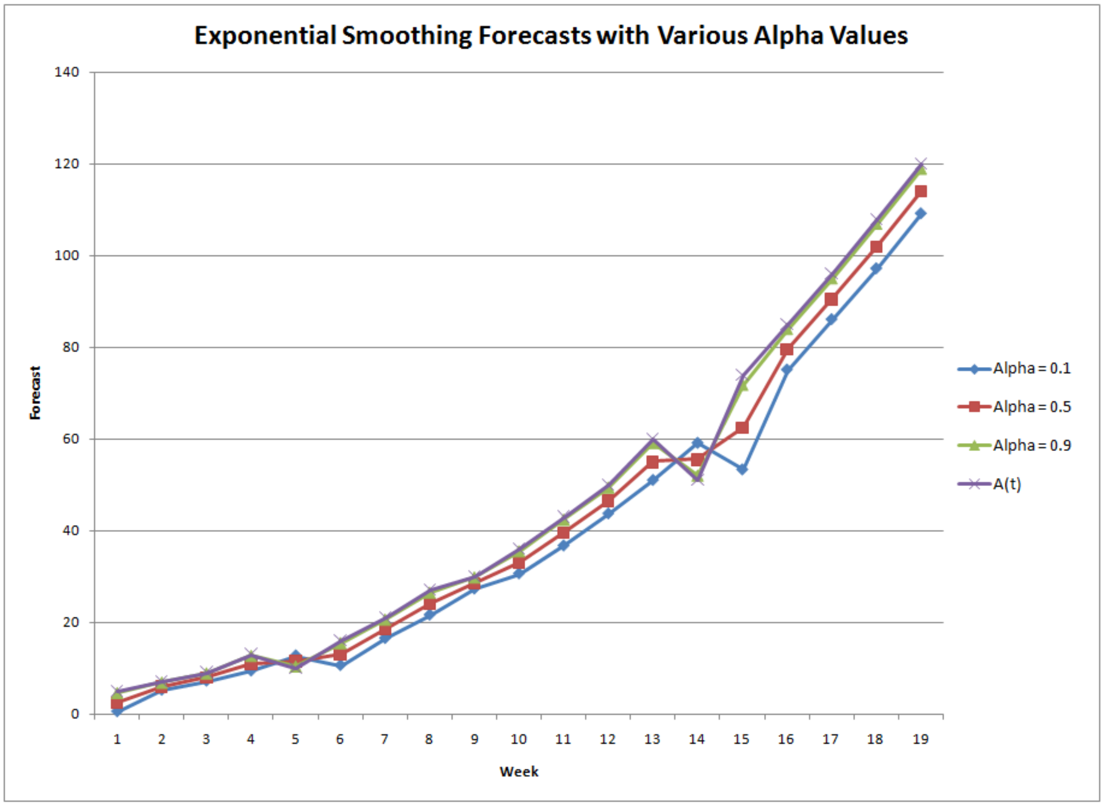


Figure 6: Exponential smoothing forecasts with alpha = 0.1, alpha = 0.5, and alpha = 0.9

As shown in the example in Figure 5, none of the three alpha values tried result in a forecast that closely estimates the demand. This is because there is an upward trend in the data that is not taken into account in the exponential smoothing technique. Additionally, Figure 5 shows that there is more influence on the forecast from the most recent value of demand as alpha increases. Figure 6 shows in a graph how the forecasts using each of the alpha values vary from each other.

Exponential Smoothing with a Linear Trend Forecasting Technique

Another forecasting technique used in this study is the exponential smoothing with a linear trend technique. This closely resembles the exponential smoothing technique previously discussed with one exception; instead of assuming a trend of zero in the data, the exponential smoothing with a linear trend technique assumes that the trend is linear. The exponential smoothing with a linear trend technique updates the slope of the trend each time a new observation is made. The exponential smoothing with a linear trend technique calculates a smoothed estimate and a smoothed trend in order to calculate forecasts. The calculations of the smoothed estimate, smoothed trend, and forecast (Hopp, 2001) are defined as:

$$F(t) = \alpha A(t) + (1 - \alpha)[F(t-1) + T(t-1)]$$

$$T(t) = \beta[F(t) - F(t-1)] + (1 - \beta)T(t-1)$$

$$f(t + \tau) = F(t) + \tau T(t)$$

where $F(t)$ = the smoothed estimate at time t

$T(t)$ = the smoothed trend at time t

α = a smoothing constant ranging from 0 to 1 that is chosen by the user

β = a smoothing constant ranging from 0 to 1 that is chosen by the user

$A(t)$ = the demand in time period t

$f(t + \tau)$ = the forecast for τ periods ahead of t

τ = the number of forecast periods ahead of the current time period

Again, as with the exponential smoothing technique the moving average of the data is controlled by the user declared value of α. When α is lower, the model will be more stable but yet less responsive to recent changes in the demand and when α is larger, the model will be less stable due to more responsiveness to recent changes in the demand. However, unlike the exponential smoothing technique, the exponential smoothing with a linear trend technique is greatly affected by the linear trend, which is controlled by the user declared value of β. When β is larger, the model is more responsive to the most recent trend. When β is lower, the model will be less responsive to the most recent trend and will retain a value closer to the previous trend rather than being changed dramatically.

Week t	Demand $A(t)$	Smoothed Estimate $F(t)$	Smoothed Trend T(t)	Forecast f(t + 1)
1	5			
2	7	6.80	0.90	7.70
3	9	8.87	1.49	10.36
4	13	12.74	2.68	15.41
5	10	10.54	0.24	10.78
6	16	15.48	2.59	18.07
7	21	20.71	3.91	24.62
8	27	26.76	4.98	31.74
9	30	30.17	4.20	34.37
10	36	35.84	4.93	40.77
11	43	42.78	5.93	48.71
12	50	49.87	6.51	56.39
13	60	59.64	8.14	67.78
14	51	52.68	0.59	53.27
15	74	71.93	9.92	81.85
16	85	84.68	11.34	96.02
17	96	96.00	11.33	107.33
18	108	107.93	11.63	119.56
19	120	119.96	11.83	131.78
20	135	134.68	13.27	
Total of Absolute Differences:				67.87

Figure 7: Smoothing with a Linear Trend for one week ahead for α = 0.9 and β = 0.5

Figure 7 shows how exponential smoothing with a linear trend is applied to the example shown earlier. With this model, the demand data is used to calculate a smoothed estimate as well as a smoothed trend. The smoothed estimate and smoothed trend are then used to calculate the forecasts. As you can see from Table B, there is a total absolute difference between the forecasts and the actual of the forecasts of approximately 68 when using α = 0.9 and β = 0.5. This is an improvement in comparison to the best of the three exponential smoothing models when using α = 0.9, which yielded an absolute total difference between the forecasts and the actual of the forecasts of approximately 161. The difference in this comparison is due to the utilization of the smoothed trend in the exponential smoothing with a linear trend technique. This gives the exponential smoothing with a linear trend technique an advantage over the exponential smoothing technique.

The Winters Method for Seasonality Technique

The last of the three forecasting techniques used in this study is the Winters method for Seasonality technique. In addition to the utilization of a smoothed estimate and smoothed trend to calculate the forecasts, the Winters method utilizes a multiplicative seasonality factor in order to account for seasonality associated with the product. Seasonality can be seen in many products associated with the weather. For example, swimming pools may see a spike in sales as warm weather approaches; in the same way, snow sleds may see an increase in sales as cold weather approaches. The calculations of the smoothed estimate, smoothed trend, multiplicative seasonality factor, and forecast for the Winters method for Seasonality (Hopp, 2001) are defined as:

$$F(t) = \alpha[A(t) / c(t - N)] + (1 - \alpha)[F(t - 1) + T(t - 1)]$$

$$T(t) = \beta[F(t) - F(t - 1)] + (1 - \beta)T(t - 1)$$

$$c(t) = \gamma[A(t) / F(t)] + (1 - \gamma)c(t - N)$$

$$f(t + \tau) = [F(t) + \tau T(t)]c(t + \tau - N), \qquad t + \tau = N + 1, \ldots, 2N$$

where $F(t)$ = the smoothed estimate at time t

$T(t)$ = the smoothed trend at time t

$c(t)$ = the multiplicative seasonality factor at time t

α = a smoothing constant ranging from 0 to 1 that is chosen by the user

β = a smoothing constant ranging from 0 to 1 that is chosen by the user

γ = a smoothing constant ranging from 0 to 1 that is chosen by the user

A(t) = the demand in time period t

f($t + \tau$) = the forecast for τ periods ahead of t

τ = the number of forecast periods ahead of the current time period

N = the number of forecast periods in a season

The Winters method for seasonality technique has advantages over the other two techniques discussed due to the inclusion of the multiplicative seasonality factor. The multiplicative seasonality factor allows the Winters method to take into account the effect of seasonality. The seasonality in the data can often be mistaken as a trend in the exponential smoothing with a linear trend technique. When the seasonality is not taken into account, as in the previously discussed techniques, it can lead to unnecessary errors in the forecasts whenever the demand peaks and then drops due to seasonality.

Year	Month	Period t	Demand $A(t)$	Smoothed Estimate $F(t)$	Smoothed Trend $T(t)$	Mult. Seasonality Factor $c(t)$	Forecast $f(t+1)$
2005	Jan	1	10			0.089	
	Feb	2	20			0.178	
	Mar	3	33			0.294	
	Apr	4	47			0.418	
	May	5	59			0.525	
	Jun	6	73			0.650	
	Jul	7	88			0.783	
	Aug	8	100			0.890	
	Sep	9	118			1.050	
	Oct	10	200			1.780	
	Nov	11	250			2.226	
	Dec	12	350			3.116	
2006	Jan	13	100	1011.00	101.10	0.098	198.00
	Feb	14	120	717.81	61.67	0.168	228.99
	Mar	15	135	491.54	32.88	0.277	219.41
	Apr	16	149	372.95	17.73	0.401	205.19
	May	17	164	320.09	10.67	0.514	214.95
	Jun	18	185	289.29	6.52	0.641	231.73
	Jul	19	201	260.50	2.99	0.773	234.57
	Aug	20	222	250.79	1.72	0.886	265.25
	Sep	21	240	230.88	-0.44	1.041	410.27
	Oct	22	350	199.97	-3.49	1.753	437.27
	Nov	23	415	187.47	-4.39	2.215	570.44
	Dec	24	530	171.40	-5.56	3.094	16.24
2007	Jan	25	205	1900.72	167.93	0.107	348.08
	Feb	26	230	1437.09	104.77	0.161	426.42
	Mar	27	256	987.28	49.32	0.261	416.10
	Apr	28	283	738.18	19.47	0.385	389.16
	May	29	305	610.19	4.73	0.501	393.87
	Jun	30	335	532.19	-3.54	0.631	408.52
	Jul	31	366	479.13	-8.50	0.765	416.84
	Aug	32	400	453.52	-10.21	0.882	461.31
	Sep	33	436	421.42	-12.40	1.035	717.14
	Oct	34	575	336.06	-19.69	1.715	700.70
	Nov	35	642	292.52	-22.08	2.197	836.86
	Dec	36	793	257.68	-23.35	3.079	25.04

Figure 8: The Winters method for seasonality technique example α = 0.9, β = 0.1 and γ = 0.9

Figure 8 shows an example of the Winters method for seasonality technique. Notice that no forecasts are generated during the first full cycle of data (12 months). The disadvantage that the Winters method for seasonality technique has when compared to the exponential smoothing and exponential smoothing with a linear trend techniques is that it requires a full cycle of data in order to start calculating forecasts. Thus, with small amounts of data, the Winters method for seasonality technique may not have enough data to produce forecasts.

4. JMP IN and VBA Usage in Project

In this project JMP IN statistical analysis software and the Visual Basic for Applications (VBA) language for Microsoft Excel are used to aid in calculating, graphing, and organizing the data used in this project. The JMP IN statistical analysis software allows for the determination of the model parameters for each forecasting model. The VBA language for Microsoft Excel allows for the implementation of the functionality of the exponential smoothing, exponential smoothing with linear trend, and the Winters method forecasting models into Microsoft Excel for this study

In this project, JMP IN is used to calculate the smoothing weights needed for each of the forecasting models; VBA for Microsoft Excel is used to calculate the forecasts and forecast errors using the specified forecasting models. Figure 9 shows the process for developing the exponential smoothing and exponential smoothing with a linear trend models. Note that for these models the seasonality in the raw data is removed before the forecasting models are fit. Figure 10 shows the process for developing the Winters model. Note that for the Winters model the raw data including the seasonal patterns is used directly in the modeling fitting stage.

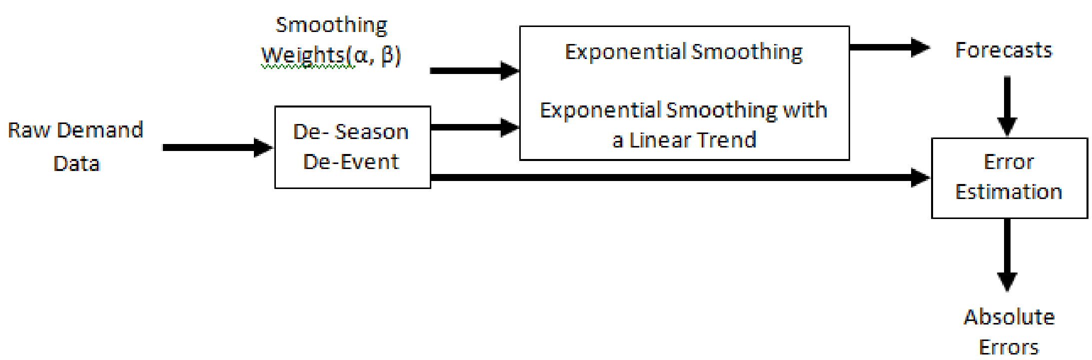


Figure 9: Flow chart of forecasting using exponential smoothing and exponential smoothing with a linear trend.

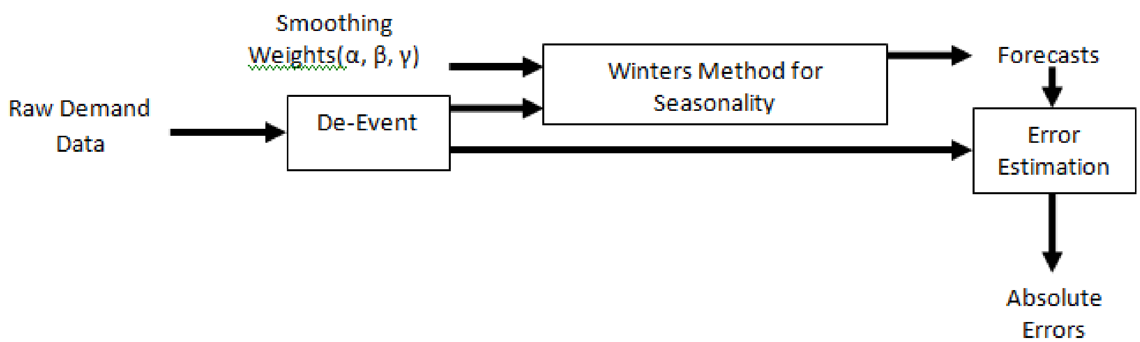


Figure 10: Flow chart of forecasting using Winters method for seasonality.

JMP IN Usage

JMP IN, statistical analysis software, was used in the study in order to determine the optimal model parameters (smoothing weights) for each forecasting model. Each smoothing model has an ARIMA model equivalent. JMP IN uses an ARIMA equivalent in order to find an estimate of the optimal model parameters. The model parameter estimation is an iterative procedure by which the log-likelihood is maximized by adjusting the estimates of the parameters. (The JMP-In help provides details on the search process).

To measure the level of effectiveness of the model parameters calculated by JMP IN the mean absolute percent error was used. The mean absolute percent error is calculated as follows:

$$\frac{\sum \frac{ABS\left(A(t) - f(t)\right)}{A(t)}}{N}$$

where A(t) = the actual demand in time period *t.*

f(t) = the forecast for time period *t.*

N = the number of forecasts for time period *t.*

The absolute error for each forecast is computed as the absolute value of the difference between the forecast and the actual, divided by the actual. These errors are averaged to get the mean absolute percent error. The average of the errors for the first 13 weeks and 26 weeks is the averaged together to find the absolute percent error for the forecast.

To understand the effectiveness of JMP IN in generating model parameters consider this example. The dataset from business unit 321 Shaving & Grooming in business group 9044 of the DAP division contains data from week 1 of 2004 through week 52 of 2007. As shown in Figure 11, running this data through the JMP IN parameter estimation returns an optimal α value of 0.7982312 for the exponential smoothing forecasting model.

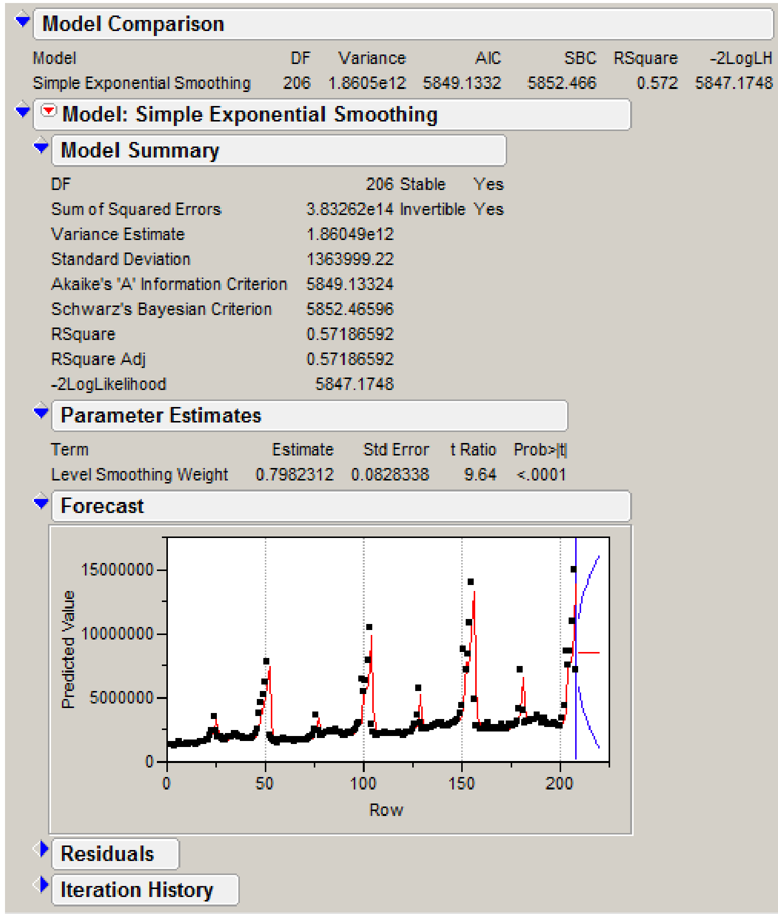


Figure 11: Screenshot of JMP IN model parameter estimation.

Using this model parameter yields a 0.095854 mean absolute percent error for the exponential smoothing model for the data. To get an idea of how α affects the error, the following graph shows the error for this dataset for different values of α. The analysis for other values of α is shown in the Figure 12.

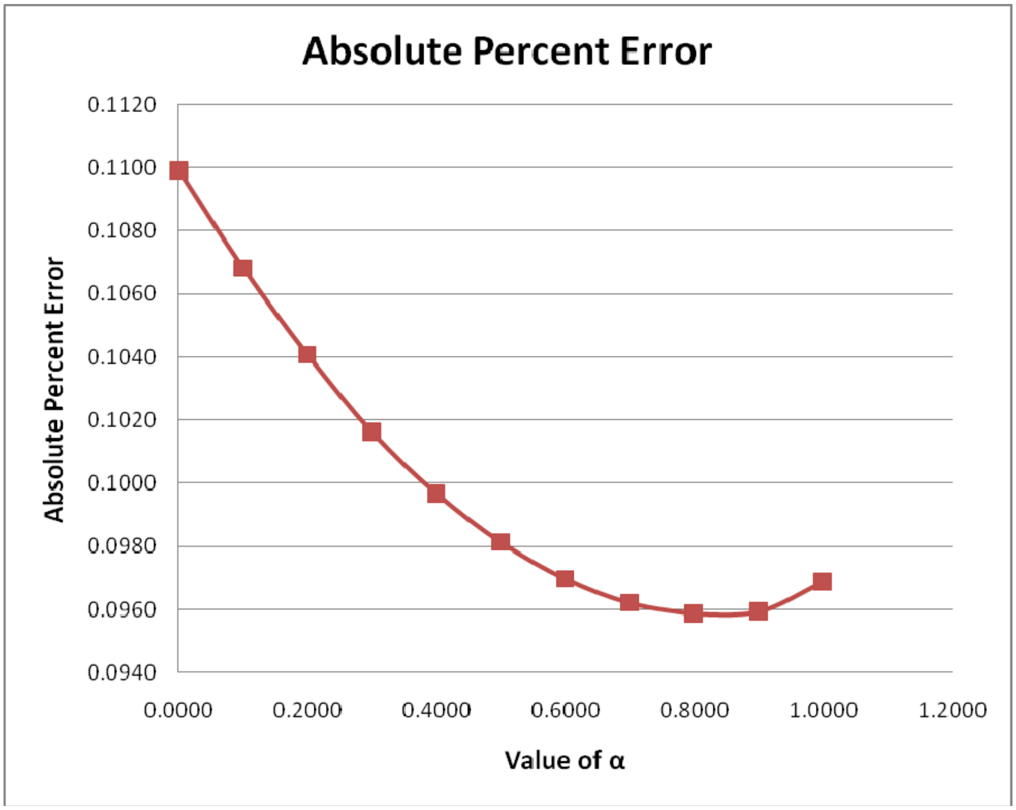


Figure 12: Absolute Percent Error for different values of α.

Notice that the graph shows the lowest absolute percent error value around a value of α of 0.8, which is approximately the value of α assigned for the model by JMP IN.

Excel Visual Basic for Applications Usage

The Visual Basic for Applications (VBA) language was used to implement the functionality of the exponential smoothing, exponential smoothing with linear trend, and the Winters method forecasting models into Microsoft Excel for this study. Each of the forecasting methods was coded in this language in order to operate on data located in Microsoft Excel worksheets. This allows for the forecast parameters to be easily customized for each forecast, as well as custom graphing of the results. This also allows the generation of forecasts to be made in a quick manner as opposed to more manual methods for generating forecasts.

For example, the exponential smoothing forecasting method requires only three parameters in addition to the data and seasonality profile in order to make forecasts from the data. These parameters (Number of Forecast Weeks, Total Number of Weeks, and Alpha Value) only need to be entered once, into the Microsoft Excel worksheet, though the values are used numerous times throughout the forecast calculations. Additionally, the VBA language allows for all of the calculations to be made in a timely and automatic manner. For instance, the calculation of the smoothed estimates and entire set of forecasts for the exponential smoothing forecast model is possible using the following VBA code:

```
With Range("E6")

    'calculate the first Smoothed Estimate = alpha * de-seasonalized data
    .Offset(1, 0) = alpha * .Offset(1, -1)

    For i = 2 To Number_of_weeks
        'calculate the remainding Smoothed Estimates
        .Offset(i, 0) = alpha * .Offset(i, -1) + (1 - alpha) * .Offset(i - 1, -1)
    Next

    For r = 1 To Number_of_weeks
        For k = 1 To Forecast_Weeks
        'calculate the forecasts
            .Offset(r, k) = .Offset(r, 0) * .Offset(k + r, -2)
        Next
    Next
End With
```

Figure 13: Sample VBA code.

As you can see in Figure 13, the calculations are controlled with simple *For* loops and use various references to the worksheet. During execution of this code, the columns for smoothed estimate and forecasts are being assigned values on the worksheet.

Forcasts for:	BG: 9044, BU: 0321 Shaving & Grooming								
	Number of Forecast Weeks:	52				Find Forecasts			
	Number of Weeks:	104							
	Alpha:	0.7982312							
					Forecasts	With	Seasonality		
t	De-Event Data	Seasonality Index	De-Season	Smoothed Estimate	+1	+2	+3	+4	+5
1	2283364	0.671609956							
2	2043506	0.626715925							
3	2087494	0.610392659							
4	2130040	0.571508741							
5	2204032	0.641721427							
6	2244304	0.699336864							
7	2323420	0.666981579							
8	2235524	0.624333765							
9	2197188	0.637295071							
10	2197134	0.647159148							
11	2146074	0.652652425							
12	2205586	0.667576277							
13	2200840	0.634861143							
14	2271442	0.669056499							
15	2235178	0.623677619							

Figure 14: Worksheet before forecasts have been made using the exponential smoothing method.

Forcasts for:	BG: 9044, BU: 0321 Shaving & Grooming								
	Number of Forecast Weeks:	52				Find Forecasts			
	Number of Weeks:	104							
	Alpha:	0.7982312							
					Forecasts	With	Seasonality		
t	De-Event Data	Seasonality Index	De-Season	Smoothed Estimate	+1	+2	+3	+4	+5
200601	2283364	0.671609956	3399836.439	2713855.52	1700816	1656517	1550992	1741539	1897899
200602	2043506	0.626715925	3260657.531	3288739.492	2007422	1879543	2110455	2299937	2193529
200603	2087494	0.610392659	3419919.897	3387785.721	1936149	2174015	2369203	2259591	2115109
200604	2130040	0.571508741	3727047.105	3665078.417	2351959	2563124	2444540	2288232	2335736
200605	2204032	0.641721427	3434561.958	3493576.335	2443187	2330151	2181158	2226439	2260900
200606	2244304	0.699336864	3209188.755	3254662.036	2170800	2031995	2074180	2106284	2124163
200607	2323420	0.666981579	3483484.51	3428140.185	2140304	2184737	2218552	2237384	2288545
200608	2235524	0.624333765	3580655.293	3561049.261	2269439	2304566	2324127	2377272	2260772
200609	2197188	0.637295071	3447677.693	3474508.424	2248560	2267646	2319499	2205830	2324642
200610	2197134	0.647159148	3395044.335	3405664.104	2222715	2273541	2162124	2278582	2124036
200611	2146074	0.652652425	3288234.16	3309785.121	2209534	2101254	2214433	2064239	2190506
200612	2205586	0.667576277	3303871.145	3300716.089	2095496	2208366	2058583	2184503	2268030
200613	2200840	0.634861143	3466647.822	3433804.567	2297409	2141587	2272585	2359479	2383481
200614	2271442	0.669056499	3394992.803	3409450.55	2126398	2256467	2342745	2366577	2340392
200615	2235178	0.623677619	3583867.582	3545758.545	2346679	2436407	2461191	2433959	2660594

Figure 15: Worksheet after forecasts have been made using the exponential smoothing method.

Similar sections of VBA code are used to calculate forecast errors, make charts, and calculate the forecasts for the exponential smoothing with a linear trend and the Winters methods.

Forcast Errors:	BG: 9044, BU: 0321 Shaving & Grooming								
	Number of Forecast Weeks:	52							
	Number of Weeks:	104							
	Alpha:	0.7982312							
					Forecast Errors				
t	De-Event	Seasonality Index	De-Season	Smoothed Estimate	+1	+2	+3	+4	+5
1	2283364	0.671609956	3399836.439	2713855.52	0.167697	0.206456	0.271848	0.209839	0.154348
2	2043506	0.626715925	3260657.531	3288739.492	0.038358	0.117602	0.042457	0.024788	0.055905
3	2087494	0.610392659	3419919.897	3387785.721	0.091027	0.013619	0.055652	0.027472	0.053864
4	2130040	0.571508741	3727047.105	3665078.417	0.067117	0.142058	0.05213	0.023578	0.063057
5	2204032	0.641721427	3434561.958	3493576.335	0.088617	0.002897	0.024319	0.013313	0.029022
6	2244304	0.699336864	3209188.755	3254662.036	0.065688	0.091043	0.055984	0.041349	0.01021
7	2323420	0.666981579	3483484.51	3428140.185	0.042594	0.005667	0.009748	0.042547	0.037613
8	2235524	0.624333765	3580655.293	3561049.261	0.032883	0.048896	0.082967	0.077841	0.027231
9	2197188	0.637295071	3447677.693	3474508.424	0.023406	0.056649	0.051648	0.002267	0.023421
10	2197134	0.647159148	3395044.335	3405664.104	0.035712	0.03081	0.017592	0.003143	0.049724
11	2146074	0.652652425	3288234.16	3309785.121	0.00179	0.045249	0.025098	0.076477	0.034518
12	2205586	0.667576277	3303871.145	3300716.089	0.047865	0.027769	0.079007	0.031684	0.060652
13	2200840	0.634861143	3466647.822	3433804.567	0.011432	0.041872	0.073282	0.103418	0.039059
14	2271442	0.669056499	3394992.803	3409450.55	0.048667	0.06567	0.095593	0.03169	0.013912
15	2235178	0.623677619	3583867.582	3545758.545	0.108275	0.139394	0.072936	0.054447	0.152573

Figure 16: Worksheet after forecast errors have been calculated.

Graphs of the forecast and absolute error were also created using VBA code. The graphs are used in a report for each business unit. Examples of these graphs are shown in Figure 17 and Figure 18. Notice that in Figure 17 there are two peaks in the forecast. One peak as summer approaches and another, larger peak, as the end of the year approaches. This may be explained by holidays, such as father's day and winter holidays. Also, notice that in Figure 18 the absolute error increases as the forecast is made for time periods further away from the current time period.

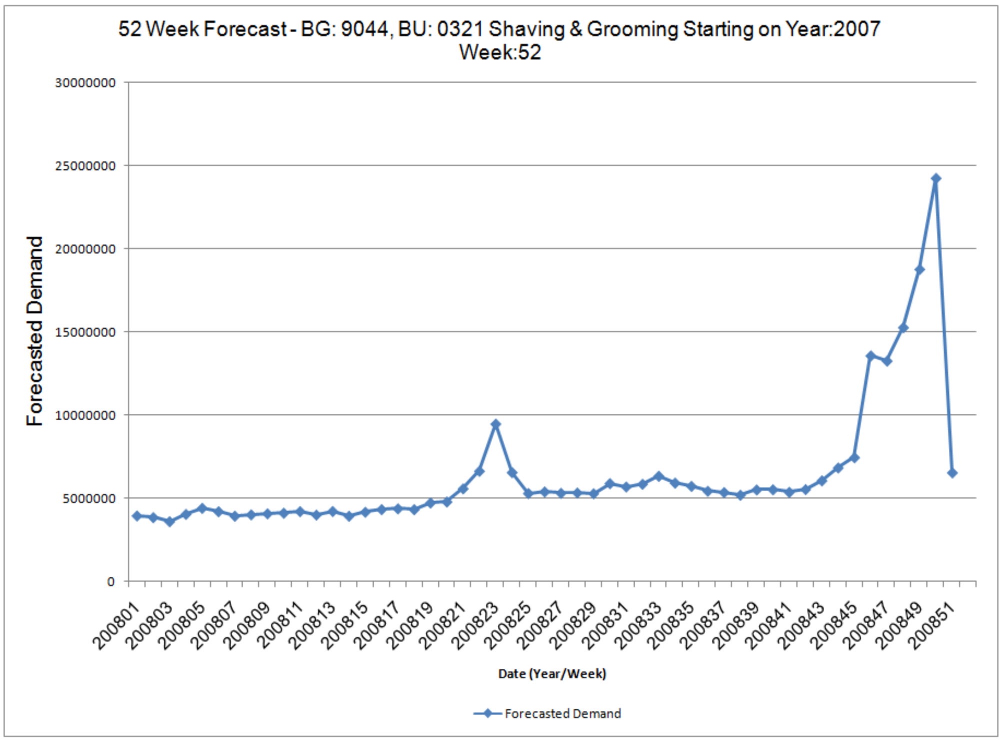


Figure 17: Example forecast chart as would be displayed in business unit report.

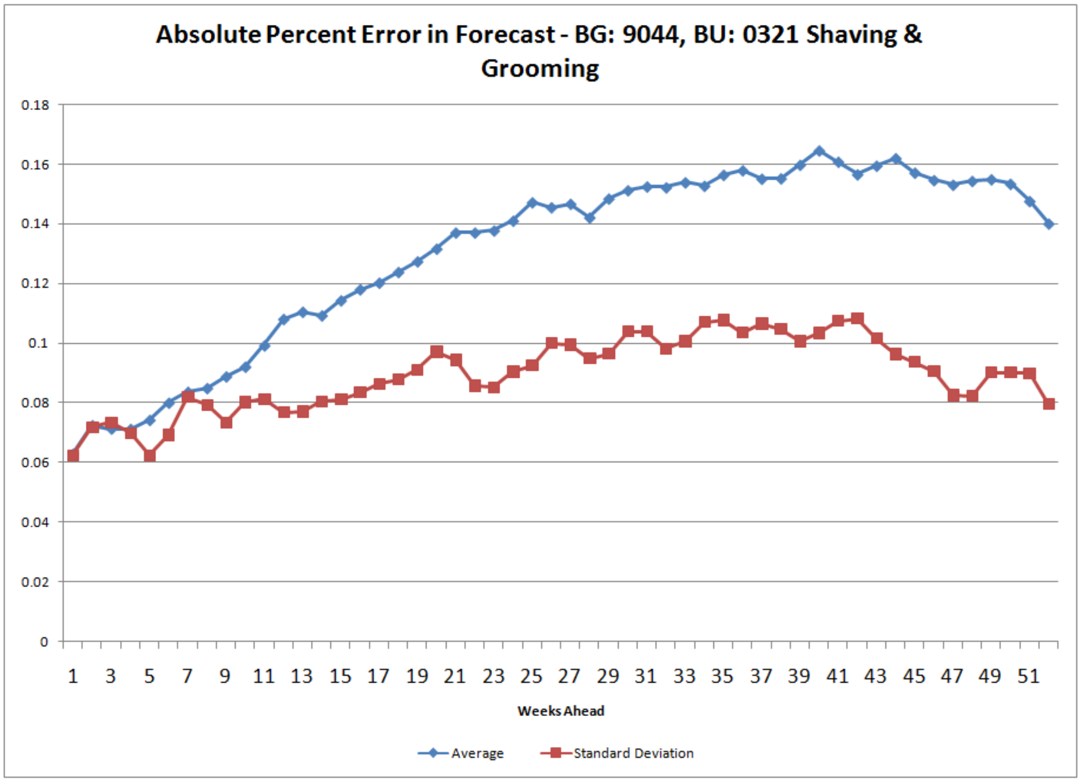


Figure 18: Example absolute error chart as would be displayed in business unit report.

5. Results, Analysis & Conclusions

A list of 12 business units (BU) was examined in the study; four business units from each of three divisions: DAP, PA, and CE. A graph of each of the best models for each business unit can be found in Appendix G through Appendix R. A BU consists of a set of different products with similar characteristics. For instance a BU may contain multiple versions of televisions, or multiple electronic shavers. As explained earlier in [Jain, 2008a], forecast error will be smaller when calculating the error for large groups of products with larger total volume rather than for a product by itself with relatively small volume. In general, the larger the group that the error is being calculated for, the smaller the error will be in comparison to the forecasting error of the individual products. This is due to combining the total sales and associated forecasts for larger groups of products, which allows for the offset of over-forecasting by under-forecasting between different products. Thus, by combining the products into BU's, the calculated forecast error should be smaller than the average of the products' individual forecast errors.

The amount of data available for each BU ranged from one year and 42 weeks to four years. Occasionally, modifications to the data needed to be made. These modifications are outlined in the table shown in Appendix A.

Summary of Results

The data for each business unit was analyzed in JMP IN in order to determine optimal model parameters for each of the forecasting models. The model parameters used for each forecasting model of each business unit can be found in Appendix B. Using the model parameters, the forecast for each scenario was calculated. Figure 19, Figure 20, and Figure 21 show the best absolute error (average of absolute error from first 13 weeks and first 26 weeks) and model for each business unit evaluated from each of three divisions. The Absolute errors of each scenario for the first 13 weeks, first 26 weeks, and the average of the first 13 and first 26 weeks can be found in Appendix C, Appendix D and Appendix E respectively.

Division	Item	Best Absolute Error	Best Model
DAP	BG: 9042, BU: 0343	0.542	Winters 52-week Period
DAP	BG: 9044, BU: 0321	0.094	Expo. Smoothing w/Trend
DAP	BG: 9044, BU: 0329	1.185	Expo. Smoothing
DAP	BG: 9050, BU: 0331	0.122	Expo. Smoothing w/Trend

Figure 19: DAP division, best absolute error and model.

Division	Item	Best Absolute Error	Best Model
PA	BG: 6922, BU: 1409	0.973	Expo. Smoothing w/Trend
PA	BG: 6922, BU: 1416	0.205	Winters 26-week Period
PA	BG: 6922, BU: 628	0.244	Expo. Smoothing w/Trend
PA	BG: 6922, BU: 1485	0.848	Expo. Smoothing

Figure 20: PA division, best absolute error and model.

Division	Item	Best Absolute Error	Best Model
CE	BG: 6914, BU: 0603	0.428	Expo. Smoothing
CE	BG: 6914, BU: 0610	0.240	Expo. Smoothing w/Trend
CE	BG: 6916, BU: 0641	0.222	Expo. Smoothing w/Trend
CE	BG: 6916, BU: 0654	0.847	Expo. Smoothing w/Trend

Figure 21: CE division, best absolute error and model.

The most common best forecasting model was the exponential smoothing with a linear trend forecasting model. The exponential smoothing with a linear trend forecasting model was best in seven of the twelve evaluated business units. The exponential smoothing forecasting model was the second best forecasting model evaluated, which was the best model in three of the twelve evaluated business units. The Winters method using a 52 week and 26 week period to calculate the model parameters via JMP IN each were the best model in one of the twelve evaluated business units.

Additionally, the coefficient of variance was calculated from the original de-season data from each business unit. The coefficient of variance, defined as the ratio of the standard deviation to the mean, is used to scale the variance of the data in order for making more effective comparisons. Appendix F shows the coefficient of variance and best absolute error for each of the evaluated business units. The relationship between the coefficient of variance and the best absolute error (average of absolute error from first 13 weeks and first 26 weeks) is shown in Figure 22.

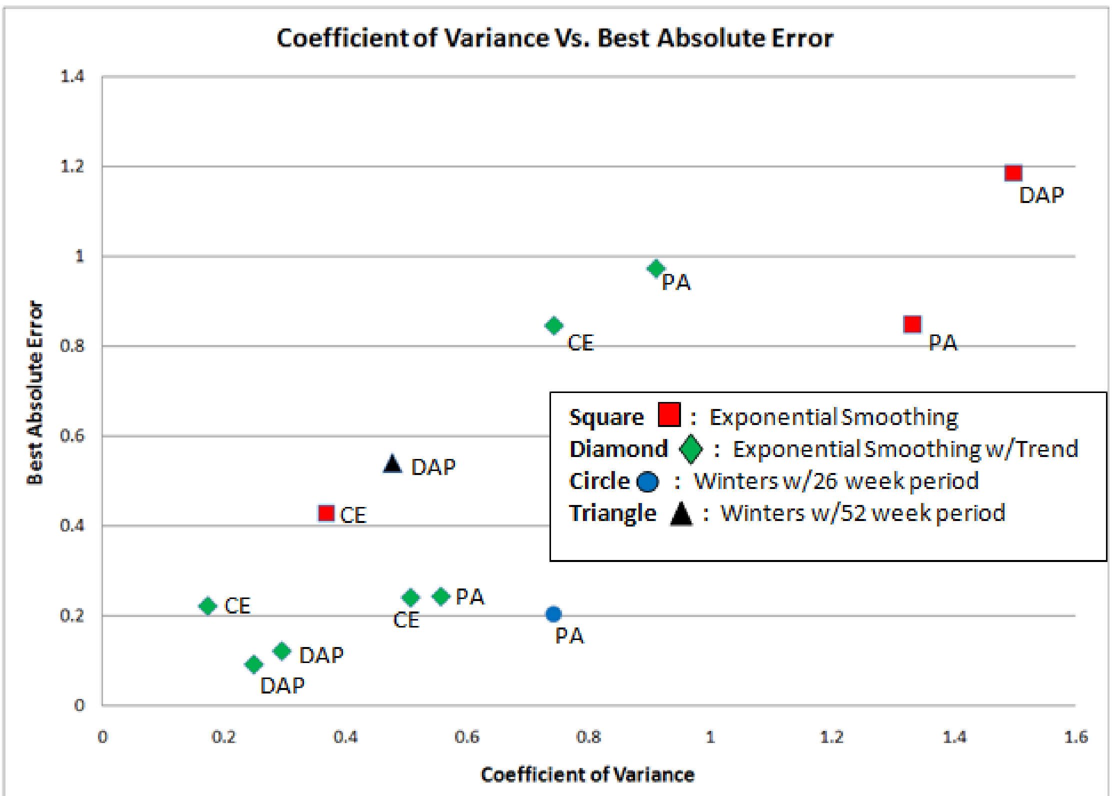


Figure 22: Coefficient of Variance Vs. Best Absolute Error

Through the coefficient of variance a scalable comparison of the variance of each of the evaluated business units can be made. It appears from Figure 22 that there is a correlation between the coefficient of variance and the best absolute error. As the coefficient of variance increases the best absolute error increases. Thus, a business unit with a higher coefficient of variance of the de-seasoned data will, in general, have more error in the forecast. There were three products where exponential smoothing was the best model. Two of those three products had the largest overall coefficient of variance out of all data sets. This can be interpreted that in general, for larger coefficient of variance values (approximately 1.0 and larger), the exponential smoothing forecasting technique is likely to be the best model. Additionally, five of the seven instances where the exponential smoothing with a linear trend forecasting technique is the best model for the data, there are smaller coefficient of variance values for the data. This can be interpreted that in general, for smaller coefficient of variance values (approximately 0.5 and smaller), the exponential smoothing with a linear trend forecasting technique is likely to be the best model.

Winters method for seasonality forecasting technique was only best when the coefficient of variance was a "medium" value, meaning that the coefficient of variance was approximately between 0.5 and 1.0. It is possible that the Winters method for seasonality forecasting technique should only be considered for cases where the coefficient of variance is between 0.5 and 1.0. Thus, the Winters method for seasonality forecasting technique can be excluded when considering forecasting techniques for data with coefficient of variance values of less than 0.5 or greater than 1.0.

Regarding the different product divisions, the DAP division mostly consisted of "small" coefficient of variance values (approximately 0.5 and smaller), with the exception of one where the coefficient of value is the largest of all that were examined. The PA division consisted of "medium" to "large" coefficient of variance values (approximately 0.5 and larger). The CE division consisted of "small" to "medium" coefficient of variance values (approximately 1.0 and smaller).

Conclusions

From the results it is apparent that the overall best model in the business units examined is the exponential smoothing with a linear trend forecasting model. This conclusion is drawn from the fact that the exponential smoothing with a linear trend forecasting model was the forecasting model which resulted in the least absolute forecasting error in seven of the twelve examined business units. The exponential smoothing forecasting model is the second best forecasting model in business units examined, being the forecasting model with the least absolute error in 3 of the twelve examined business units and often the second best forecasting model to the exponential smoothing with a linear trend forecasting model. These two models often had similar results, with small differences in the model parameters. These small differences in the model parameters account for the difference in results of the two models.

The Winters method forecasting models had the lowest absolute error in two of the twelve forecasting models; however, on average, had a significantly larger absolute error than the exponential smoothing and exponential smoothing with a linear trend forecasting models. There are two possible explanations for the decline in quality of forecasts made through the Winters method forecasting models in comparison to the estimate and exponential smoothing with a linear trend forecasting models. The first possible explanation is the complexity of the model. Although the Winters forecasting model accounts for more factors than the other examined models, it is also more complex due to the increased amount of model parameters. This allows more room for error when determining model parameters. Secondly, the Winters method forecasting model explicitly calculates and updates a multiplicative seasonality factor throughout its forecasting calculation the exponential smoothing and exponential smoothing with a linear trend forecasting models use a seasonality factor, which is calculated from the first years of data and remains unchanged during the forecasting calculations. By using the multiplicative seasonality factor, which is controlled by a model parameter, the Winters method forecasting model allows room for error to be made.

Though the exponential smoothing with a linear trend forecasting model is the model with the lowest absolute error in seven of the twelve examined business units, the smoothed trend model parameter was nearly zero in most of those cases. If an exponential smoothing with a linear trend forecasting model has an associated smoothed trend model parameter of zero, the model will mimic an exponential smoothing forecasting model. Thus, it is evident that the minor differences in the model parameters often gave the exponential smoothing with a linear trend forecasting model a small increase in forecast quality over the exponential smoothing forecasting model. It must be noted that if the associated smoothed trend model parameter in an exponential smoothing with a linear trend forecasting model is very large, the forecasting results can greatly differ from the real results. This is because with a large smoothed trend model parameter, the model will forecast a large increase in sales each period, thus the forecasting model can easily over estimate the forecasts for each sales period.

Overall, the exponential smoothing with a linear trend forecasting method is the best forecasting model most often for the examined business units. The exponential smoothing with a linear trend model should be used in most cases with the exception of cases where the smoothed trend model parameter is large; in which case, the exponential smoothing model should be used. The Winters method forecasting models had much variability in the resulting forecasts of the examined business units due to complexity in the estimation of the model parameters. Thus, the Winters method, while good in theory, isn’t necessarily the best choice for forecasting in practice with the examined business units and similar products.

Appendix A: Data Modifications

Division	Item	Modification Notes
DAP	BG: 9042, BU: 0343	The zeros at the beginning of the data (first twelve weeks) were removed.
DAP	BG: 9044, BU: 0321	N/A
DAP	BG: 9044, BU: 0329	2006W28 sales data changed from -28 to 1.
DAP	BG: 9050, BU: 0331	N/A
PA	BG: 6922, BU: 1409	Year 2006, week 22 is missing and was replaced with '1' for the forecasting models.
PA	BG: 6922, BU: 1416	N/A
PA	BG: 6922, BU: 628	Year 2006, Weeks 1-5 use data that was calculated instead of actual data
PA	BG: 6922, BU: 1485	Year 2006, Weeks 1-5 use data that was calculated instead of actual data.
CE	BG: 6914, BU: 0603	Week 53 of Year 2004 was removed from data for calculations.
CE	BG: 6914, BU: 0610	Week 53 of Year 2004 was removed from data for calculations.
CE	BG: 6916, BU: 0641	Week 53 of Year 2004 was removed from data for calculations.
CE	BG: 6916, BU: 0654	Week 53 of Year 2004 was removed from data for calculations.

Appendix B: Model Parameters

Division	Item	Data Dates	Expo. Smooth	Expo. Smooth w/Trend	Winters 13-week Period	Winters 18-week Period	Winters 26-week Period	Winters 52-week Period
	BG: 9042		α = 72125262	α = 0.73308775	α = 0.69901041	α = 0.66937524	α = 0.63637703	α = 0.00646775
DAP	BU: 0343	2004W01 - 2007W52		β = 0.0000003	β = 0.0000007	β = 0.0000007	β = 0.0000007	β = 0
					γ = 0	γ = 0.010757266	γ = 0	γ = 1
	BG: 9044		α = 0.7982312	α = 0.80380971	α = 0.7401608	α = 0.73123193	α = 0.61650458	α = 0.59007494
DAP	BU: 0321	2004W01 - 2007W52		β = 0.00000523	β = 0.0000008	β = 0.00003509	β = 0.00002396	β = 0
					γ = 0	γ = 0.27292719	γ = 0	γ = 1
	BG: 9044		α = 0.91482307	α = 0.91941264	α = 0.89328264	α = 0.91829	α = 0.85390916	α = 0.72940106
DAP	BU: 0329	2004W01 - 2007W52		β = 0.00000002	β = 0.00000725	β = 0	β = 0.00001045	β = 0
					γ = 0.2222902	γ = 0	γ = 0.61862643	γ = 1
	BG: 9050		α = 0.70954701	α = 0.71327608	α = 0.71963473	α = 0.67046220	α = 0.70234129	α = 0.47405075
DAP	BU: 0331	2004W01 - 2007W52		β = 0.00000012	β = 0.00000379	β = 0	β = 0	β = 0
					γ = 0.02361246	γ = 0.12590545	γ = 0	γ = 0
	BG: 6922		α = 0.4874798	α = 0.47915901	α = 0.44255813	α = 0.2902392	α = 0.38925946	α = 0.33543961
PA	BU: 1409	2006W11 - 2007W52		β = 0	β = 0	β = 0	β = 0	β = 0
					γ = 0.66509273	γ = 0.55925562	γ = 1	γ = 0.41493875
	BG: 6922		α = 0.80549559	α = 0.81727297	α = 0.81339417	α = 0.8025641	α = 0.79650439	α = 0.51748708
PA	BU: 1416	2006W11 - 2007W52		β = 0	β = 0	β = 0	β = 0	β = 0
					γ = 0.1434142	γ = 0.09208897	γ = 0.13616472	γ = 0.79328733
	BG: 6922		α = 0.45948432	α = 0.45087688	α = 0.44953452	α = 0.46300289	α = 0.3814008	α = 0.18369711
PA	BU: 628	2005W01 - 2007W52		β = 0	β = 0.00067028	β = 0	β = 0	β = 0
					γ = 0.26865336	γ = 0.25951488	γ = 1	γ = 0.43204167
	BG: 6922		α = 0.90635172	α = 0.95398657	α = 0.85398657	α = 0.89396976	α = 0.88556641	α = 0.89479211
PA	BU: 1485	2005W01 - 2007W52		β = 0.00002769	β = 0.00017456	β = 0.00005926	β = 0	β = 0
					γ = 1	γ = 0	γ = 0	γ = 0
	BG: 6914		α = 0.57420164	α = 0.558356207	α = 0.5267661	α = 0.54363054	α = 0.47939267	α = 0.31516784
CE	BU: 0603	2004W01 - 2007W52		β = 0.00000508	β = 0	β = 0.00001289	β = 0.00004153	β = 0
					γ = 0	γ = 0.04994867	γ = 0.06623176	γ = 0
	BG: 6914		α = 0.28887911	α = 0.29361216	α = 0.2804814	α = 0.26382129	α = 0.2261859	α = 0.04512578
CE	BU: 0610	2004W01 - 2007W52		β = 0.01294252	β = 0.01345443	β = 0	β = 0	β = 1
					γ = 0.24776887	γ = 0.24713891	γ = 0.46821469	γ = 1
	BG: 6916		α = 0.72077068	α = 0.72897076	α = 0.65899967	α = 0.70461353	α = 0.54514565	α = 0.07369705
CE	BU: 0641	2004W01 - 2007W52		β = 0	β = 0.00003499	β = 0.00001351	β = 0.00005182	β = 0.00235265
					γ = 0.08295784	γ = 0.0866416	γ = 0.09483562	γ = 0.0743526
	BG: 6916		α = 0.39503709	α = 0.40304435	α = 0.38848137	α = 0.37777762	α = 0.35972126	α = 0.25431207
CE	BU: 0654	2004W01 - 2007W52		β = 0	β = 0	β = 0.00000732	β = 0	β = 0
					γ = 0	γ = 0.01414339	γ = 0	γ = 0

Appendix C: Average Absolute Error for First 13 Weeks

Division	Item	Expo. Smoothing	Expo. Smoothing with Trend	Winters 13-week Period	Winters 18-week Period	Winters 26-week Period	Winters 52-week Period	Best Model
DAP	BG: 9042, BU: 0343	0.681928786	0.682034582	2.657241731	2.658394445	2.674388136	0.530861719	Winters 52-week Period
DAP	BG: 9044, BU: 0321	0.084475485	0.082314035	0.106862995	0.103703835	0.106274056	0.102827301	Expo. Smoothing w/Trend
DAP	BG: 9044, BU: 0329	0.908443297	0.910393746	3.970671896	3.965796357	4.003479308	6.399797471	Expo. Smoothing
DAP	BG: 9050, BU: 0331	0.119023963	0.115679225	0.124149693	0.121923061	0.124110245	0.121890165	Expo. Smoothing w/Trend
Division	Item							Best Model
PA	BG: 6922, BU: 1409	1.102459695	1.049083627	3.767276626	3.435535418	3.671578262	3.554621167	Expo. Smoothing w/Trend
PA	BG: 6922, BU: 1416	0.341827575	0.340756241	0.180653674	0.180437523	0.180326698	0.187307134	Winters 26-week Period
PA	BG: 6922, BU: 628	0.226519319	0.212035904	0.222345938	0.222186653	0.260259421	0.282731742	Expo. Smoothing w/Trend
PA	BG: 6922, BU: 1485	0.569060839	0.569717115	0.572989241	0.570375435	0.570203024	0.569572266	Expo. Smoothing
Division	Item							Best Model
CE	BG: 6914, BU: 0603	0.448506227	0.450864592	0.607494715	0.60281074	0.604463912	0.626228748	Expo. Smoothing
CE	BG: 6914, BU: 0610	0.262243545	0.228173885	0.335879085	0.318121584	0.332939131	5.708639445	Expo. Smoothing w/Trend
CE	BG: 6916, BU: 0641	0.210890243	0.207588543	0.225410591	0.226296105	0.223475507	0.269384075	Expo. Smoothing w/Trend
CE	BG: 6916, BU: 0654	0.732561429	0.72949583	0.850826756	0.844325401	0.84870705	0.837306754	Expo. Smoothing w/Trend

Appendix D: Average Absolute Error for First 26 Weeks

Division	Item	Expo. Smoothing	Expo. Smoothing with Trend	Winters 13-week Period	Winters 18-week Period	Winters 26-week Period	Winters 52-week Period	Best Model
DAP	BG: 9042, BU: 0343	0.875410879	0.878871829	2.973545368	2.972633951	2.982366109	0.55297612	Winters 52-week Period
DAP	BG: 9044, BU: 0321	0.107231995	0.105536501	0.129575119	0.126031884	0.128568767	0.121046361	Expo. Smoothing w/Trend
DAP	BG: 9044, BU: 0329	1.460850812	1.463395628	24.55237168	24.49184791	24.67906589	30.68507111	Expo. Smoothing
DAP	BG: 9050, BU: 0331	0.132133385	0.128458558	0.144434417	0.141925063	0.144453084	0.142231451	Expo. Smoothing w/Trend
Division	Item							Best Model
PA	BG: 6922, BU: 1409	0.926894008	0.896347802	3.712563763	3.482425592	3.650481188	3.570161442	Expo. Smoothing w/Trend
PA	BG: 6922, BU: 1416	0.676105241	0.675603409	0.228924014	0.2290211	0.229083001	0.244314081	Winters 26-week Period
PA	BG: 6922, BU: 628	0.28598824	0.275553546	0.287717041	0.287460477	0.324756845	0.33974094	Expo. Smoothing w/Trend
PA	BG: 6922, BU: 1485	1.12697448	1.128873435	1.133935633	1.129484655	1.12828465	1.127588982	Expo. Smoothing
Division	Item							Best Model
CE	BG: 6914, BU: 0603	0.408332266	0.411689234	0.776683126	0.772316937	0.773202572	0.790976002	Expo. Smoothing
CE	BG: 6914, BU: 0610	0.273486249	0.252798598	0.398673467	0.368343909	0.388481094	8.746061952	Expo. Smoothing w/Trend
CE	BG: 6916, BU: 0641	0.237746012	0.235917447	0.237020223	0.238358978	0.233485393	0.281778516	Expo. Smoothing w/Trend
CE	BG: 6916, BU: 0654	0.962039638	0.96441254	0.934496813	0.928242486	0.93144682	0.915494491	Expo. Smoothing w/Trend

Appendix E: Average Absolute Error of the first 13 weeks and first 26 weeks

Division	Item	Expo. Smoothing	Expo. Smoothing with Trend	Winters 13-week Period	Winters 18-week Period	Winters 26-week Period	Winters 52-week Period	Best Model
DAP	BG: 9042, BU: 0343	0.778669832	0.780453206	2.815393549	2.815514198	2.828377122	0.54191892	Winters 52-week Period
DAP	BG: 9044, BU: 0321	0.09585374	0.093925268	0.118219057	0.11486786	0.117421411	0.111936831	Expo. Smoothing w/Trend
DAP	BG: 9044, BU: 0329	1.184647055	1.186894687	14.26152179	14.22882213	14.3412726	18.54243429	Expo. Smoothing
DAP	BG: 9050, BU: 0331	0.125578674	0.122068891	0.134292055	0.131924062	0.134281664	0.132060808	Expo. Smoothing w/Trend

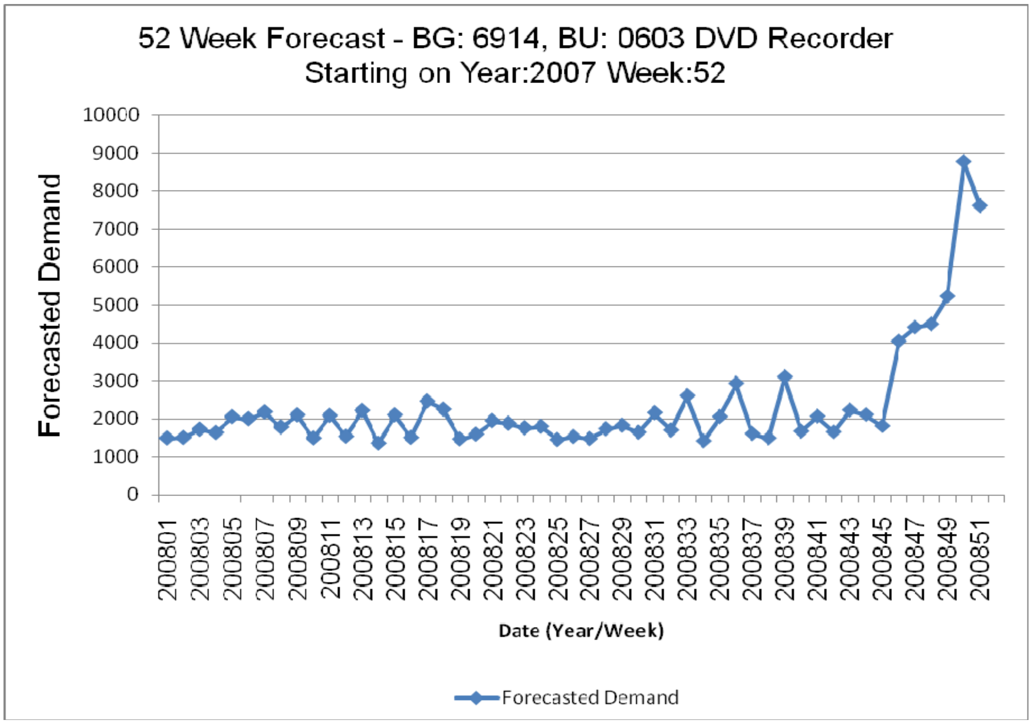
Division	Item	Expo. Smoothing	Expo. Smoothing with Trend	Winter's 13-week Period	Winter's 18-week Period	Winter's 26-week Period	Winter's 52-week Period	Best Model
PA	BG: 6922, BU: 1409	1.014676851	0.972715714	3.739920195	3.458980505	3.661029725	3.562391304	Expo. Smoothing w/Trend
PA	BG: 6922, BU: 1416	0.508966408	0.508179825	0.204788844	0.204729312	0.204704849	0.215810608	Winters 26-week Period
PA	BG: 6922, BU: 628	0.256253779	0.243794725	0.255031489	0.254823565	0.292508133	0.311236341	Expo. Smoothing w/Trend
PA	BG: 6922, BU: 1485	0.848017659	0.849295275	0.853462437	0.849930045	0.849243837	0.848580624	Expo. Smoothing

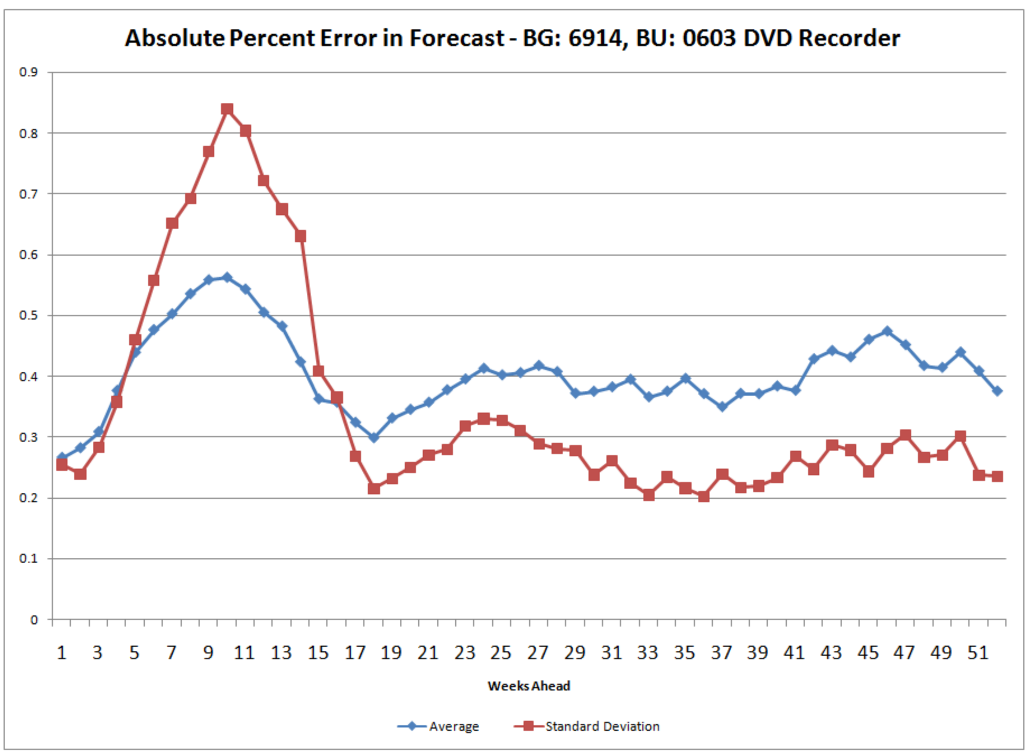
Division	Item	Expo. Smoothing	Expo. Smoothing with Trend	Winter's 13-week Period	Winter's 18-week Period	Winter's 26-week Period	Winter's 52-week Period	Best Model
CE	BG: 6914, BU: 0603	0.428419246	0.431276913	0.69208892	0.687563838	0.688833242	0.708602375	Expo. Smoothing
CE	BG: 6914, BU: 0610	0.267864897	0.240486241	0.367276276	0.343232747	0.360710112	7.227350699	Expo. Smoothing w/Trend
CE	BG: 6916, BU: 0641	0.224318127	0.221752995	0.231215407	0.232327541	0.22848045	0.275581295	Expo. Smoothing w/Trend
CE	BG: 6916, BU: 0654	0.847300534	0.846954185	0.892661785	0.886283944	0.890076935	0.876400623	Expo. Smoothing w/Trend

Appendix F: Coefficient of variance and best absolute

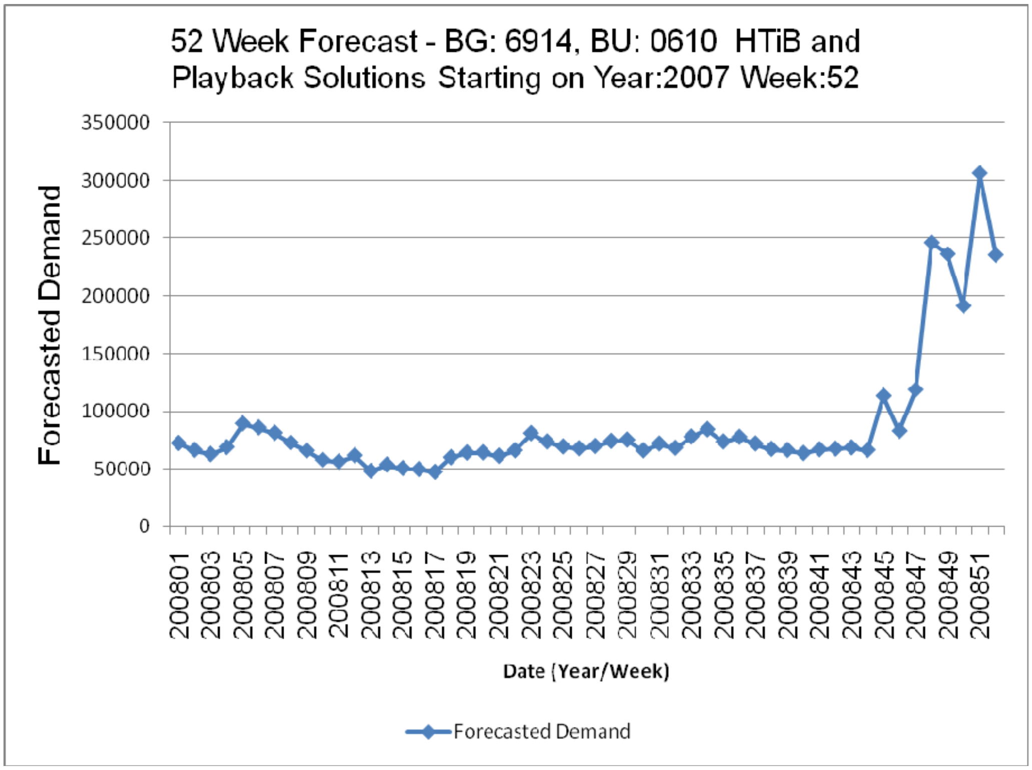
Buisness Group and Unit	Division	Coefficient of Variance	Best Absolute Error	Best Model
BG: 9044, BU: 0321 Shaving & Grooming	DAP	0.248317052	0.093925268	Expo. Smoothing w/Trend
BG: 9044, BU: 0329 Shaving Accessories	DAP	1.498229526	1.184647055	Expo. Smoothing
BG: 9050, BU: 0331 Sonicare Oral Health	DAP	0.29465262	0.122068891	Expo. Smoothing w/Trend
BG: 9042, BU: 0343 Senseo	DAP	0.477522854	0.54191892	Winters 52-week Period
BG: 6922, BU: 628 Home Control	PA	0.556716933	0.243794725	Expo. Smoothing w/Trend
BG: 6922, BU: 1409 PC Peripherals	PA	0.909589915	0.972715714	Expo. Smoothing w/Trend
BG: 6922, BU: 1416 Audio Video Communication	PA	0.74203453	0.204704849	Winters 26-week Period
BG: 6922 BU: 1485 Mobility	PA	1.332389975	0.848017659	Expo. Smoothing
BG: 6914, BU: 0603 DVD Recorder	CE	0.369067551	0.428419246	Expo. Smoothing
BG: 6914, BU: 0610 HTiB and Playback Solutions	CE	0.506081401	0.240486241	Expo. Smoothing w/Trend
BG: 6916, BU: 0641 Mainstream Audio & Multimedia	CE	0.172947054	0.221752995	Expo. Smoothing w/Trend
BG: 6916, BU: 0654 Personal Audio & Multimedia	CE	0.743114807	0.846954185	Expo. Smoothing w/Trend

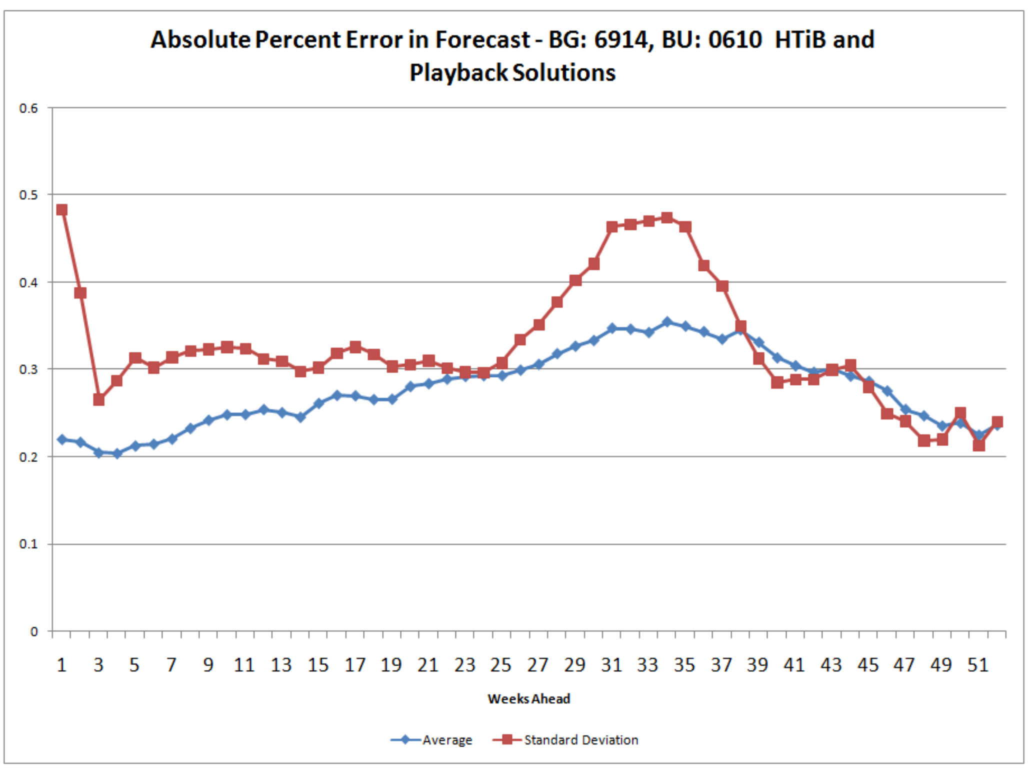
Appendix G: Best Forecast Model for BG: 6914, BU: 0603 (Exponential Smoothing)



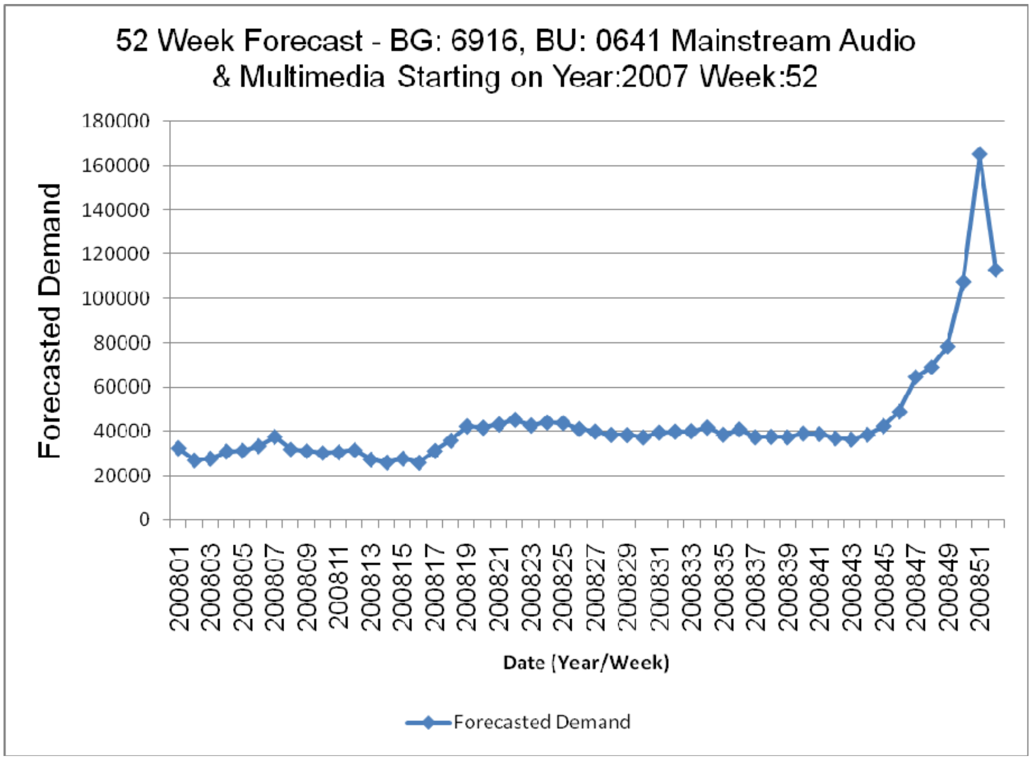


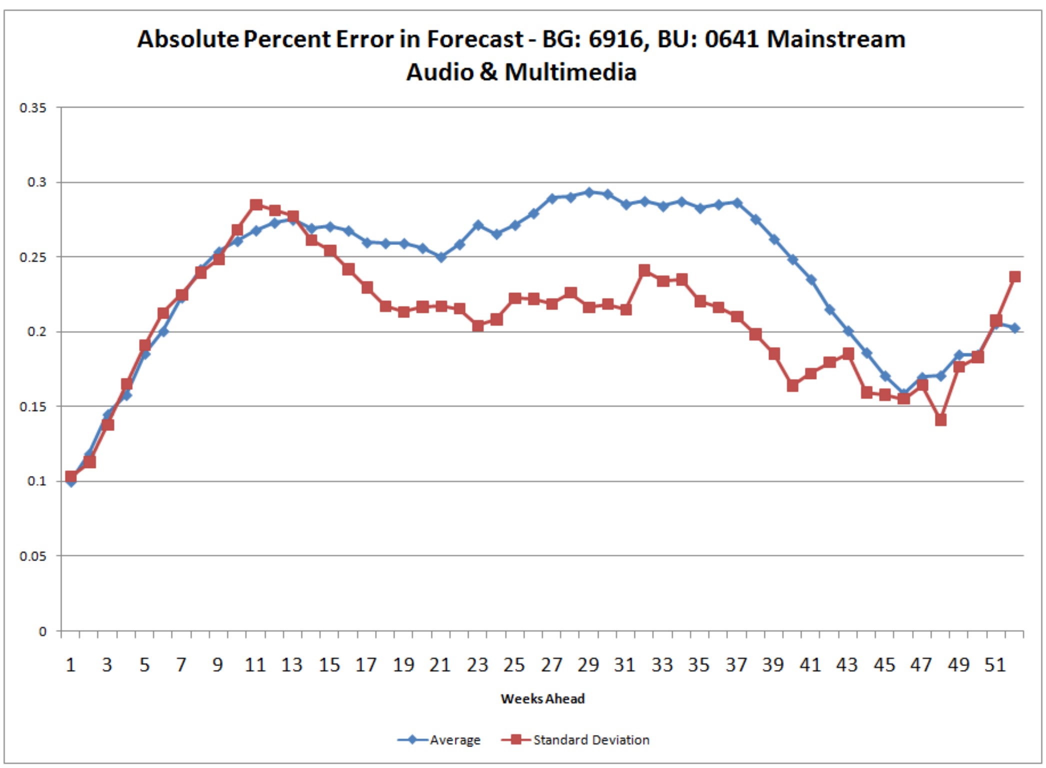
Appendix H: Best Forecast Model for BG: 6914, BU: 0610 (Exponential Smoothing with a Linear Trend)



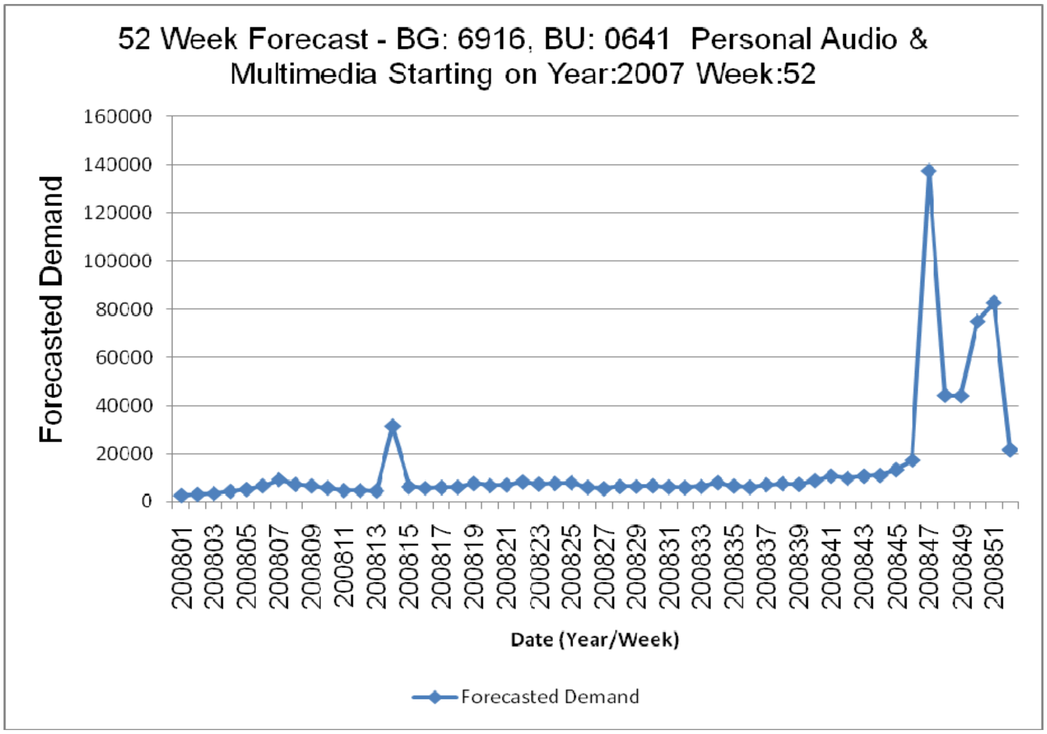


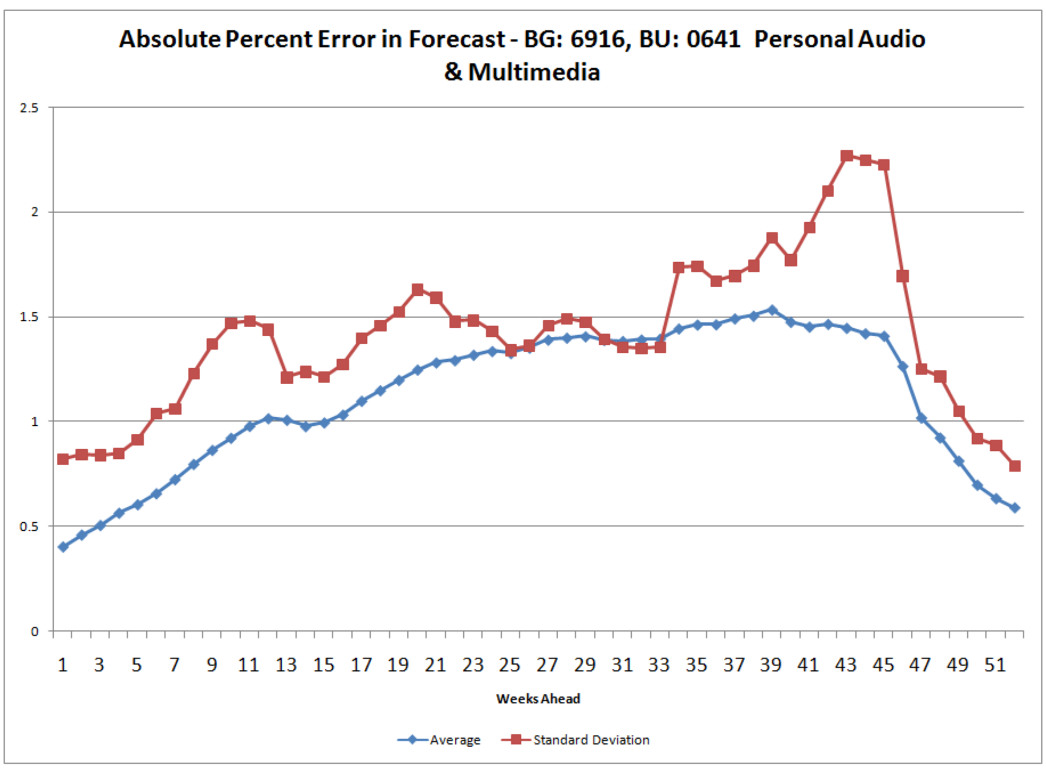
Appendix I: Best Forecast Model for BG: 6916, BU: 0641 (Exponential Smoothing with a Linear Trend)



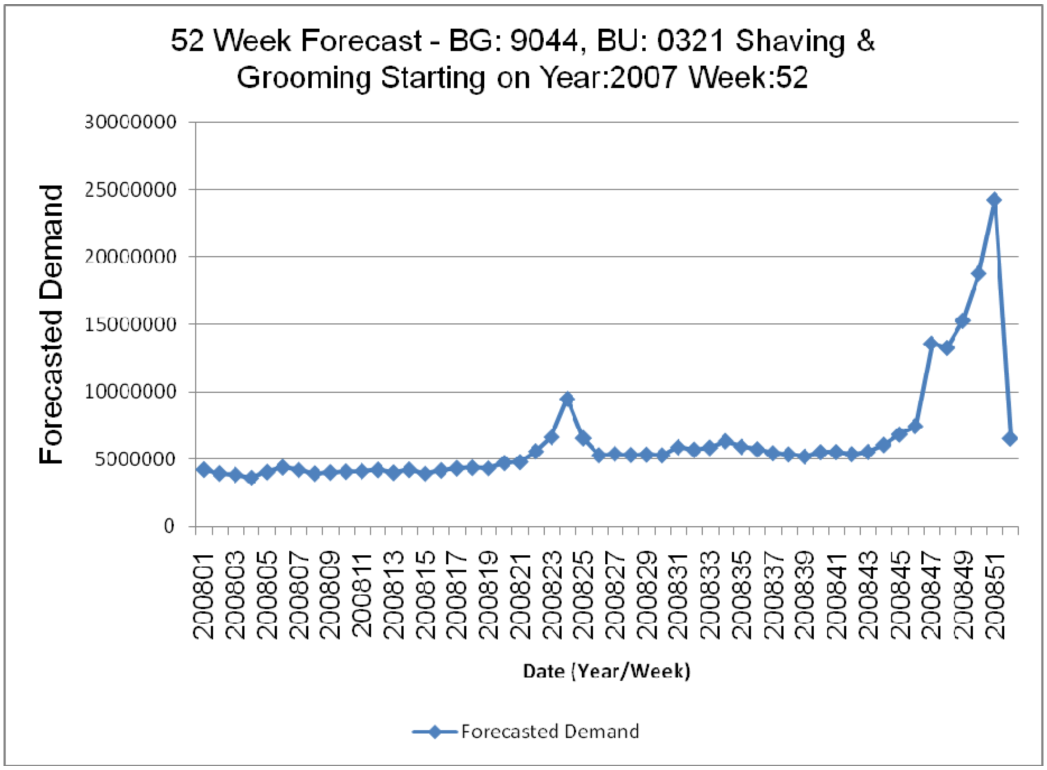


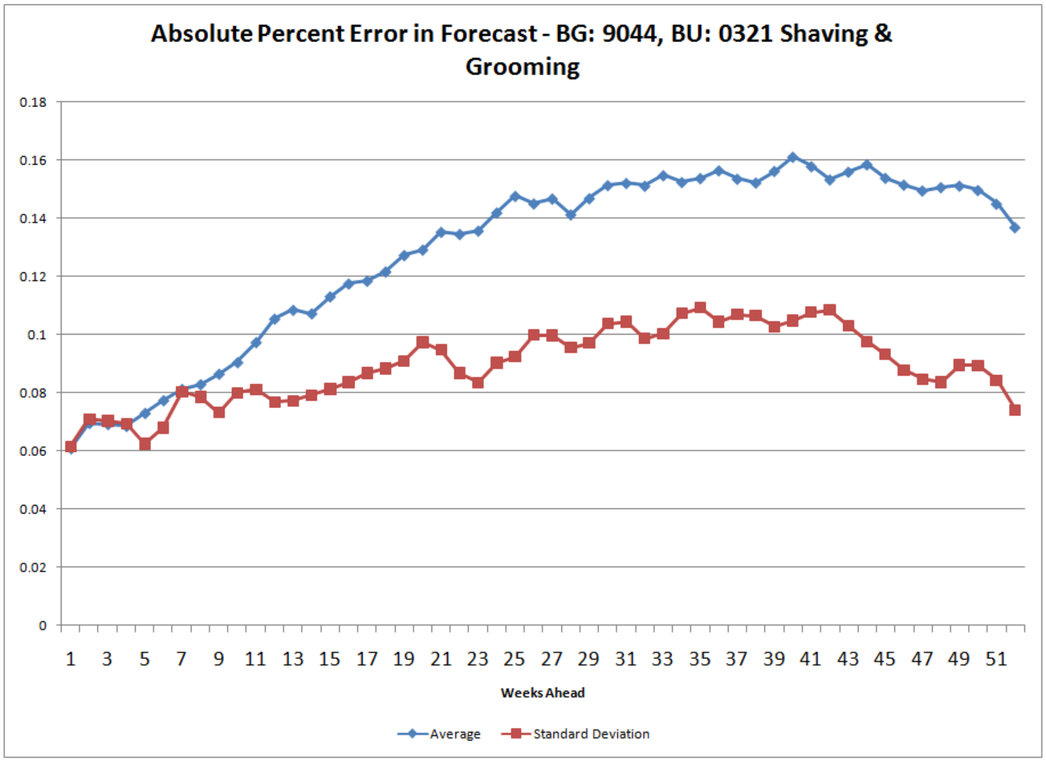
Appendix J: Best Forecast Model for BG: 6916, BU: 0654 (Exponential Smoothing with a Linear Trend)





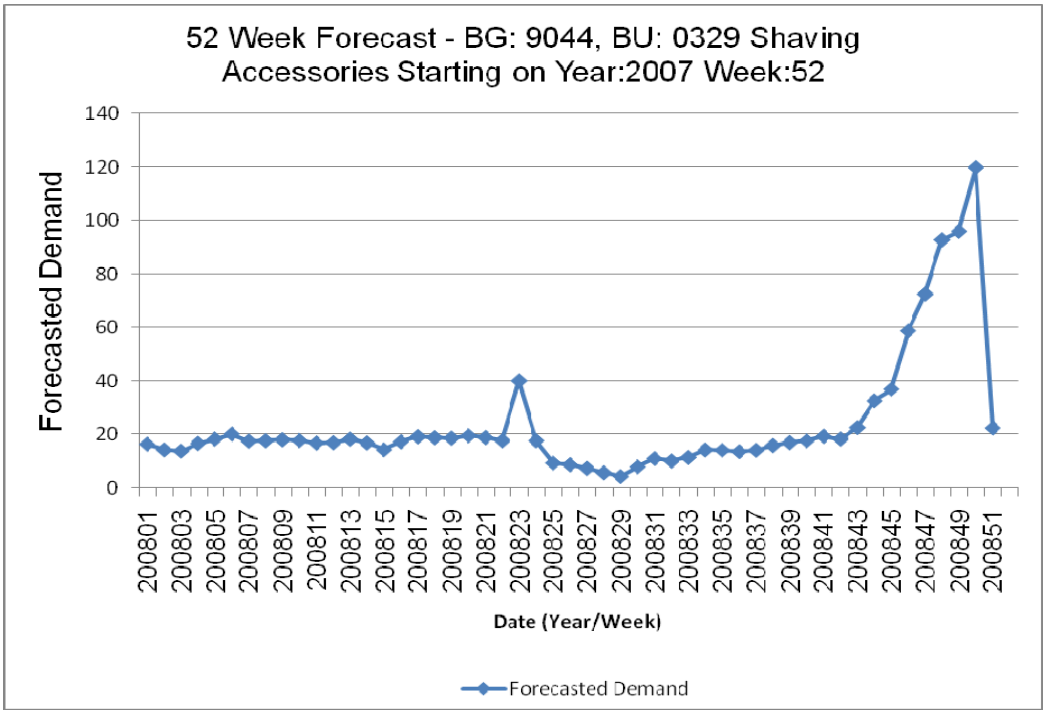
Appendix K: Best Forecast Model for BG: 9044, BU: 0321 (Exponential Smoothing with a Linear Trend)

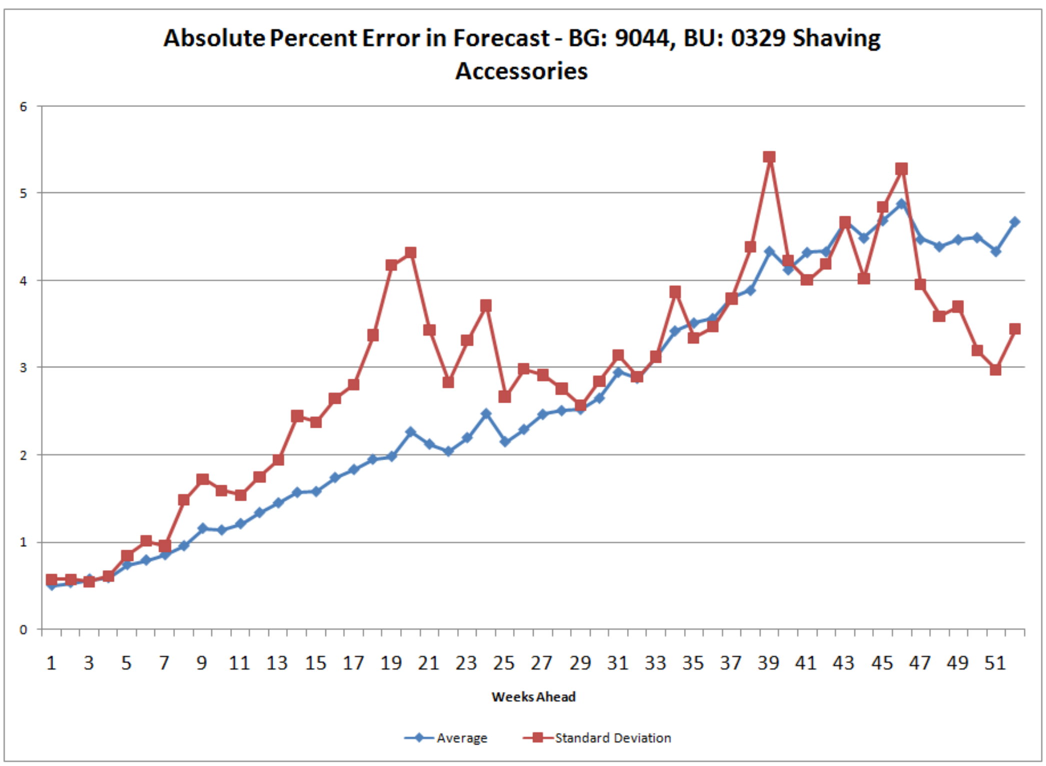




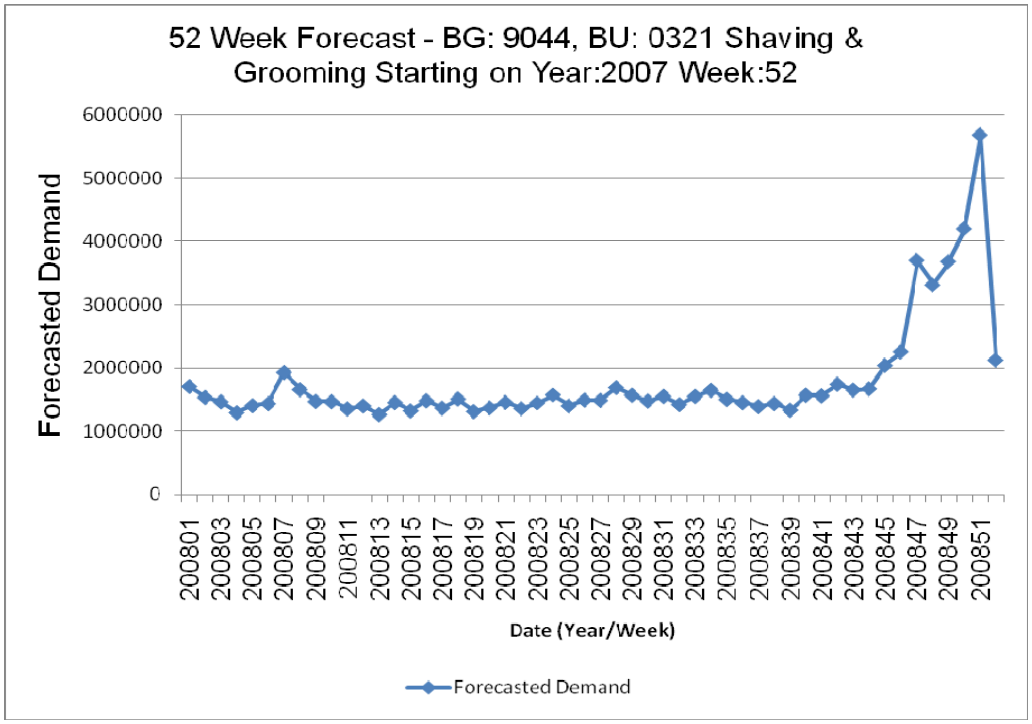
Absolute Percent Error in Forecast - BG: 9044, BU: 0321 Shaving & Grooming
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51
Weeks Ahead
Average
Standard Deviation

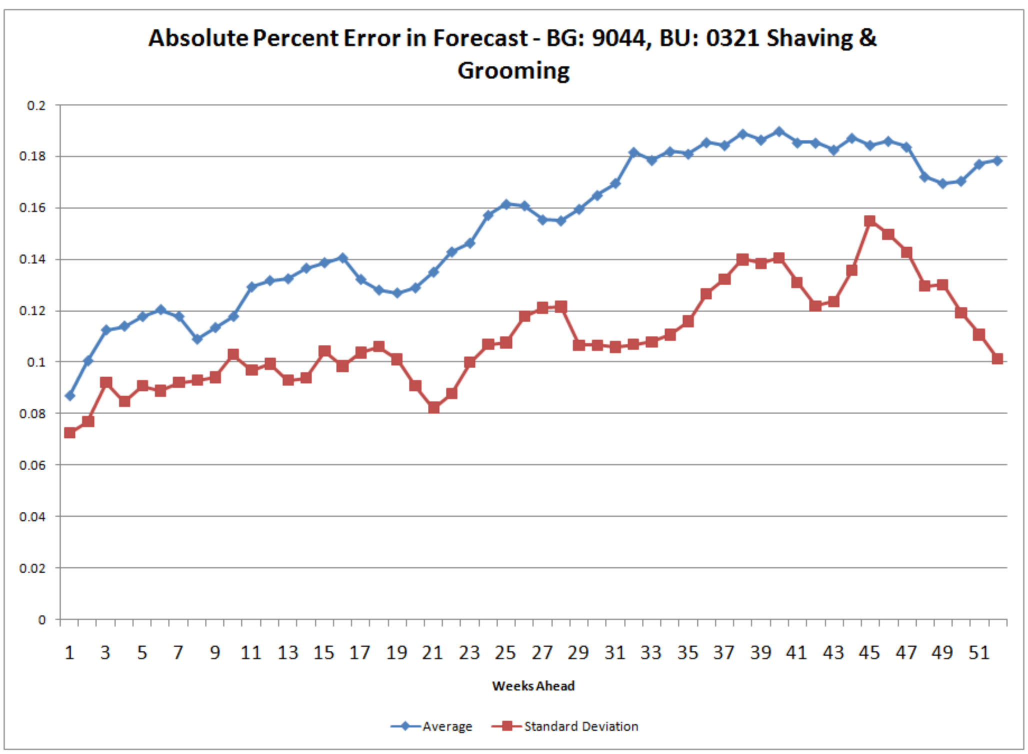
Appendix L: Best Forecast Model for BG: 9044, BU: 0329 (Exponential Smoothing)



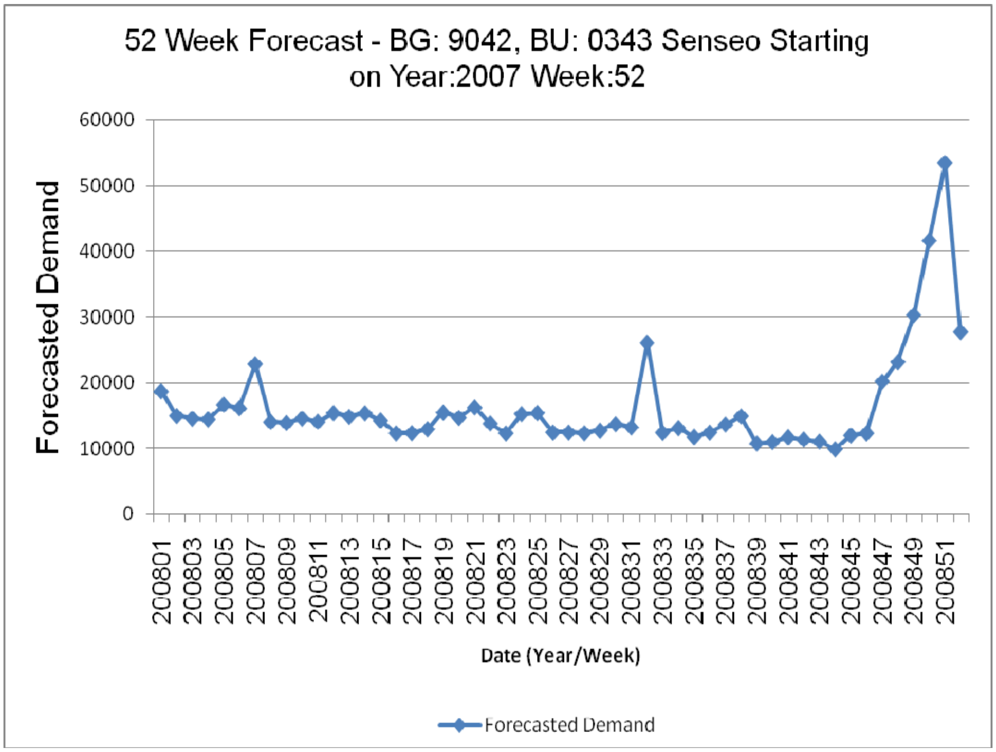


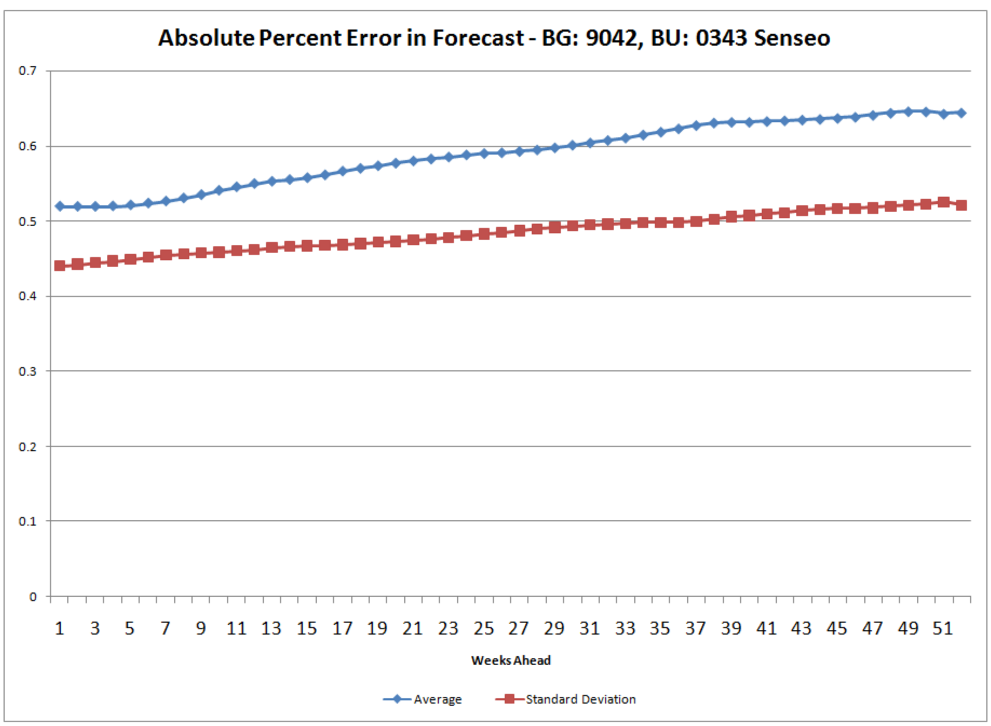
Appendix M: Best Forecast Model for BG: 9050, BU: 0331 (Exponential Smoothing with a Linear Trend)



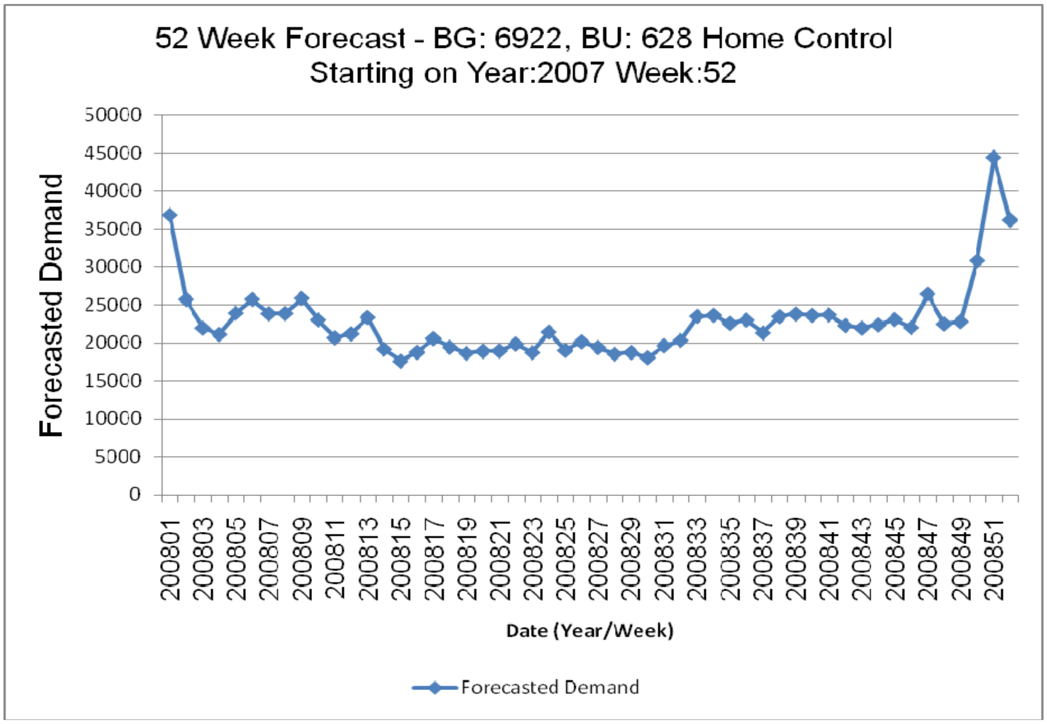


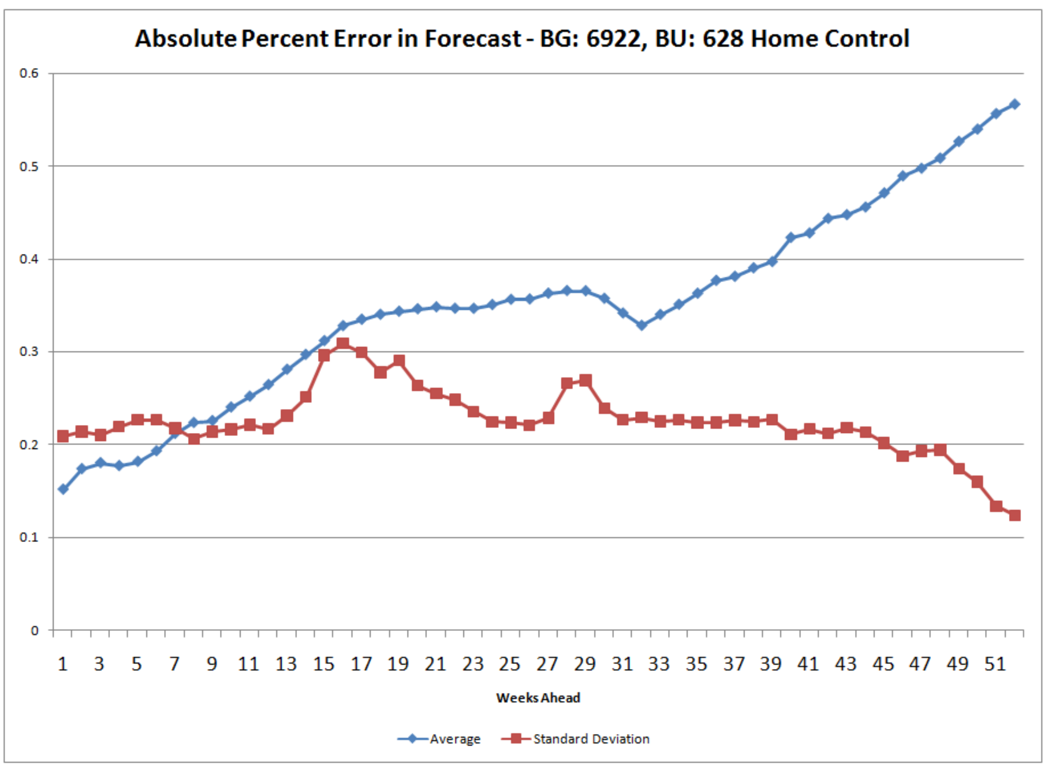
Appendix N: Best Forecast Model for BG: 9042, BU: 0343 (Winters Method with 52-Week Period)



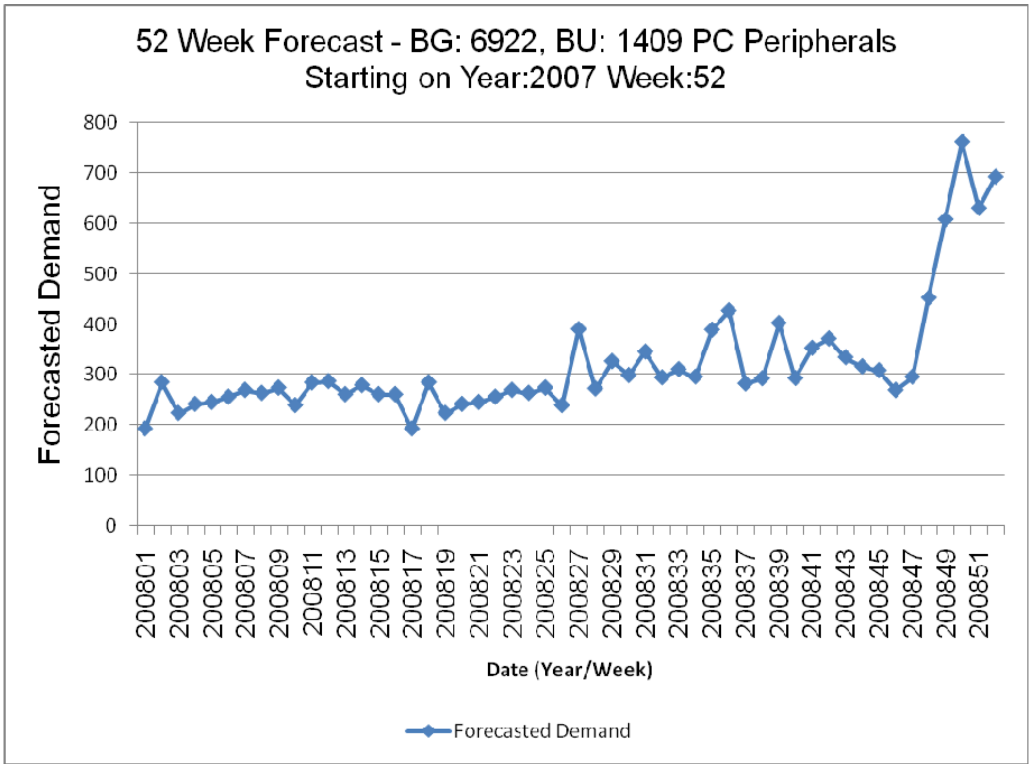


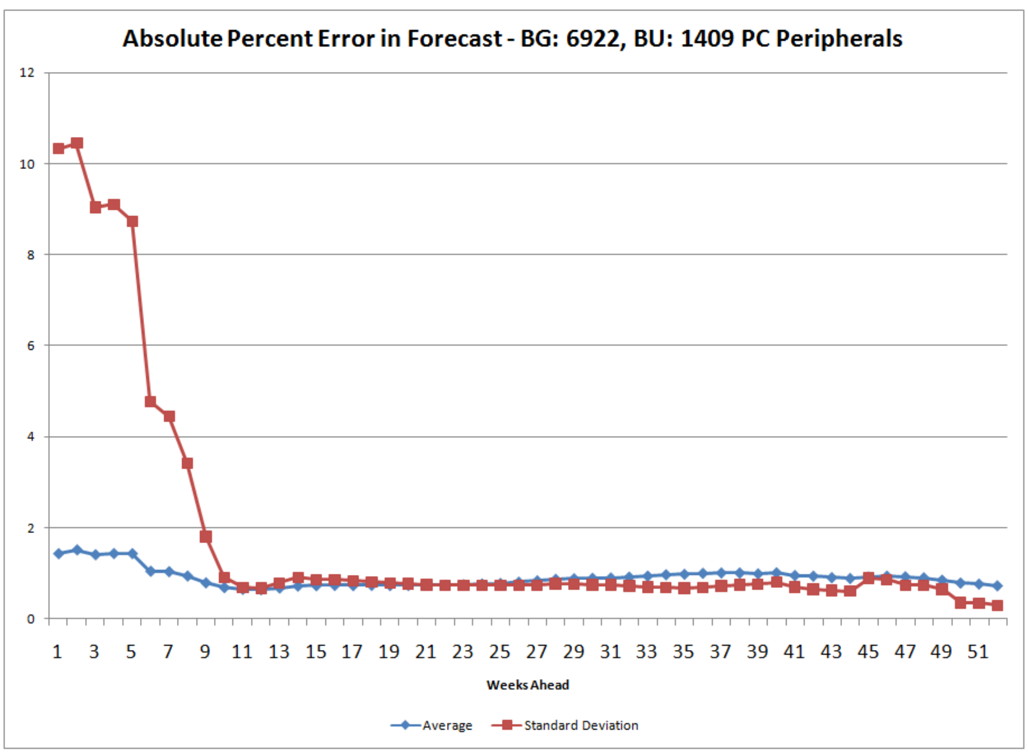
Appendix O: Best Forecast Model for BG: 6922, BU: 628 (Exponential Smoothing with a Linear Trend)



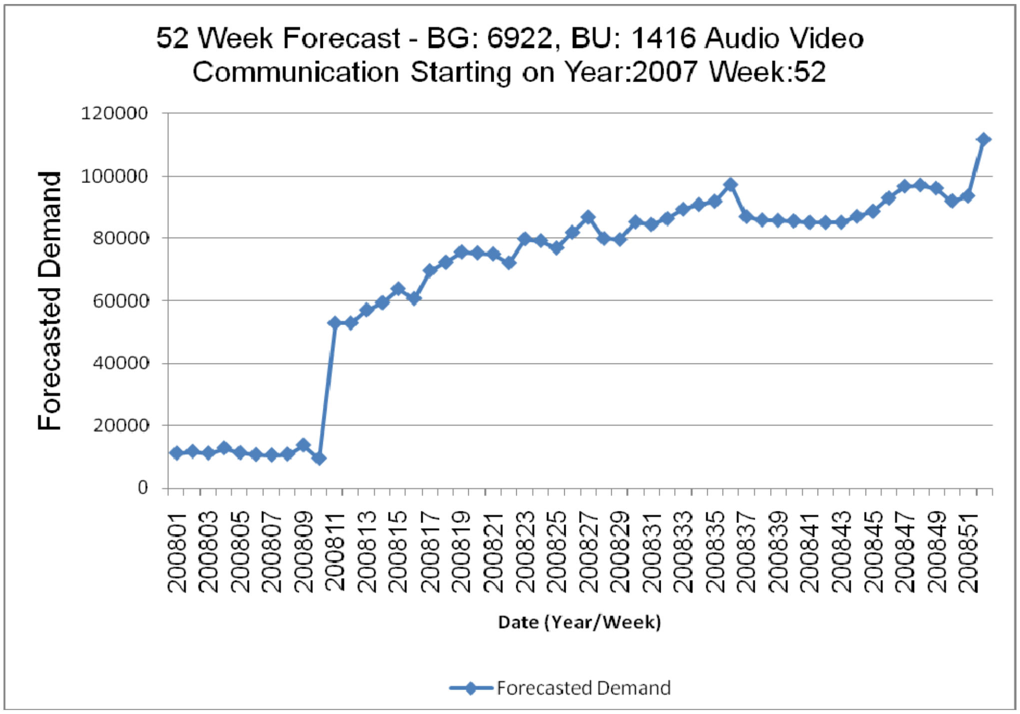


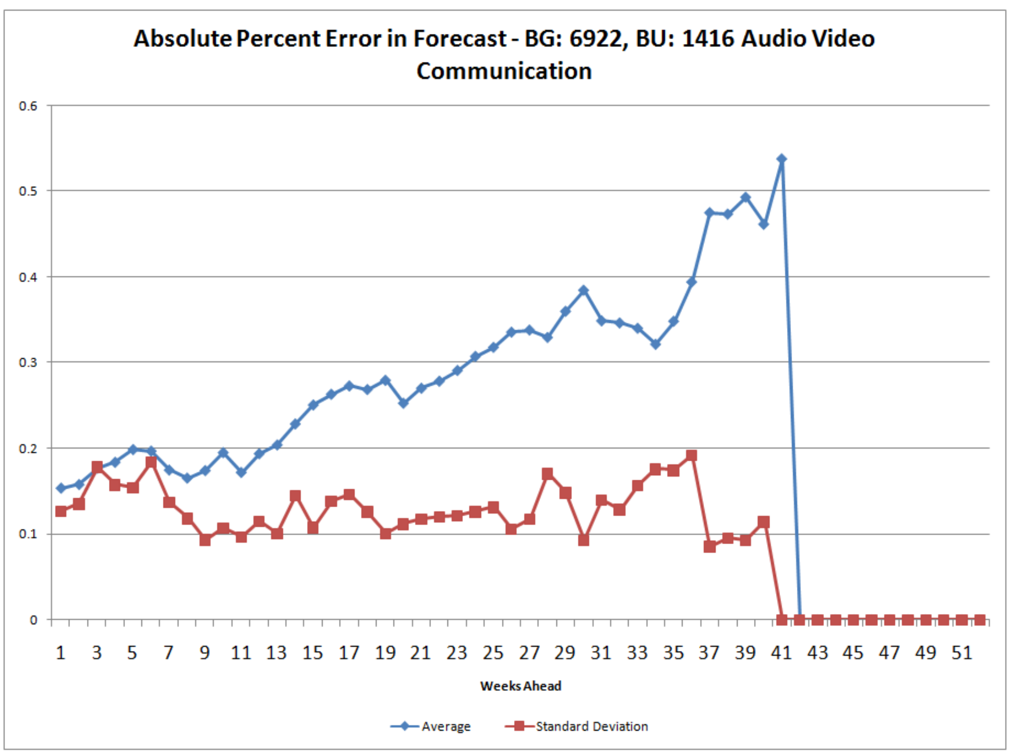
Appendix P: Best Forecast Model for BG: 6922, BU: 1409 (Exponential Smoothing with a Linear Trend)



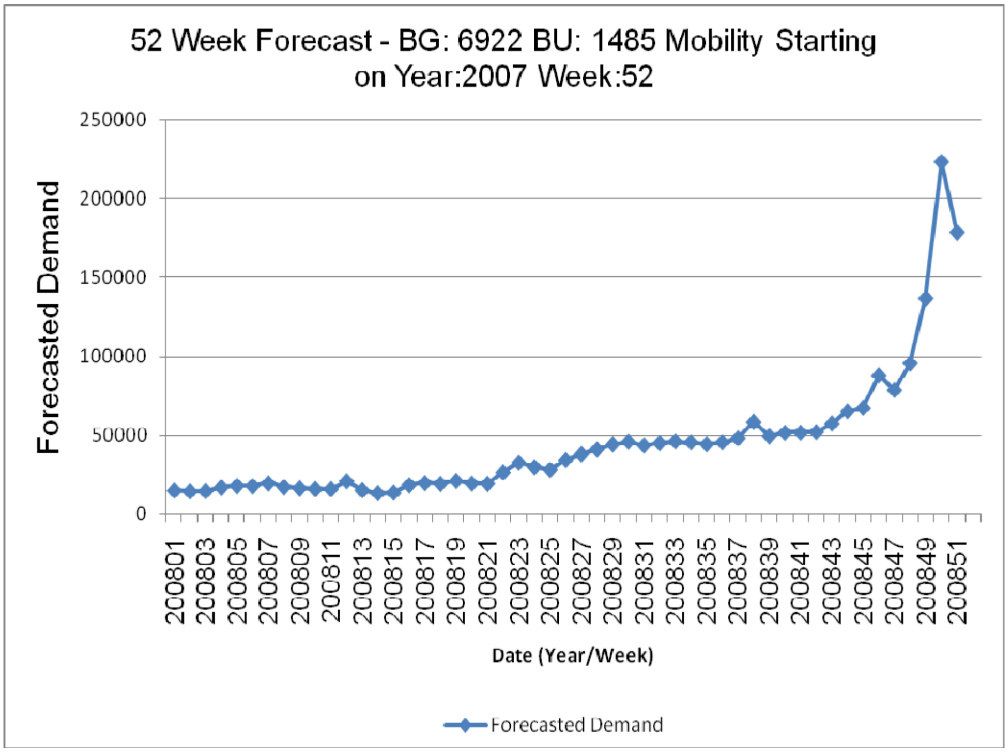


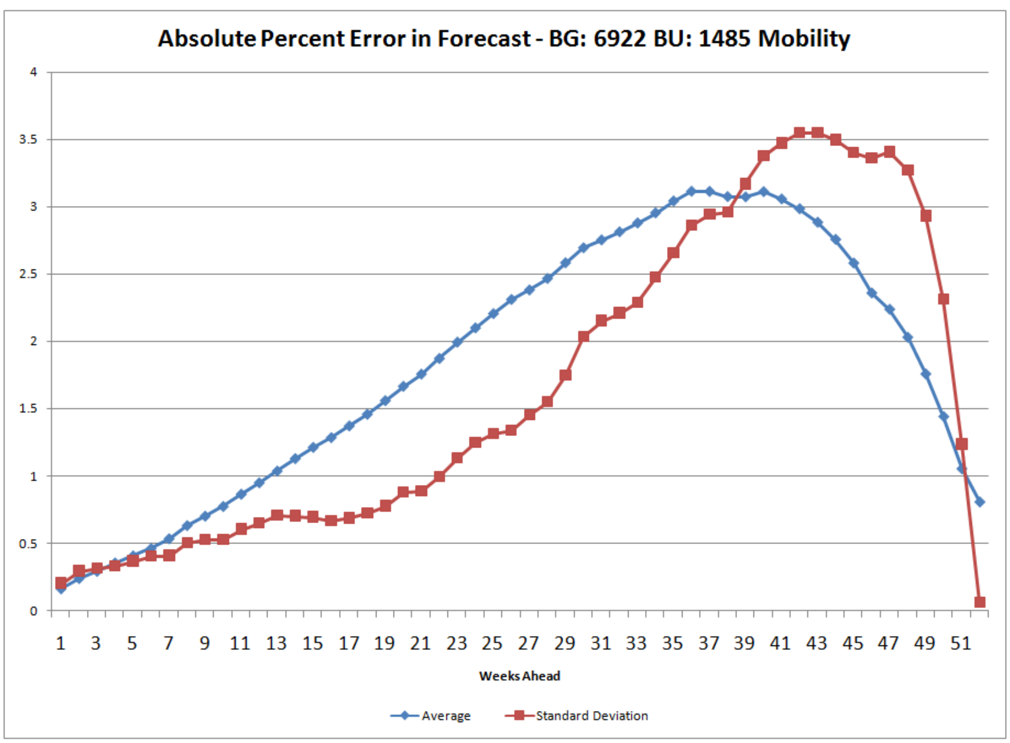
Appendix Q: Best Forecast Model for BG: 6922, BU: 1416 (Winters Method with 26-Week Period)





Appendix R: Best Forecast Model for BG: 6922, BU: 1485 (Exponential Smoothing)





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