

Universidad Popular Autónoma del Estado de Puebla



Demand Forecasting at Renfro Corporation

Empirical work of Mexico presented to obtain:

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ABSTRACT

In the current context of the economy where the market place is volatile and dynamic, the basic operations process, moving from the supplier's raw material to finished good to the customer's hands takes time. Companies can no longer simply wait for demand to occur and then react to it with the right product at the right place at the right time. Instead, they must sense demand signals and shape future demand in anticipation of customer behavior so they can react immediately to customer orders. This paper seeks to demonstrate that modeling forecasting has effects over Renfro's Corporation top seventeen styles forecast accuracy and because of that, performs better than the naïve forecast. Using the Holt-Winters and the Box Jenkins methods to forecast 7 months in advance taking in consideration Shipments data and in few cases POS data from February fiscal year 2011 to June Fiscal Year 2015, We estimate the accuracy on both the modeling and the naïve method versus the actual values from July FY15 to January FY16. The most important results are the following ones: 1.- The modeling forecast perform 4 times better than the naïve forecast; 2.-The modeling forecast has effect over the company forecast accuracy; 3.-The modeling forecast help on saving around \$ 289,930.30 USD FY15 from June 2015 to January 2016. This indicates that the modeling forecast performed much better than the naïve forecast for the empirical case of Renfro Mexico.

Key words: forecast, Renfro, Mexico, sales, accuracy, performance, point of sale, shipments, naïve.

CHAPTER 1

Introduction

Companies are using advance analytics, to sense demand signals associated with consumer behavior patterns and shape future demand using predictive analytics and data mining technology.

Demand forecast accuracy improvement drives reduction in safety stock, inventory days on hand, storage cost, freight cost and last but not least improves customer service but also predicting future demand determines the quantities of raw materials, amount of finished goods inventories, number of products that need to be shipped, number of people to hire, number of plants to build, right down the number of office supplies that should be purchased.

Forecasting provides a valuable input to different areas of the company; some of the most important according with Dr Iris Yeung (professor at City University of Hong Kong) are marketing: where the forecast provides promotional investment for coming periods, human resources: where the forecast can provide the number of workers, recruiting and training required in order accomplish goals, operations: where predictions of demand for each product can provide specific weeks and months production schedules and inventory maintenance and finally finance: where the forecast can provide in advance gross sales, margins, revenue and new capital acquisitions at predicted rates.

Demand forecasters are fundamental to drive performance improvement in the company, their models can capture the relationships and influences of factors other than trend and seasonality, such as price, advertising, sales promotions, marketing events, and economic information. According to Michael Gilliland (author of *The Business Forecasting Deal*) a good forecast of demand, far enough into the future, allows an organization to invest only in the facilities, equipment, materials, and staffing that it needs to profitably fulfill that demand.

CHAPTER 2

2. Research objectives

2.1 General objective:

Improve the forecast accuracy at Renfro Mexico identifying the best forecast methods for the Mexican socks Market.

2.2 Specific objective:

I. Measure the forecast improvement for the top 17 SKU between the old forecast methods versus the new applied methods from July fiscal year 2015 to January fiscal year 2016.

CHAPTER 3

3. Hypothesis

Based on the theoretical Framework, the hypothesis proposed for this research are:

H0: Modeling forecasting process has no effect over the company forecast accuracy.

H1: Modeling forecasting process has effect over the company forecast accuracy.

CHAPTER 4

4. Feasibility of the research

It is planned to analyze the top seller 17 SKU's which represents than 49% of the annual FY14 sales volume.

For the time series data shipments data will be used and it will be obtained from QlikView internal Renfro Corp software that stores the company data based in the mainframe system.

Finally the old forecasting methods will be comparing with the ones purpose in this analysis to identify the room for improvement and measure how this new forecasting methods impact the company results.

CHAPTER 5

5. Theoretical framework

5.1 Demand forecast

5.1.1 Definitions

A forecast is a series of time – phased plans carefully architected in a data model of products, calendars, channels, and regions. C.W. Chase Jr., (2013).

Forecasting is about predicting the future as accurately as possible, given all of the information available, including historical data and knowledge of any future events that might impact the forecast. R.J. Hyndman., (2014)

Forecasting is often perceived as having the sole function of delivering a single number for the organization to manage operations and financial planning, so the organization can make better financial plans, manage asset planning more effectively, plan spending behavior more wisely, and work within a range of probabilities, which makes actual performance more predictable. M. Covas, (2014)

Demand Forecast is an unbiased prediction or estimate of actual demand value at future time. L, J. Chaman, & J. Malehorn, (2012)

5.2 Types of forecasting

There are two different forecasting methods according with Dr. Jain L. Chaman, (Author “Fundamentals of demand planning & forecasting”, 2012) the Qualitative Methods and the Quantitative Methods.

5.2.1 Qualitative methods

According to studies by Institute of Business and Forecasting (2010) seventeen percent of the companies use qualitative methods to manage their sales predictions, these

methods include: decision trees, sales force estimates, executive opinion, surveys & market research.

The qualitative methods also known as “Judgmental” methods are usually used when historical data is not available and generally are based on an expert opinion to predict future events.

5.2.1.1 Disadvantages

One of the most common disadvantages of the qualitative methods according to Iris Yeung (2001) is that this kind of methods are always subjective and are based on an expert opinion or in many other cases are based on the sales force beliefs and convenience.

5.2.1.2 Advantages

This method is very useful when historical data is not available and can be used when there is not enough quantitative expertise due to that no mathematical background is required, also has the advantage of being a low cost method comparing it with the quantitative ones according to Lawless Mark (2014).

5.2.2 Quantitative methods

The quantitative methods are commonly used when historical data are available and according with the Institute of Forecasting Studies (2010) seventy percent of the companies use this kind of methods; out of this seventy percent exist fifty-three percent that use time series methods like: trend, moving average, filter, smoothing, decomposition, naïve and ARIMA; and seventeen percent use cause & effect methods like: regressions, econometrics and neural network. Many companies do not use quantitative methods because they do not have enough quantitative expertise and/or resources.

According to Mark Lawless (2014), the amount of data to be used in preparing a forecast varies from product to product and from industry to industry and models should be periodically re-evaluated to ensure accuracy.

We must remember that sophisticated models are not necessarily better than simple models and that models that fit historical data well does not always give the best forecast.

5.2.2.1 Disadvantages

This kind of models need extensive data to work properly and also modeling expertise, both of these inputs are expensive for the company if accuracy is not enough according with the company and industry requirements. (Iris Yeung, 2001)

We must remember that sophisticated models are not necessarily better than simple models and that models that fit historical data well does not always give the best forecast.

5.2.2.2 Advantages

Some of the quantitative methods can evaluate the impact of changes in other forecast variables, which can be very useful to shape future demand. Quantitative methods can be very accurate to derive series of change from one period to another, also this kind of methods are likely to show the greatest accuracy when large changes are involved or much data is available according with J. Scott Armstrong (2001).

CHAPTER 6

6. Forecasting at Renfro Mexico

6.1 Renfro methods

According with J. Guerard, (2013) there are many traditional methods for forecasting: exponential smoothing, time series, naïve forecasting, regressions and composite model forecast which often involves expert forecasts.

For many years the forecasting at Renfro Mexico has been done using a Naïve forecast to predict future demand.

6.2 Naïve forecast

The Naïve forecast is a safe way to forecast if the Stock Keeping Unit (SKU) shows stable environment and slow rate of change if any. Mark Lawless (2014). The model assumes that recent period will be the best predictions for the future:

$$F_{t+1} = Y_t \quad (1)$$

Where:

F_{t+1} = Future Sales

Y_t = Actual Sales

Renfro Mexico has used for many years the naïve forecast method which according with Charles W. Chase Jr (2014) is based on an expert's good feeling judgmental override to a simple base line forecast that built on altered sales history.

The company planning method for demand generation is to assume that what will happen next year will be more or less the same, with some incremental adjustments based on assumptions related to business goals and objectives rather than current conditions.

$$F_{t+1} = Y_t + \text{Inflation} + \text{Business Goals} + \text{new stores} \quad (2)$$

As Scott Finley (Manager – Advance Analytics at Cardinal Health) mention on his presentations “Applying forecast value added at Cardinal Health” for the IBF, if the company is doing worse than a naïve forecast, then the company is wasting time and resources, if the company is doing better then, the process is adding value.

The goal for the new forecast process at Renfro Mexico is to beat the naïve forecast, to improve top seller SKU forecast and total forecast to improve accuracy.

6.3 Data

For this work a total of 60 months of shipments data were analyzed for each SKU even that is well known that the point of sale (POS) data should be the first data options and that the orders is the second best option to forecast.

The POS data should be the first option due that the POS describes the consumer behavior, the received orders should be the second best options because truly describes the retailer needs, the orders result a better option than the shipments due that if an order is partial filled the shipments wont reflect the total amount of that orders and subsequently they will not reflect that demand on the future.

Neither the POS nor the customers’ orders are available for the Mexico data, the first one due that not all our customers had track of that and the second one due that the Renfro Mexico software does not store orders.

For each of the top 17 SKU’s data from February fiscal year (FY) 2011 to June FY 2015 was applied, styles that were the same composition and packaging but had their name changed over the time were combined in order to have a stable and exact database.

The data was adjusted according with the shipments dates in order to have accurate data due that, in some occasions the product was shipped at the end of one month but invoiced and subsequently the shipment recorded in the following month.

Some SKU'S have more sales volume than others, below table 1 describes the sales volume of each SKU based on FY14 dozen sales.

The sum of these 17 SKU'S represents 49% of the total FY14 dozen sales were the 1180 other SKU'S represent the other 51% of the FY14 sales.

Table 1: Top Seller seventeen SKU's.

Rank	Style	Color	Size	Shipments (Dozens) FY14	Percentage of the total FY14 shipments
1st	M990W6-F-M / M990W6-M	WHITE	100130	113,155	12.9%
2nd	M595W6-F-M / M595W6-M	WHITE	100130	74,835	8.5%
3rd	M218W6-M	WHITE	100130	38,302	4.4%
4th	C880W6-M	WHITE	MEDIUM/070085/M	25,063	2.9%
5th	M990AS6-M	WHITE	100120	22,187	2.5%
6th	M795W6-F-M / M795W6-M	WHITE	100130	22,116	2.5%
7th	M990WB6-F-M / M990WB6-M	WH/BK	100130	18,906	2.2%
8th	D880W6-M	WHITE	SMALL	17,052	1.9%
9th	M945AS6-M	WHITE	100120	14,540	1.7%
10th	F095W6-M	WHITE	090110	12,217	1.4%
11th	M821W6-M	WHITE	060120	12,124	1.4%
12th	C943W6-M	WHITE	MEDIUM / M	11,559	1.3%
13th	F925W6-M	WHITE	090110	11,400	1.3%
14th	B880WX-M	WHITE	090110	11,005	1.3%
15th	M986G6-M	GREY	060120	8,928	1.0%
16th	M595WB6-F-M / M595WB6-M	WH/BK	100130	8,731	1.0%
17th	C880WX-M	WHITE	070085	8,727	1.0%

ClickView data 2015

6.4 Models and methods.

Calculating an appropriate and reliable forecast is an important activity in economics and marketing but also in commerce where many areas in the company depend on this task; there are many different types of forecasting procedures, but no simple answer as to which is the best. Chatfield, Chris, (1988).

Just as any medical problem would need an special treatment, the different types of forecasting problems require different solutions, and in Renfro we naturally wish to be discriminating in order to try to choose the best option to get more accurate forecast, and so the choice of method depends on a variety of considerations including the

properties of the data such as trend, the objectives, the number of periods to be forecast, the number of series to be forecast, the item status, the customer, the minimum error and the available data. Chatfield, Chris, (2000).

As a good example of how difficult is to choose the best forecast model Collopy, (1992), takes in to consideration ninety-nine different recommendations before creating a general one.

For this work several models and techniques were applied to the top 17 SKU'S, the strategy of evaluation to choose a forecasting method select one model after evaluating an extensive range of models for each of the 17 top SKU'S.

After evaluating the properties of the data, the objectives, the number of periods to be forecasted, the total number of SKU to be forecasted, the item status to know if it is a replenishment Item or a Fashion item and the available data; after the models were specified, their performance characteristics were validated by the comparison of its forecast with historical data for the process it was designed to forecast. After the 17 models selection two models were mainly used at this work, those are: the Holt-Winters which according with Prajakta S. K (2004) results an extraordinary method when a time series exhibit seasonal behavior, such as demand of toys or apparel which is our case; and the Box Jenkins model, below farther explanation of both.

6.4.1 Holt-winters

Chatfield (2000) defines the Holt-Winters as the more general form of exponential smoothing which allows for trend and additive or multiplicative seasonality and in order to handle that a third parameter needs to be added to the double exponential smoothing equation.

The apparel market annual sales had peaks in the months of November and December due to Christmas season and perhaps during different events (e.g. father's day, back to school). This pattern is likely to repeat every year, however, the relative amount of increase in sales during those peaks may change year after year, that why for this work

both the additive and the multiplicative models were used, below the overview of both methods.

6.4.1.1 Additive seasonal model

In the additive seasonal model the sales increase smoothly year after year and is appropriate for a time series in which the amplitude of the seasonal pattern is independent of the average level of the series (E.g. increasing one million dollars every year).

Below the additive seasonal model according to Kalekar (2004).

It is assumed that the time series is represented by the model:

$$Y_t = b_1 + b_2 t + S_t + \epsilon_t \quad (3)$$

Where:

b_1 Is the permanent component

b_2 Is a linear trend component

S_t Is an additive seasonal factor

ϵ_t Is the random error component

Let the length of the season be L periods.

The seasonal factors are defined so that they sum to the length of the season

The estimates of model parameters are given by:

$$\sum_{1 \leq t \leq L} S_t = 0 \quad (4)$$

Notation used:

R_t Current deseasonalized level of the process at the end of period T .

At The end of a time period t , let:

$\bar{R}_t$ Estimate of the deseasonalized level.

$\bar{G}_t$ estimate of the trend.

$\bar{S}_t$ estimate of seasonal component (seasonal index).

The procedure for updating the estimates of the model parameters is described below according with Kalekar, (2004).

1. Overall Smoothing

$$\bar{R}_t = \alpha (Y_t - \bar{S}_{t-L}) + (1 - \alpha) * (\bar{R}_{t-1} + \bar{G}_{t-1}) \quad (5)$$

Where $0 < \alpha < 1$ is a smoothing constant.

2. Smoothing of the trend factor

$$\bar{G}_t = \beta * (\bar{R}_t - \bar{S}_{t-L}) + (1 - \beta) * \bar{G}_{t-1} \quad (6)$$

Where $0 < \beta < 1$ is the second smoothing constant

The estimate of the trend component is simply the smoothed difference between two successive estimates of the deseasonalized level.

3. Smoothing of the seasonal index

$$\bar{S}_t = \gamma * (Y_t - \bar{R}_t) + (1 - \gamma) * \bar{S}_{t-1} \quad (7)$$

Where $0 < \gamma < 1$ is the third smoothing constant

The estimate of the seasonal component is a combination of the most recently observed seasonal factor given by the demand Y_t divided by the deseasonalized series level estimate $\bar{R}_t$ and previous best seasonal factor estimate for this time period. Kalekar, (2004)

The Holt-Winters additive seasonal model for the next period is given by the below equation:

$$Y_t = \bar{R}_{t-1} + \bar{G}_{t-1} + \bar{S}_{t-L} \quad (8)$$

6.4.1.2 Multiplicative seasonal model

In the multiplicative seasonal model the sales may increase by a certain factor and the seasonal component is thus multiplicative. This model is appropriate for a time series in which amplitude of the seasonal pattern is proportional to the average level of the series

Below the multiplicative seasonal model according to Kalekar (2004).

It is assumed that the time series is represented by the model:

$$\gamma_t = (b_1 + b_2 t)S_t + \epsilon_t \quad (9)$$

Where:

S_t is a multiplicative seasonal factor this time.

The procedure for updating the estimates of the model parameters is described below according with Kalekar, (2004).

1. Overall Smoothing

$$\bar{R}_t = \alpha \frac{\gamma_t}{\bar{S}_{t-L}} + (1-\alpha) * (\bar{R}_{t-1} + \bar{G}_{t-1}) \quad (10)$$

Where $0 < \alpha < 1$ is a smoothing constant.

2. Smoothing of the trend factor

$$\bar{G}_t = \beta * (\bar{S}_t - \bar{S}_{t-1}) + (1 - \beta) * \bar{G}_{t-1} \quad (11)$$

Where $0 < \beta < 1$ is the second smoothing constant

Where again, the estimate of the trend component is simply the smoothed difference between two successive estimates of the deseasonalized level.

3. Smoothing of the seasonal index

$$\bar{S}_t = \gamma * (Y_t / \bar{S}_t) + (1 - \gamma) * \bar{S}_{t-1} \quad (12)$$

Where $0 < \gamma < 1$ is the third smoothing constant

The estimate of the seasonal component is a combination of the most recently observed seasonal factor given by the demand Y_t divided by the deseasonalized series level estimate R_t and previous best seasonal factor estimate for this time period. Kalekar, (2004)

The Holt-Winters multiplicative seasonal model for the next period is given by the below equation:

$$Y_t = (\bar{R}_{t-1} + \bar{G}_{t-1})\bar{S}_{t-L} \quad (13)$$

Forecast for multiple step-ahead forecast:

$$Y_{t+T} = (\bar{R}_{t-1} + T * \bar{G}_{t-1})\bar{S}_{t-T-L} \quad (14)$$

Since the initial values and the number of full seasons are essential for this model, in this work were used between three ($3L$ periods) and four ($4L$ periods) years of data depending on the analyzed SKU.

Suppose that data from m seasons is available and let $\bar{X}_j, j = 1, 2, 3, \dots, mL$ denote the average of the observation during the j^{th} seasons.

Estimation of the trend component:

$$\bar{G}_0 = \frac{\bar{Y}_m - \bar{Y}_1}{(m-1)L} \quad (15)$$

Estimation of the deseasonalized level:

$$\bar{R}_0 = \bar{x}_1 - \frac{L}{2} \bar{G}_0 \quad (16)$$

Estimation of the seasonal component:

$$\bar{S}_t = \frac{\bar{\chi}_t}{\bar{\chi}_i - \left[\frac{L+1}{2-j}\right] \bar{G}_0} \quad (17)$$

Where:

$\bar{\chi}_t$ is the average for the season corresponding to the t index

J is the position of the period t within the season.

6.4.2 Box Jenkins – Seasonal ARIMA

Autoregressive integrated moving average models (ARIMA) is developed systematic method created by George Box and Gwilym Jenkins use full for business and economic data.

The Box Jenkins method refers to a systematic way of identifying, fitting checking, and using integrated autoregressive, moving average time series model. This method is appropriate for time series of at least 50 observations. (17)

The seasonal AR and MA terms predict X_t using data values and errors at times with lags that are multiples of the spans of the seasonality.

The seasonal part of the ARIMA model has the same structure as the non-seasonal part.

ARIMA terminology:

The ARIMA model is classified as an ARIMA $(p,d,q)*(P,D,Q)S$

P = the number of autoregressive terms.

d = the number of non-seasonal differences.

q = the number of moving average terms.

P = the number of seasonal autoregressive terms.

D = the number of seasonal differences.

Q = the number of seasonal moving-average terms.

S = time span of repeating seasonal pattern

Whit out differencing operations, the models is written as:

$$\Phi(\beta S)\phi(\beta)(X_t - \mu) = \Theta(\beta S)\theta(\beta)W_t \quad (18)$$

The non-seasonal components are:

$$\text{AR: } \varphi(\beta) = 1 - \varphi_1\beta - \dots - \varphi_p\beta^p \quad (19)$$

$$\text{MA: } \theta(\beta) = 1 + \theta_1\beta + \dots + \theta_q\beta^q \quad (20)$$

The seasonal components are:

$$\text{Seasonal AR: } \Phi(\beta^S) = 1 - \Phi_1\beta^S - \dots - \Phi_P\beta^{PS} \quad (21)$$

$$\text{Seasonal MA: } \Theta(\beta^S) = 1 + \Theta_1\beta^S + \dots + \Theta_Q\beta^{QS} \quad (22)$$

Note that on the left side of equation (18) have the seasonal and the non-seasonal AR components which multiply each other and the right side of equation (18) have the seasonal and non-seasonal MA components multiplying each other. (The Pennsylvania State University, 2015)

One of the advantage of seasonal ARIMA models is that has a solid underlying theory, stable estimation of time-varying trends and seasonal patterns and relatively few parameters according with Nau, Robert (2014).

6.5 Error term

For error measurement the Mean absolute percentage error (MAPE) was used in this work, this is the most commonly used measure of forecasting performance, computed by taking the average of all absolute percentage errors, this according Gilliland, M. (2010).

$$MAPE = \left(\frac{1}{n}\right) * \sum \text{Max}|PE| \quad (23)$$

Where percentage error (PE) = [(F-A) / A] x 100, and the sum is taken over n observations of the actual.

6.6 Renfro top 17 SKU's

Las Fiscal Year (FY15) from February 2014 to January 2015 Renfro Mexico Registered total sales for 823,174 dozens with a total of 1,402 different socks styles including core business items, fashion items and different brands such as: Fruit Of the Loom, Polo Ralph Lauren, Dr Scholl's, Starter, Faded Glory, Jerzees and Hot Sox.

Renfro Top 17 SKU represent 1.2% of the total number of styles, these items represented 49% of the total fiscal year 2015 (FY15) sales.

As well as FY15, for FY14 the top 17SKU's represent 49% of the annual sales adding together a total amount of 430,844 dozens versus a total company shipments for 879,783 dozens with a total of 1197 styles.

For every single of the top 17 SKU's several model were applied (all of them available under the author's possession) in order to find the one that fitted better the data to produce the most accurate results.

6.6.1 M990W6-F-M

The M990W6-F-M is a men's ultimate comfort crew sock with six pairs in a bag, this style is Renfro Mexico top seller and represented 12.9% of the total FY14 dozens shipments.

To analyze this SKU data from February FY11 to June FY15 was used, to obtain the most accurate results several methods were applied.

Before applying any process, the data was adjusted to avoid extreme values and to reflect the closest match to the actual shipments, with this I want to clarify that movements from month to month were applied if shipments were made in one month and invoiced the next month due that the sales are reflected on the system until they are invoiced, and that is why for example if a shipment was made in October but invoiced in November in the adjusted data the shipment would appear on October.

Table 2: M990W6-F-M Monthly shipped dozens.

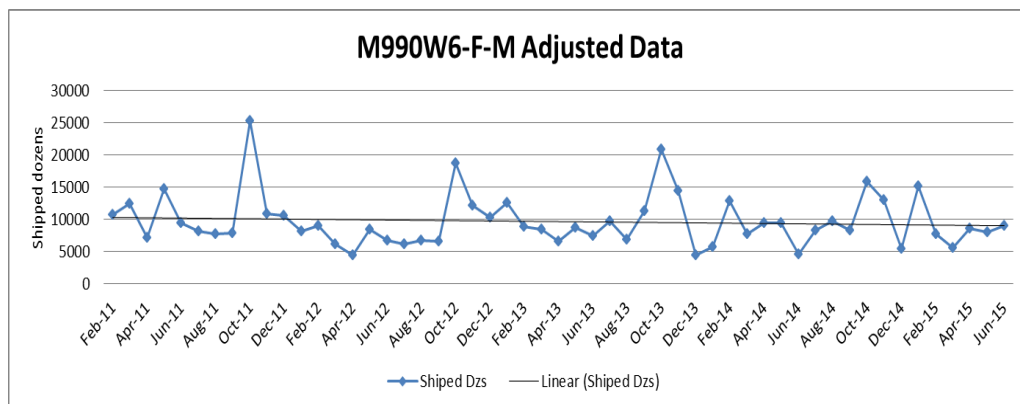
	Shipped Dozens													
	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	JAN	TOTAL	Variation %
FY2011	10,737	12,394	7,185	14,665	9,501	8,124	7,701	7,853	25,331	10,890	10,543	8,150	133,073	vs Last year
FY2012	9,045	6,166	4,414	8,429	6,724	6,100	6,698	6,570	18,775	12,115	10,344	12,615	107,994	-19%
FY2013	8,854	8,439	6,621	8,739	7,360	9,756	6,878	11,268	20,895	14,388	4,377	5,667	113,240	5%
FY2014	12,792	7,678	9,498	9,438	4,515	8,307	9,710	8,323	15,861	12,978	5,370	15,147	119,616	6%
FY2015	7,773	5,589	8,544	7,998	8,952									

QlickView data 2015

In table 2 we can see the adjusted shipment dozens historic, from February FY11 thru June FY15. Also from table1 and more graphically in graph 1 we can identify picks on the months on October and this is cause basically because the retailers want to prevent for the Christmas season incremental.

It is clear from graph 1 that as most of the apparel product, toys, school supplies, etc., we can identify trend and seasonality in the months of October which consider with the actual retail Christmas shipments.

Graph 1: M990W6-F-M Monthly shipments.

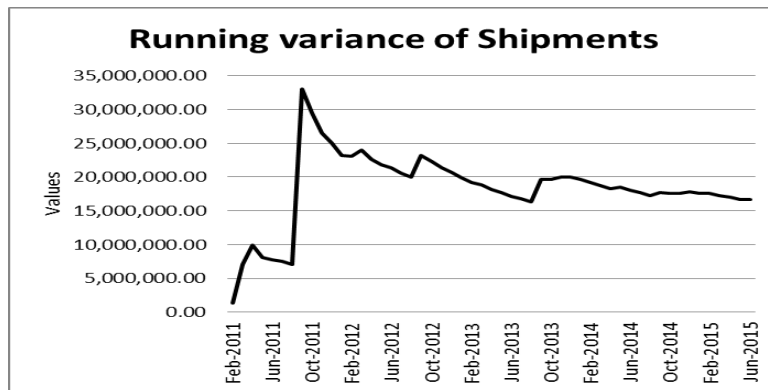


QlickView data 2015

In order to achieve accuracy several models were applied after the data adjustment; resulting the Holt Winters in additive form the one that fit better the previous actual values using the mean absolute percentage error as the error at a 95% confidence level.

A data transformation was applied to convert the data from values to logarithms to smooth the series as showed on graph 2 and graph 3 were the running variance of the shipments is run in values for the graph 2 and in logarithms for graph 3.

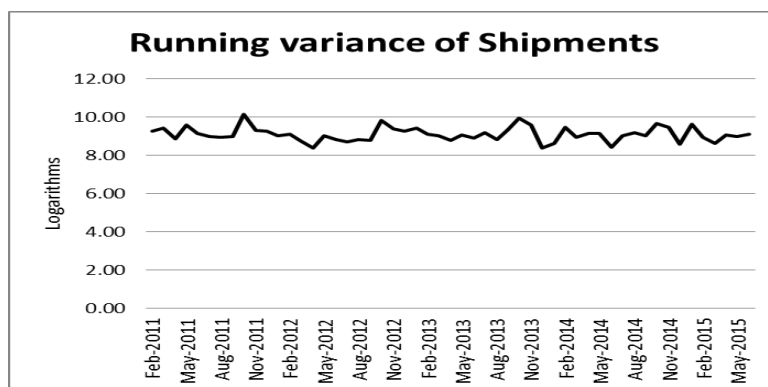
Graph 2: Running shipments variance.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 3 shows a smother movement through the series, avoiding the pics from the series in values.

Graph 3: Running logarithms variance.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

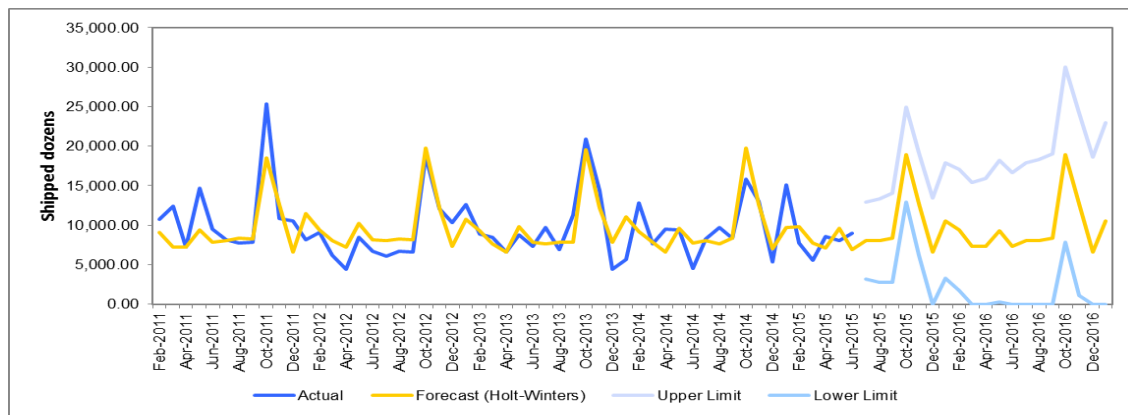
Table 3: Results.

Accuracy Measures	Value	Forecast Statistics	Value
Mean Absolute Percentage Error (MAPE)	22.52%	Mean	9,712.85
R-Square	67.26%	Standard Deviation	4,299.56
Adjusted R-Square	65.54%		
Method Statistics	Value		
Method Selected	Holt Winters		
Level	0.00		
Seasonal	0.28		
Trend	1.00		
Decomposition type	Additive		

John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

From table 3 it can be deduce that more weight is placed on the previous values that to the more recent ones because of the small smoothing constants for the level and the seasonal but, in other hand the trend will adapt more quickly to genuine changes in the shipments pattern because of the large smoothing constant as Goodwin, Paul (2010) mention, below table 3 and graph 4 show the model results were it can be seen that the upper and lower limit represent the 95% confidence level of the series:

Graph 4: Model graph results.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Once the results were obtained; a monthly seasonal index was applied to the results obtaining the final FY15 forecast.

Table 4: M990W6-F-M results comparison.

	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14	Jan-15	TOTAL
FY15 Naïve Forecast	9,388	8,990	10,590	17,227	15,235	8,366	6,951	76,748
FY15 Naïve Forecast / MAPE	-30.3%	-25.4%	-38.1%	-17.8%	-20.5%	19.6%	35.4%	-8.9%
Holt-Winters	7,405	7,191	8,136	16,825	12,541	6,282	10,329	68,708
FY15 Holt-winters / MAPE	-2.8%	-0.3%	-6.1%	-15.0%	0.8%	39.6%	4.0%	2.5%
Actual FY15	7,206	7,168	7,671	14,628	12,648	10,404	10,764	70,488

Data from Renfro's network

Table 4 shows the comparison between the Naïve forecast (with a total of 8.9% error) and the Holt-Winters method (with a total of 2.5% error) against the actual values resulting the second one to be the best fit to the actual values at the monthly and at the total level as showed on Table 4.

The naïve forecast exceed the forecast by 6,260 dozens which according with the standard cost per dozen of this product, this over-forecast would it cost the company \$509,683 pesos more due to the production, 39 warehouse locations and around 3 extra shipments from Campeche to Queretaro, plus of course the extra operations labor cost.

In the other hand the statistical forecast was 1,780 dozens below the actual sales, this does not mean we had customer service issues, the orders were full fitted all year long due that a safety stock of 10,100 dozens prevent that.

6.6.2 M595W6-F-M

The M595W6-F-M is a men's ultimate comfort ankle sock with six pairs in a bag, this style is Renfro Mexico second seller and represented 8.3% of the total FY15 dozens shipments.

To analyze this SKU data from February FY11 to June FY15 was used. Before applying any process, the data was adjusted to avoid extreme values and to reflect the closest match to the actual shipments.

Several models were applied in order to find the one that fit better the data.

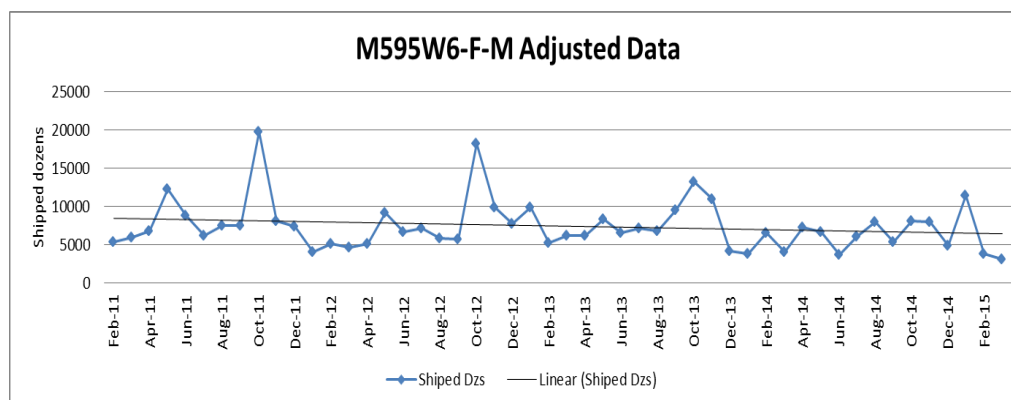
Table 5: M995W6-F-M Monthly shipped dozens.

	Shipped Dozens												TOTAL	Variation %
	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	JAN		vs Last year
FY2011	5,387	5,952	6,837	12,295	8,895	6,235	7,569	7,490	19,737	8,087	7,453	4,132	100,066	
FY2012	5,119	4,631	5,138	9,209	6,714	7,166	5,899	5,712	18,225	9,876	7,797	9,906	95,391	-5%
FY2013	5,223	6,219	6,247	8,393	6,525	7,221	6,842	9,548	13,281	11,019	4,141	3,894	88,552	-7%
FY2014	6,564	4,035	7,239	6,688	3,686	6,122	8,060	5,342	8,176	8,025	4,935	11,492	80,364	-9%
FY2015	3,834	3,138	6,420	7,527	6,105									

ClickView data 2015

From table 2 we can see the adjusted shipment dozens historic, from February FY11 thru June FY15. Also from table 5 and more graphically in graph 5 we can identify picks on the months on October like in the M990W6-F-M and once more that is caused by the Christmas season provisions, but also for this SKU a second pick can be identify in May and that is because the retailers want inventory to full fill all the picks on their stores for father's day. Once again we can identify trend and seasonality on this style and that is why a model that accepts both was used.

Graph 5: M995W6-F-M Monthly shipments.

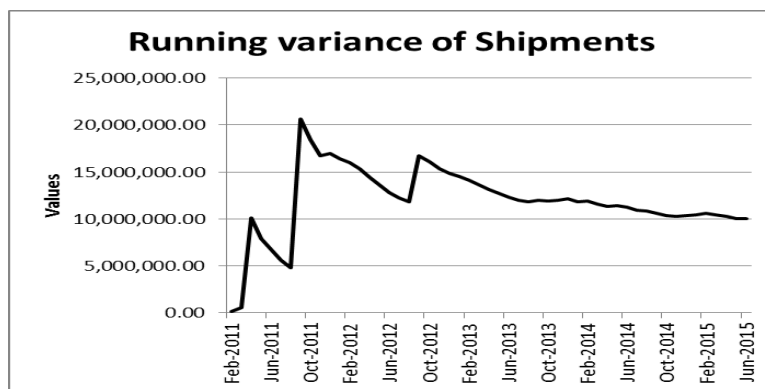


ClickView data 2015

After the data adjustment, different methods and models were applied; being the Holt Winters in additive form the one that fit better the previous actual values using the mean absolute percentage error as the error term at a 95% confidence level.

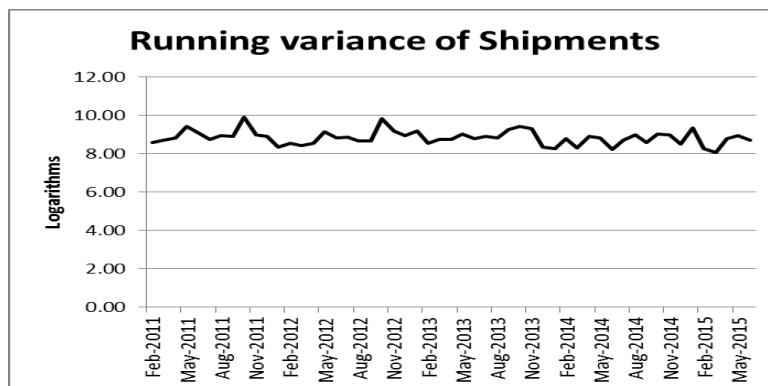
A data transformation was applied to convert the data from values to logarithms to smooth the series as showed on graph 6 and graph 7 were the running variance of the dozen shipments is run in values for the graph 6 and in logarithms for graph 7.

Graph 6: Running shipments variance.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 7: Running logarithms variance.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

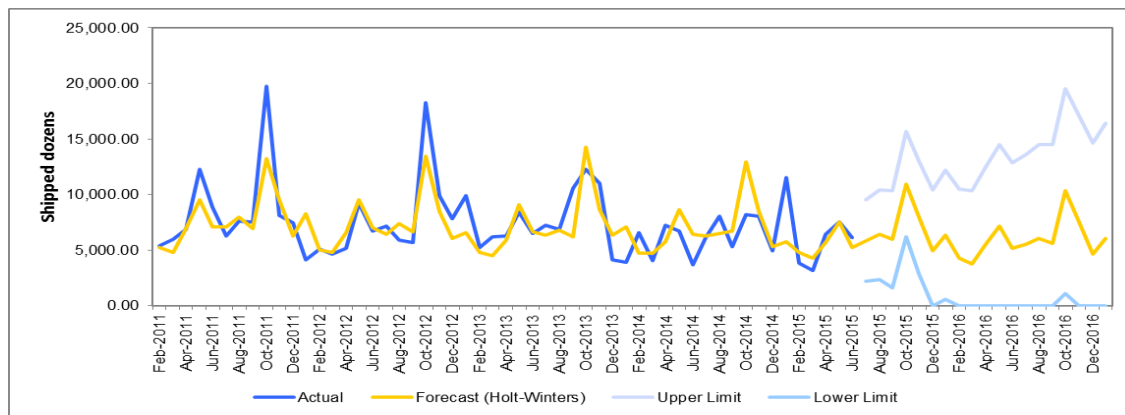
Below, table 6 shows the model results and graph 8 shows the new forecast and how it fits the actual values of the series:

Table 6: Results.

Accuracy Measures	Value	Forecast Statistics	Value
Mean Absolute Percentage Error (MAPE)	21.67%	Mean	7,384.83
R-Square	52.23%	Standard Deviation	3,172.46
Method Statistics	Value		
Method Selected	Holt Winters		
Level	0.01		
Seasonal	0.23		
Trend	0.13		
Decomposition type	Additive		

John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 8: Plotted forecast.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 6 shows the additive Holt-Winters results and hence it can be deduced that more weight was applied to the less recently shipments than to the new estimates due that the value of the level, seasonal and trend coefficients are closest to zero.

The upper and lower limit from graph 8 represents the 95% confidence level of the series and ones the results were obtained; a monthly seasonal index was applied to the results obtaining the final FY15 forecast with in the 95% confidence limit.

Table 7: M995W6-F-M results comparison.

	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14	Jan-15	TOTAL
FY15 Naïve Forecast	6347	7921	7104	8861	9904	4496	5514	50,147
FY15 Naïve Forecast / MAPE	-14.6%	-37.0%	-18.1%	9.9%	-45.5%	24.4%	21.1%	-6.9%
Holt-Winters	6038	6038	6038	11321	7547	5283	6792	49,056
FY15 Holt-winters / MAPE	-9.0%	-4.4%	-0.4%	-15.1%	-10.9%	11.1%	2.9%	-4.6%
Actual FY15	5538	5781	6014	9834	6807	5945	6993	46,911

Data from Renfro's network

Table 7 shows the comparison between the Naïve forecast with an over forecast of 6.9% error and the Holt-Winters method with a total over forecast of 4.6% error against the actual values resulting the second one to be the most accurate at the monthly level and at the total level as showed on table 7.

The naïve forecast exceeds the forecast by 3,236 dozens vs 2,145 of the statistical forecast, which equals a difference of 1,091 dozens between both methods. According with the standard cost per dozen of this product the statistical forecast prevent a production that would it cost the company \$80,475 pesos, plus the extra operations labor cost.

6.6.3 M218W6-M

The M218W6-M is a men's ultimate comfort tubular sock with six pairs per package, according with it sales records, this style is the third best seller for Renfro Mexico and represented 4.4% of the total FY15 shipments.

To analyze this model data from February FY11 to June FY15 several methods were applied. Before applying any process, the data was adjusted to avoid extreme values and to reflect the closest match to the actual shipments.

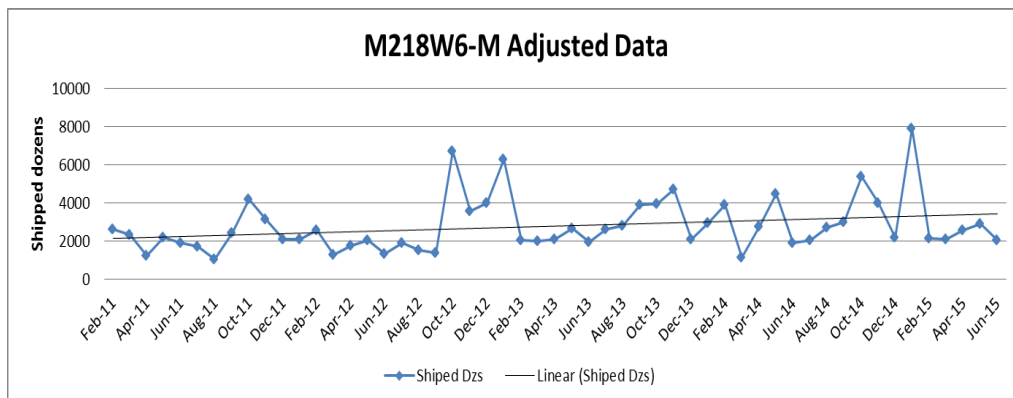
Table 8: M218W6-M Monthly shipped dozens.

Shipped Dozens														
	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	JAN	TOTAL	Variation % vs
FY2011	2598	2346	1242	2190	1890	1731	1049	2424	4199	3148	2080	2078	26975	Last year
FY2012	2593	1275	1742	2047	1332	1910	1536	1369	6732	3585	3990	6273	34383	27%
FY2013	2068	2007	2100	2643	1929	2634	2799	3891	3954	4740	2101	2943	33809	-2%
FY2014	3885	1164	2778	4461	1921	2049	2727	2992	5361	4023	2181	7923	41464	23%
FY2015	2142	2079	2567	2883	2029									

ClickView data 2015

From table 8 we can see the adjusted shipments dozens historic, from February FY11 thru June FY15. Also from table 8 and more graphically in graph 9 we can identify picks on the months on October like in the two previous styles and once more that is caused by the Christmas season provisions from the retailers, also an spike on January can be identify and this is mainly caused because Soriana and Walmart fill their store picks from the Christmas sales. It can be identify seasonal and trend from graph 9 and that is why a model that accepts both was used to forecast this item.

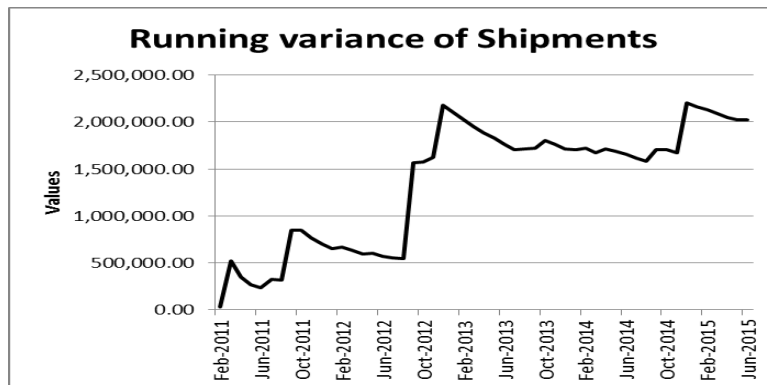
Graph 9: M218W6-M Monthly shipments.



ClickView data 2015

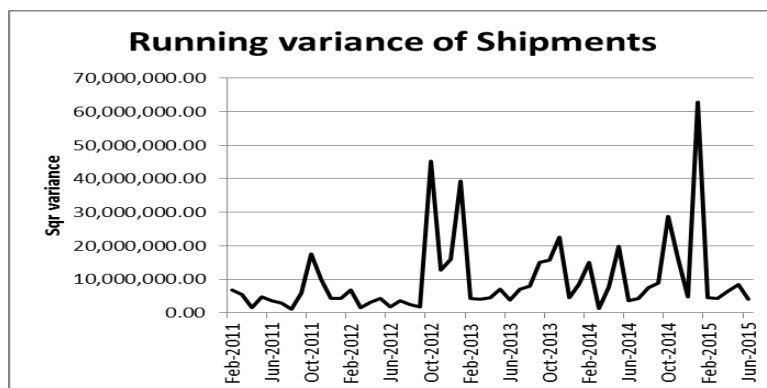
An square transformation was applied to the data to smooth the series as showed on graph 10 and graph 11 were the running variance of the dozen shipments is run in values for the graph 10 and in square values for graph 11.

Graph 10: Running shipments variance.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 11: Running square variance.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

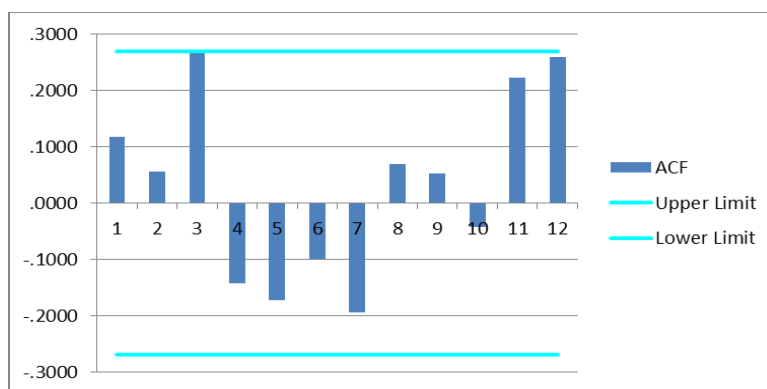
After the data adjustment, different methods and models were applied; the Box Jenkins method in an additive form was used with an ARIMA (0,0,0)*(1,1,1) model to handle seasonality within a 95% confidence limit.

From this model was found that the shipments are a stationary variable and the only thing that determines the behavior of shipments for this model is a seasonal movement, not the autoregressive movement or the moving average.

By looking at the autocorrelation function (ACF) and partial autocorrelation (PACF) plots of the differenced series in graph 12 and graph 13 respectively, both perform within the limits, also it can be identified for graph 12 the coefficients of correlation between the time series and lags of itself and in graph 13 the partial autocorrelation coefficients between the series and each of the lags.

Also in both it can be seen a fall after the third lag which correspond to the month of May since the data starts with the fiscal year in February, the May decrement is because starting in May the sales move barely flat until the Christmas season purchases due to the type of sock.

Graph 12: Autocorrelation function (ACF).



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 13: Partial autocorrelation function (PACF).



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Below table 9 shows the model results were the forecast exceeds the accuracy of a simple average by 72.68%, with an average error of 16.57%.

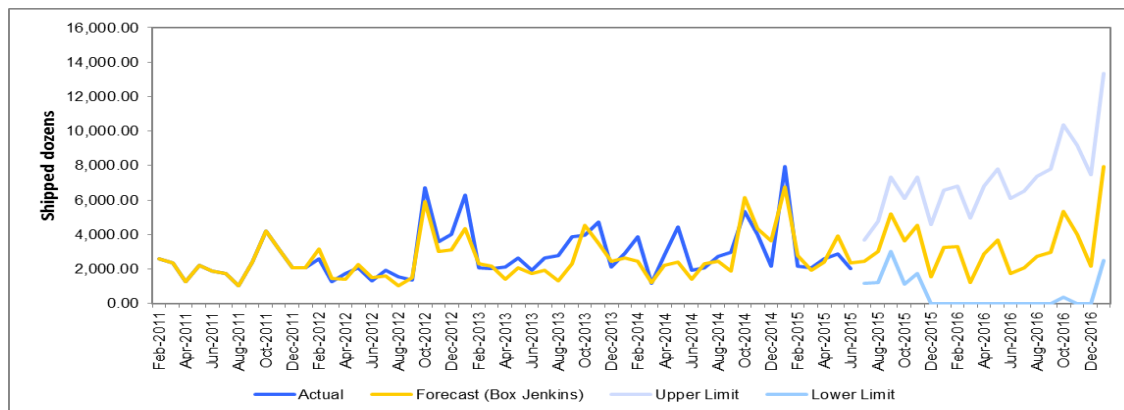
Table 9: Results.

Accuracy Measures		Value	Forecast Statistics		Value
Mean Absolute Percentage Error (MAPE)		16.57%	Mean		2,798.66
R-Square		72.68%	Standard Deviation		1,421.60
Method Statistics		Value			
Method Selected		Box Jenkins			
Model Selected		ARIMA(0,0,0) * (1,1,1)			
T-Test For Seasonal AR		-7.23			
T-Test For Seasonal MA		-2.26			

John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Below graph 14 shows the plotted forecast and the upper and lower limits with in the 95% confidence limit.

Graph 14: Plotted forecast.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 10: M218W6-M results comparison.

	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14	Jan-15	TOTAL
FY15 Naïve Forecast	2331	2799	3679	5807	4378	2948	2414	24,358
FY15 Naïve Forecast / MAPE	24.8%	-37.4%	-46.9%	-18.4%	-10.9%	24.3%	52.4%	4.3%
Box Jenkins	2224	2224	2805	5560	4077	2965	5189	25,045
FY15 Box Jenkins / MAPE	28.2%	-9.2%	-12.0%	-13.4%	-3.3%	23.9%	-2.3%	1.6%
Actual FY15	3099	2037	2505	4905	3948	3897	5073	25,464

Data from Renfro's network

A monthly seasonal index was applied to the results obtaining the final FY15 forecast with in the 95% confidence limit.

Table 10 shows the comparison between the Naïve forecast with an under forecast of 4.3% error and the Box Jenkins ARIMA (0,0,0)*(1,1,1) with a total under forecast 1.6% error) against the actual values resulting the second one to be the most accurate at the total level and more stable at the monthly level as showed on table 7.

Even though that both methods were very close to the real values the ARIMA model performed much better at the monthly level and that means that the company can have a better idea of the future demand and also, the company will be ready to give the best customer service full filling orders every month.

7. CONCLUSION

Using the forecast modeling with shipments and POS data from Feb fiscal year 2011 to June fiscal year 2015, it was examinaated whether the forecast modeling proccess has efect over the company forecast accuracy at Renfro Mexico.

Table 11: Top 17 SKU's forecasting results.

TOP 17	Style	Used Model	Modeling Forecast	Naïve Forecast	Actual	Modeling Forecast Error	Naïve Forecast Error
1	M990W6-F-M	Holt-Winters	68,708.01	76,747.73	70,488.00	2.5%	-8.9%
2	M595W6-F-M	Holt-Winters	49,056.15	50,146.96	46,910.83	-4.6%	-6.9%
3	M218W6-M	Box Jenkins ARIMA	25,044.55	24,357.56	25,464.00	1.6%	4.3%
4	C880W6-M	Holt-Winters	13,503.54	15,230.90	14,520.00	7.0%	-4.9%
5	M990AS6-M	Holt-Winters	17,200.43	16,560.37	17,897.83	3.9%	7.5%
6	M795W6-F-M	Holt-Winters	12,498.81	15,535.40	11,617.00	-7.6%	-33.7%
7	M990WB-F-M	Holt-Winters	14,447.09	12,695.73	15,432.42	6.4%	17.7%
8	D880W6-M	Holt-Winters	10,934.05	14,372.30	11,571.00	5.5%	-24.2%
9	M945AS6-M	Holt-Winters	10,348.38	9,461.35	10,618.92	2.5%	10.9%
10	F095W6-M	Holt-Winters	9,307.21	11,797.50	9,085.00	-2.4%	-29.9%
11	M821W6-M	Holt-Winters	9,912.25	7,582.44	10,469.50	5.3%	27.6%
12	C943W6-M	Holt-Winters	7,685.16	12,538.42	6,135.00	-25.3%	-104.4%
13	F925W6-M	Holt-Winters	6,445.67	7,962.19	6,746.00	4.5%	-18.0%
14	B880WX-M	Holt-Winters	6,543.95	8,732.81	6,685.83	2.1%	-30.6%
15	M986G6-M	Holt-Winters	6,863.73	4,260.96	7,738.00	11.3%	44.9%
16	M595WB6-M	Holt-Winters	6,086.48	4,986.18	6,316.00	3.6%	21.1%
17	C880WX-M	Holt-Winters	6,675.00	7,101.99	5,870.00	-13.7%	-21.0%
TOTAL TOP 17 ACCURACY			281,260.47	300,070.79	283,565.33	0.8%	-5.8%

The obtained results are displayed in table 11th and in them we can see that in sixteen of the seventeen analized SKU's the modeling forecast performed better than the Naïve forecast, in the one that the Naïve forecast performed better the diference between both methods was 4.9% which did not represent any aditional charges to the company due to the company safety stock for that particular style.

The Modeling forecast exhibit an average of 6% absolute MAPE for the top 17 SKU's versus the naïve forecast which exhibit an average of 24% absolute MAPE for the top 17 SKU's.

Adding thogheter the top 17th SKU's results it can be concluded that at the current standart production cost, current shipping cost and labor operations cost, the modeling forecast save the company vs the naïve forecast the production, transportations and operation cost of around 34,931.36 dozens which at last fiscal year cost per dozens represent around \$ 289,930.30 USD.

Tacking the study results in consideration we can reject the null hypothesis and conclude that the modeling forecast has effect over the company forecast accuracy.

The modeling forecasting is currently being aplied at Renfro Mexico on the top 17th SKU's providing the corporate with a better future prediction about the market and providing the best customer serviceand inventory manadgment under thos styles.

APPENDIX ONE:

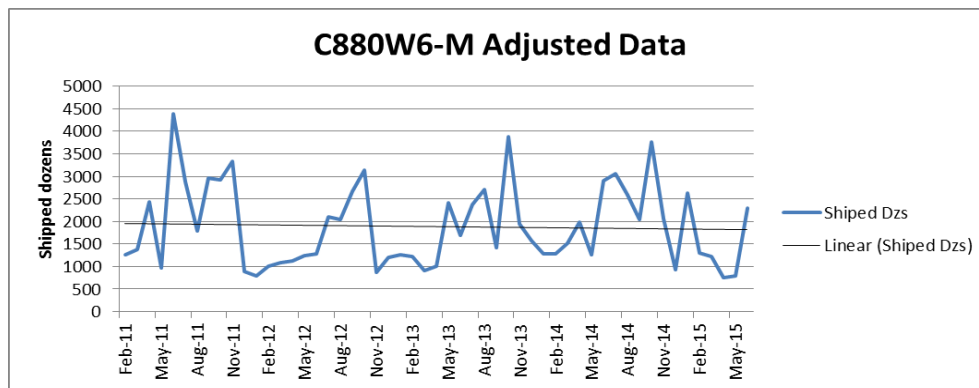
1. C880W6-M

Table 12: C880W6-M Monthly shipped dozens.

Shipped Dozens														
	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	JAN	TOTAL	Variation %
FY2011	1,180	453	2,076	540	3,918	1,371	900	1,864	1,231	1,810	551	579	16,471	vs Last year
FY2012	834	990	979	1,101	1,163	1,986	1,596	1,513	2,334	878	584	893	14,849	-10%
FY2013	658	520	738	1,750	1,373	1,677	2,401	1,209	2,824	1,017	1,296	1,017	16,478	11%
FY2014	1,008	1,098	1,504	879	2,700	1,660	2,380	1,878	2,224	1,116	513	2,445	19,405	18%
FY2015	831	867	750	673	2,001									

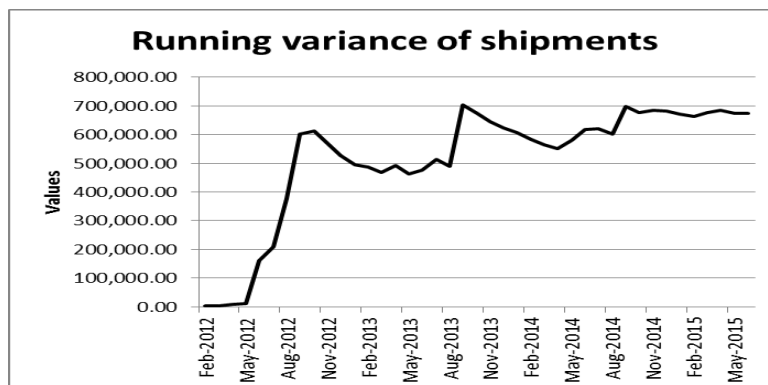
ClickView data 2015

Graph 15: M880W6-M Monthly shipments.



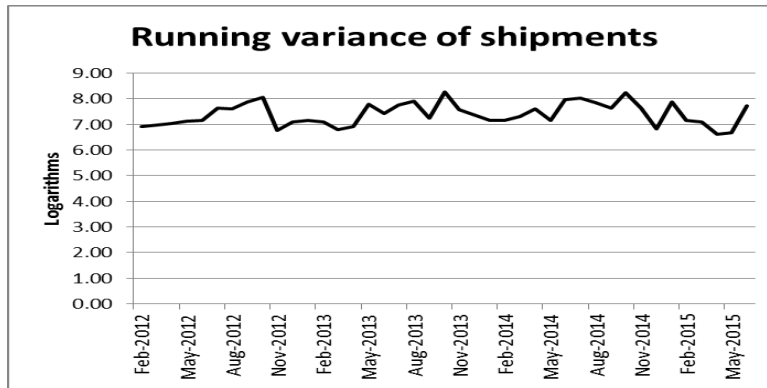
ClickView data 2015

Graph 16: Running shipments variance.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 17: Running logarithms variance.



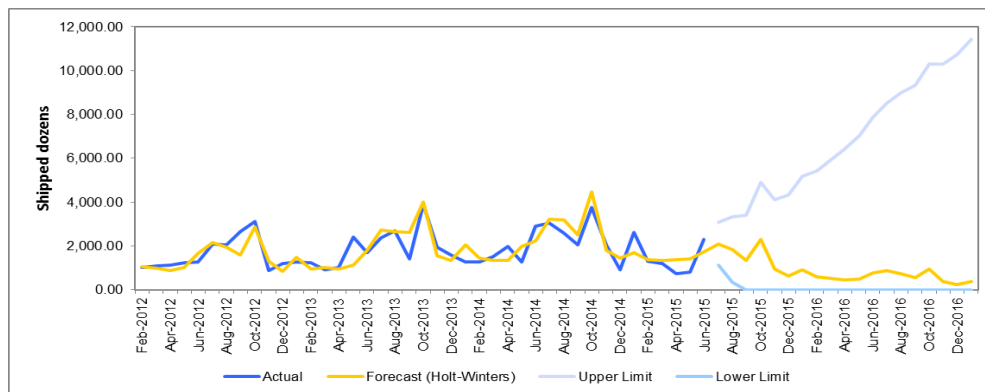
John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 13: Results.

Accuracy Measures	Value	Forecast Statistics	Value
Mean Absolute Percentage Error (MAPE)	25.41%	Mean	1,799.72
R-Square	59.60%	Standard Deviation	821.31
Method Statistics	Value		
Method Selected	Holt Winters		
Level	0.06		
Seasonal	0.28		
Trend	1.00		
Decomposition type	Additive		

John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 18: Model graph results.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015

Table 14: C880W6-M results comparison.

	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14	Jan-15	TOTAL
FY15 Naïve Forecast	2355	1923	2472	1948	3078	1125	2330	15,231
FY15 Naïve Forecast / MAPE	7.5%	-7.5%	-37.1%	20.6%	-63.9%	49.7%	-28.6%	-4.9%
Holt-Winters	2544	2348	1761	3131	1370	979	1370	13,504
FY15 Holt-winters / MAPE	0.1%	-31.3%	2.3%	-27.6%	27.1%	56.3%	24.4%	7.0%

Actual FY15	2547	1788	1803	2454	1878	2238	1812	14,520
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Data from Renfro's network

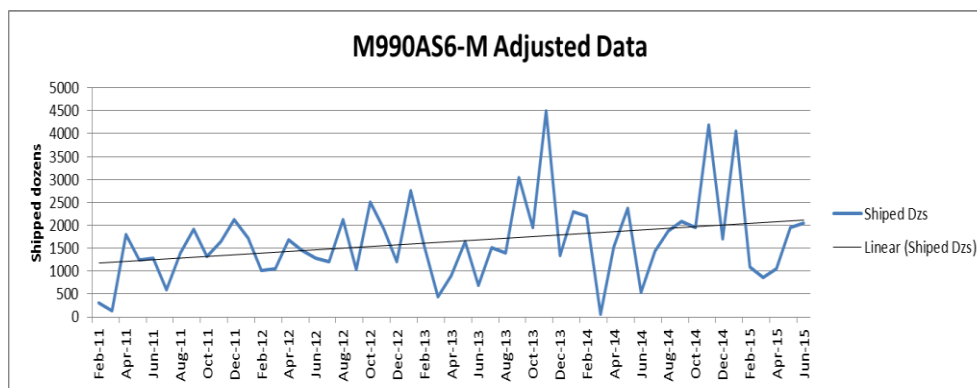
2. M990AS6-M

Table 15: M990AS6-M Monthly shipped dozens.

	Shipped Dozens												TOTAL	Variation %
	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	JAN		vs Last year
FY2011	299	131	1,807	1,239	1,290	603	1,397	1,908	1,323	1,644	2,119	1,725	15,483	
FY2012	1,009	1,053	1,690	1,452	1,283	1,209	2,124	1,032	2,511	1,932	1,203	2,757	19,254	24%
FY2013	1,573	448	891	1,647	681	1,518	1,404	3,033	1,950	4,492	1,349	2,293	21,277	11%
FY2014	2,205	54	1,536	2,364	546	1,443	1,866	2,084	1,956	4,188	1,698	4,065	24,005	13%
FY2015	1,098	864	1,059	1,959	3,429									

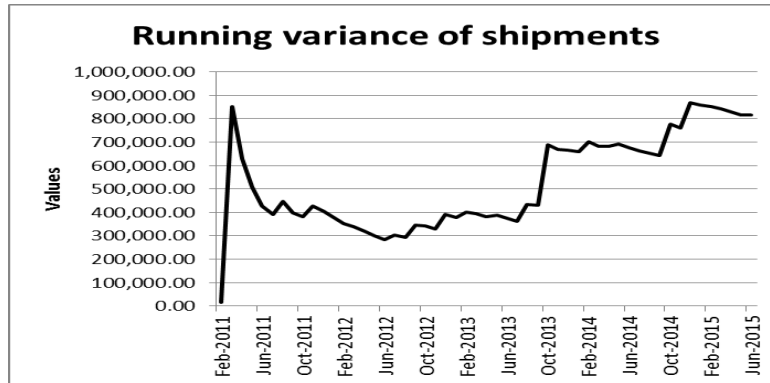
QlickView data 2015

Graph 19: M990AS6-M Monthly shipments.



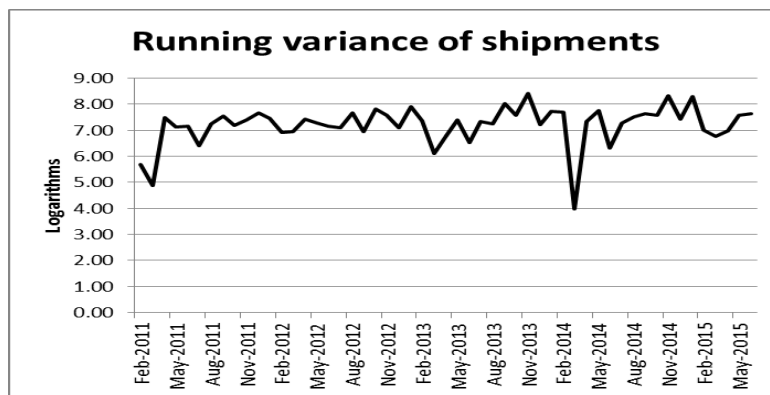
QlickView data 2015

Graph 20: Running shipments variance.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015

Graph 21: Running logarithms variance.



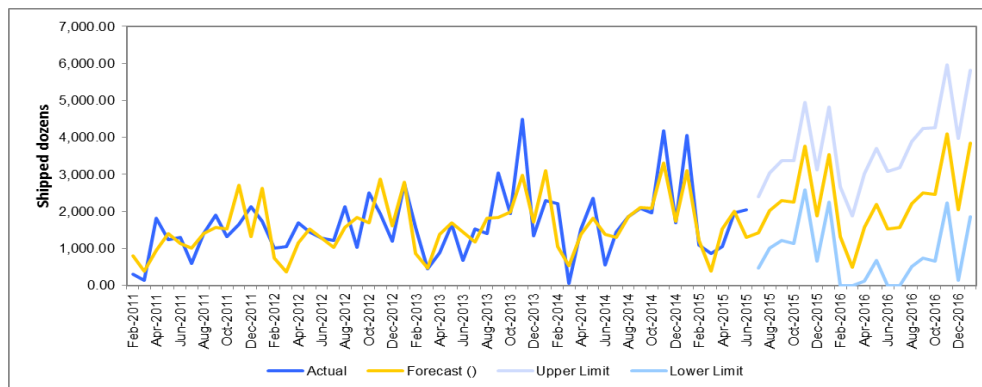
John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015

Table 16: Results.

Accuracy Measures		Value	Forecast Statistics		Value
Mean Absolute Percentage Error (MAPE)		52.57%	Mean		1,642.45
R-Square		55.25%	Standard Deviation		903.03
Method Statistics		Value			
Method Selected		Holt Winters			
Level		0.01			
Seasonal		0.14			
Trend		0.12			
Decomposition type		Additive			

John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015

Graph 22: Model graph results.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015

Table 17: M990AS6-M results comparison.

	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14	Jan-15	TOTAL
FY15 Naïve Forecast	1674	1179	2252	2129	3861	2926	2540	16,560
FY15 Naïve Forecast / MAPE	-45.7%	32.0%	-10.1%	33.9%	3.3%	-63.1%	35.9%	7.5%
Holt-Winters	1433	2031	2295	2257	3760	1889	3536	17,200
FY15 Holt-winters / MAPE	-24.7%	-17.1%	-12.2%	29.9%	5.8%	-5.3%	10.8%	3.9%
Actual FY15	1149	1734	2045.917	3219	3993	1793.917	3963	17,898

Data from Renfro's network

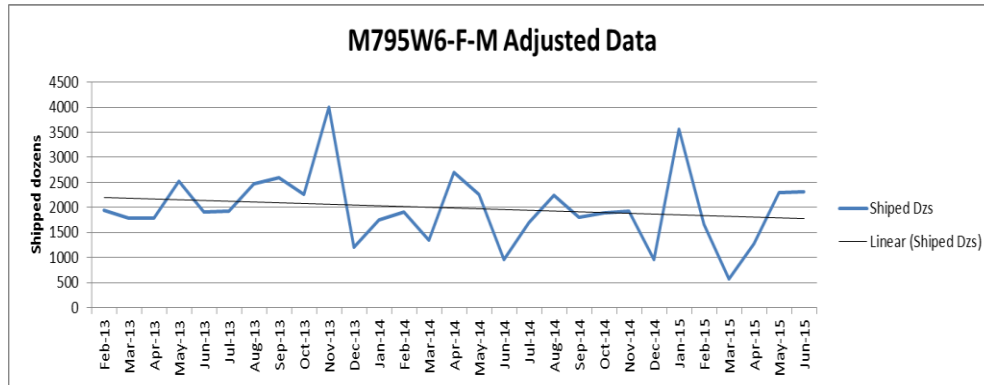
3. M795W6-F-M

Table 18: M795W6-F-M Monthly shipped dozens.

	Shipped Dozens													
	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	JAN	TOTAL	Variation % vs Last year
FY2013	1,943	1,777	1,791	2,524	1,914	1,925	2,471	2,598	2,256	3,993	1,214	1,743	26,147	
FY2014	1,902	1,353	2,694	2,256	954	1,692	2,250	1,809	1,893	1,926	966	3,558	23,253	-11%
FY2015	1,668	570	1,284	2,303	2,319									

QlickView data 2015

Graph 23: M795W6-F-M Monthly shipments.



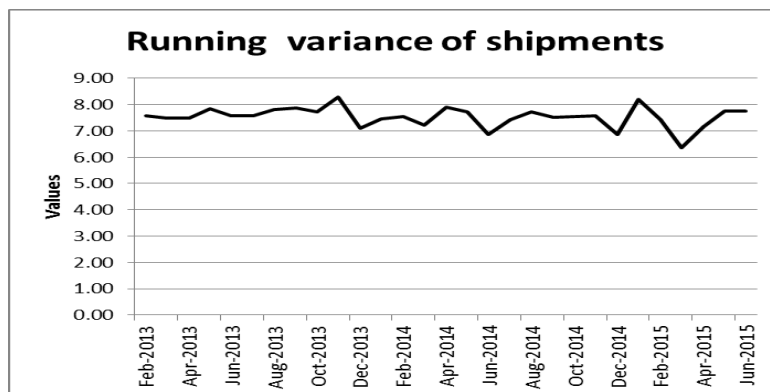
QlickView data 2015

Graph 24: Running shipments variance.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 25: Running logarithms variance.



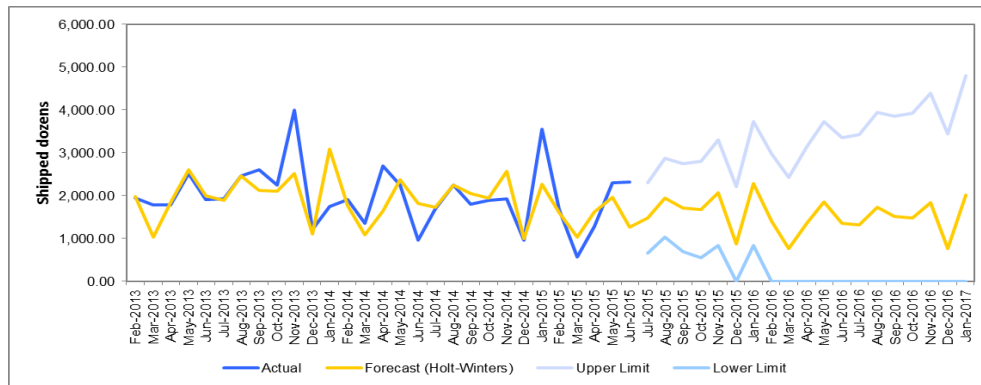
John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 19: Results.

Accuracy Measures	Value	Forecast Statistics	Value
Mean Absolute Percentage Error (MAPE)	21.64%	Mean	1,984.28
R-Square	26.66%	Standard Deviation	715.05
Method Statistics	Value		
Method Selected	Holt Winters		
Level	0.03		
Seasonal	0.29		
Trend	0.22		
Decomposition type	Additive		

John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 26: Model graph results.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 20: M795W6-F-M results comparison.

	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14	Jan-15	TOTAL
FY15 Naïve Forecast	1853	2219	2087	2040	3134	1584	2618	15,535
FY15 Naïve Forecast / MAPE	-23.3%	-37.2%	-89.6%	28.4%	-131.7%	-6.2%	-53.6%	-33.7%
Holt-Winters	1562	1758	1758	2148	2539	976	1758	12,499
FY15 Holt-winters / MAPE	-3.9%	-8.7%	-59.6%	24.6%	-87.6%	34.5%	-3.1%	-7.6%
Actual FY15	1503	1617	1101	2848	1353	1491	1704	11,617

Data from Renfro's network

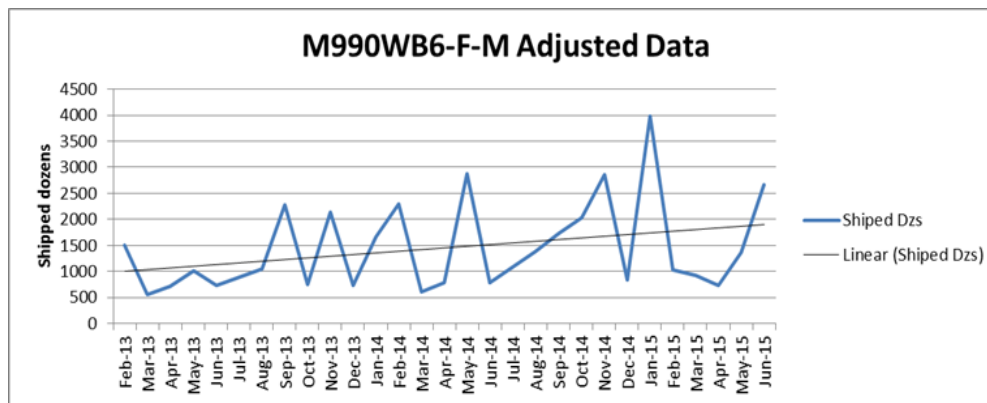
4. M990WB6-F-M

Table 21: M990WB6-F-M Monthly shipped dozens.

Shipped Dozens														
	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	JAN	TOTAL	Variation % vs
FY2013	1,500	550	720	1,017	729	882	1,041	2,271	744	2,136	732	1,668	13,990	Last year 44%
FY2014	2,301	600	783	1,721	777	1,089	1,388	1,735	2,031	2,859	837	3,981	20,102	
FY2015	1,021	918	726	1,366	2,664									

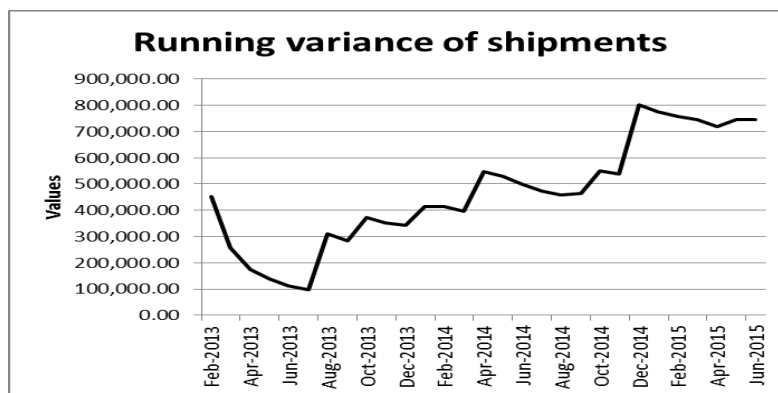
QlickView data 2015

Graph 27: M990WB6-F-M Monthly shipments.



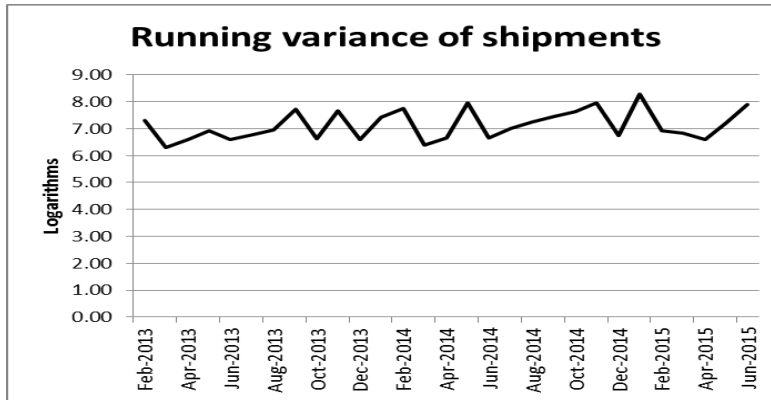
QlickView data 2015

Graph 28: Running shipments variance.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 29: Running logarithms variance.



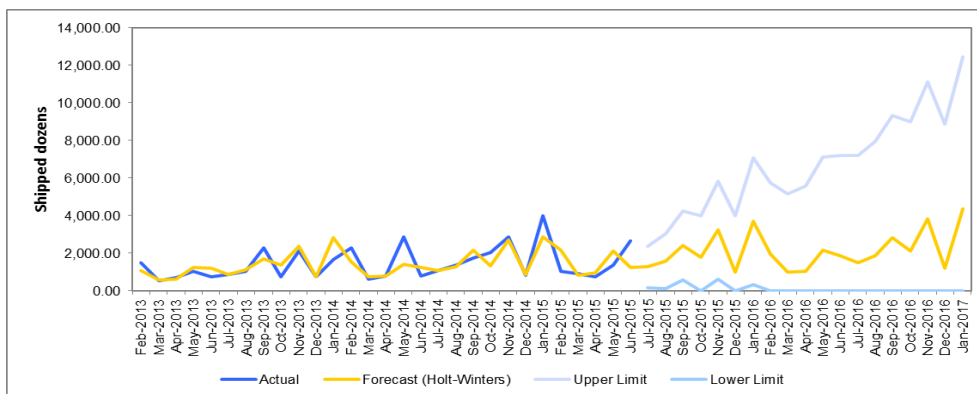
John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 22: Results.

Accuracy Measures	Value	Forecast Statistics	Value
Mean Absolute Percentage Error (MAPE)	30.21%	Mean	1,446.08
R-Square	45.41%	Standard Deviation	864.05
Method Statistics	Value		
Method Selected	Holt Winters		
Level	0.02		
Seasonal	0.31		
Trend	0.67		
Decomposition type	Additive		

John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 30: Model graph results.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 31: M990WB6-F-M results comparison.

	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14	Jan-15	TOTAL
FY15 Naïve Forecast	1471	1116	1948	1597	3203	910	2451	12,696
FY15 Naïve Forecast / MAPE	-32.2%	26.4%	-33.7%	51.2%	-51.5%	68.3%	20.7%	17.7%
Holt-Winters	1556	1778	1556	2223	3112	889	3334	14,447
FY15 Holt-winters / MAPE	-39.8%	-17.3%	-6.7%	32.0%	-47.1%	69.0%	-7.9%	6.4%
Actual FY15	1113	1515.5	1457.5	3270.5	2114.917	2871	3090	15,432

Data from Renfro's network

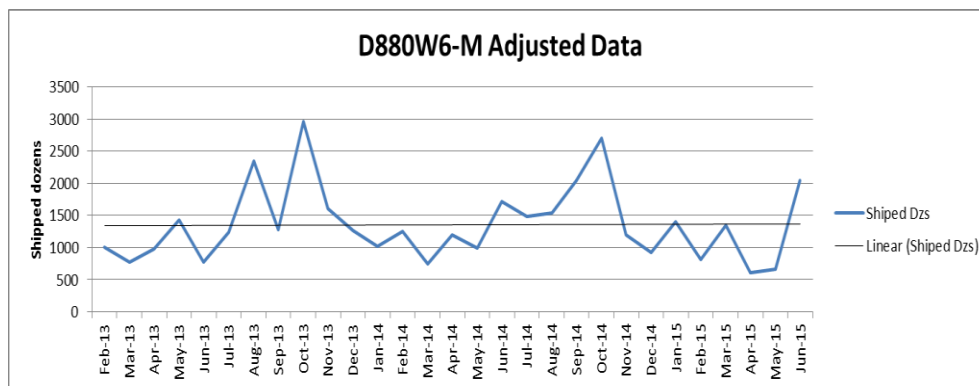
5. D880W6-M

Table 23: D880W6-M Monthly shipped dozens.

Shipped Dozens														Variation % vs Last year
	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	JAN	TOTAL	
FY2013	1,005	771	979	1,436	774	1,239	2,347	1,285	2,958	1,611	1,272	1,018	16,693	3%
FY2014	1,248	750	1,195	990	1,723	1,488	1,540	2,052	2,706	1,191	924	1,401	17,208	
FY2015	813	1,350	609	669	2,046									

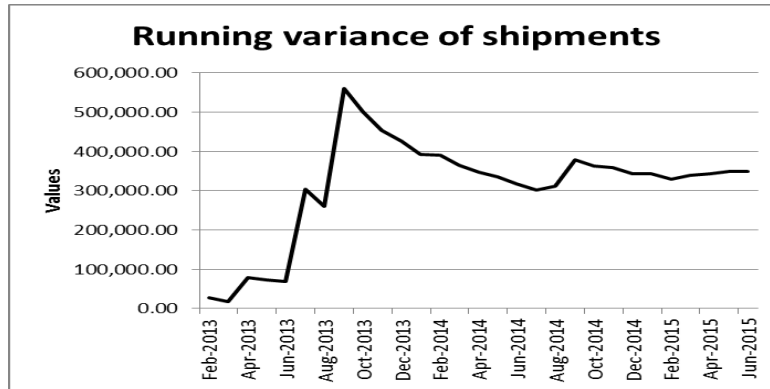
QlickView data 2015

Graph 32: D880W6-M Monthly shipments.



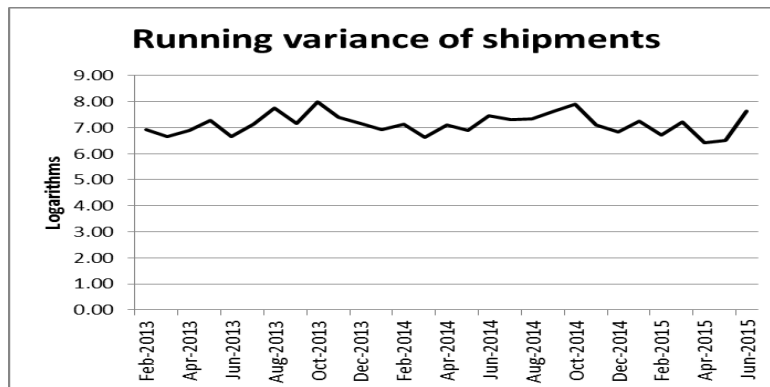
QlickView data 2015

Graph 33: Running shipments variance.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 34: Graph 35: Running logarithms variance.



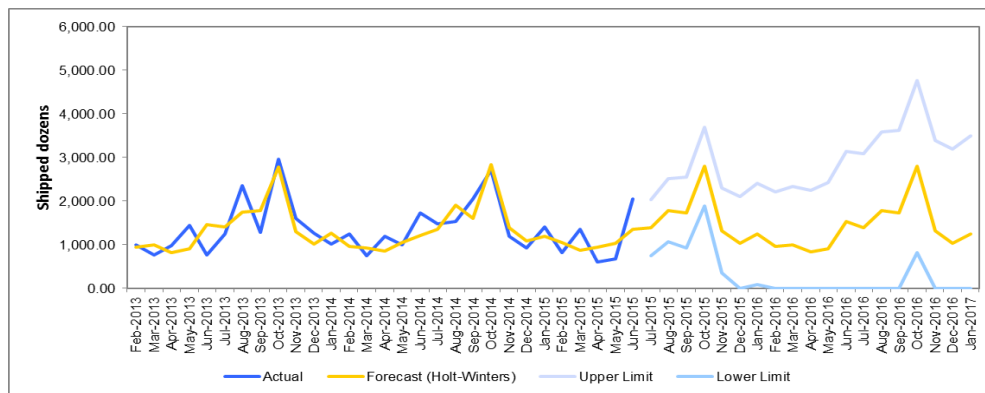
John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 24: Results.

Accuracy Measures		Value	Forecast Statistics		Value
Mean Absolute Percentage Error (MAPE)		26.01%	Mean		1,358.19
R-Square		61.92%	Standard Deviation		590.26
Method Statistics		Value			
Method Selected		Holt Winters			
Level		0.00			
Seasonal		0.30			
Trend		0.00			
Decomposition type		Additive			

John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 36: Model graph results.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 25: D880W6-M results comparison.

	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14	Jan-15	TOTAL
FY15 Naïve Forecast	2409	2012	2532	2991	2419	644	1366	14,372
FY15 Naïve Forecast / MAPE	-32.3%	-29.0%	-81.9%	-22.3%	-39.5%	62.2%	-49.7%	-24.2%
Holt-Winters	1657	1822	1657	2319	1325	994	1160	10,934
FY15 Holt-winters / MAPE	9.0%	-16.8%	-19.0%	5.1%	23.6%	41.8%	-27.2%	5.5%
Actual FY15	1821	1560	1392	2445	1734	1707	912	11,571

Data from Renfro's network

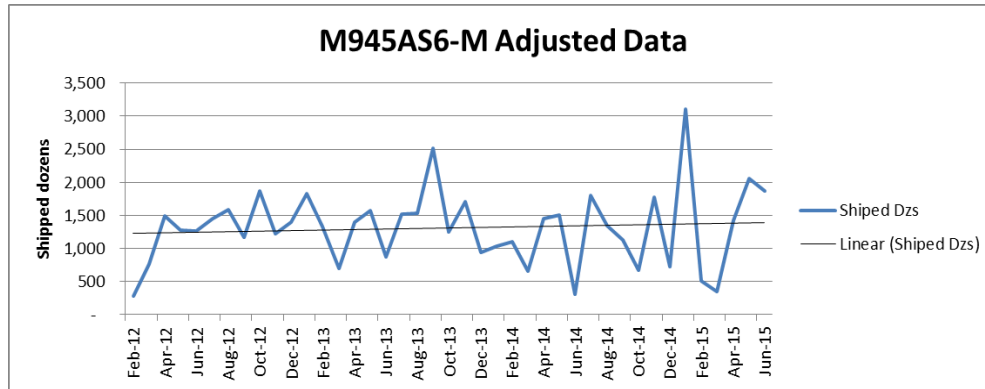
6. M945AS6-M

Table 26: M945AS6-M Monthly shipped dozens.

Shipped Dozens														
	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	JAN	TOTAL	Variation % vs Last year
FY2012	285	759	1,494	1,281	1,265	1,455	1,587	1,167	1,872	1,224	1,396	1,833	15,618	
FY2013	1,330	694	1,401	1,577	867	1,518	1,539	2,508	1,248	1,707	938	1,034	16,359	5%
FY2014	1,107	663	1,446	1,506	309	1,806	1,344	1,133	666	1,776	723	3,102	15,581	-5%
FY2015	510	348	1,419	2,061	1,869									

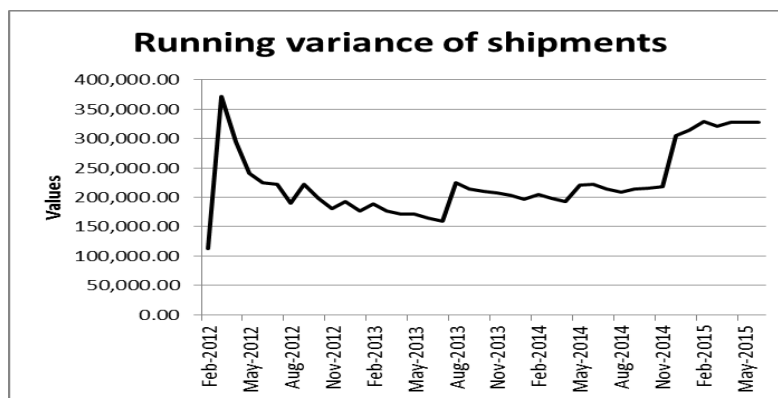
QlickView data 2015

Graph 37: M945AS6-M Monthly shipments.



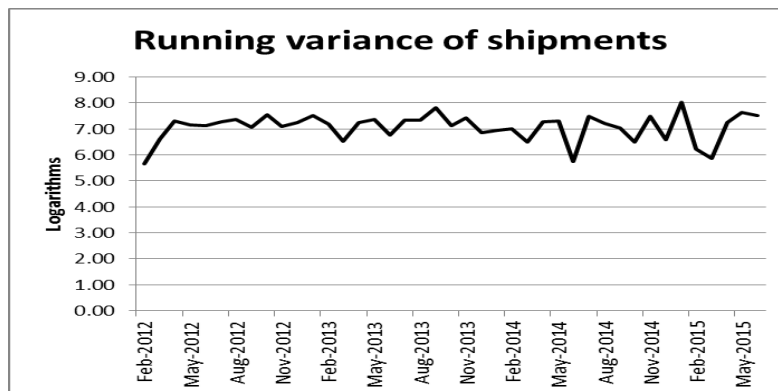
QlickView data 2015

Graph 38: Running shipments variance.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 39: Graph 40: Running logarithms variance.



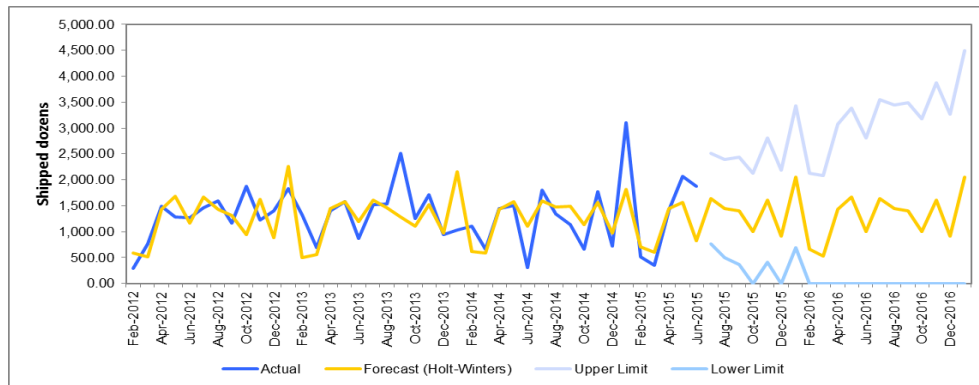
John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 27: Results.

Accuracy Measures	Value	Forecast Statistics	Value
Mean Absolute Percentage Error (MAPE)	34.25%	Mean	1,311.32
R-Square	23.48%	Standard Deviation	572.58
Method Statistics	Value		
Method Selected	Holt Winters		
Level	0.00		
Seasonal	0.23		
Trend	0.00		
Decomposition type	Additive		

John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 41: Model graph results.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 28: M945AS6-M results comparison.

	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14	Jan-15	TOTAL
FY15 Naïve Forecast	1846	981	1542	745	2024	1421	903	9,461
FY15 Naïve Forecast / MAPE	-74.8%	36.8%	35.8%	45.2%	-40.8%	-121.1%	58.4%	10.9%
Holt-Winters	1478	1478	1971	1478	1643	986	1314	10,348
FY15 Holt-winters / MAPE	-40.0%	4.8%	18.0%	-8.8%	-14.3%	-53.4%	39.4%	2.5%
Actual FY15	1,056.0	1,552.5	2,402.9	1,359.0	1,437.0	642.5	2,169.0	10,619

Data from Renfro's network

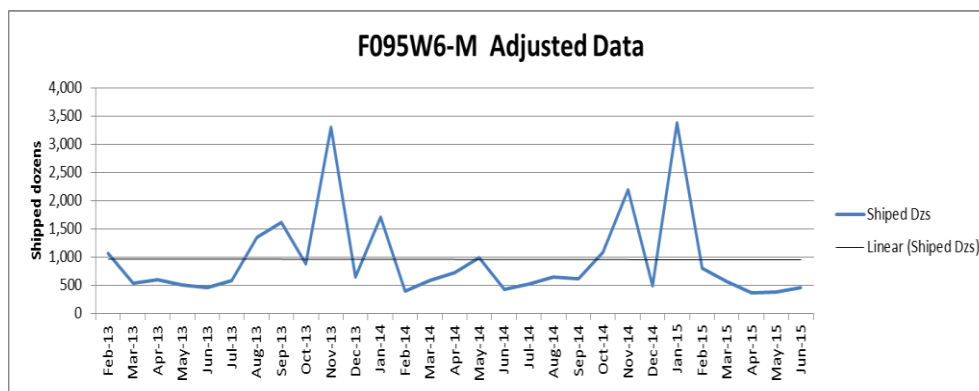
7. F095W6-M

Table 29: F095W6-M Monthly shipped dozens.

Shipped Dozens													
	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	JAN	TOTAL
FY2013	1,067	534	596	510	456	585	1,358	1,623	882	3,300	651	1,707	13,268
FY2014	393	579	732	990	432	531	645	624	1,086	2,197	489	3,387	12,085
FY2015	804	567	372	390	468								

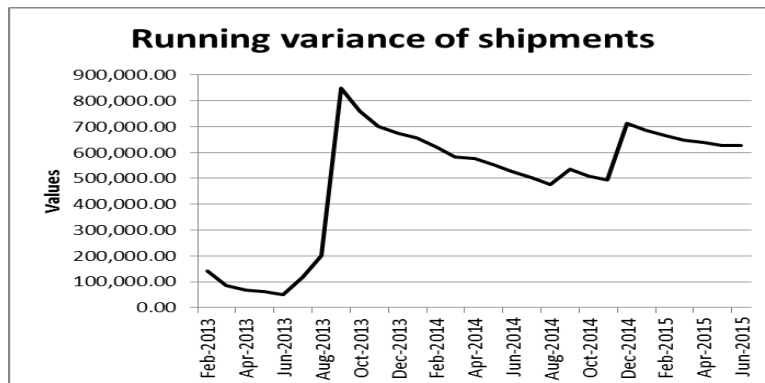
ClickView data 2015

Graph 42: F095W6-M Monthly shipments.



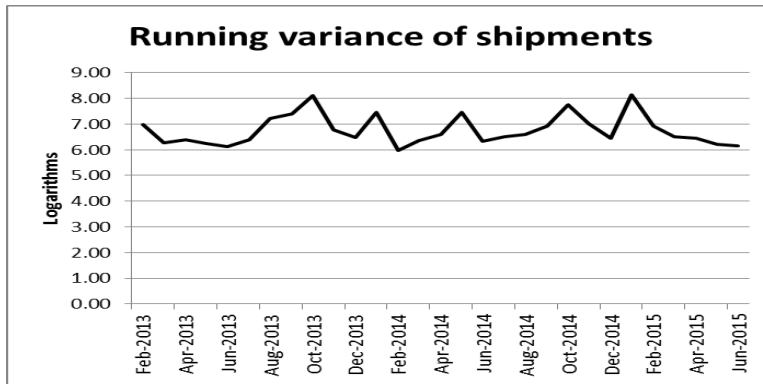
ClickView data 2015

Graph 43: Running shipments variance.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 44: Running logarithms variance.



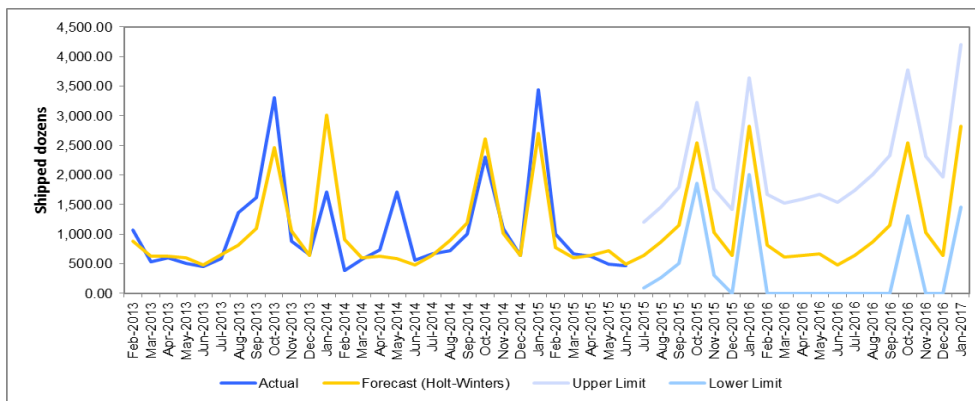
John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 30: Results.

Accuracy Measures		Value	Forecast Statistics		Value
Mean Absolute Percentage Error (MAPE)		23.39%	Mean		1,047.08
R-Square		69.05%	Standard Deviation		791.69
Method Statistics		Value			
Method Selected		Holt Winters			
Level		0.00			
Seasonal		0.19			
Trend		0.00			
Decomposition type		Additive			

John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 45: Model graph results.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 31: F095W6-M results comparison.

	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14	Jan-15	TOTAL
FY15 Naïve Forecast	665	825	1165	2343	2189	2671	1940	11,797
FY15 Naïve Forecast / MAPE	21.0%	-18.5%	-64.6%	-11.7%	-51.0%	-152.3%	13.2%	-30%
Holt-Winters	776	1034	1293	905	2973	646	1680	9,307
FY15 Holt-winters / MAPE	7.8%	-48.6%	-82.6%	56.8%	-105.2%	39.0%	24.8%	-2.4%
Actual FY15	841	696	708	2097	1449	1059	2235	9,085

Data from Renfro's network

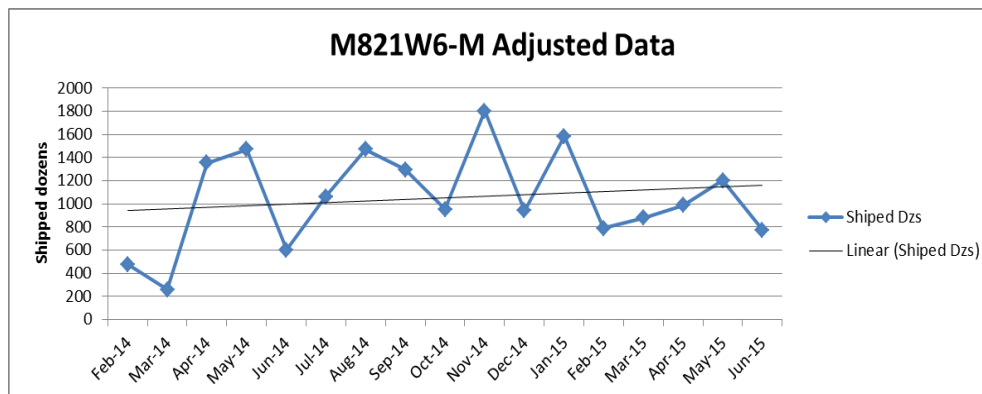
8. M821W6-M

Table 32: M821W6-M Monthly shipped dozens.

Shipped Dozens													
	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	JAN	TOTAL
FY2014	477	258	1,352	1,470	600	1,062	1,471	1,294	951	1,801	939	1,584	13,258
FY2015	789	879	987	1,200	2,730								

QlickView data 2015

Graph 46: M821W6-M Monthly shipments.



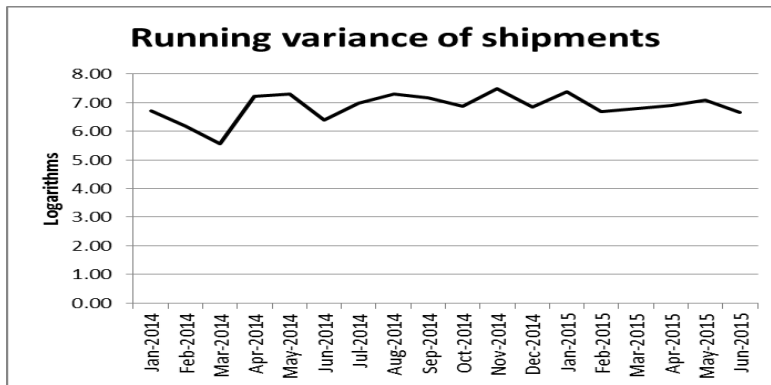
QlickView data 2015

Graph 47: Running shipments variance.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 48: Running logarithms variance.



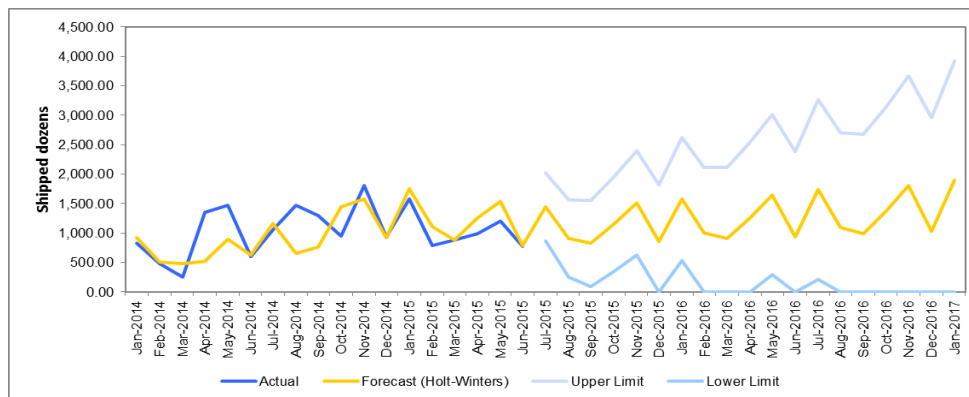
John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 33: Results.

Accuracy Measures		Value	Forecast Statistics		Value
Mean Absolute Percentage Error (MAPE)		27.35%	Mean		1,039.27
R-Square		4.96%	Standard Deviation		404.68
Method Statistics		Value			
Method Selected		Holt Winters			
Level		0.30			
Seasonal		0.18			
Trend		0.02			
Decomposition type		Additive			

John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 49: Model graph results.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 34: M821W6-M results comparison.

	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14	Jan-15	TOTAL
FY15 Naïve Forecast	1274	548	1386	1063	947	1460	905	7,582
FY15 Naïve Forecast / MAPE	-212.4%	58.5%	-15.9%	59.7%	60.6%	-57.0%	42.7%	27.6%
Holt-Winters	1279	1599	1599	1279	2078	959	1119	9,912
FY15 Holt-winters / MAPE	-213.5%	-21.1%	-33.7%	51.5%	13.5%	-3.1%	29.1%	5.3%
Actual FY15	408	1320.5	1195.5	2634.5	2403	930	1578	10,470

Data from Renfro's network

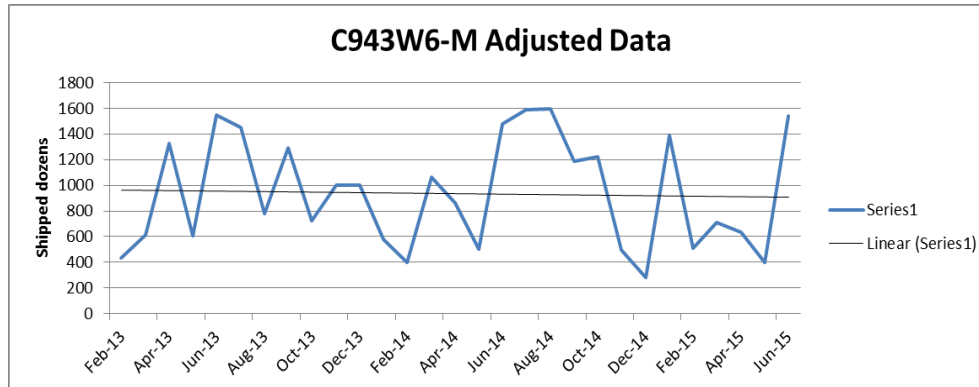
9. C943W6-M

Table 35: C943W6-M Monthly shipped dozens.

Shipped Dozens													
	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	JAN	TOTAL
FY2013	431	615	1,327	610	1,548	1,452	783	1,293	723	999	999	582	11,361
FY2014	399	1,062	861	504	1,476	1,590	1,599	1,186	1,221	498	282	1,392	12,069
FY2015	513	723	633	402	1,539								

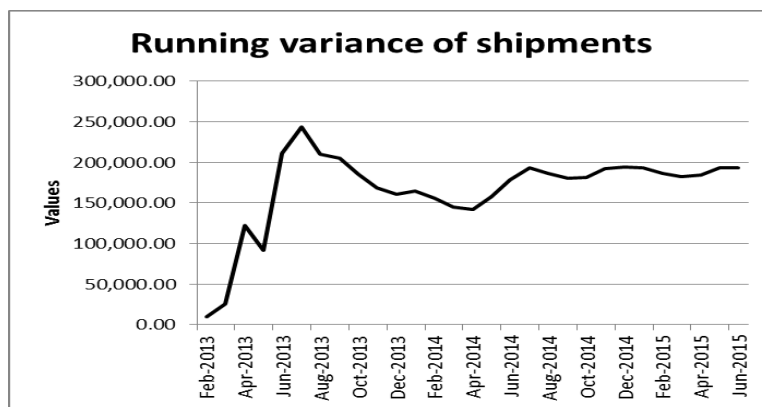
QlickView data 2015

Graph 50: C943W6-M Monthly shipments.



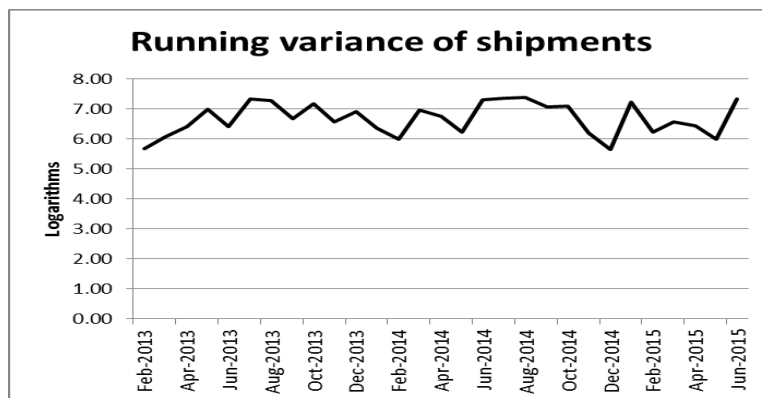
ClickView data 2015

Graph 51: Running shipments variance.



John Galt Solution -Forecast Wizard 7.1 used with ClickView data 2015.

Graph 52: Running logarithms variance.



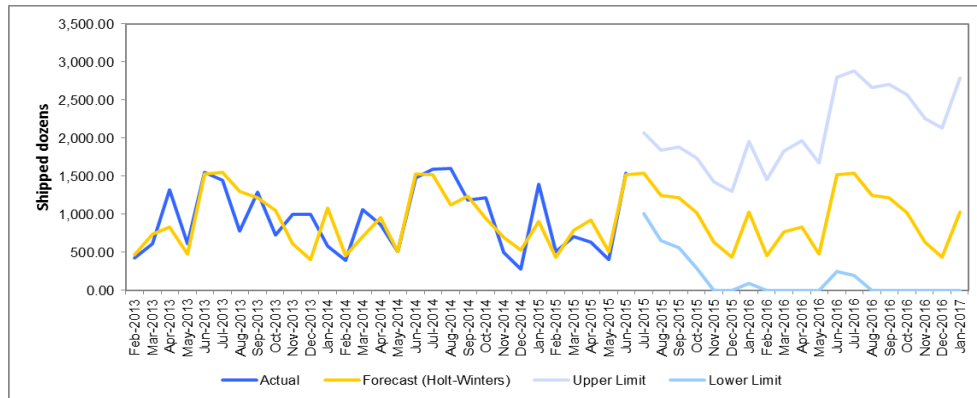
John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 36: Results.

Accuracy Measures	Value	Forecast Statistics	Value
Mean Absolute Percentage Error (MAPE)	27.05%	Mean	938.86
R-Square	55.12%	Standard Deviation	430.25
Method Statistics	Value		
Method Selected	Holt Winters		
Level	0.00		
Seasonal	0.29		
Trend	0.00		
Decomposition type	Additive		

John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 53: Model graph results.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 37: C943W6-M results comparison.

	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14	Jan-15	TOTAL
FY15 Naïve Forecast	1710	1719	1988	1771	2111	1125	2115	12,538
FY15 Naïve Forecast / MAPE	-127.0%	-57.0%	-100.8%	-67.2%	-215.5%	-33.0%	-192.5%	-104.4%
Holt-Winters	1469	1356	1130	1356	791	565	1017	7,685
FY15 Holt-winters / MAPE	-95.1%	-23.9%	-14.2%	-28.1%	-18.3%	33.2%	-40.7%	-25.3%
Actual FY15	753	1095	990	1059	669	846	723	6,135

Data from Renfro's network

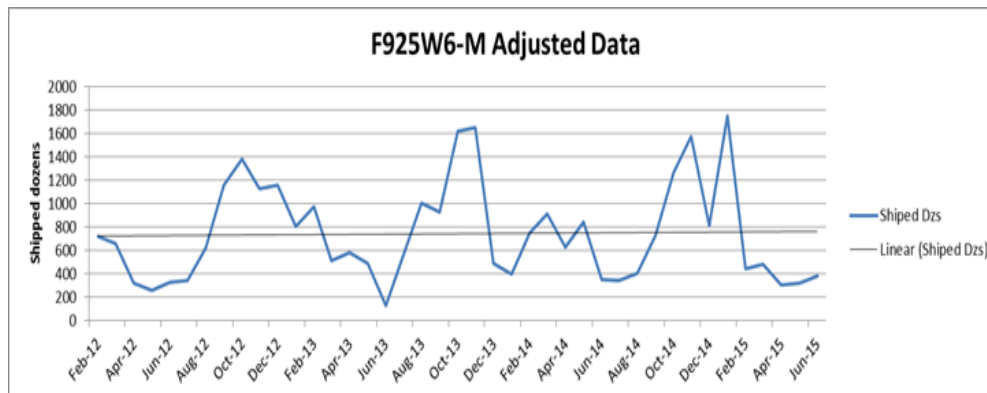
10. F925W6-M

Table 38: F925W6-M Monthly shipped dozens.

Shipped Dozens														
	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	JAN	TOTAL	Variation %
FY2012	722	660	318	261	330	341	624	1,162	1,384	1,132	1,161	807	8,900	vs Last year
FY2013	975	516	579	489	129	562	1,008	930	1,620	1,652	492	400	9,352	5%
FY2014	753	915	627	840	348	345	402	725	1,263	1,572	815	1,748	10,353	11%
FY2015	441	486	306	318	378									

QlickView data 2015

Graph 54: F925W6-M Monthly shipments.



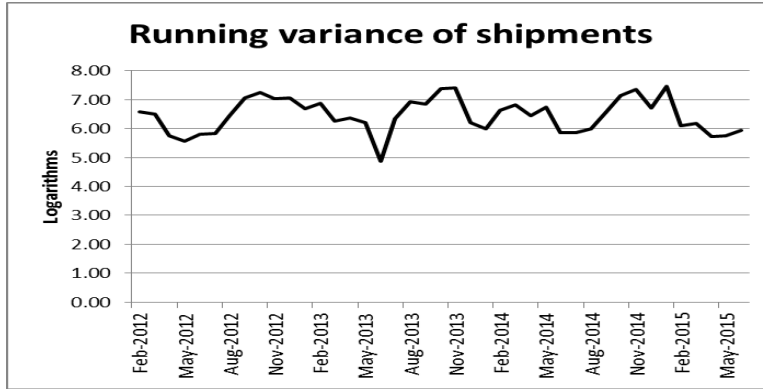
QlickView data 2015

Graph 55: Running shipments variance.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 56: Running logarithms variance.



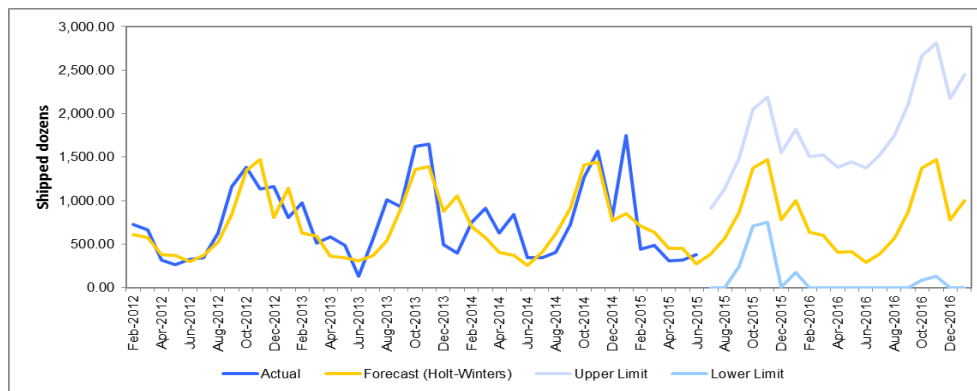
John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 39: Results.

Accuracy Measures		Value	Forecast Statistics		Value
Mean Absolute Percentage Error (MAPE)		34.50%	Mean		744.71
R-Square		56.48%	Standard Deviation		426.87
Method Statistics		Value			
Method Selected		Holt Winters			
Level		0.00			
Seasonal		0.22			
Trend		0.00			
Decomposition type		Additive			

John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 57: Model graph results.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 40: F925W6-M results comparison.

	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14	Jan-15	TOTAL
FY15 Naïve Forecast	516	438	919	1465	1436	1797	1391	7,962
FY15 Naïve Forecast / MAPE	24.1%	-18.7%	-55.6%	10.9%	-37.2%	-223.8%	25.2%	-18.0%
Holt-Winters	627	716	1074	1432	1343	537	716	6,446
FY15 Holt-winters / MAPE	7.8%	-94.1%	-81.8%	12.9%	-28.3%	3.2%	61.5%	4.5%
Actual FY15	680	369	591	1644	1047	555	1860	6,746

Data from Renfro's network

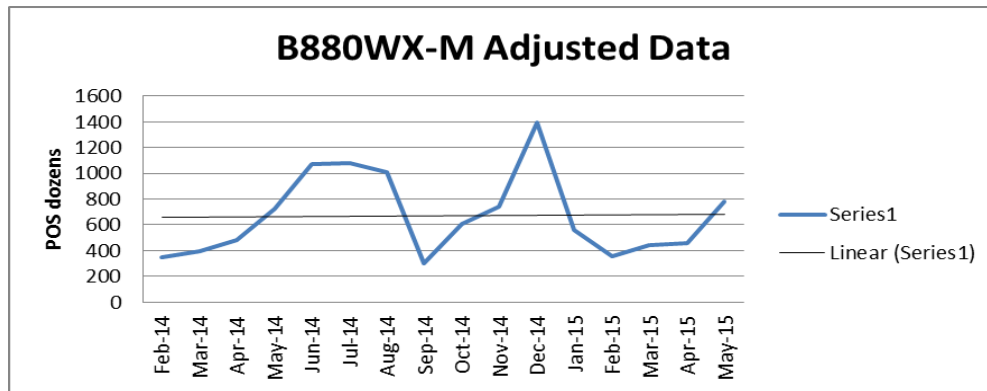
11. B880WX-M

Table 41: B880WX-M Monthly POS dozens

Shipped Dozens													
	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	JAN	TOTAL
FY2014	346	397	485	725	1,068	1,082	1,005	300	608	744	1,394	564	8,718
FY2015	354	439	462	777									

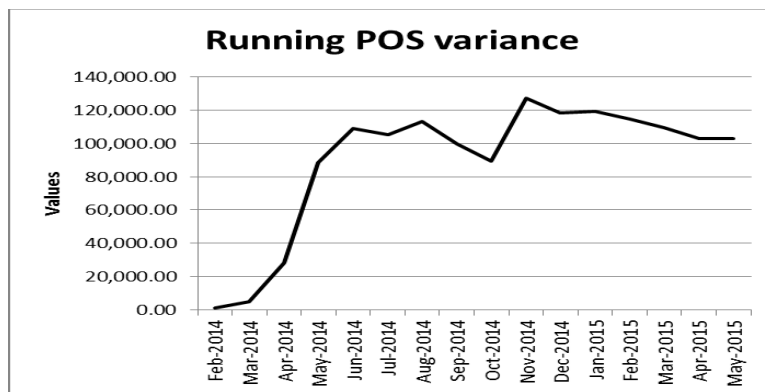
QlickView data 2015

Graph 58: C943W6-M Monthly shipments.



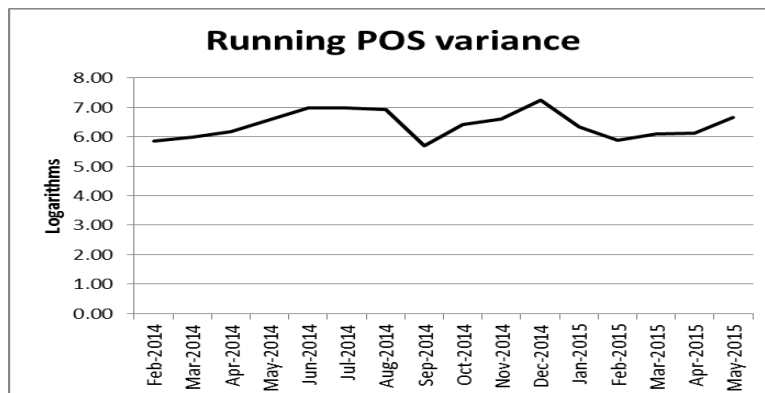
QlickView data 2015

Graph 59: Running POS variance.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 60: Running logarithms variance.



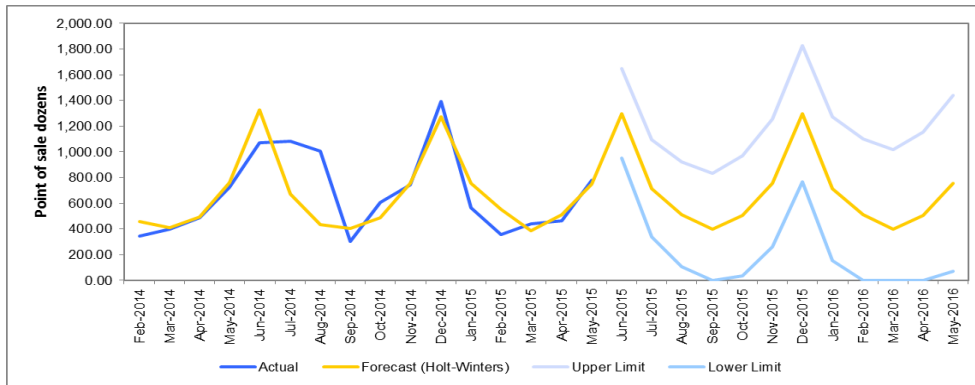
John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 42: Results.

Accuracy Measures	Value	Forecast Statistics	Value
Mean Absolute Percentage Error (MAPE)	21.39%	Mean	671.90
R-Square	54.97%	Standard Deviation	321.15
Method Statistics	Value		
Method Selected	Holt Winters		
Level	0.00		
Seasonal	0.21		
Trend	0.00		
Decomposition type	Additive		

John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 61: Model graph results.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 43: B880WX-M results comparison.

	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14	Jan-15	TOTAL
FY15 Naïve Forecast	1406	323	1866	1936	925	988	1290	8,733
FY15 Naïve Forecast / MAPE	45.6%	36.1%	-324.0%	-128.8%	41.1%	-252.9%	-180.5%	-30.6%
Holt-Winters	1227	960	410	1750	854	788	555	6,544
FY15 Holt-winters / MAPE	52.5%	-90.2%	6.8%	-106.9%	45.6%	-181.4%	-20.7%	2.1%
Actual FY15	2585	505	440	845.8333	1570	280	460	6,686

Data from Renfro's network

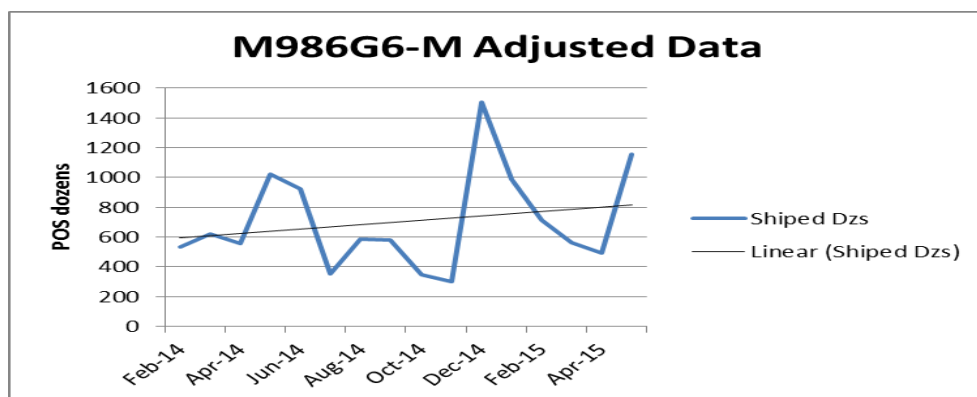
12. M986G6-M

Table 44: M986G6-M Monthly POS dozens

Shipped Dozens													
	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	JAN	TOTAL
FY2014	533	619	556	1,022	924	354	584	580	350	301	1,507	987	8,315
FY2015	711	565	492	1,158									

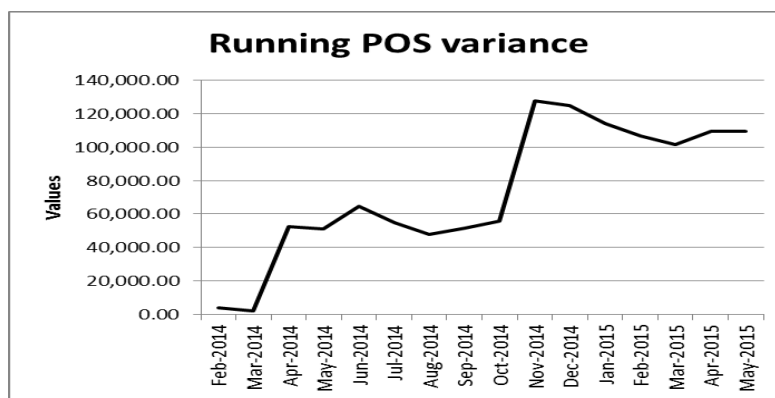
QlickView data 2015

Graph 62: C943W6-M Monthly shipments.



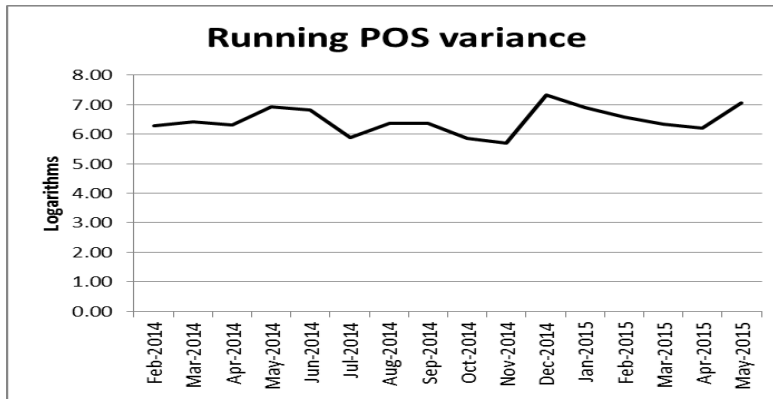
QlickView data 2015

Graph 63: Running POS variance.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 64: Running logarithms variance.



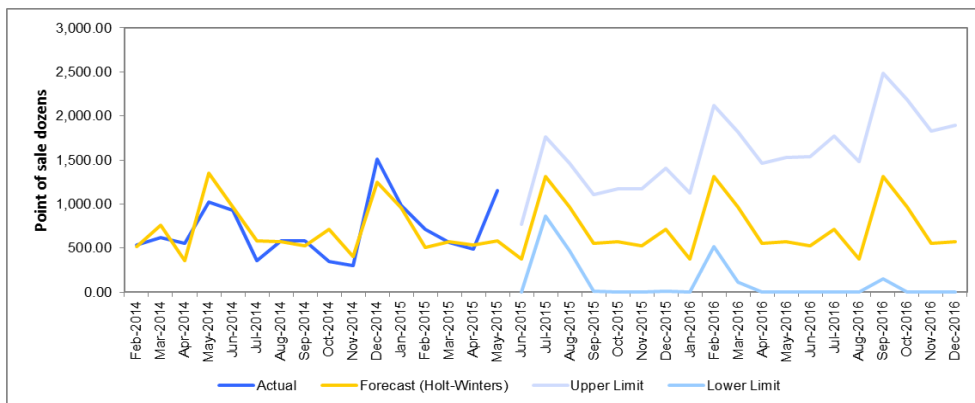
John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 45: Results.

Accuracy Measures		Value	Forecast Statistics		Value
Mean Absolute Percentage Error (MAPE)		26.54%	Mean		702.50
R-Square		50.64%	Standard Deviation		330.96
Method Statistics		Value			
Method Selected		Holt Winters			
Level		0.00			
Seasonal		0.28			
Trend		0.00			
Decomposition type		Additive			

John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 65: Model graph results.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 46: M986G6-M results comparison.

	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14	Jan-15	TOTAL
FY15 Naïve Forecast	92	503	210	0	1427	1183	846	4,261
FY15 Naïve Forecast / MAPE	34.4%	60.1%	76.3%	100.0%	35.6%	-100.1%	44.6%	44.9%
Holt-Winters	1013	1350	900	788	1350	675	788	6,864
FY15 Holt-winters / MAPE	-620.8%	-7.2%	-1.9%	29.8%	39.0%	-14.2%	48.4%	11.3%
Actual FY15	140.5	1260	883	1122	2214.5	591	1527	7,738

Data from Renfro's network

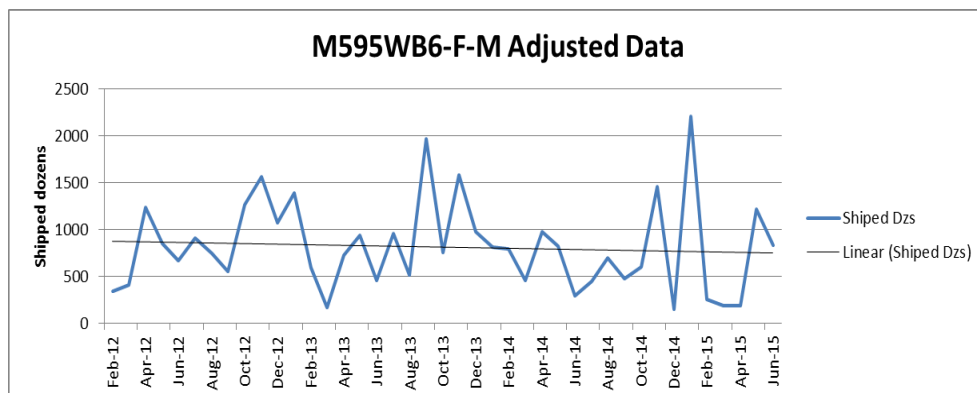
13. M595WB6-F-M

Table 47: M595WB6-F-M Monthly shipped dozens.

	Shipped Dozens													
	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	JAN	TOTAL	
FY2012	344	411	1,237	852	670	909	753	561	1,267	1,569	1,077	1,392	11,040	
FY2013	597	173	729	939	465	960	514	1,965	756	1,587	980	816	10,479	-5%
FY2014	801	456	975	825	294	453	696	478	600	1,458	156	2,205	9,397	-10%
FY2015	261	192	192	1,224	834									

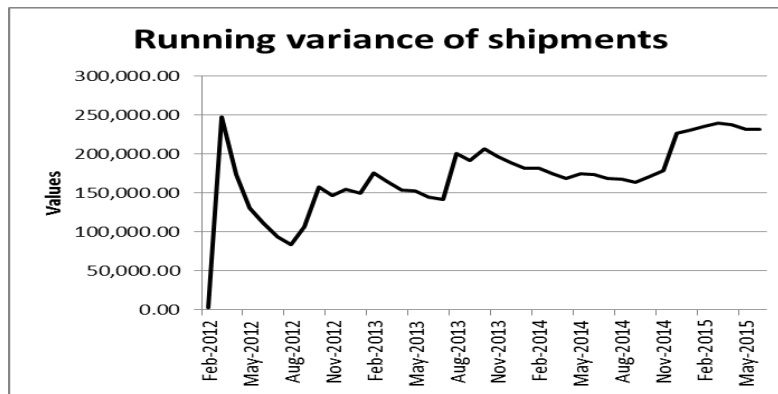
QlickView data 2015

Graph 66: M595WB6-F-M Monthly shipments.



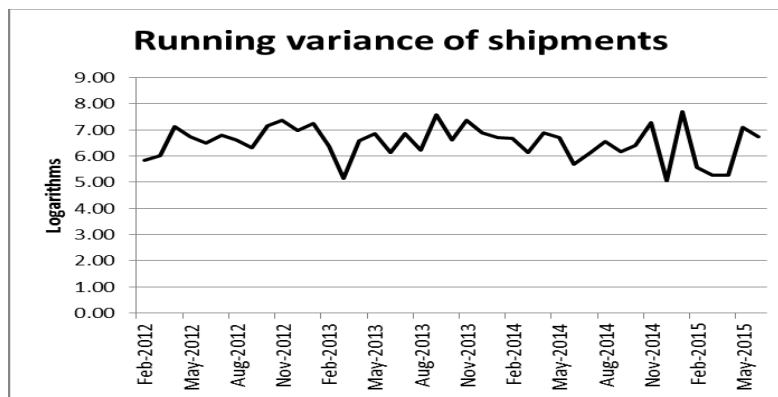
QlickView data 2015

Graph 67: Running shipments variance.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 68: Running logarithms variance.



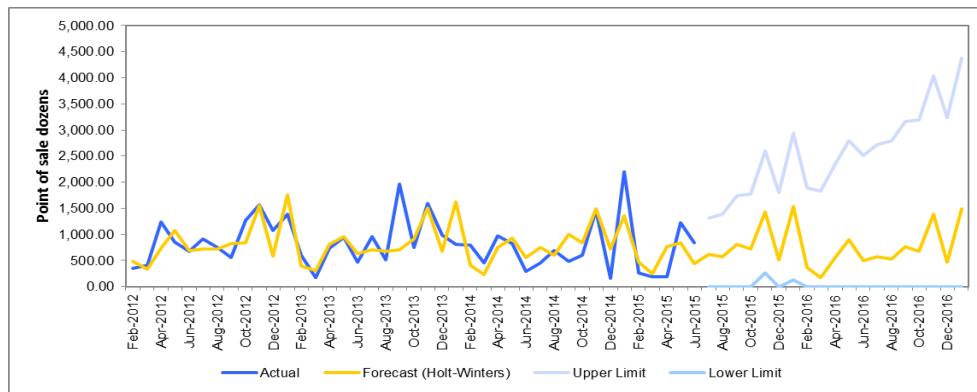
John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 48: Results.

Accuracy Measures		Value	Forecast Statistics		Value
Mean Absolute Percentage Error (MAPE)		50.67%	Mean		819.95
R-Square		35.20%	Standard Deviation		481.21
Method Statistics		Value			
Method Selected		Holt Winters			
Level		0.01			
Seasonal		0.26			
Trend		0.37			
Decomposition type		Additive			

John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 69: Model graph results.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 49: M595WB6-F-M results comparison.

	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14	Jan-15	TOTAL
FY15 Naïve Forecast	547	606	417	316	1677	433	990	4,986
FY15 Naïve Forecast / MAPE	15.6%	33.7%	41.6%	70.3%	-140.0%	58.7%	19.5%	21.1%
Holt-Winters	806	806	716	806	1343	627	985	6,086
FY15 Holt-winters / MAPE	-24.3%	12.0%	-0.2%	24.1%	-92.1%	40.2%	20.0%	3.6%
Actual FY15	648	915	714.5	1062	699	1047.5	1230	6,316

Data from Renfro's network

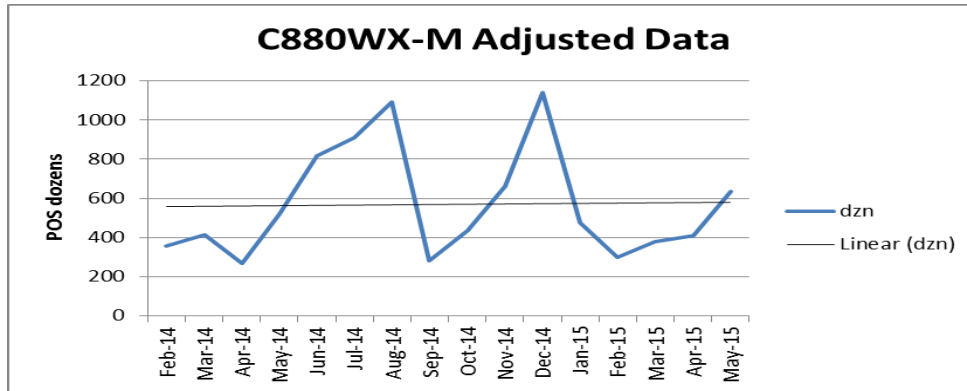
14. C880WX-M

Table 50: M880WX-M Monthly shipped dozens.

Shipped Dozens													
	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	JAN	TOTAL
FY2014	356	414	267	519	818	910	1,092	280	435	663	1,140	478	7,372
FY2015	301	380	412	638									

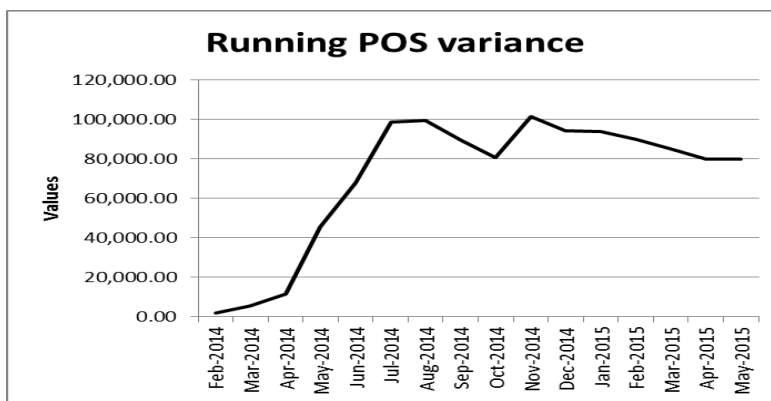
QlickView data 2015

Graph 70: M595WB6-F-M Monthly shipments.



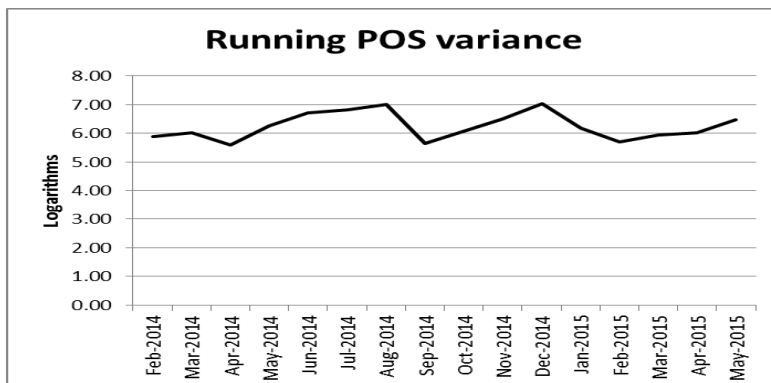
ClickView data 2015

Graph 71: Running POS variance.



John Galt Solution -Forecast Wizard 7.1 used with ClickView data 2015.

Graph 72: Running logarithms variance.



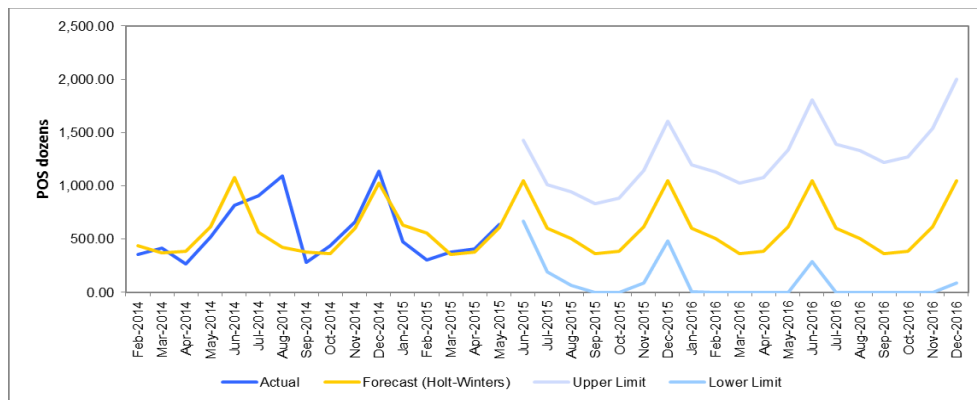
John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 51: Results.

Accuracy Measures	Value	Forecast Statistics	Value
Mean Absolute Percentage Error (MAPE)	27.19%	Mean	568.88
R-Square	33.88%	Standard Deviation	282.44
Method Statistics	Value		
Method Selected	Holt Winters		
Level	0.00		
Seasonal	0.20		
Trend	0.00		
Decomposition type	Additive		

John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Graph 73: Model graph results.



John Galt Solution -Forecast Wizard 7.1 used with QlickView data 2015.

Table 52: M595WB6-F-M results comparison.

	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14	Jan-15	TOTAL
FY15 Naïve Forecast	1170	323	780	2581	430	851	968	7,102
FY15 Naïve Forecast / MAPE	53.1%	-61.3%	-83.4%	-173.1%	68.4%	-305.4%	-311.8%	-21.0%
Holt-Winters	1170	1325	395	1850	1150	335	450	6,675
FY15 Holt-winters / MAPE	53.1%	-562.5%	7.1%	-95.8%	15.4%	-59.5%	-91.5%	-13.7%
Actual FY15	2495	200	425	945	1360	210	235	5,870

Data from Renfro's network

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