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ISDS 526
BUSINESS FORECASTING FOR ANALYTICAL DECISION MAKING

Project Report 3
Mobile Home shipments
Spring 2017

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1. Executive Summary

Kim Brite and Larry Short develop Mobile-Home parks and are contemplating opening more facilities. However, they know that their sales highly depend on the sales for Mobile-Homes but lack any forecasts for the year 2004. To better manage their cash flow, they are seeking a forecast from us. Having done our analysis, we recommend using a moderate strategy that would not over forecast their sales. The time series data starting from 1988 to end of 2003 was used to create the forecast. We analyze the data for any patterns such as trend, cyclicity and seasonality that may exist. We then fit the forecasted values using Moving Averages and Centered Moving Averages to confirm the patterns. We conclude that a downward trend exists in the time series. In addition, we compare between the Box Jenkins model and Regression models and check for the accuracy of the model. Having done all analysis, we are confident the Regression Model values, specifically the Quadratic Regression model is more suitable to forecast sales and would mean Kim Brite and Larry Short adopt a moderately cautious strategy.

2. The Forecasting Problem

Larry Short and Kim Brite develop exclusive mobile-home parks and are contemplating opening more facilities. However, they lack insight in terms of what the future sales of Mobile Homes might look like. They have hired us as consultants to forecast the sales of Mobile Homes and make recommendations that will help them manage their cash flow better and make decisions as to how many more facilities to open. The framework below in Figure 2.1 shows the process of the issue at hand. The goal is to forecast the sales of Mobile Homes for next year. In addition, we also to analyze if any relationship exists between MHS, unemployment insurance claims and benefit claims.

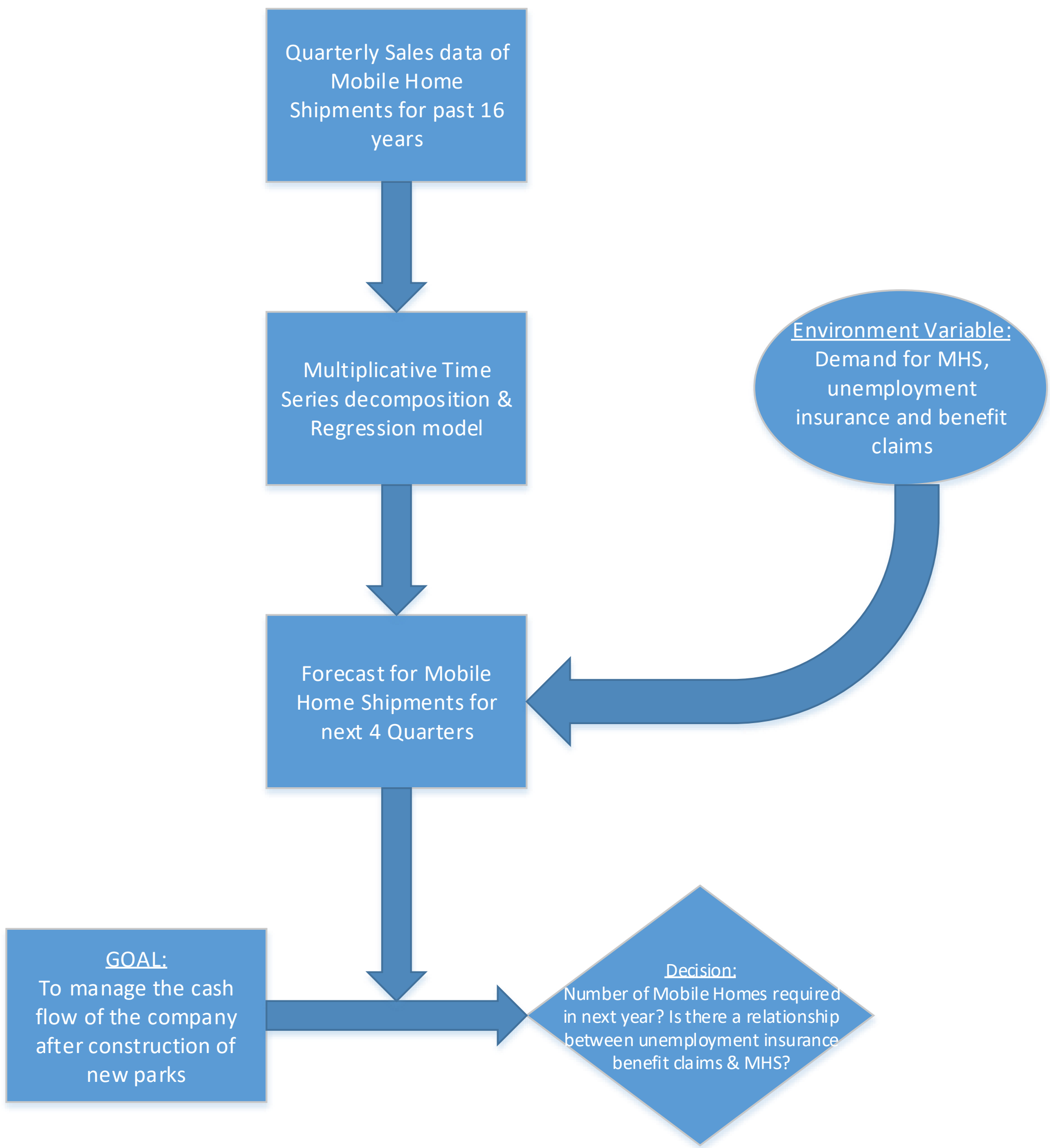

Figure 2.1: Graphical Representation of Decision Framework

In the next section, we examine the time series to analyze any patterns such as trend and seasonality that might exist. This is done by using graphical representations and the autocorrelation function of Forecast Pro.

3. Examining Data Patterns

3.1 Objective

In this section the aim is to produce and find patterns within the time series using Forecast Pro. We use visuals and autocorrelation analysis to achieve this. To further analyze the time series for existence of trend or seasonality, we will use simple and seasonal differencing.

3.2 Analysis of Time series

The graph shown below in Figure 3.2.1 contains all the sales of Mobile Home (MHS) starting from March 1988 to December 2003. By looking at the time series graph below we can draw some rough conclusions, however detailed analysis is necessary to support it.

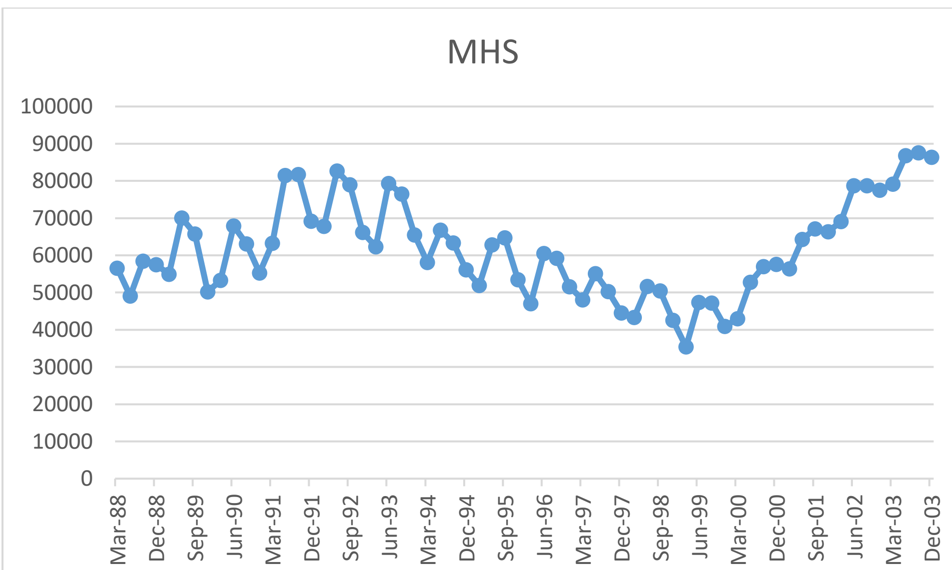

Figure 3.2.1: Time Series of Mobile Home Shipments

The time series that has troughs and peaks indicates the presence of seasonality in the time series. Troughs are generally observed in the first and the last quarter of the time series. Also, there are peaks observed throughout the time series during the second and the third quarter. A time series that shows periodic increases or decreases that may be weekly, monthly or yearly is said to be seasonal. However, just graphically observing the time series is not a conclusive indication of trend or seasonality.

To identify the trend and seasonality in the time series, further analysis is required to draw conclusions. In the next section, we perform autocorrelation analysis, a statistical tool which helps drill down further and investigate the possibility of trend and seasonality in the time series.

3.3 Auto correlation Analysis

Autocorrelation is the relationship between a variable and delayed copy of the same variable. To further analyze the time series, we use the autocorrelation function in Forecast Pro to generate correlogram.

Auto correlation analysis helps us to understand the possibility of trend and seasonality in the time series. Figure 3.3.1 shown below is the correlogram of the time series as generated by Forecast Pro. In the figure, we can see that the consecutive time intervals of mobile home shipments/sales are correlated to each other. Also, we can see that the values of the time series are gradually declining to zero. This pattern in the time series indicates a possibility of trend in the data. However, ACF is not a clear indicator of time series patters and requires further analysis. With the help of seasonal differencing of time series, it is possible to remove the seasonal components so that trend can be clearly visible.

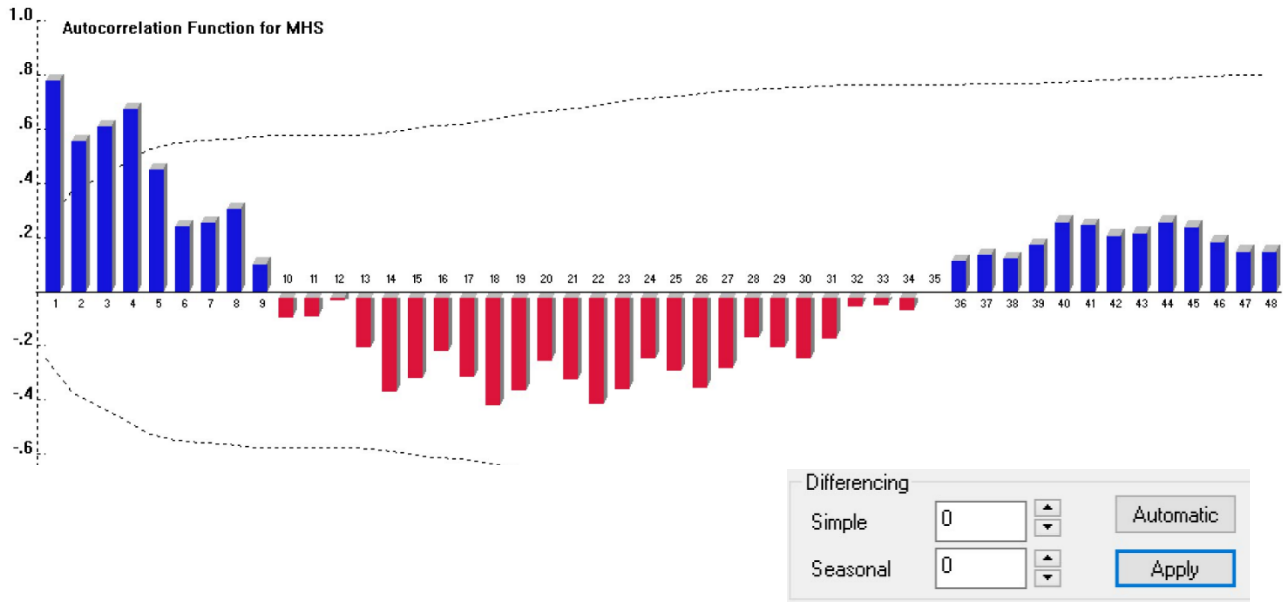

Figure 3.3.1: Auto Correlation without any Differencing

A trend exists in the time series when the initial autocorrelation coefficients are correlated to each other and are different from zero, but eventually drop to zero. The Figure 3.3.2 shown below is the correlogram with seasonal differencing of the time series. It shows similar characteristics, where we see that initial values are similar to each other and they eventually drop to zero. Hence, we can conclude that there is trend in the time series.

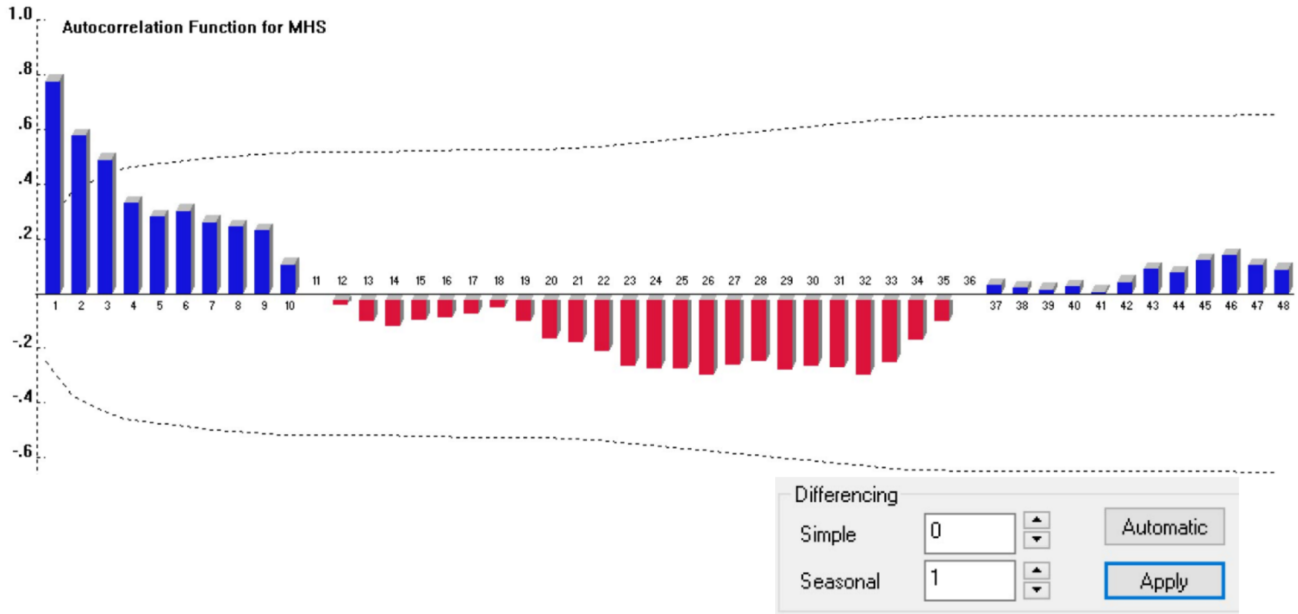

Figure 3.3.2: ACF with Seasonal Differencing of Time Series

Furthermore, by just the visual representation of the time series in Figure 3.3.1, it is difficult to comment on the possibility of seasonality of the time series.

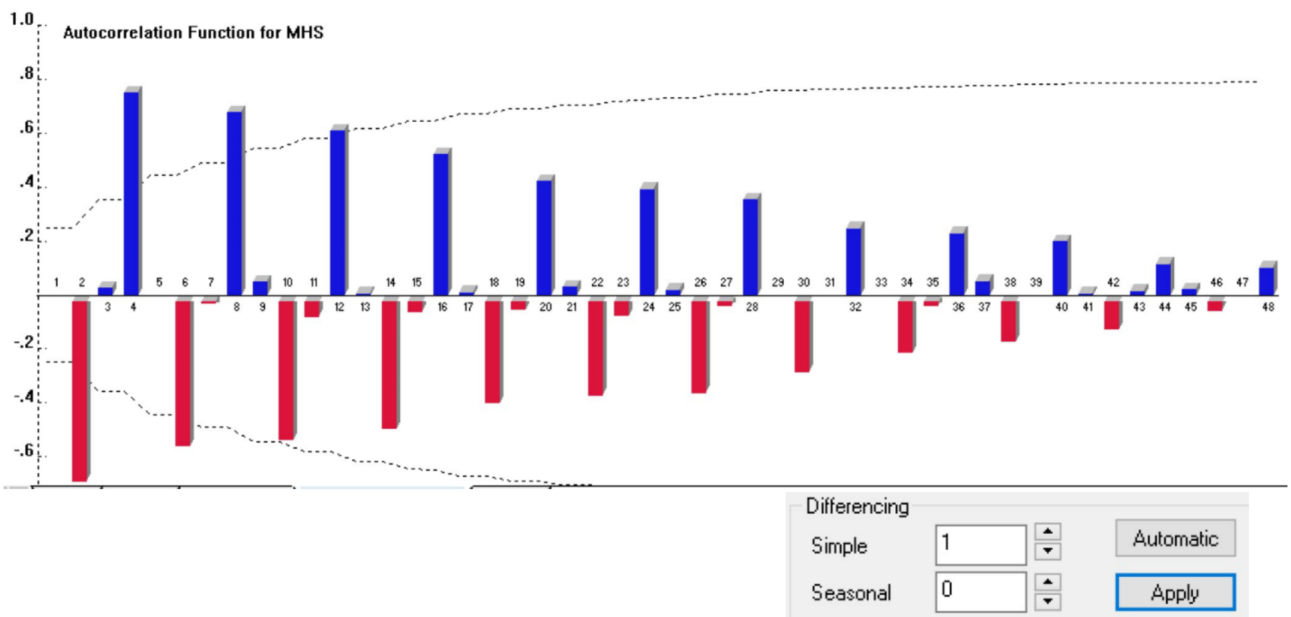

Figure 3.3.3: ACF with Simple Differencing of Time Series

However, we know that ACF is not always conclusive, so to get an idea about seasonality we will perform simple differencing of time series**.** Figure 3.3.3 shown above shows only the seasonal components of the time series. The figure above is a graphical representation of first order simple differencing of time series. In the time series, we can clearly see that there are spikes at time intervals approximately four months apart. This indicates the presence of seasonality in time series which is visible specifically at time intervals 4, 8. 12, 16 etc.

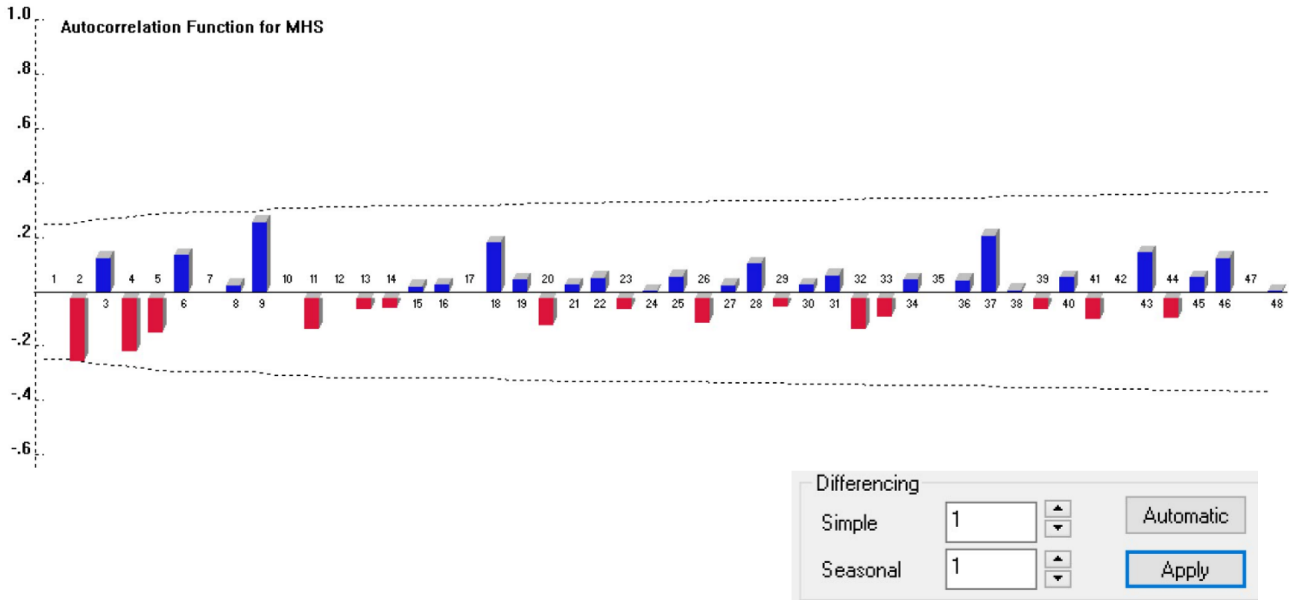

Figure 3.3.4: ACF with First Order Simple and Seasonal Differencing of Time Series

The Figure 3.3.4 shown above is the correlogram with simple and seasonal differencing. We can see the ACF plot with the combination of first order simple and seasonal differencing. We have successfully removed the trend and minimized the seasonality to great extent. As can be seen the time series is flat and there are no autocorrelations left except for at lag 12.

In the next section, we will discuss more in detail about the different components of the time series.

4. Multiplicative time series decomposition

4.1 Objective

There are number of different methods for decomposing a time series. In this section, we will be using multiplicative classical time series decomposition to analyze the time series because it is simple and consistent. Time series has 4 components: Trend, Seasonality, Cycle and Irregularity. There are two types of decomposition models multiplicative and additive. We will be using multiplicative model because time series is related and directly proportional to the increases and decreases of seasonality and cyclicity. Refer to appendix for the calculations and other summary outputs.

The equation for multiplicative model is as follows:

$$Y = T \times S \times C \times I$$

Where Y is the variable to be forecasted, S is the seasonal index, C is the cyclical factor and I is the irregularity. In the next section, we will begin our analysis of seasonality.

4.2 Analysis of seasonality

A time series is said to have seasonality when data exhibits periodic increases or decreases over weeks, months, quarters or years. In this section, we will be going through 4 steps as follows:

Step 1 Moving Average
Moving average is calculated to remove the seasonality and trend so that long term trend and cycle are visible. MHS data is quarterly and we assume that seasonality is quarterly. To find the moving average we will use the following formula:

$$MA = (Y_{t-2} + Y_{t-1} + Y_t + Y_{t+1})/4.$$

After calculating the values, we observed that moving average is not centered as the series has even number of periods. To solve this problem, we calculate the Centered moving average(CMA).

Step 2 Centered Moving Average
CMA is calculated to analyze trend and cycle effectively. The formula for calculating CMA is as follows:

$$CMA = (MA_t + MA_{t+1})/\ 2$$

From the below Figure 4.2.1, we can see that CMA data is smoother and observes clear trend and cycle in the series. Whereas MHS series is irregular and contains seasonal fluctuations. Next step in our analysis is to calculate Seasonal Factor (SF)

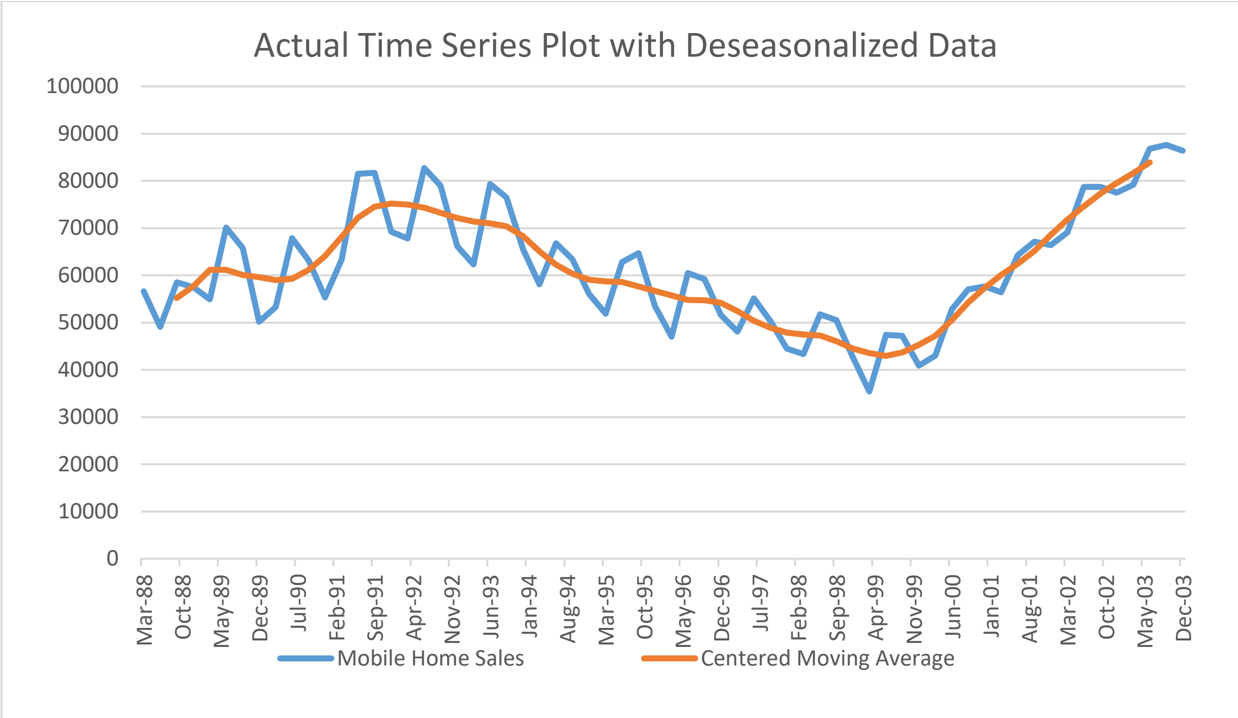

Figure 4.2.1: Comparison of Actual Data with De-Seasonalized Data

Step 3 Finding the Seasonal Factor (SF)
By calculating CMA, the data is de-seasonalized so seasonal factor can be calculated by dividing the actual value of time series with CMA values. The formula for seasonal factor is as follows

$$SF = Yt / CMA$$

The standard value for SF is 1 which means no seasonal fluctuations. If SF is greater than 1, it indicates that the actual values of MHS are more than the average in the period and the reverse happens when SF is less than 1. The next and final step is to calculate seasonal indices

Step 4 Finding the Seasonal Index (SI)
Seasonal index is the measurement of seasonal variation. Seasonal indices are calculated to smooth or remove the variability in the seasonal factors. Average of seasonal factors results in respective seasonal indices. If the time series is monthly seasonal indices must add up to 12 and 4 for quarterly data which is our case. From the below table, we can see that seasonal indices add up to 4.00017. To make the seasonal indices to 4 we multiply each index with multiplier. The formula for multiplier is as follows:

Multiplier = (n-period / sum of the unadjusted averages)

Average (Unadjusted SI)	0.903481	1.090387	1.067397	0.938852
SUM of 4 Unadjusted Seasonal Indexes				4.000117

After multiplying with multiplier, we obtain the adjusted seasonal indices. From the Figure 4.2.2, we can see observe the seasonal indices for different quarters. Seasonal index of quarter 1 is 0.9034, it means that the sales of MHS should be adjusted downward by that factor. Similarly, sales should be adjusted upwards when the seasonal index is more than 1. From the figure 4.2.2, we can say that Q1, Q4 are below average and Q3, Q4 are above average. From this analysis, we can say that data contains seasonality but is very minimum as the range is in between 0.9 and 1.1.

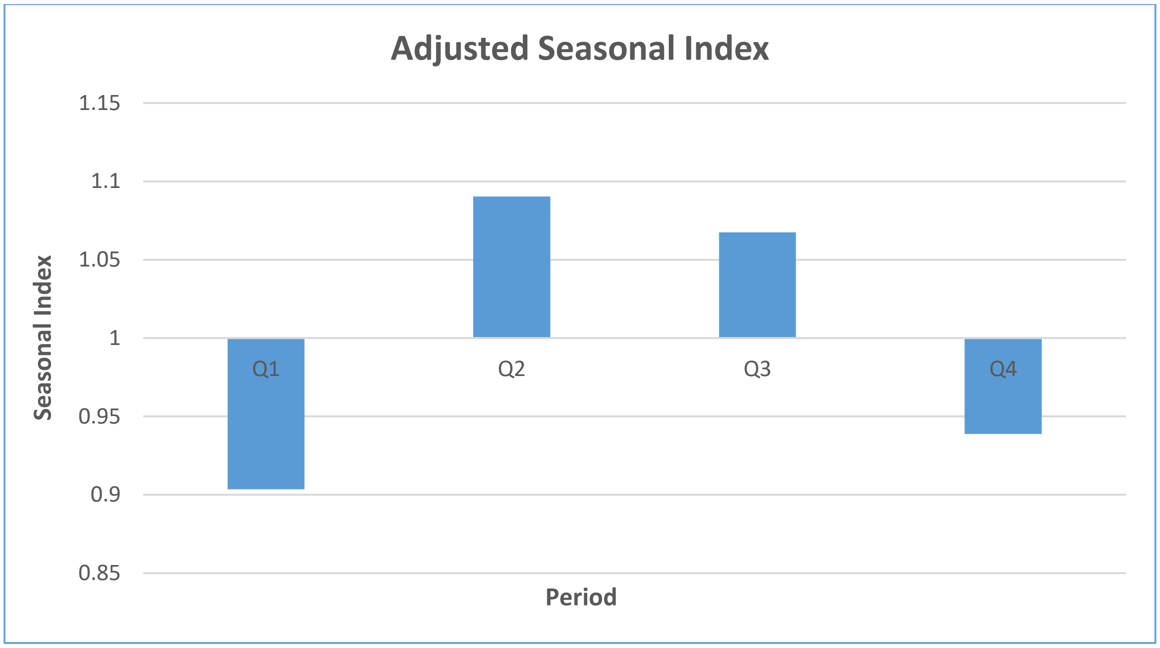

Figure 4.2.2: Adjusted Seasonal Indexes

In the next section, we discuss about the trend in the time series.

4.3 Analysis of Trend

A time series is said to be exhibiting trend when data has long term increases or decreases in it. By calculating CMA, we removed seasonality in it so that we can calculate trend and cyclicity. To calculate long term trend, we use simple linear regression on Centered moving average(CMA). This equation is used to find the forecasted and historic trend values. The equation is as follows:

$$CMAT = a + b^* (time)$$

Where: a is the intercept, b is the slope of the trend line and Centered moving average trend(CMAT) is the dependent variable. After performing regression, we obtain the following equation

$$CMAT = 62558.9830 + (-53.1019) * time$$

CMAT can be calculated at different time periods by substituting (time) in the equation with desired values.

By observing Figures 4.3.1 and Figure 4.3.2, we can see that the trend is gradually decreasing. Figure 4.3.1 illustrates centered moving average trend for the MHS data.

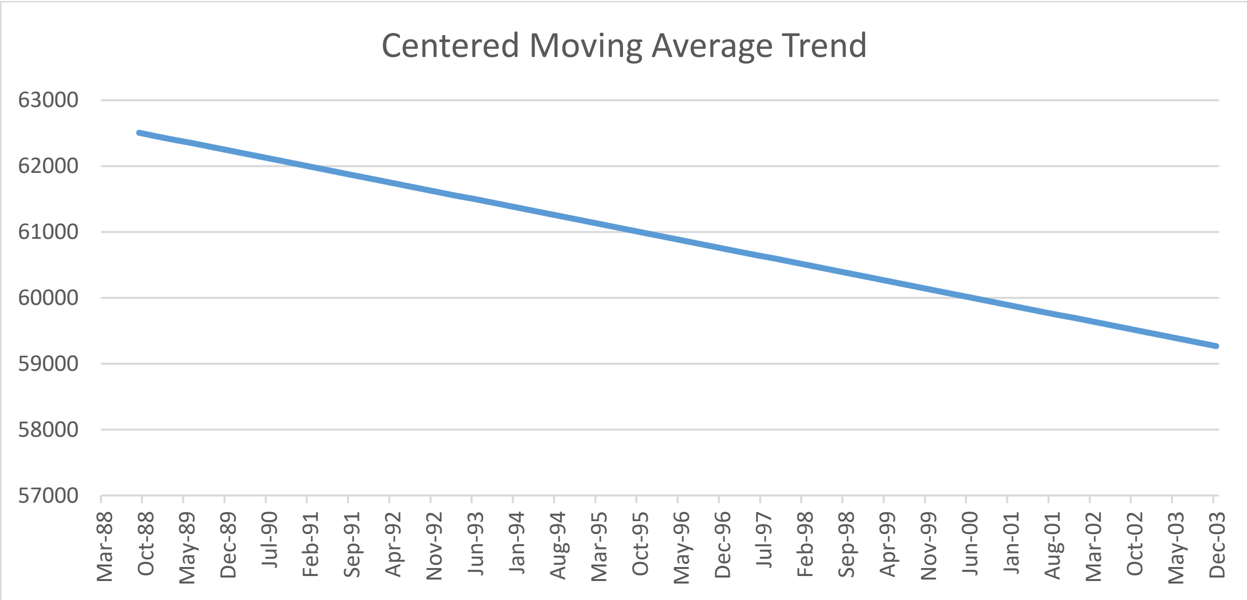

Figure 4.3.1: Centered moving average trend

Figure 4.3.2 below illustrates the time series of CMA, CMAT and MHS. We can observe same decrease of trend from the below figure too.

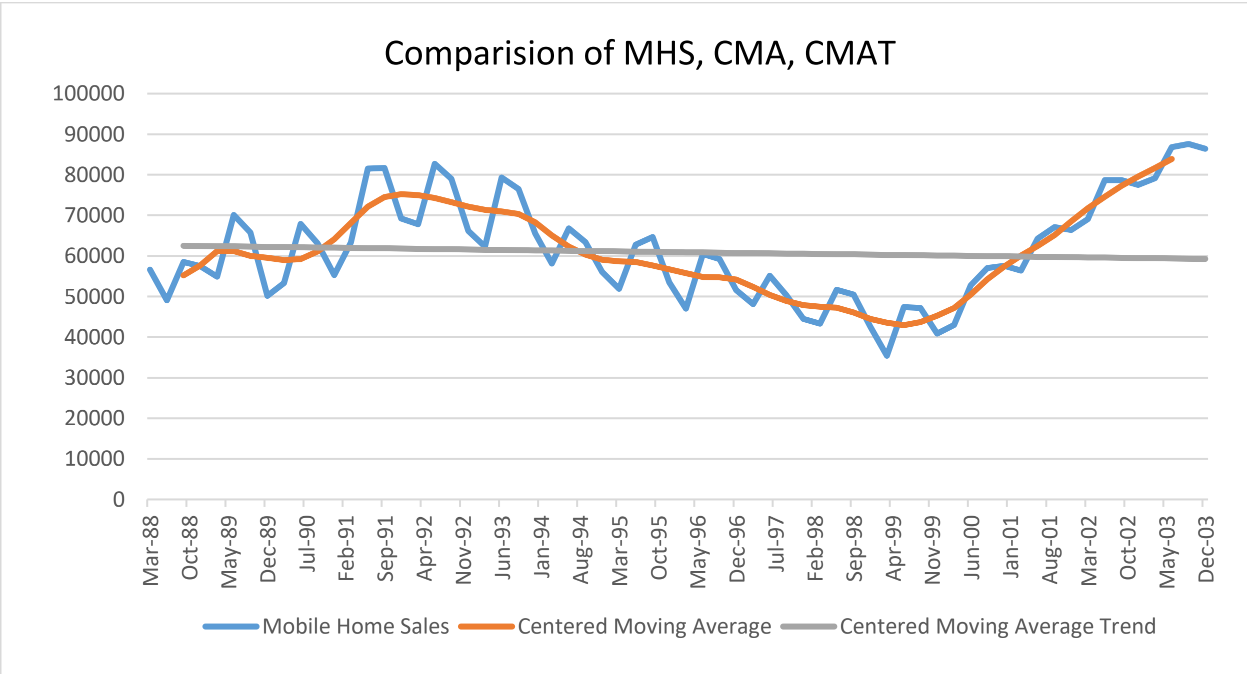

Figure 4.3.2: MHS, CMA, CMAT

In the next section, we analyze the cyclical component of the time series.

4.4 Measuring the Cyclical Factor

A time series exhibits cyclicity when the data exhibits extended wave like movement. This cyclical component is measured using cycle factor(CF). It is defined as ratio of CMA to CMAT.

$$CF = CMA / CMAT$$

Cyclical factor is difficult to predict but looking at the time series we can have an estimate about the rise and fall of the time series. When the Cycle factor is 1 it means that there is no cyclicity. If CF is more than 1, it means that de-seasonalized value of the time series at that period is above the long-term trend. When CF is less than 1, it indicates that de-seasonalized value of the time series is below the long-term trend.

For example, during March 92 CF = 1.214 means that CMA was 21.4% more than the long-term trend of that period. For quarter 3 in 1988 CF = 0.8833 means that CMA was 11.67% less than the long-term trend of that period.

Figure 4.4.1 illustrates the cyclic factor calculated from the MHS data.

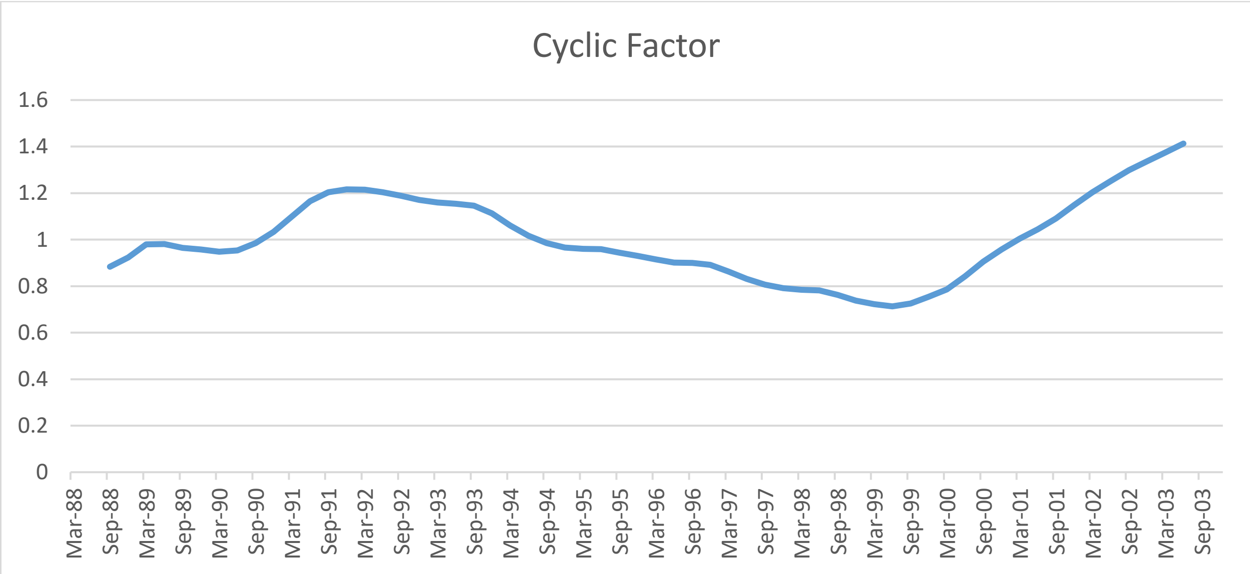

Figure 4.4.1: Cyclic Factor

5. Analysis of Fitted Forecast

5.1 Objective

In this section, we will plot the actual MHS values and fit the model with forecasted values which were achieved using time series decomposition method. The components we used to get fitted forecasts are trend, seasonality and cycle factor. Shown below in Figure 5.1.1 is the graph comparing the actual or historical values of mobile house shipment with its forecast values.

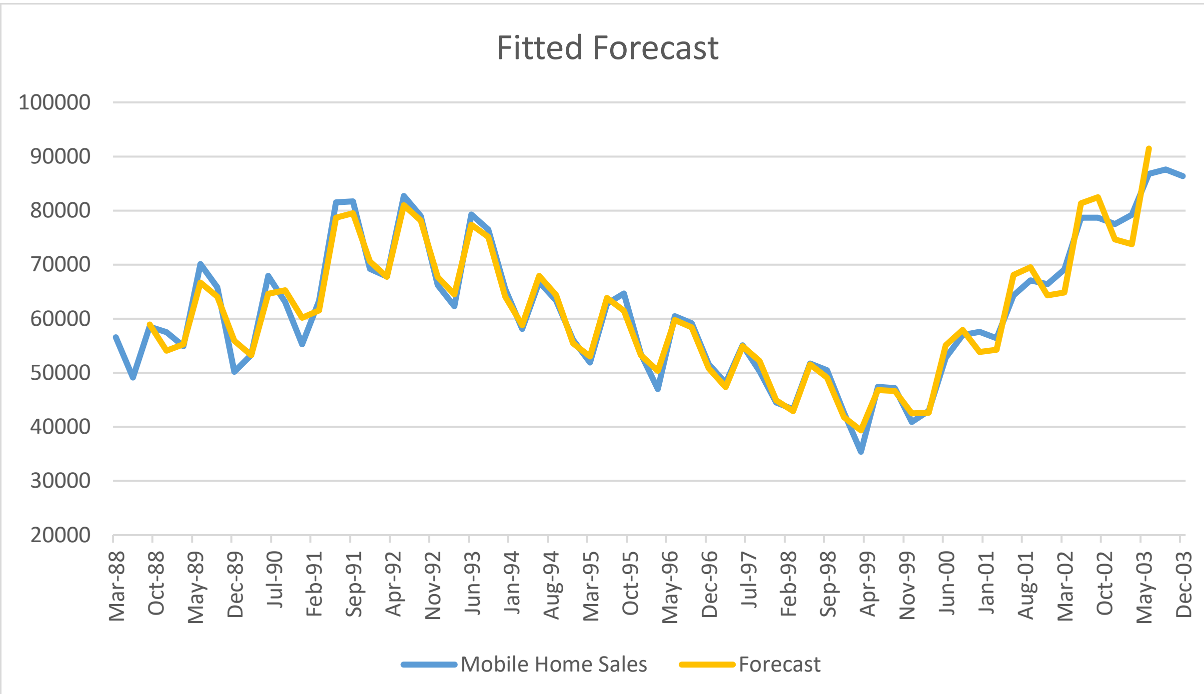

Figure 5.1.1: MHS Values vs Fitted Values

As our model is multiplicative, the following four-time series decomposition components were multiplied to get the fitted forecast values.

1. Centered Moving Average Trend (CMAT)
2. Seasonal indexes (SI)
3. Cycle Factors (CF)
4. Irregularity (I)

There is no event involved in the data so, we have assumed the value of irregularity as 1 that means the time series is regular.

Y (Fitted Forecast Value) = (CMAT)* (SI)* (CF)* (I)

In the above figure 4.1.1 fitted forecast values are represented using yellow line and actual mobile house shipment values in blue line. As we can see that the forecasted values fit well with the actual values. The fitted values capture both the trend and cyclicity of actual values and predicts the seasonal peaks and troughs among the quarters efficiently, which indicates the strength of our model.

Now as we have confirmed our decomposition model, in the next section we will forecast the values of MHS data of quarters Q1 to Q4 of 2004.

6. Forecasts

To forecast the values of MHS in 2004, we will be requiring cycle factors. These cycle factors are different from the ones we used to find the fitted forecast values. We will forecast the cycle factors using two methods, they are Box Jenkins and quadratic Regression method.

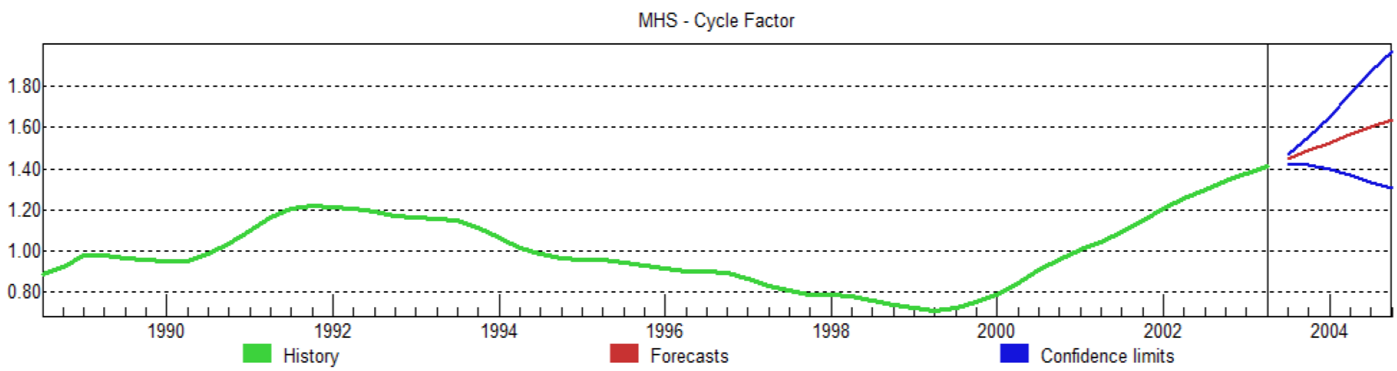

Figure 6.1: Cycle factors forecasts using Box-Jenkins

The above Figure 6.1 depicts the forecasts of cycle factor that were obtained using Box-Jenkins model in Forecast Pro.

2004 Quarter	Box-Jenkins
Q1	1.526
Q2	1.5645
Q3	1.6021
Q4	1.6398

Exhibit 6.2: 2004 Cycle Factors for Box-Jenkins model

Now that we have achieved the cycle factors for quarters Q1 to Q4 of 2004, we will produce the forecast values using the equation.

Forecast (Y) = CMAT*SI*CF(Box-Jenkins)

The below exhibit 6.3 shows the forecasted values of MHS in 2004. We can observe that the forecasted cycle factors are quite high which leads to higher forecast values of MHS. It seems that influence of trend and seasonality are quite low compared to cycle factors.

2004 Quarter	Centered Moving Average Trend(T)	Seasonal Index(SI)	Cycle Factor(CF)	Irregularity(I)	Forecast (Y)
Q1	59213.56	0.90	1.53	1	81636.08
Q2	59160.46	1.09	1.56	1	100919.49
Q3	59107.36	1.07	1.60	1	101075.17
Q4	59054.25	0.94	1.64	1	90913.08

Exhibit 6.3: MHS Forecast Values using Box-Jenkins

Now we will forecast the cycle factor values using regression method. Regression analysis is used to find the relationship between the variables. In our case the dependent variable is cycle factor of actual MHS values and independent variable is the number of people who claimed unemployment insurance benefit and is referred by “X”.

By using regression method, we assume that the relationship between 2 variables in the past continues in the future. Now we will be checking couple of regression models before forecasting the cycle factors using regression method. Firstly, the quadratic model and followed by the linear model.

Model 1: Quadratic regression model

Following is the linear regression equation

$CF = bo + (b1)X + (b2)X^2$

CF= Cycle factor

X= Number of initial claims of unemployment insurance benefit

Upon executing the regression equation of CF values on X and X^2, we can observe the adjusted R^2 for this model as 61.83% and the P-values for bo (intercept) is 3.30 %, X is 0.625% and X^2 is 3.129%. All the three p-values are low and are statistically significant.

Model 2: Linear regression model

Following is the linear regression equation:

$Cf = bo + (b1)$X

CF= Cycle factor

X= Number of initial claims of unemployment insurance benefit

After running the regression, we can observe the adjusted R^2 for this model as 59.28% and the P-value for bo is very high at 97.43%.

We can observe that increase in number of independent variables increases the R^2 value which also indicates that the time series data in non- linear. The quadratic regression model has higher adjusted R^2 that means it fits the model better than the linear regression model. Though the difference between R^2 is slightly over 2% but the p-values for components of the regression equations are significant. Thus, we prefer quadratic model over the linear model. Below is the exhibit showing the forecasted cycle factors using quadratic regression method.

2004 Quarter	Regression
Q1	1.0202
Q2	0.9838
Q3	0.9722
Q4	0.9321

Exhibit 6.4: 2004 Cycle Factors for Quadratic Regression model

Now that we have chosen quadratic model for forecasting the cycle factors, following exhibit 6.5 shows the forecasted values of MHS data in 2004 using quadratic regression method.

2004 Quarter	Centered Moving Average Trend(T)	Seasonal Index(SI)	Cycle Factor(CF)	Irregularity(I)	Forecast (Y)
Q1	59213.56	0.90345476	1.02	1	54576.90
Q2	59160.46	1.09035512	0.98	1	63461.68
Q3	59107.36	1.06736592	0.97	1	61334.19
Q4	59054.25	0.93882420	0.93	1	51674.64

Exhibit 6.5: MHS Forecast Values using Quadratic Regression Method

The following exhibit shows the comparison between the forecast values of MHS using both the methods and the actual values for 2004.

2004	Mobile House Shipments Actual Value	Forecast Box-Jenkins	Forecast Quadratic Regression
Q1	35.40	81.64	54.58
Q2	47.30	100.92	63.46
Q3	47.20	101.08	61.33
Q4	40.90	90.91	51.67

Exhibit 6.6: Forecasted and Actual Values of MHS

7. Evaluation of Forecast Accuracy

In this section, we will analyze the forecast accuracy between the two models Box-Jenkins and Quadratic Regression using mean average percentage error (MAPE). The following exhibit shows the comparison of MAPE values between both the methods.

2004 Quarter	MAPE Box-Jenkins	MAPE Quadratic Regression
Q1	130.61%	54.17%
Q2	113.36%	34.17%
Q3	114.14%	29.95%
Q4	122.28%	26.34%
Average MAPE	120.10%	36.16%

Exhibit 7.1: Average MAPE Values for Box-Jenkins and Quadratic Regression Model

MAPE for Box-Jenkins model is 120.10% which is very high compared to the 36.16% MAPE of quadratic regression model. From the exhibit 5.5 we can observe that Box-Jenkins model overestimates the actual MHS values. Cycle factor plays a pivotal role in this overestimating of actual values, this might be because the model has less number of observations to learn from. Thus, it makes very difficult to predict the cycle factor.

Box Jenkins has CF values over 1.5, which are obtained by heavily relying on its past data to predict the future. These high values indicate that there will be affluent increase in mobile home shipments in 2004.

Coming to the regression model where CF values are obtained using the times series, the decomposition method has performed much better. The reason might be because it has incorporated the economic indicators into the model and it doesn't rely only of the previous data of MHS for predicting the future. In the next section, we will be discussing about the conclusion and recommendations.

8. Conclusion and Recommendations

Kim Brite and Larry short develop mobile-home parks and are contemplating developing more similar facilities. However, they are not sure what the forecast for the Mobile Homes sale will be over the next year and are seeking some input.

From our analysis, we can say that cycle is the most influential factor in forecasting MHS data. For forecasting CF values, we found that regression is the best approach using external data. From our regression analysis, we conclude that initial claims of unemployment insurance benefit has a strong relation with MHS.

Our forecasted values differ significantly when comparing the Box Jenkins against the Quadratic and Linear Regression Model. Upon inspection of the MAPE values, we suggest using one of the Regression Model and to take a cautious approach. More specifically the Quadratic Regression model as the R^2 value is much better and the values are significant based on p-value. Using this model, we forecast the sales for the year 2004 to be 231,045 as compared to 373,675 when using the Box Jenkins model. This recommendation also stems from the analysis we conducted earlier by fitting MA and CMA on the actual values. The analysis showed that the time series exhibits a downward trend and it would be best not to over forecast. With the forecasts in hand it is advisable that Kim Brite and Larry short to not be overly aggressive by expanding right away and manage their cash flow better. It is better for them to wait now and expand their business when the shipments are starting to increase and has an upward trend.

Appendix

1. Forecast Calculation using Deseasonalized Components

Quarter	Period	Mobile Home Sales	Moving Average	Centered Moving Average	Centered Moving Average Trend	Cyclic Factor	Seasonal Factor	Seasonal Index	Forecast
Q1	Mar-88	56600						0.903455	
Q2	Jun-88	49100						1.090355	
Q3	Sep-88	58500	55425	55212.5	62505.88	0.883317	1.059543	1.067366	58931.9
Q4	Dec-88	57500	55000	57625	62452.78	0.922697	0.997831	0.938824	54099.7
Q1	Mar-89	54900	60250	61162.5	62399.67	0.980173	0.897609	0.903455	55257.6
Q2	Jun-89	70100	62075	61162.5	62346.57	0.981008	1.146127	1.090355	66688.8
Q3	Sep-89	65800	60250	60050	62293.47	0.963985	1.095754	1.067366	64095.3
Q4	Dec-89	50200	59850	59575	62240.37	0.957176	0.842635	0.938824	55930.5
Q1	Mar-90	53300	59300	58962.5	62187.27	0.948144	0.903964	0.903455	53270.0
Q2	Jun-90	67900	58625	59262.5	62134.16	0.953783	1.14575	1.090355	64617.2
Q3	Sep-90	63100	59900	61150	62081.06	0.985002	1.031889	1.067366	65269.4
Q4	Dec-90	55300	62400	64100	62027.96	1.033405	0.862715	0.938824	60178.6
Q1	Mar-91	63300	65800	68125	61974.86	1.099236	0.929174	0.903455	61547.9
Q2	Jun-91	81500	70450	72187.5	61921.76	1.165786	1.129004	1.090355	78710.0
Q3	Sep-91	81700	73925	74487.5	61868.66	1.203962	1.096828	1.067366	79505.4
Q4	Dec-91	69200	75050	75200	61815.55	1.216522	0.920213	0.938824	70599.6
Q1	Mar-92	67800	75350	75012.5	61762.45	1.214532	0.903849	0.903455	67770.4
Q2	Jun-92	82700	74675	74300	61709.35	1.204031	1.113055	1.090355	81013.4
Q3	Sep-92	79000	73925	73237.5	61656.25	1.187836	1.078682	1.067366	78171.2
Q4	Dec-92	66200	72550	72125	61603.15	1.170801	0.917851	0.938824	67712.7
Q1	Mar-93	62300	71700	71387.5	61550.04	1.159829	0.872702	0.903455	64495.4
Q2	Jun-93	79300	71075	70987.5	61496.94	1.154326	1.117098	1.090355	77401.6
Q3	Sep-93	76500	70900	70375	61443.84	1.145355	1.087034	1.067366	75115.9
Q4	Dec-93	65500	69850	68287.5	61390.74	1.112342	0.95918	0.938824	64110.0
Q1	Mar-94	58100	66725	65087.5	61337.64	1.061135	0.892645	0.903455	58803.6
Q2	Jun-94	66800	63450	62275	61284.53	1.016162	1.072662	1.090355	67901.9
Q3	Sep-94	63400	61100	60325	61231.43	0.985197	1.050974	1.067366	64388.8
Q4	Dec-94	56100	59550	59050	61178.33	0.965211	0.950042	0.938824	55437.6
Q1	Mar-95	51900	58550	58712.5	61125.23	0.960528	0.883968	0.903455	53044.1
Q2	Jun-95	62800	58875	58550	61072.13	0.958702	1.072588	1.090355	63840.3

Quarter	Period	Mobile Home Sales	Moving Average	Centered Moving Average	Centered Moving Average Trend	Cyclic Factor	Seasonal Factor	Seasonal Index	Forecast
Q3	Sep-95	64700	58225	57612.5	61019.02	0.944173	1.12302	1.067366	61493.6
Q4	Dec-95	53500	57000	56712.5	60965.92	0.930233	0.943355	0.938824	53243.1
Q1	Mar-96	47000	56425	55737.5	60912.82	0.915037	0.843238	0.903455	50356.3
Q2	Jun-96	60500	55050	54812.5	60859.72	0.900637	1.103763	1.090355	59765.1
Q3	Sep-96	59200	54575	54712.5	60806.62	0.899779	1.08202	1.067366	58398.3
Q4	Dec-96	51600	54850	54175	60753.52	0.891718	0.952469	0.938824	50860.8
Q1	Mar-97	48100	53500	52387.5	60700.41	0.86305	0.918158	0.903455	47329.7
Q2	Jun-97	55100	51275	50387.5	60647.31	0.830828	1.093525	1.090355	54940.3
Q3	Sep-97	50300	49500	48900	60594.21	0.807008	1.02863	1.067366	52194.2
Q4	Dec-97	44500	48300	47875	60541.11	0.790785	0.929504	0.938824	44946.2
Q1	Mar-98	43300	47450	47475	60488.01	0.784866	0.912059	0.903455	42891.5
Q2	Jun-98	51700	47500	47262.5	60434.9	0.78204	1.093891	1.090355	51532.9
Q3	Sep-98	50500	47025	46037.5	60381.8	0.76244	1.096932	1.067366	49138.9
Q4	Dec-98	42600	45050	44512.5	60328.7	0.737833	0.957035	0.938824	41789.4
Q1	Mar-99	35400	43975	43562.5	60275.6	0.722722	0.812626	0.903455	39356.7
Q2	Jun-99	47400	43150	42937.5	60222.5	0.712981	1.10393	1.090355	46817.1
Q3	Sep-99	47200	42725	43675	60169.39	0.725867	1.08071	1.067366	46617.2
Q4	Dec-99	40900	44625	45300	60116.29	0.753539	0.90287	0.938824	42528.7
Q1	Mar-00	43000	45975	47200	60063.19	0.785839	0.911017	0.903455	42643.1
Q2	Jun-00	52800	48425	50512.5	60010.09	0.841733	1.045286	1.090355	55076.6
Q3	Sep-00	57000	52600	54275	59956.99	0.905232	1.050207	1.067366	57931.3
Q4	Dec-00	57600	55950	57387.5	59903.89	0.957993	1.003703	0.938824	53876.8
Q1	Mar-01	56400	58825	60087.5	59850.78	1.003955	0.938631	0.903455	54286.3
Q2	Jun-01	64300	61350	62450	59797.68	1.044355	1.029624	1.090355	68092.7
Q3	Sep-01	67100	63550	65137.5	59744.58	1.090266	1.030129	1.067366	69525.5
Q4	Dec-01	66400	66725	68525	59691.48	1.147986	0.968989	0.938824	64332.9
Q1	Mar-02	69100	70325	71775	59638.38	1.203504	0.962731	0.903455	64845.5
Q2	Jun-02	78700	73225	74612.5	59585.27	1.252197	1.054783	1.090355	81354.1
Q3	Sep-02	78700	76000	77262.5	59532.17	1.297828	1.018605	1.067366	82467.4
Q4	Dec-02	77500	78525	79537.5	59479.07	1.337235	0.974383	0.938824	74671.7
Q1	Mar-03	79200	80550	81662.5	59425.97	1.374189	0.969845	0.903455	73778.4
Q2	Jun-03	86800	82775	83887.5	59372.87	1.412893	1.034719	1.090355	91467.2
Q3	Sep-03	87600	85000					1.067366	
Q4	Dec-03	86400						0.938824	

2. Adjusted and Unadjusted Seasonal Indexes Calculation

	Seasonal Indexes				
	Q1	0.90			
	Q2	1.09			
	Q3	1.07			
	Q4	0.94			
	SF	Q1	Q2	Q3	Q4
	1988			1.06	1.00
	1989	0.90	1.15	1.10	0.84
	1990	0.90	1.15	1.03	0.86
	1991	0.93	1.13	1.10	0.92
	1992	0.90	1.11	1.08	0.92
	1993	0.87	1.12	1.09	0.96
	1994	0.89	1.07	1.05	0.95
	1995	0.88	1.07	1.12	0.94
	1996	0.84	1.10	1.08	0.95
	1997	0.92	1.09	1.03	0.93
	1998	0.91	1.09	1.10	0.96
	1999	0.81	1.10	1.08	0.90
	2000	0.91	1.05	1.05	1.00
	2001	0.94	1.03	1.03	0.97
	2002	0.96	1.05	1.02	0.97
	2003	0.97	1.03		
	sum	13.55	16.36	16.01	14.08
# of Observations		15	15	15	15
Average (Unadjusted SI)		0.903481	1.090387	1.067397	0.938852
SUM of 4 Unadjusted Seasonal Indexes					4.000117
Multiplier					0.999971
Seasonal Indexes		0.90	1.09	1.07	0.94
SUM of 4 Adjusted Seasonal Indexes					4.00