

Acknowledgments

This project could not have been successful without the love and support of my wife, Tanya and my parents, Mario and Martha. Thanks also to Dr. Tom Bowlin (my “guide”), Dr. Zerwekh and Dr. Keller for their knowledge and encouragement.

I am very grateful to Lucille and Michael Hobbs for their friendship, understanding and financial support. Finally, thank you to Tom Decker, Pat Jackson and Brian Zellar for all their contributions and hard work on this project.

Executive Summary

This project studied and analyzed Electronic Controls, Inc.'s forecasting process for three high-demand products. In addition, alternative forecasting methods were developed to compare to the current forecast method. The following is a list of the main findings:

- The three selected products showed a prominent irregular component.
- The optimal forecasting method for each product was different.
- The current forecasting method produced unacceptable forecasts for two of the selected products.
- Two of the model-based forecasts were more accurate than the forecast produced by the current process.

The following are the main recommendations to improve the current forecasting process:

- Electronic Controls should keep track of the sales data instead of the shipping data to forecast the demand of each product.
 - Electronic Controls should keep track of the forecasting error in order to calculate the accuracy measures.
 - Implementing the tracking signal for the forecast of each product will improve the accuracy of the current forecasting process.
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Table of Contents

Acknowledgments	0
Executive Summary.....	2
Table of Contents	3
Index Table.....	5
Table of Figures	7
Introduction.....	8
Literature Review	9
Methodology.....	10
Current Inventory Forecast Process	10
Development of Alternative Forecast Process.....	10
Current and Alternative Forecast Process Comparison.....	19
Results.....	20
Current Inventory Forecast Process	20
Model-Based Forecast Process	25

Evaluation of Forecasting Process: Model-Based Vs Judgmental Forecast	46
Conclusions and Recommendations.....	49
Suggestions for Additional Work	52
References / Bibliography.....	54
APPENDIX A.....	56

Index

Table 1 - Inventory Planning Report	21
Table 2 - Sales Analysis Sheet for the OE331	23
Table 3 – OE315 Shipments Historical Data	25
Table 4 - OE320 Historical Data.....	26
Table 5 - OE331 Historical	26
Table 6- Adjusted OE315 Data	29
Table 7- Adjusted OE320 Data.....	30
Table 8 - Adjusted OE331 Data.....	31
Table 9- Results from Model-Base Forecasting Methods for the OE315	37
Table 10 - Results from the Trend Forecasting Methods for the OE320.....	38
Table 11 - Results from the Trend Forecasting Methods for the OE331.....	38
Table 12 - OE315 Forecast for 2005	39
Table 13 - OE320 Forecast for 2005.....	40
Table 14 - OE331 Forecast for 2005	40

Table 15 - Accuracy Measures for OE315 Forecast (2005)	41
Table 16 - Accuracy Measures for OE320 Forecast (2005)	42
Table 17 - Accuracy Measures for OE331 Forecast (2005)	43
Table 18 - Forecast and Accuracy Measures for the OE320 12 Month Linear Regression	44
Table 19 - Forecast and Accuracy Measures for the OE331 12 Months Linear Regression.....	45
Table 20 – Forecasted Values and Accuracy Measures for OE315	46
Table 21 – Forecasted Values and Accuracy Measures for OE320	47
Table 22– Forecasted Values and Accuracy Measures for OE331	48

Table of Figures

Figure 1 – Scatter Diagram for the OE315 Historical Data.....	27
Figure 2 - Scatter Diagram for the OE320 Historical Data.....	27
Figure 3 - Scatter Diagram for the OE331 Historical Data.....	28
Figure 4 - Scatter Diagram for the OE315 Adjusted Data.....	32
Figure 5 - Scatter Diagram for the OE320 Adjusted Data.....	32
Figure 6 - Scatter Diagram for the OE331 Adjusted Data.....	33
Figure 7 - Autocorrelation Analysis for the OE315 Adjusted Data.....	34
Figure 8 - Autocorrelation Analysis for the OE320 Adjusted Data.....	35
Figure 9 - Autocorrelation for the OE331 Adjusted Data	36

Introduction

Electronic Controls, Inc. is a privately owned company located in Kansas City, Missouri, which develops innovative control solutions for the building automation industry. Inventory is an essential component of this company and can greatly effect its financial situation.

Currently, the company calculates its inventory level based on a judgmental forecasting process. Judgmental forecasting is built around the idea that the knowledge and intuition of the company's experts are the best tools to forecast the future demand of products. While this method has been working satisfactorily, no forecasting process is perfect. It is in Electronic Control's best interest to investigate the accuracy of the current process and whether or not there are more effective alternatives to be applied.

Statistical and forecasting theories will be studied and applied to achieve these main goals:

- Study and understand the current Electronic Controls forecasting process
- Evaluate the accuracy of the current forecasting process
- Develop alternative forecasting methods
- Compare the current and alternative forecasting methods
- Recommend ways to make the forecast more accurate

Electronic Controls' management will be presented with the results of this investigation. They can then take the appropriate measures to improve forecasting.

Literature Review

The main component of this project required research in time series forecast theory. That research encompassed the following areas: comprehension and identification of the time series components, understanding and application of different forecasting methods and evaluation of the forecasting results. The following titles cover the above-mentioned topics in detail:

1. Bowerman, Bruce L., Richard T. O'Connell and Anne B. Koehler. 2005. *Forecasting, Time Series, and Regression*.
2. Hanke, John E. Dean W. Wichern and Arthur G. Reitsch. 2001. *Business Forecasting*.

A Companion to Economic Forecasting by the editors Michael P. Clements and David F. Hendry has a chapter dedicated to judgmental forecasting. This chapter discusses the format and the strengths and weaknesses of judgmental forecasting. In addition, it compares judgmental and model-based forecasts.

The books listed below are dedicated to the study of inventory management and the application of forecasting in the inventory management process. Of special interest was the study of areas that explain the process of modeling the product demand accurately and of learning the forecasting methods that are most widely implemented by other companies.

1. Axsäter, Sven. 2000. *Inventory Control*.
 2. Toomey, John W. 2000. *Inventory Management: Principles, Concepts and Techniques*.
 3. Seth, Suresh P., Houmin Yan and Hanqin Zhang. 2005. *Inventories and Supply Chain Management with Forecast Updates*.
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Methodology

The explanation of research required in the project is divided into three main sections. The first section is the explanation of research required to understand the current inventory forecast process. The second section concerns development of a preferred alternative forecast method. The last section addresses and analyzes the comparisons made between the results of the current forecast process and those of the studied alternative forecasting methods.

Current Inventory Forecast Process

To understand how the current inventory forecast method works, interviews were performed to supplement information available from personal experience. The interviewees included personnel from the management, accounting and production departments. The personal experience was gained through direct observation of business meetings and other interactions that the personnel in charge of forecasting had during the last two months. The business meetings attended included only those related to the current forecasting method.

Development of Alternative Forecast Process

Electronics Controls' executives selected three products for which to develop alternative model-based forecasts. The products were selected because they are considered high-demand products. They are the OE315, the OE320 and the OE331. The alternative forecasting model-based process was developed according to the forecasting process explained by Hanke John (2001) in the following steps:

1. Data Collection
2. Data Reduction or Condensation
3. Model Building and Evaluation
4. Model Extrapolation
5. Forecast Evaluation

For the **data collection** step, it is important to collect the proper data and to verify that the data are correct. Ideally, sales data are used to develop the forecast of a product's demand. Unfortunately, Electronic Controls does not keep track of this data. Thus, the amount of products shipped was used instead to forecast the demand for the three selected products. Electronic Controls receives the three selected products monthly, therefore, shipments data were also recorded monthly.

For the **data reduction or condensation** step, data that are not relevant to the problem at hand are eliminated to make the data more representative and thus improve the accuracy of the forecast. Shipment data were collected from January 2000 until August of 2005. Any previous data were removed from the analysis because shipments for the three selected products did not become consistent until the year 2000. Several authors advise against using the shipping data instead of sales data to forecast the future demand (Axsater 2000, Toomey 2000 and Sethi 2005). The main reason behind this is that shipping information could include late or incomplete orders that could reduce the accuracy of the forecast. In an effort to adjust the shipping data to more accurately resemble sales data, historical shipping records were analyzed to identify data points at which late or

incomplete orders occurred. The identified data points were then adjusted in order to reflect sales as opposed to shipping data. Other modifications were made to the data to eliminate once in a lifetime events that did not reflected the normal demand of the products.

In the **model building and evaluation** step, a forecasting method is selected based on its ability to minimize forecasting error and on the expected ease of implementation. Highly sophisticated methods may be more accurate, but they are more complicated to put into action. In most cases, balance needs to be found between sophistication and accuracy.

The shipping data for each product were divided into two sets, one set being from the years 2000 to 2004 and the other set including only data from 2005. The 2000-2004 data set was used only to fit the different parameters of the studied forecasting methods. The 2005 data set was used to test the accuracy of the forecasting methods.

The 2000-2004 data sets for the different products were analyzed to identify which of the following components were present:

1. **Trend** is the component that represents the underlying sustained growth or decline in the data.
 2. **Seasonal** components are typically found in quarterly, monthly or weekly data. Seasonal variations refer to stable patterns of change that appear and repeat over some time frame.
 3. **Cyclical** components are a series of wavelike fluctuations in data of more than one year's duration.
 4. The **irregular** component consists of unpredictable or random fluctuations.
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The tools applied to identify the different components in the 2000-2004 data sets were the scatter diagram and autocorrelation analysis:

- **Scatter diagrams** plot the shipments-time points on a two-dimensional graph (Hanke 2001). The diagrams help to illustrate any patterns in the data and, at the same time, identify the components that created the patterns.
- Autocorrelation is the correlation between a variable lagged one or more periods and itself (Hanke 2001). In **autocorrelation analysis**, the patterns in autocorrelation coefficients for different time lags are studied to identify data components.

Another important aspect that can be studied from autocorrelation analyses is whether or not the time series data being analyzed can be characterized as random. The **Ljung and Box Q (LBQ) statistic** was applied to test if the 2000-2004 data sets could be considered random. The Q statistic is derived through the equation

$$Q = n(n+2) \sum_{k=1}^m (r_k^2) / (n-k).$$

Where:

- n is the number of observations in the time series.
- k is the time lag.
- m is the number of time lags to be tested.
- r_k is the sample autocorrelation function of the residuals lagged k time periods.

This test assumes that Q statistics from autocorrelation of a time series follow a Chi-square distribution with the degrees of freedom equal to m minus the number of parameters to be estimated

in the model (Hanke 2001). MINITAB statistical software was employed to calculate the LBQ statistic values for autocorrelation analyses for the three selected products.

After the different components in the data were identified, reasonable forecasting methods were selected and applied to create forecasts for the three selected products. The methods were then evaluated to determine which were more accurate. The methods evaluated are shown below:

1. Naïve
2. Linear Regression
3. Moving Average
4. Exponential
5. Double exponential

The **naïve** forecasting method assumes that more recent data values are the best predictors of future values. The model is $\hat{Y}_{t+1} = Y_t$. Where \hat{Y}_{t+1} is the forecast made at time t for the time $t+1$. This forecast method disregards all of the earlier observations and, because of that, it tracks changes quickly.

The **linear regression** forecasting method produces the line that best fits a collection of X - Y points. The linear regression fitted line follows the model $\hat{Y} = b_0 + b_1X$, where \hat{Y} is a calculated Y value for a given X value, b_0 is the intercept and b_1 is the slope of the line. The parameters to be calculated for this method were the b_0 and b_1 values. The b_0 and b_1 values were determined from the 2000-2004 data sets and the application of the MINITAB software package. MINITAB uses the

method of least squared errors to determine the best fitted line and the respective b_0 and b_1 values for the 2000-2004 data sets.

The **moving average** forecasting method uses the average of a constant number of most recent data points. As new values become available, the moving average includes the latest value and discards the oldest value. The moving average follows the model: $\hat{Y}_{t+1} = (Y_t + Y_{t-1} + \dots + Y_{t-k+1})/k$. Where \hat{Y}_{t+1} is the forecast made for the next data point, Y_t is the value at period t and k are the number of terms in the moving average. The parameter to be calculated for this method was the k value. The k value was determined by using the 2000-2004 data sets and the application of MINITAB software package to manually calculate accuracy for the k values from one to twelve. The most accurate k value was the one selected.

The **simple exponential** method provides an exponentially weighted moving average of all the previous data points. The simple exponential method follows the model $\hat{Y}_{t+1} = \alpha Y_t + (1 - \alpha) \hat{Y}_t$. Where \hat{Y}_{t+1} is the forecast made for the next data point, Y_t is the value at period t , \hat{Y}_t is the old forecast for period t and α is the smoothing constant ($0 < \alpha < 1$). The parameter to be calculated for this method was the α value. The α value was determined by using the 2000-2004 data sets and the application of the MINITAB software package to calculate the α value that provided the most accurate forecast. MINITAB automatically selects the α by fitting the entire range of possible values to the equation and selecting the α that minimizes the sum of squared errors.

The **double exponential** method provides an exponentially weighted moving average of all the previous data points and allows for evolving local trends in a time series. The double exponential

method uses different constants to directly smooth the level and the slope. The three equations that model the double exponential method are:

- The exponentially smoothed series: $L_t = \alpha Y_t + (1 - \alpha) (L_{t-1} + T_{t-1})$
- The trend estimate: $T_t = \beta (L_t - L_{t-1}) + (1 - \beta) T_{t-1}$
- Forecast p period of time into the future: $\hat{Y}_{t+p} = L_t + p T_t$

Where:

- \hat{Y}_{t+p} is the forecast made p periods into the future.
- Y_t is the actual value at period t .
- α is the smoothing constant ($0 < \alpha < 1$).
- L_t is the newly smoothed value.
- β is the smoothing constant for the trend ($0 < \beta < 1$).
- T_t is the trend estimate.
- p is the periods to be forecast into the future.
- \hat{Y}_{t+p} is the forecast for p periods into the future.

The parameters to be calculated for this method were the α and β values. The α and β values were determined by using the 2000-2004 data sets and the application of the MINITAB software

package to calculate the α and β values that gave the most accurate forecast. MINITAB selects the α and β by fitting the entire range of possible values for both variables to the equations and selecting the α and β that minimize the sum of squared errors.

The various methods applied to evaluate the accuracy of the different forecasting methods are explained below.

- **Mean Absolute Percentage Error (MAPE):** measures the accuracy of forecasted time series values. It expresses accuracy as a percentage and provides an idea of how large the magnitude of the errors is compared to the actual values.

$$\text{MAPE} = (1/n) * \sum_{t=0 \text{ to } n} (|Y_t - \hat{Y}_t| / Y_t) \text{ and } Y_t \neq 0.$$

Where Y_t is the actual value at time t , \hat{Y}_t is the forecasted value for time t and n is the number of observations. (From MINITAB software package, help files).

- **Mean Absolute Deviation (MAD):** measures the accuracy of forecasted time series values. It expresses accuracy in the same units as the data, which helps conceptualize the amount of error.

$$\text{MAD} = (1/n) * \sum_{t=0 \text{ to } n} (|Y_t - \hat{Y}_t|).$$

Where Y_t is the actual value at time t , \hat{Y}_t is the forecast value for time t and n is the number of observations. (From MINITAB software package, help files).

- **Mean Squared Deviation (MSD):** measures the accuracy of forecasted time series values. Like the MAD, it expresses accuracy in the same units as the data, but it is a more sensitive measure of unusually large forecast errors than MAD.

$$\text{MSD} = (1/n) * \sum_{t=0}^{t=n} (|Y_t - \hat{Y}_t|)^2.$$

Where Y_t is the actual value at time t , \hat{Y}_t is the forecast value for time t and n is the number of observations. (From MINITAB software package, help files).

- **Mean Percentage Error (MPE):** expresses accuracy as a percentage and provides an idea if the forecast is consistently overestimating or underestimating values.

$$\text{MPE} = (1/n) * \sum_{t=0}^{t=n} ((Y_t - \hat{Y}_t) / Y_t) \text{ and } Y_t \neq 0.$$

Where Y_t is the actual value at time t , \hat{Y}_t is the forecast value for time t and n is the number of observations. (Hanke, John 2001).

In the **Model Extrapolation** step, the monthly forecast for 2005 was generated. The two methods that gave the best accuracy measures for each product for the 2000-2004 data sets were applied to forecast the 2005 points. The same parameters used to fit the forecasting methods to the 2000-2004 data sets were used to create the 2005 forecast. Only the points from January to August 2005 were included in the forecast because data from the remaining months did not yet exist.

In the **Forecast Evaluation** step, the forecasted values were compared to the historical values. The accuracy of the methods was also compared to alternative forecasting methods to select the one

that best fit the application. The forecasting errors were analyzed in order to see if the parameters in the method needed to be modified or fine-tuned. The 2005 data sets were used in the analysis.

The tool that was used to evaluate whether or not the parameters calculated from the 2000-2004 data sets are still appropriate to perform the 2005 monthly forecast was the tracking signal. The

tracking signal used in this research is a ratio that compares the cumulative sum of errors to MAD (Bowerman, 2005). It is derived through the formula:

$$\text{Tracking Signal} = (\sum_{t=0}^{t=n} (Y_t - \hat{Y}_t)) / \text{MAD}.$$

Where Y_t is the actual value at time t , \hat{Y}_t is the forecast value for time t and n is the number of observations. Accurate forecasting methods should produce the same amount of positive and negative errors, creating a tracking signal close to zero. A tracking signal above ± 5 (level recommended by Toomey, 2000) indicates that the forecast is constantly over or underestimating the real value, and thus the forecasting error is larger than an accurate forecasting method could reasonably produce.

Current and Alternative Forecast Process Comparison

While the present judgmental forecasting process has been useful for the company, it has never been compared to other forecasting processes. No forecasting process is perfect, but it is important for any company to investigate, in the very least, the accuracy of its forecasting process. Before starting the comparison, the forecast used in the current process was recreated from Electronic Controls' historical records. Then, the current forecast for each product was compared to the alternative process forecasts developed in the previous section. Finally, observations were recorded and the best forecasting process was selected for each product.

Results

Current Inventory Forecast Process

Electronic Controls experts participate in a forecasting meeting held the first week of each month to study the status of Electronic Controls' inventory and to generate forecasts for the different products in inventory. In the meeting, experts analyze two documents to make decisions about inventory levels. The documents are the Sales Analysis Sheet (SAS) and the Inventory Planning Report (IPR). The SAS contains information about the previous shipping information including the average of the last 3, 6 and 12 months. It also includes the total shipments for the last 3, 6 and 12 months as well as the maximum amount of shipments in the last 12 months. Table 2 shows an example of the SAS for the product OE331. Electronic Controls' experts study the SAS as a foundation to calculate the future demand forecasts. The IPR has the information about Electronics Controls' products, their current inventory status and current orders. Table 1 shows an example of the IPR for the product OE331. The most important information from the IPR is the "Assy at Vendor" (Assembly at Vendor) and the "Min on Hand" (Minimum on Hand) values for each product.

The "Assy at Vendor" value, or lot size, is the amount of the product received each desired period, in this case monthly, from the supplier(s). At the same time, the lot size is also the forecasted amount to be sold during that same period. For the OE331 the lot size is 300 units per month. Selecting or adjusting the "Assy at Vendor" value is the main goal of the monthly forecasting meetings.

The “Min on Hand” value is the safety stock quantity and is assigned during the monthly forecasting meetings. Safety stock is a given amount of extra inventory set aside to protect against fluctuations in demand or supply (Toomey 2000). Upper management, using expert opinion, assign these values with the goal of maintaining the lowest inventory level possible while still servicing customers efficiently. For the OE331 the “Min on Hand” value is 200 units. The “Min on Hand” value is important to the forecasting process because it is included in some of the rules followed by the company’s experts to assign or adjust the “Assy at Vendor” value.

Part Number	Description	On Order	STOCK	Assy at Vendor	Work Order Number	WIP	Notes	Min on Hnd	Re-order Qty
OE331	Total OE331	362	424	300/ mo OEM & Suntron			Ave: 278, Max 411	200	200
OE331-AT	TUC-5R PLUS ASSY & TEST		205						
OE331-21-AAON	CONTROLLER, TUC-5R+ AAON P/N# R20700	350	200		200	=	Release quantity		
OE331-21-CUSTOM	TUC-5R PLUS W/BACKPLATE, CUSTOM CODE	3							
OE331-21-DM	DEMAND MONITOR CONTROLLER	1							
OE331-21-DS	TUC-5R PLUS W/BACKPLATE								
OE331-21-GPCPLUS	GENERAL PURPOSE CONTROLLER PLUS (TUC5R+)	5	3		Planned		Will advise		
OE331-21-HCCO	HCCO CONTROLLER BOARD								
OE331-21-MUA	MUA CONTROLLER BOARD		4		Planned		Ave: 6, Max 12	5	10

Table 1 - Inventory Planning Report

The following are the rules management use to generate “Assy at Vendor” values:

1. The lot size for the three selected products for this study (OE315, OE 320 and OE331) can only be changed every 4 months because these products are complex and it takes time for the suppliers to change their production lines.
 2. The company’s experts use the shipping averages of the last three, six and twelve months from the SAS to assign the lot size. The averages are studied to detect any trends in the monthly shipments. If a trend is detected, the experts use the average of the last three months and adjust the average to reflect the magnitude and direction of the trend. For example, the average numbers for the OE331 were 278, 275 and 261. Because an upward trend is detected, 300 is selected as the lot size. The amount the average is adjusted depends on the experience and knowledge of the experts. If no trend is detected, the experts usually round the average for the last three-months up or down. Table 2 shows the Sales Analysis Sheet for the OE331.
 3. The “Assy at Vendor” value is decreased if the inventory level runs above the “Min on Hand” value plus the “Assy at Vendor” value for three to six months in a row. In the case of the OE331, the inventory level would have to be constantly above 500 units, as the “Min on Hand” value is 200 and the “Assy at Vendor” value is 300, in order for the “Assy at Vendor” value to be decreased.
 4. In some cases, management asks the supplier to delay a shipment instead of decreasing the lot size until inventory reaches normal levels. This method is used depending on the suppliers’ preference and their ability to change their production lines.
-

5. The “Assy at Vendor” value is increased if the inventory level runs below the “Min on Hand” value number for three to six months in a row. In the case of the OE331, the inventory level would have to be constantly below 200 to increase the “Assy at Vendor”.
6. If the inventory level runs below the “Min on Hand” value, but management do not believe it is a trend, then an extraordinary order is made for the amount of units management believes could restore balance to the inventory.
7. The “Assy at Vendor” can also be adjusted in any direction if the experts in the company predict that external factors may increase or decrease demand for a certain product.

Part Number	Unit Name	Averages			Totals			Maximum
		3 mo.	6 mo.	12 mo.	3 mo.	6 mo.	12 mo.	Month
OE331	TOTAL	278	275	261	835	1,648	3,134	411
OE331-21	TUC-5R PLUS MOUNTED ON BACKPLATE	2	1	14	5	8	172	152
OE331-21-AAON	CONTROLLER, TUC-5R+ AAON P/N# R20700	215	222	207	645	1,330	2,483	350
OE331-21-CUSTOM	TUC-5R PLUS W/BACKPLATE, CUSTOM CODE	2	6	3	7	34	40	25
OE331-21-DS	TUC-5R PLUS W/BACKPLATE		1	1		3	7	4
OE331-21-GPCPLUS	GENERAL PURPOSE CONTROLLER PLUS (TUC5R+)	8	4	2	23	26	26	11
OE331-21-MUA	MUA CONTROLLER BOARD	6	6	6	19	34	66	12
MG746-CAV	CAV CONTROLLER PACKAGE				1	1	1	1
MG750-VAV	VAV CONTROLLER PACKAGE	2	1	1	6	6	11	5
OE747	CV-C CONTROLLER PACKAGE	14	10	6	43	62	74	40

Table 2 - Sales Analysis Sheet for the OE331

While the three, six and twelve month averages are used in the current forecasting process, the final decision is highly influenced by the instinct and knowledge of the experts present at the meeting. Because of this, the forecasting process can be classified as judgmental forecasting. Judgmental forecasting focuses on the incorporation of forecasters' opinions and experiences into

the prediction process (Clements and Hendry 2002). Electronic Controls' experts prefer this method because it is simple and few data need to be prepared before the meeting. Simplicity is especially important in a small company like Electronic Controls, as the experts have many roles and cannot dedicate large amounts of time to the forecasting process. Another factor in the preference of these kinds of forecasting methods is that small companies do not have the resources or structure to gather the necessary data required to build an accurate model-based forecast.

While Judgmental Forecasting is widely used in industry and it has provided advantages in certain situations, it is not without its weaknesses. Clements and Hendry (2002) mention the following factors that affect the accuracy of this kind of forecasting:

- The format in which the data are presented influences the forecast. Graphical presentation is generally superior to tabular, with the exception of long-term forecasts in series with high noise.
- Judgmental forecasting can be influenced by the biased decisions of the forecaster. Examples of the relevant biases in forecasting include: illusory correlation (false beliefs regarding the relativity of certain variables), selective perception (discounting information on the basis of its inconsistency with the forecaster's beliefs), underestimating uncertainty, optimism and overconfidence. (Clements and Hendry 2002).

Another weakness that can be observed in Electronics Controls is that the accuracy of the forecast depends mainly on the knowledge of few members of the forecasting team. If any of the

experts do not participate in the process, the results do not have the same quality as they do if all are present.

Model-Based Forecast Process

The alternative forecasting model-based process was developed according to the forecasting process explained by Hanke John (2001) in the following steps: data collection, data reduction or condensation, model building and evaluation, model extrapolation and forecast evaluation.

Data Collection

The data analysis was initiated by gathering the historical data for the monthly shipments of the selected products. The monthly shipments are the data that the current judgmental method utilizes.

The historical data are shown in table 3, table 4 and table 5.

OE315	2000	2001	2002	2003	2004	2005
Jan	48	41	80	124	33	84.00
Feb	49	77	34	70	35	102.00
Mar	92	69	94	77	40	119.00
Apr	71	82	182	56	48	84.00
May	85	56	39	39	59	33.00
Jun	89	96	51	45	55	65.00
Jul	109	68	50	36	74	36.00
Aug	82	79	86	70	92	52.00
Sep	72	62	51	80	82	N.A.
Oct	79	78	51	82	55	N.A.
Nov	119	64	40	78	67	N.A.
Dec	174	92	30	28	58	N.A.

Table 3 – OE315 Shipments Historical Data

OE320	2000	2001	2002	2003	2004	2005
Jan	265	467	360	265	136	337.00
Feb	302	354	451	399	222	397.00
Mar	583	406	453	305	283	543.00
Apr	369	497	620	279	364	560.00
May	694	415	310	308	262	378.00
Jun	669	330	286	515	360	309.00
Jul	463	645	419	275	335	417.00
Aug	603	477	355	374	380	663.00
Sep	509	385	265	448	447	N.A.
Oct	534	589	648	388	239	N.A.
Nov	592	270	299	326	361	N.A.
Dec	1208	462	344	211	559	N.A.

Table 4 - OE320 Historical Data

OE331	2000	2001	2002	2003	2004	2005
Jan	60	106	161	177	113	217.00
Feb	163	110	15	178	134	185.00
Mar	404	204	177	233	134	411.00
Apr	132	155	365	252	131	289.00
May	94	112	179	278	226	277.00
Jun	124	176	180	198	388	269.00
Jul	139	135	160	226	291	257.00
Aug	211	245	145	207	251	446.00
Sep	195	116	106	81	225	N.A.
Oct	81	219	133	47	227	N.A.
Nov	182	269	133	238	264	N.A.
Dec	205	165	344	131	224	N.A.

Table 5 - OE331 Historical

Data Reduction or Condensation

The scatter diagrams of the monthly shipments for the three selected products were created as tools to identify any abnormalities in the data. Figures 1, 2 and 3 show the scatter diagrams of the OE315, OE320 and OE331 historical data. **Abnormalities** are points that do not reflect the sales

demand of the products. The abnormalities could be caused by special circumstances such as late or incomplete shipments or once in a lifetime shipments. The adjustments made to the data to more accurately reflect the sales demand are explained below.

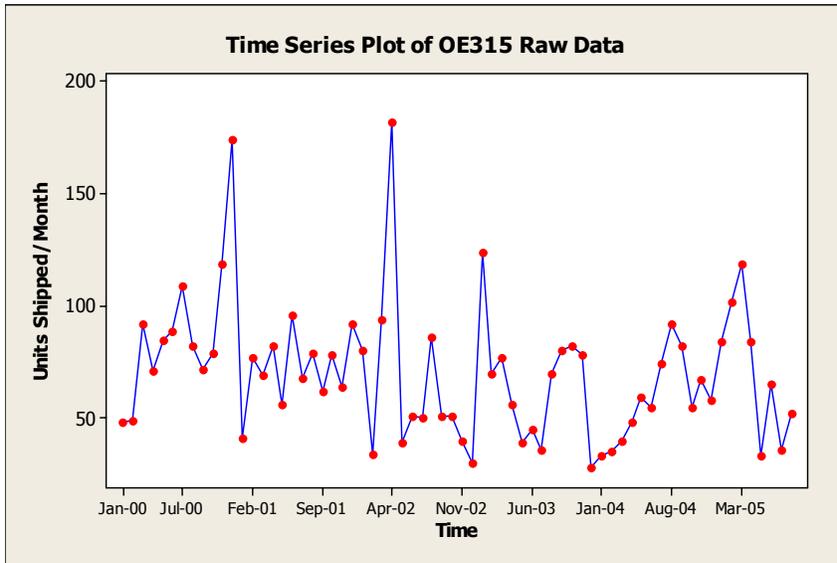


Figure 1 – Scatter Diagram for the OE315 Historical Data

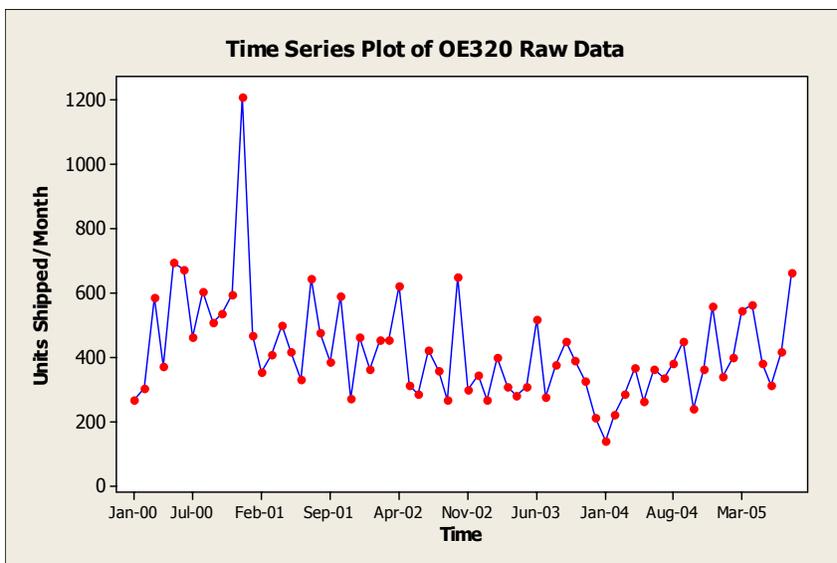


Figure 2 - Scatter Diagram for the OE320 Historical Data

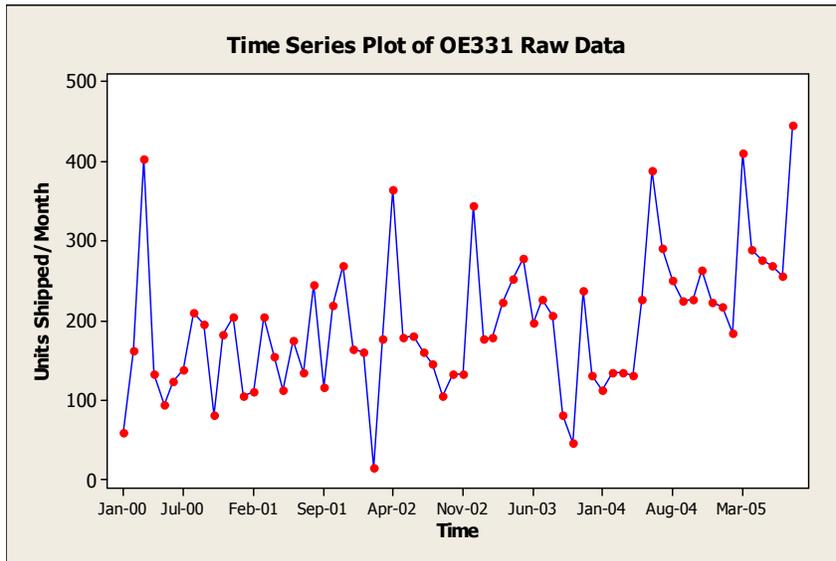


Figure 3 - Scatter Diagram for the OE331 Historical Data

The following adjustments were identified and addressed in the OE315 historical data:

- The first abnormality identified was in December 2000. A customer opening a new distribution center that needed to be stocked caused this abnormality. The quantity of units ordered for the new distribution center was extracted from the data set, since the situation represented an once-in-a-lifetime event and did not reflect the normal demand of the product.
- The second abnormality took place in February and March of 2005 when the same customer ordered 100 units extra which were shipped half in February and half in March. The extra 100 units were also extracted.¹

¹ In addition, for orders like this the customer usually gives Electronics Controls enough notice (more than the supplier lead time) to allow for an extraordinary order from the supplier to be on time for the ship date.

- The third abnormality identified was in April 2002. This abnormality was due to an error in the database and showed the same order twice. One of the orders was extracted from the data set.

Table 6 shows the adjusted historical data for the OE315.

OE315	2000	2001	2002	2003	2004	2005
Jan	48	41	80	124	33	84.00
Feb	49	77	34	70	35	52.00
Mar	92	69	94	77	40	69.00
Apr	71	82	96	56	48	84.00
May	85	56	39	39	59	33.00
Jun	89	96	51	45	55	65.00
Jul	109	68	50	36	74	36.00
Aug	82	79	86	70	92	52.00
Sep	72	62	51	80	82	N.A.
Oct	79	78	51	82	55	N.A.
Nov	119	64	40	78	67	N.A.
Dec	84	92	30	28	58	N.A.

Table 6- Adjusted OE315 Data

The following adjustments were identified and addressed in the OE320 historical data:

- The abnormality identified in December 2000; was caused by a customer opening a new distribution center that needed to be stocked. The quantity of units ordered for the new distribution center was extracted from the data set, as this was an once-in-a-lifetime event and did not reflect the normal demand of the product. Another similar abnormality took place in August 2005 when the same customer ordered 300 extra units. These extra units were also extracted.

Table 7 shows the adjusted historical data for the OE320.

OE320	2000	2001	2002	2003	2004	2005
Jan	265	467	360	265	136	337.00
Feb	302	354	451	399	222	397.00
Mar	583	406	453	305	283	543.00
Apr	369	497	620	279	364	560.00
May	694	415	310	308	262	378.00
Jun	669	330	286	515	360	309.00
Jul	463	645	419	275	335	417.00
Aug	603	477	355	374	380	363.00
Sep	509	385	265	448	447	N.A.
Oct	534	589	648	388	239	N.A.
Nov	592	270	299	326	361	N.A.
Dec	1208	462	344	211	559	N.A.

Table 7- Adjusted OE320 Data

The following adjustments were identified and addressed in the OE331 historical data:

- The abnormalities identified at points March 2000, December 2003, June 2004, March 2005 and August 2005 were caused by the introduction of new clients that needed a one-time solution to a specific problem. They needed a single or a couple of large orders and never ordered again. The orders from these customers were extracted since they did not reflect the normal demand of the product.
- The abnormality for April 2002 was due to Electronic Controls running out of inventory in February and sending double the amount of the product once the inventory recovered, which was in April. In this case, the double order was reduced by half for April and the other half was added to February.

Table 8 shows the adjusted historical data for the OE331.

OE331 (Adjusted)	2000	2001	2002	2003	2004	2005
Jan	60	106	161	177	113	217.00
Feb	61	110	156	178	134	185.00
Mar	94	204	177	183	134	211.00
Apr	72	155	215	172	131	289.00
May	94	112	179	184	226	277.00
Jun	86	176	180	193	238	269.00
Jul	139	135	160	226	141	257.00
Aug	211	245	145	197	251	246.00
Sep	195	116	106	81	225	N.A.
Oct	81	219	133	47	227	N.A.
Nov	182	269	133	238	264	N.A.
Dec	205	165	344	131	224	N.A.

Table 8 - Adjusted OE331 Data

Model Building and Evaluation

The process of determining what method would best fit the 2000- 2004 data sets began after the data were adjusted. The first step is to plot the products' data sets to identify the components present. The possible components are trend, seasonal, cyclical and irregular. Figures 4, 5 and 6 show the scatter diagram of the selected products' adjusted historical data.

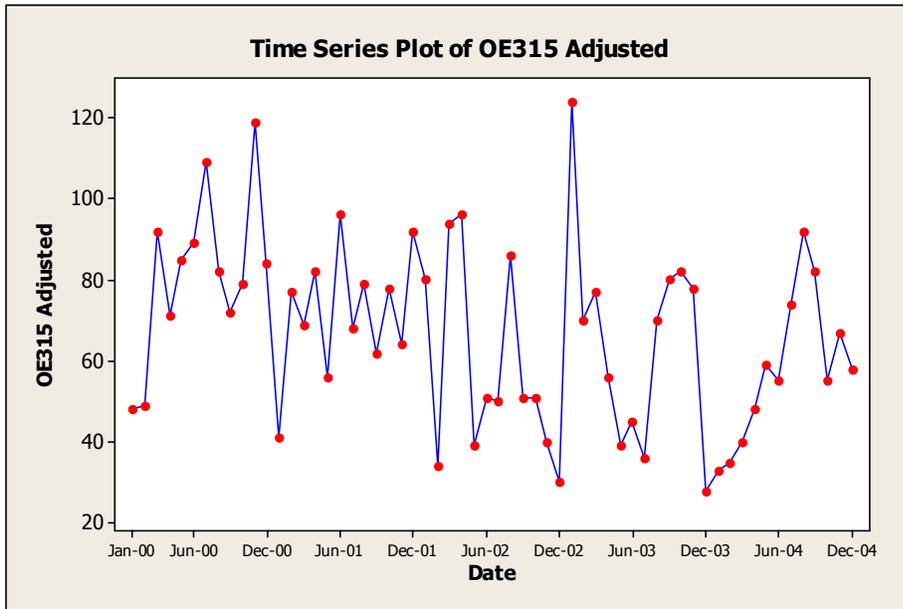


Figure 4 - Scatter Diagram for the OE315 Adjusted Data

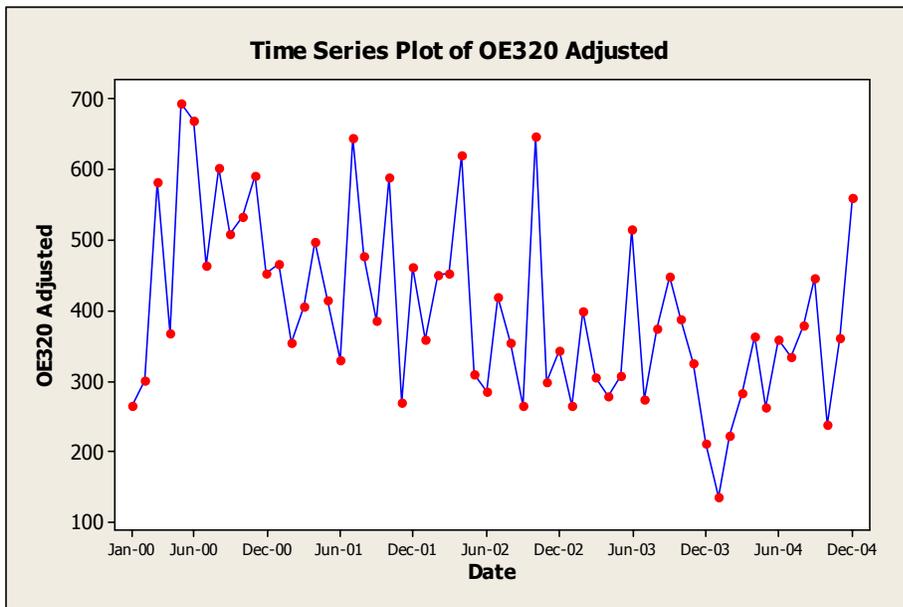


Figure 5 - Scatter Diagram for the OE320Adjusted Data

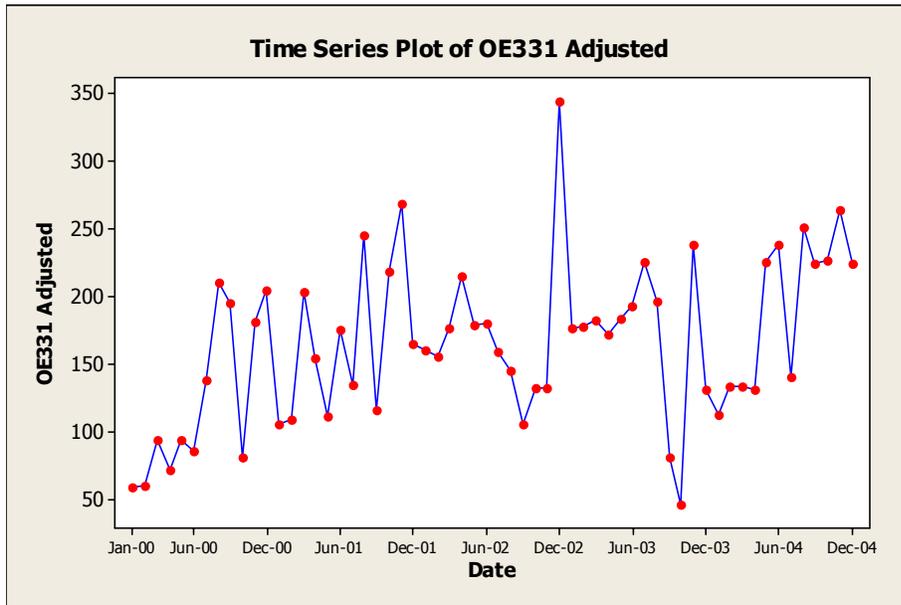


Figure 6 - Scatter Diagram for the OE331 Adjusted Data

The time series for both Figures 4 and 5 seem to have a slight trend downwards. In figure 4, shipments decrease from about 80 to 60 units a month. In figure 5, shipments decrease from about 500 to 350 units a month. No other components (cyclical or seasonal) can be easily identified in Figures 4 and 5. In Figure 6, the adjusted data seem to have a slight trend upward and no seasonal or cyclical components appear to be present. The trend goes from about 100 to 200 units shipped per month. Because the plots of the time series did not clearly show any seasonal or cyclical components, the autocorrelation analysis for each of the time series was performed in an effort to identify any overlooked components in the scatter diagram analysis.

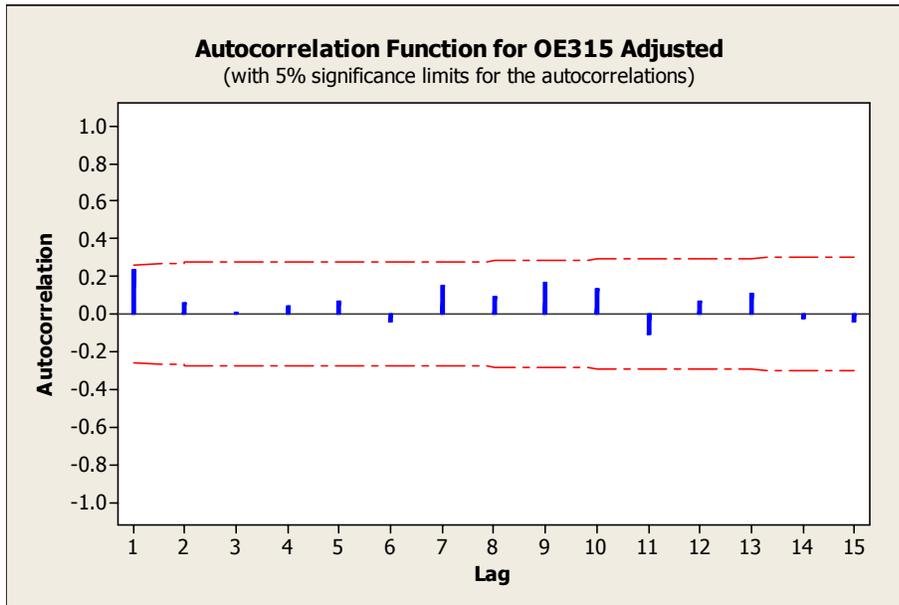


Figure 7 - Autocorrelation Analysis for the OE315 Adjusted Data

Further analysis of the OE315 autocorrelation analysis (Figure 7) does not show signs of any other component. A trend downward can be noticed in the first three lags. For the OE315 the Q statistic for 15 lags is 12.14, less than the Chi-square value of 24.99 tested at the 5% significance level. Thus, statistically, it appears that the series is random.

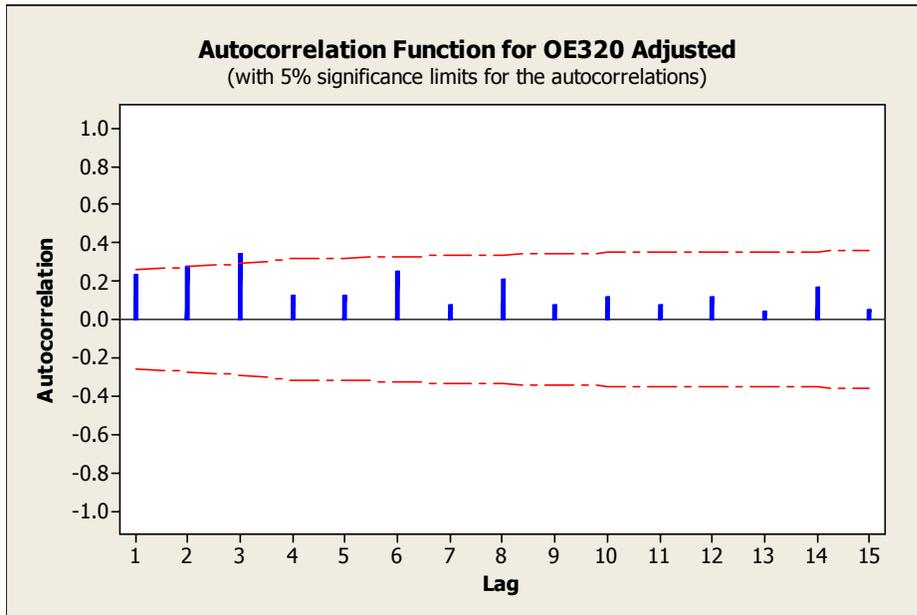


Figure 8 - Autocorrelation Analysis for the OE320 Adjusted Data

The autocorrelation analysis of the OE320 (Figure 8) displays somewhat of a trend in the first three lags and a possible cyclical component every three lags. For the OE320 the Q statistic for 15 lags is 31.83, greater than the Chi-square value of 24.99 tested at the 5% significance level. Thus, statistically, it appears that the series is not random.

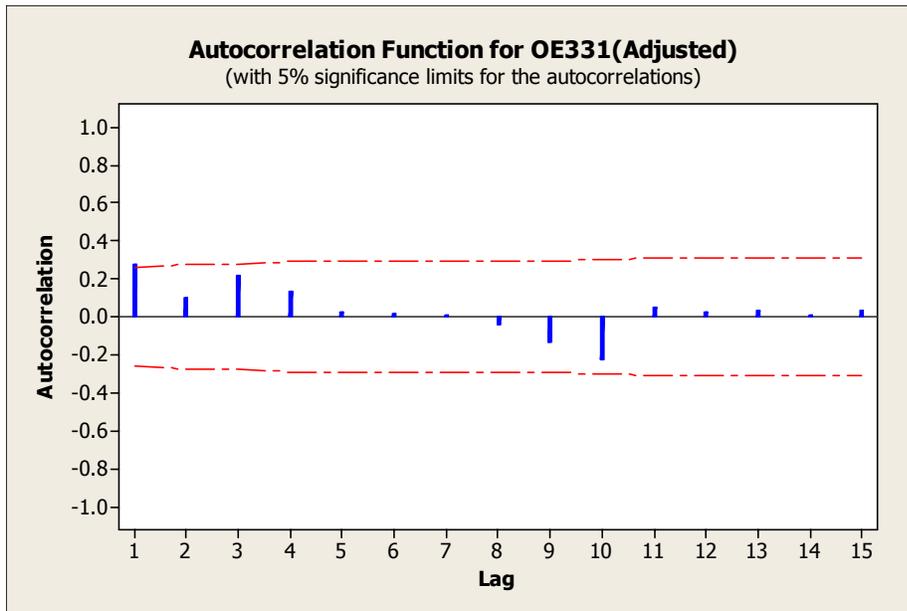


Figure 9 - Autocorrelation for the OE331 Adjusted Data

The autocorrelation analysis of the OE331 (Figure 9) a trend pattern can be identified in the first five lags. In addition, a possible seasonal component that can be seen in the 10th lag may need more exploration since it is clear but not significant. For the OE331 the Q statistic for 15 lags is 14.42, less than the Chi-square value of 24.99 tested at the 5% significance level. Thus, statistically, it appears that the series is random.

From the scatter diagram analysis, it is clear that the three time series have some degree of a trend. The autocorrelation analyses show no significant cyclical or seasonal components in any of the time series. In addition, it shows that the time series for the OE315 and OE331 can be considered to be random or to have a dominant irregular component. Based on the previous information, the methods to forecast the selected products need to handle trend and irregular components. The methods selected are shown below.

- **Naïve** effectively handles irregular component.
- **Linear Regression** effectively handles trend component.
- **Moving Average** effectively handles irregular component.
- **Simple Exponential** effectively handles irregular component.
- **Double exponential** effectively handles irregular and trend components.

Table 9, Table 10 and Table 11 summarize the methods used in this section, the parameters that were selected to do the forecast and the accuracy measures for the three selected products.

OE315				
Naive	Linear Regression	Moving Averaging	Exponential	Double Exponential
	$Y_t = 123.744 + 1.35049*t$	$k = 11$	$\text{Alpha} = 0.08155$	$\text{Alpha (level)} 0.695$ $\text{Beta (trend)} 0.044$
MAPE 33.473	MAPE 31.123	MAPE 32.616	MAPE 33.153	MAPE 31.543
MAD 20.712	MAD 17.404	MAD 18.06	MAD 17.849	MAD 18.951
MSD 764.542	MSD 444.580	MSD 503.063	MSD 483.028	MSD 652.197

Table 9- Results from Model-Base Forecasting Methods for the OE315

For the OE315, the forecast created following the linear regression method produced the smallest MSD followed by the MSD from the simple exponential method. The values for the MAD of all the different forecasting method were similar to each other, producing a range from the smallest to the largest of only three units. The same observation was true for the values MAPE values, since the range of variation was only 2% between all the different methods. Because of the previous information, the linear regression and the simple exponential method are the most accurate for the OE315.

OE320				
Naive	Linear Regression	Moving Averaging	Exponential	Double Exponential
	$Y_t = 504.176 - 3.31562*t$	$k = 6$	Alpha 0.134377	Alpha (level) 0.417 Beta (trend) 0.0544
MAPE 32.9 MAD 125.8 MSD 24463.1	MAPE 25.8 MAD 92.2 MSD 12885.8	MAPE 26.0 MAD 89.7 MSD 12375.7	MAPE 27.5 MAD 96.8 MSD 14119.4	MAPE 26.4 MAD 99.9 MSD 15773.2

Table 10 - Results from the Trend Forecasting Methods for the OE320

For the OE320, the forecast created following the moving average method produced the smallest MSD followed by the MSD from the linear regression method. The MAD value for all the different forecasting methods was similar, except for the one generated by the naïve method. Without the naïve method, the range of variation from the smallest to the largest was of only ten units. For the MAPE values, the one from the linear regression method was the smallest followed closely by the one from the moving average method. The rest of the MAPE values were at least five percent away from the moving average method. Because of the previous information, the linear regression and the moving average method are the most accurate for the OE 320.

OE331				
Naive	Linear Regression	Moving Averaging	Exponential	Double Exponential
	$Y_t = 123.744 + 1.35049*t$	$k = 4$	Alpha = 0.22685	Alpha (level)= 0.8224 Beta (trend)= 0.01
MAPE 32.37 MAD 49.97 MSE 4981.29	MAPE 34.08 MAD 43.30 MSE 2997.47	MAPE 29.31 MAD 43.06 MSE 3469.57	MAPE 29.26 MAD 41.94 MSE 3188.99	MAPE 33.42 MAD 48.50 MSE 4377.59

Table 11 - Results from the Trend Forecasting Methods for the OE331

For the OE331, the forecast created following the linear regression method produced the smallest MSD followed by the MSD from the simple exponential method. The MAD value for the simple exponential methods was the most accurate, followed only by the moving average and the linear regression that stayed within two units. For the MAPE values, the ones from the simple

exponential method were the smallest followed closely by the ones from the moving average method. The rest of the MAPE values were at most five percent away from the moving average method. Because of the previous information, the linear regression and the simple exponential method are the most accurate for the OE 331.

Model Extrapolation

In the model extrapolation section, the forecasts for the 2005 shipments of the three selected products were created. Two forecasts were created for each product using the two most accurate forecasting methods selected in the Model Building and Evaluation section. The parameters used in the forecasts were derived from the analysis of the 2000-2004 data sets. Tables 12, 13 and 14 show the results of the different forecasting methods for each product.

OE315 Forecasts			
Time	Sales	Linear Regression	Exponential
Jan	84.00	54.71	58.00
Feb	52.00	54.31	60.08
Mar	69.00	53.90	59.43
Apr	84.00	53.49	60.20
May	33.00	53.08	62.10
Jun	65.00	52.68	59.77
Jul	36.00	52.27	60.19
Aug	52.00	51.86	58.26

Table 12 - OE315 Forecast for 2005

OE320 Forecasts			
Time	Sales	Moving Average	Linear Regression
Jan	337.00	386.83	301.92
Feb	397.00	387.17	298.61
Mar	543.00	390.00	295.29
Apr	560.00	406.00	291.98
May	378.00	459.50	288.66
Jun	309.00	462.33	285.35
Jul	417.00	420.67	282.03
Aug	363.00	434.00	278.71

Table 13 - OE320 Forecast for 2005

OE331 Forecasts			
Time	Sales	Exponential	Linear Regression
Jan	217.00	228.00	206.12
Feb	185.00	227.12	207.47
Mar	211.00	223.75	208.82
Apr	289.00	238.73	210.18
May	277.00	242.75	211.53
Jun	269.00	245.49	212.88
Jul	257.00	247.37	214.23
Aug	246.00	248.14	215.58

Table 14 - OE331 Forecast for 2005

Forecast Evaluation

To verify that the residuals of the selected forecasting methods are random and that no other components were left out of the model, autocorrelation analyses of the residuals of the two most accurate forecasting methods selected in the Model Building and Evaluation section were performed. All the autocorrelation analyses of the residuals indicated random series because the autocorrelation coefficients were below the 5% significance limit. The findings suggest that the forecasting methods selected accommodate all the components in the time series. Appendix A shows autocorrelation analyses results for the two forecasting methods selected per product.

Model-Based Forecast for OE315		
	Linear Regression	Exponential
MAD	15.75	16.53
MSD	355.23	362.25
MAPE	27.85%	33.02%
MPE	0.23%	-12.72%
Tracking Signal	3.09	-0.18

Table 15 - Accuracy Measures for OE315 Forecast (2005)

Table 15 shows the accuracy measures for the 2005 OE315 forecasts. After comparing the results from the 2000-2004 forecasts with the results from the 2005 forecasts, it is evident that the forecasts for 2005 are more accurate. This finding is most apparent in the linear regression method because the MSD is 89 units lower, the MAD is 2 units lower and the MAPE is 3% lower than the 2000-2004 linear regression forecast. The 2005 simple exponential forecast is more accurate than the 2000-2004 simple exponential forecast but the magnitude of the improvement is less obvious than in the 2005 linear regression forecast. Having a more accurate forecast in 2005 than in 2000-

2004 indicates that the parameters selected for the linear regression and the simple exponential methods continue to be appropriate in 2005. In addition, both tracking signals are below ± 5 (linear regression 3.09, simple exponential -0.18), which reiterates that the parameters continue to be appropriate in 2005.

Model-Based Forecast for OE320		
	Moving Average	Linear Regression
MAD	84.52	122.68
MSD	10614.11	22246.11
MAPE	20.57%	26.94%
MPE	-6.03%	26.94%
Tracking Signal	-0.50	8.0

Table 16 - Accuracy Measures for OE320 Forecast (2005)

Table 16 shows the accuracy measures for the 2005 OE320 forecasts. After comparing the results from the 2000-2004 moving average forecast with the results from the 2005 moving average forecast, it is evident that the 2005 results are more accurate. The MAD is 5.6 units lower, the MSD is 2271 units lower and the MAPE is 5.4% lower than the 2000-2004 moving average forecast. Having a more accurate forecast in 2005 than in 2000-2004 indicates that the parameters selected for the moving average method continue to be appropriate in 2005. In addition, the tracking signal is well below ± 5 (-0.5), which reiterates that the parameters continue to be appropriate in 2005.

Comparing the results from the 2000-2004 linear regression forecast with the results from the 2005 linear regression forecast shows that the 2005 results are less accurate. The MAD is 30.5 units higher, the MSD is 9360 units higher and the MAPE is 0.3% higher than the 2000-2004 linear regression forecast. Having a less accurate forecast in 2005 than in 2000-2004 indicates that the

parameters selected for the linear regression method may no longer be appropriate in 2005. In addition, the tracking signal is well above ± 5 (8.0), which reiterates that the parameters do not continue to be appropriate in 2005.

Model-Based Forecast for OE331		
	Exponential	Linear Regression
MAD	26.35	38.64
MSD	1281.20	2129.16
MAPE	10.43%	14.87%
MPE	3.86%	11.84%
Tracking Signal	4.14	6.84

Table 17 - Accuracy Measures for OE331 Forecast (2005)

Table 17 shows the accuracy measures for the 2005 OE331 forecasts. After comparing the results from the 2000-2004 simple exponential forecast with the results from the 2005 simple exponential forecast, it is evident that the 2005 results are more accurate. The MAD is 15.6 units lower, the MSD is 1907 units lower and the MAPE is 18.8% lower than the 2000-2004 simple exponential forecast. Having a more accurate forecast in 2005 than in 2000-2004 indicates that the parameters selected for the simple exponential method continue to be appropriate in 2005. In addition, the tracking signal is below ± 5 (4.14), which reiterates that the parameters continue to be appropriate in 2005.

Comparing the results from the 2000-2004 linear regression forecast with the results from the 2005 linear regression forecast shows that the 2005 results are more accurate. The MAD is 4.7 units lower, the MSD is 868 units lower and the MAPE is 19.2% lower than the 2000-2004 linear regression forecast. Having a more accurate forecast in 2005 than in 2000-2004 can indicate that the

parameters selected for the linear regression method continue to be appropriate in 2005. On the other hand, the tracking signal is well above ± 5 (6.8), which means that the parameters might not be appropriate in 2005. While the accuracy parameters remained stable, the tracking signal indicates that the linear regression method is constantly underestimating the real values, giving a strong indication that the parameter are no longer accurate.

Of all the forecasting methods analyzed in this section, the only ones that fail to prove that their parameters continue to be appropriate are the linear regressions for the OE320 and OE331. The main cause of the linear regression failure is suspected to be the range of the fitting data set (2000-2004). Older data may not be relevant to calculate future value forecasts. To see if using data that are more recent improves the results, new forecasts were created using only the previous 12 months up to the point to be forecasted as the fitting data set.

OE 320 12 months Linear Regression				
Month	Sales	Forecast	Equation	Accuracy Measures
Jan	337.00	473.09	$y = 22.168x + 184.91$	MAD = 101.64
Feb	397.00	434.82	$y = 13.703x + 256.68$	MSD = 12830.99
Mar	543.00	425.66	$y = 10.049x + 295.02$	MAPE = 26.58%
Apr	560.00	470.13	$y = 13.559x + 293.86$	MPE = -17.16%
May	378.00	525.65	$y = 19.587x + 271.02$	Tracking Signal = -3.92
Jun	309.00	489.95	$y = 12.608x + 326.05$	
Jul	417.00	446.78	$y = 6.6189x + 360.73$	
Aug	363.00	436.61	$y = 4.0035x + 384.56$	

Table 18 - Forecast and Accuracy Measures for the OE320 12 Month Linear Regression

Table 18 shows the results of the adjustments in the OE320 linear regression method for 2005.

The new accuracy measures are an improvement over the original 2005 forecast: The MAD

decreased by 21.0 units and the MSD decreased by 9415 units. The most significant result is the reduction of the tracking signal to the acceptable level of 3.92. Therefore, the adjusted forecast (seen in Table 18) replaces the original linear regression method (seen in Table 13) for the remainder of the project.

OE 331 12 months Linear Regression				
Month	Sales	Forecast	Equation	Accuracy Measures
Jan	217.00	271.66	$y = 12.203x + 113.02$	MAD = 38.02
Feb	185.00	263.04	$y = 9.5455x + 138.95$	MSD = 1953.00
Mar	211.00	243.50	$y = 5.8846x + 167$	MAPE = 16.66%
Apr	289.00	230.30	$y = 2.8671x + 193.03$	MPE = -7.00%
May	277.00	238.97	$y = 2.1748x + 210.7$	Signal Tracking = -2.26
Jun	269.00	256.61	$y = 4.2343x + 201.56$	
Jul	257.00	271.80	$y = 6.1748x + 191.53$	
Aug	246.00	261.01	$y = 3.028x + 221.65$	

Table 19 - Forecast and Accuracy Measures for the OE331 12 Months Linear Regression

Table 19 shows the results of the adjustments in the OE331 linear regression method for 2005. The new accuracy measures are very similar to the original 2005 forecast: The MAD decreased by 0.60 units, the MSD decreased by 176 units and the MAPE decreased by 2%. The most significant change is the reduction of the tracking signal to the acceptable level of 2.26. Having the tracking signal at an acceptable level warrants using the adjusted forecast (seen in Table 19) to replace the original linear regression method (seen in Table 14) for the remainder of the project.

Once the forecasts have acceptable parameters, one forecasting method is selected for each product based on the accuracy measures. The most accurate method for the OE315 is the linear regression method, for the OE320 it is the moving average method and for the OE331 it is the

simple exponential method. The forecasts from these methods are considered the end-result of the entire model-based process. In the next section, the results from the model-based process are compared to the forecasts that the current Electronic Controls' process developed for 2005.

Evaluation of Forecasting Process: Model-Based Vs Judgmental Forecast

Before performing the comparison between the model-based and the judgmental forecast processes, it is necessary to reproduce the judgmental forecasts for 2005 and to calculate their accuracy measures. Figures 20, 21 and 22 show the 2005 judgmental forecast for the three selected products. These data were obtained from the historical records of Electronic Controls.

Judgmental Values For OE315			
Time	Sales	Forecast	Accuracy Measures
Jan	84.00	100.00	MAD = 37.875
Feb	52.00	100.00	MSD = 1876.375
Mar	69.00	60.00	MAPE = 83.80 %
Apr	84.00	100.00	MPE = 80.54%
May	33.00	100.00	Tracking Signal = -7.52475
Jun	65.00	100.00	
Jul	36.00	100.00	
Aug	52.00	100.00	

Table 20 – Forecasted Values and Accuracy Measures for OE315

The results from Table 20 are compared to the linear regression method results from Table 15. In this comparison, it is evident that the linear regression results are more accurate because the MSD is 1520 units smaller, the MAD is 22 units smaller and the MAPE is 55.9% smaller than the judgmental forecast results. It is important to notice that the tracking signal for the judgmental

forecast is above the acceptable limit of ± 5.0 , indicating that the current forecast parameters are not adequate.

Judgmental Values For OE320			
Time	Sales	Forecast	Accuracy Measures
Jan	337.00	300.00	MAD = 63.75
Feb	397.00	400.00	MSD = 7231.25
Mar	543.00	400.00	MAPE = 14.52%
Apr	560.00	400.00	MPE = 2.97%
May	378.00	400.00	Tracking Signal = 3.20
Jun	309.00	400.00	
Jul	417.00	400.00	
Aug	663.00	400.00	

Table 21 – Forecasted Values and Accuracy Measures for OE320

The results from Table 21 are compared to the moving average method results from Table 16. In this comparison, it is evident that the judgmental forecast results are more accurate because the MSD is 3328 units smaller, the MAD is 20.8 units smaller and the MAPE is 6% smaller than the moving average results. It is important to notice that the tracking signal for the judgmental forecast is within the acceptable limit of ± 5.0 , indicating that the current forecast parameters are adequate.

Judgmental Values For OE331			
Time	Sales	Forecast	Accuracy Measures
Jan	217.00	200.00	MAD = 35.375
Feb	185.00	200.00	MSD = 1851.375
Mar	211.00	300.00	MAPE = 15.10%
Apr	289.00	300.00	MPE = 13.10%
May	277.00	300.00	Tracking Signal = -7.04
Jun	269.00	300.00	
Jul	257.00	300.00	
Aug	246.00	300.00	

Table 22– Forecasted Values and Accuracy Measures for OE331

The results from Table 22 are compared to the simple exponential method results from Table 17. In this comparison, it is evident that the simple exponential results are more accurate because the MSD is 570 units smaller, the MAD is 9 units smaller and the MAPE is 4.7% smaller than the judgmental forecast results. It is important to notice that the tracking signal for the judgmental forecast is above the acceptable limit of ± 5.0 , indicating that the current forecast parameters are not adequate.

Conclusions and Recommendations

The following are the main conclusions from the analyses generated during this project:

1. The study of the current Electronic Controls, Inc. forecasting process shows that the process is highly dependant on the knowledge and instincts of the experts that produce the forecast. Even when historical data are analyzed, the resulting forecast can be considered a judgmental one.
 2. During the creation of a model-based process for the selected products the following was encountered:
 - 2.1. Ideally, sales data should be utilized when forecasting the demand of a product. Electronic Controls does not keep record of this data, therefore shipping data were used instead. Shipping data are not optimal in the creation of a forecast for the demand of a product because shipments can be delayed or only partially shipped. In order to use shipping data, the abnormalities must be filtered out in order for the shipping data to reflect sales demand more accurately.
 - 2.2. The 2000-20004 data sets had a dominant irregular component that made the OE315 and OE331 appear to be random.
 - 2.3. The most accurate forecasting methods for each product are different. For the OE315 it is the linear regression, for the OE320 it is the moving average and, for the OE331, it is the single exponential.
-

- 2.4. Using the 2000-2004 data sets to calculate the parameters for each forecasting method is not optimal for all methods. Calculating the linear regression parameters using the previous 12 months up to the forecasting point gives better results for the OE320 and the OE331.
3. When the accuracy measures were calculated for the current judgmental based forecasting process, it was observed that the forecasts for the OE315 and the OE331 were inaccurate. Their tracking signals fell outside of the acceptable range, indicating that the current forecasting parameters were not appropriate.
4. When comparing the model-based process to the judgmental based process, the model-based forecasts gave results that are more accurate for the OE315 and the OE331. The judgmental-based forecasts gave better results only for the OE320.

After analyzing information gathered in this project, it is recommended that Electronic Controls implement some or all of the following suggestions to improve their current forecasting process.

1. Electronic Controls needs to keep records of the quantities of products sold per month. The sales data can be used instead of the shipping data to produce forecasts that are more accurate.
 2. Electronic Controls needs to keep track of the forecasting error in order to maintain updated accuracy measures. Having updated accuracy measures would give the experts a better indication of how the forecast is performing allowing them to adjust more quickly thus making the forecasts more accurate.
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3. The current judgmental process could be fine tuned by using a tracking signal to produce a more accurate forecast. The tracking signal could eliminate inaccurate parameters such as the ones observed in the OE315 and OE331 forecasts.
 4. The model-based methods can be applied as a tool to make a complete and informed judgment of future product demand.
 5. Electronic Controls uses only tabular format to analyze the data utilized to generate the demand forecast as is shown in Table 1 and Table 2. Changing the data to a graphical format may benefit the accuracy of the forecast because it would allow the experts to visualize the fluctuations of the historical data (Clements, 2002).
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Suggestions for Additional Work

Several questions that fell outside of the scope of this project were raised during its development. In order to gain a full understanding of the needs of inventory control forecasting, further research can be performed with respect to those questions. The following is a list of some of the questions and topics to be researched in the future:

1. Finding the most accurate method for each product might be too time consuming when trying to forecast the demand of the entire range of products offered by Electronic Controls. Further studies need to be performed with the goal of finding one or few method(s) that are most effective in handling Electronic Controls' full range of products. A variation could be to study how to categorize the products in the hopes of limiting the number of forecasting methods to one per category. Products could be categorized as follows: Products with high, medium and low sales volumes or products at different stages of their lifecycles.
 2. The fitting period from 2000-2004 was not optimal for all the forecasting methods. More investigation is needed to find the optimal fitting period for the different forecasting methods and to find how to identify which historical data are relevant and which are not.
 3. This project was based on monthly demand for three products. Some products might give forecasts that are more accurate when a different time period is selected. For some products it is harder to change the amount of units delivered as opposed to changing the delivery date. Some studies can be performed to see if changing the delivery date instead of the amount of units delivered could produce similar or better accuracy measures.
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4. Further research can be performed on calculating safety stocks, reordering levels and lot size from the forecast results. The final goal of having an accurate forecast is to be able to maintain more efficient inventory levels.
 5. Most of the accounting and inventory control software packages have forecasting modules. It may be in the best interest of the company to investigate what the state of the art is in forecasting software modules.
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APPENDIX A

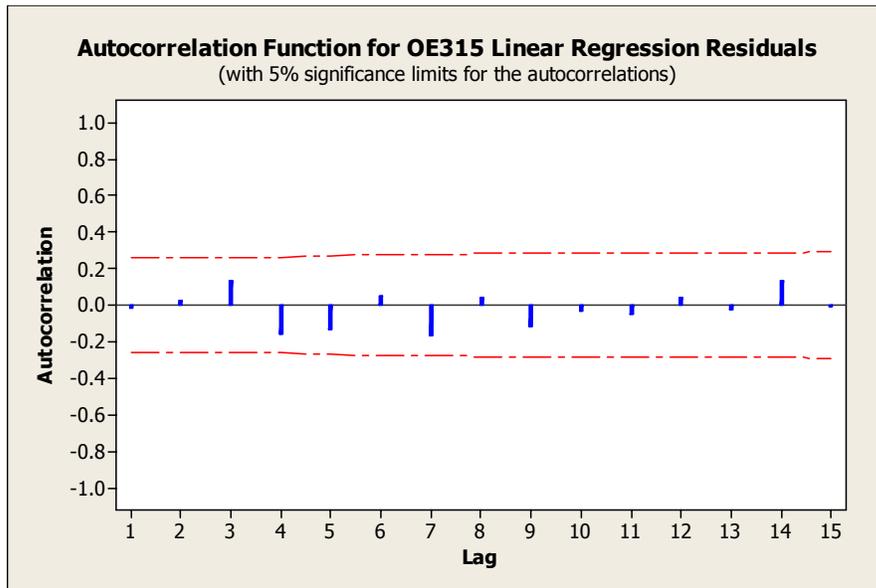


Figure 10 – Autocorrelation Function for the OE315 Linear Regression

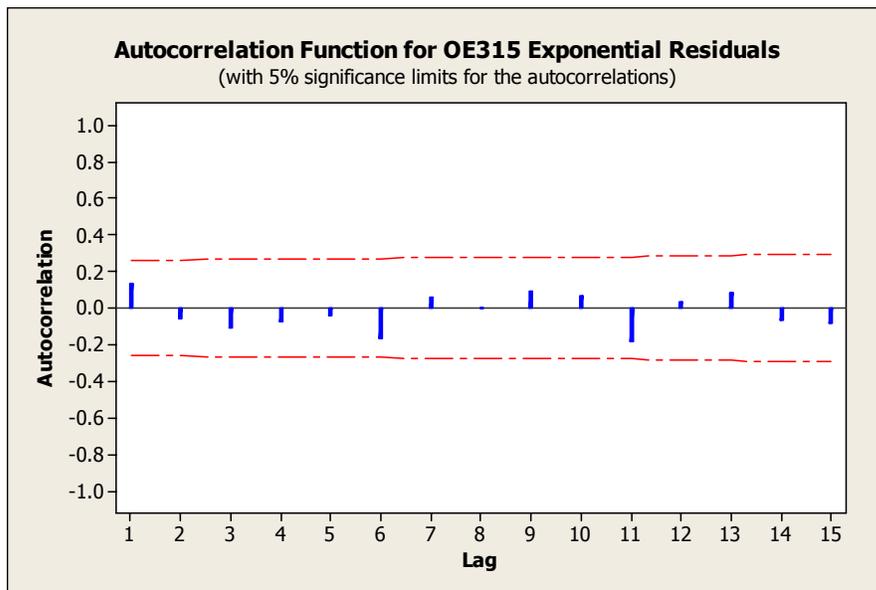


Figure 11– Autocorrelation Function for the OE315 Exponential

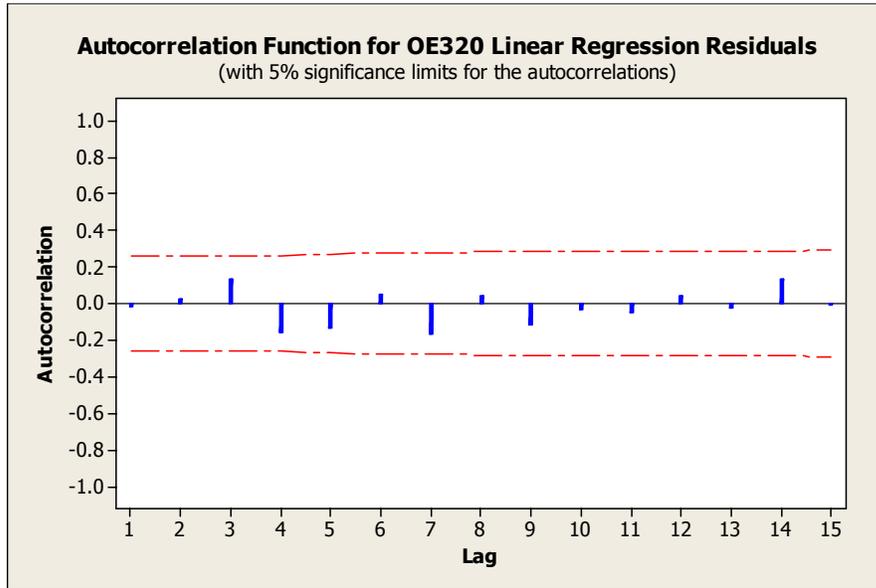


Figure 12– Autocorrelation Function for the OE320 Linear Regression

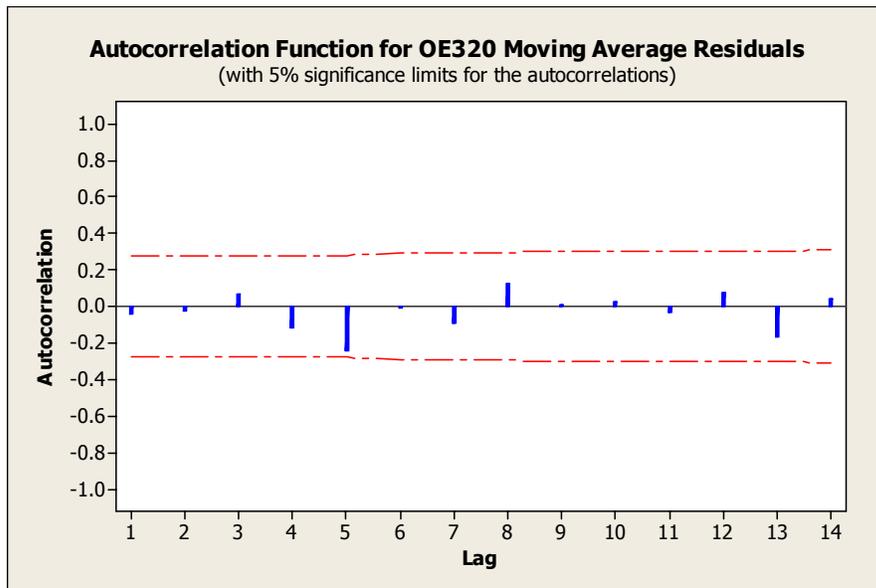


Figure 13– Autocorrelation Function for the OE320 Moving Average

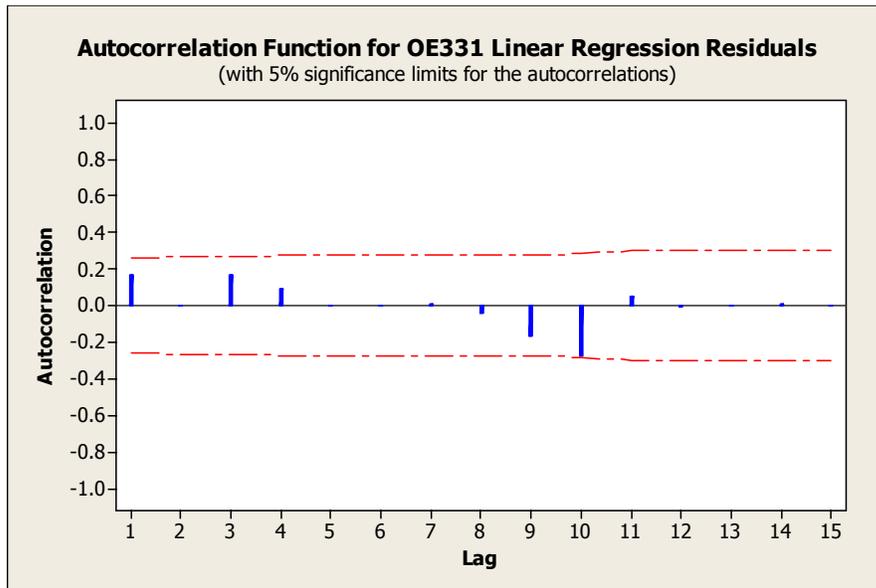


Figure 14– Autocorrelation Function for the OE331 Linear Regression

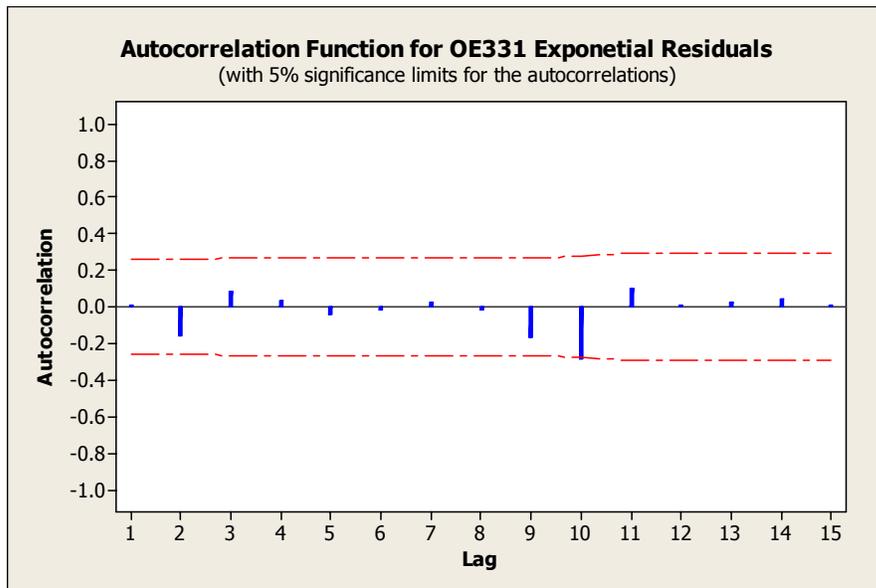


Figure 15– Autocorrelation Function for the OE331 Exponential