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Introduction

Sale for Tuxedo shirts is vary from season to season in a year in Washington DC. In the situation, the growth of business is required business owner to find more capital or fund. In the requirement of financial institute, business owner should provide the business forecast for at least future 12 months for finance approval. The purpose of project is to consider the various time series models for forecasting the Sale volume and subject to utilize that model to forecast it in future period.

In here, we are using the Minitab software for statistical tool on this project.

Data Analysis and Model Fitting

The sale volume has been collected monthly for 8 years. First, we shall plot the time series data without any adjustments.

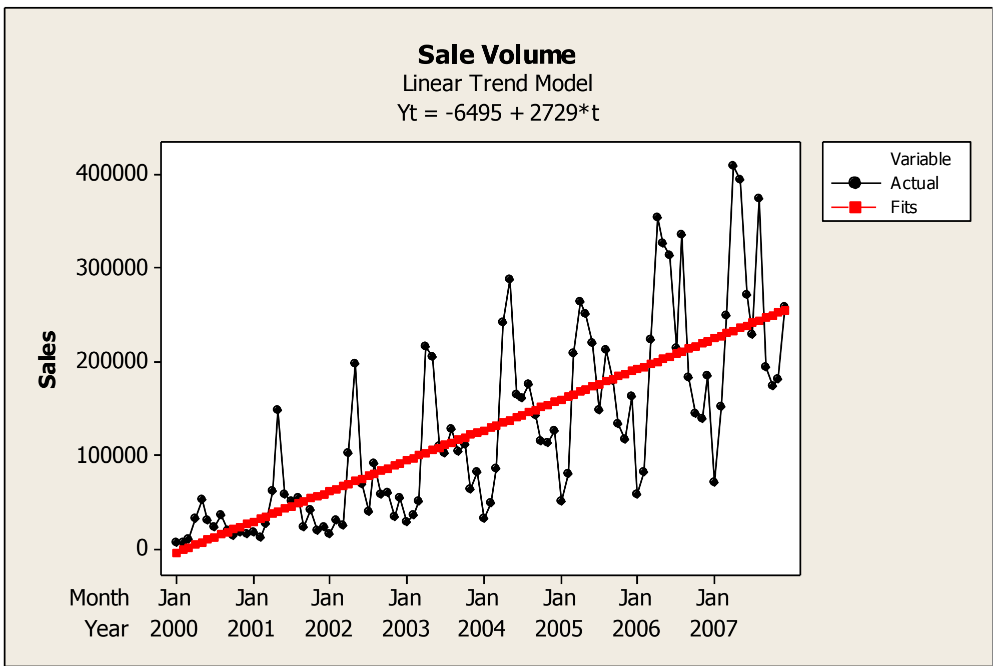

Fig. 1 The sale volume for last 8 years

Figure 1 presents the sale volume in the past 8 years. Also, we can see obviously that the increasing trend of data over the time period and the seasonal effect during a year. However, it is better to bring the theoretical for supporting those observations.

Next, we plot correlogram for the sample autocorrelation. We can see in Fig.2 that the autocorrelation pattern is tend to repeat every 12-period cycle. We can confident on Fig.2 that there is a seasonal effect for 12-period. Also, the autocorrelation result is seemed to appear in the positive area, which can imply non-stationary data.

By considering the result on both Fig.1 and Fig.2, we decide to take the 1st difference of lag 12 data for minimizing the seasonal effect and trend removal. After this action, we find that there is slightly remaining trend in data diff12 (first difference of 12 lag), which is presented in Fig.3. Then, we prefer to remove the remaining trend by taking the 1st difference of diff12, which we initiate new variable called "diff1diff12". In Fig.4, we can see by observation that the diff1diff12 is nearly remaining trend.

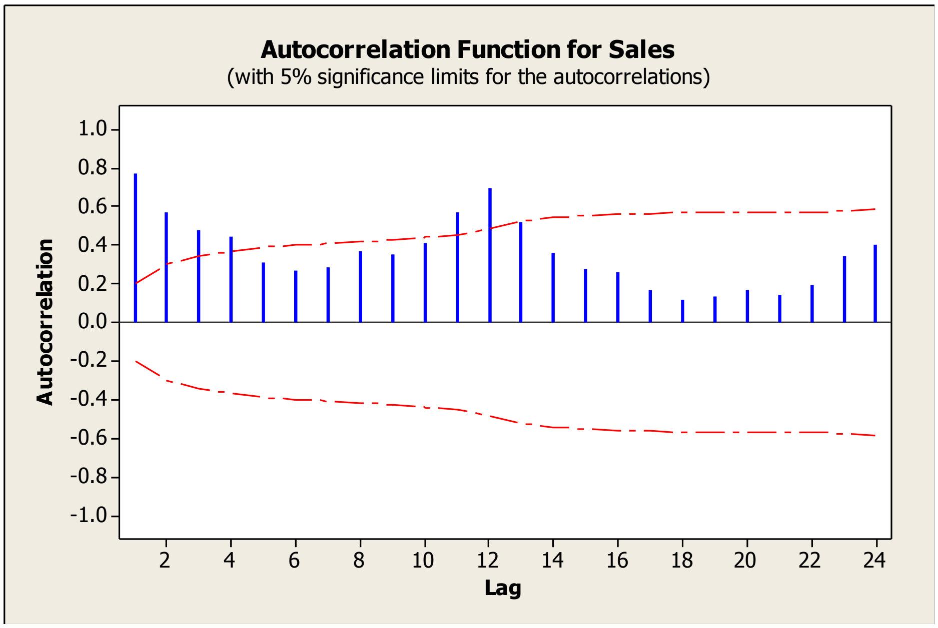

Fig.2 The autocorrelation of Sale volume

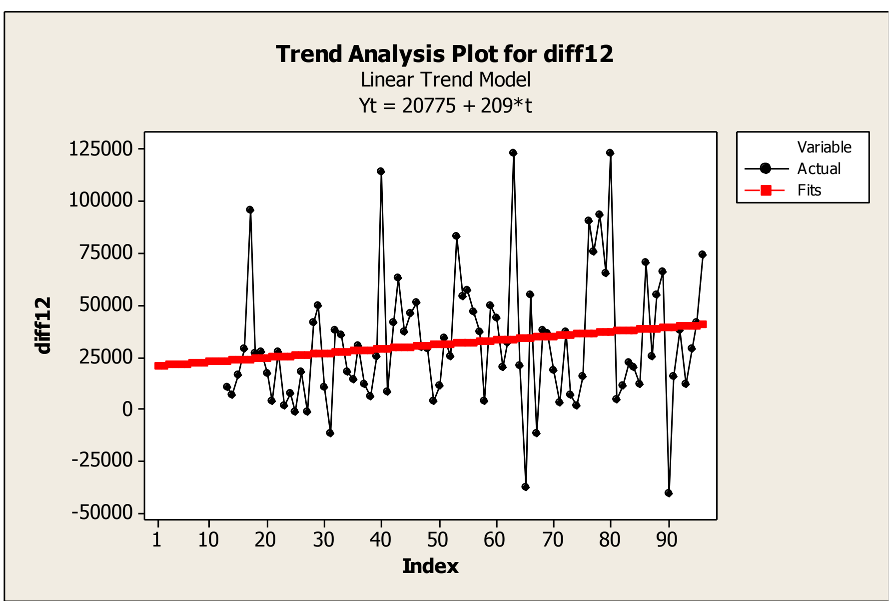

Fig.3 The time series data diff12 after 1st difference of 12 lag

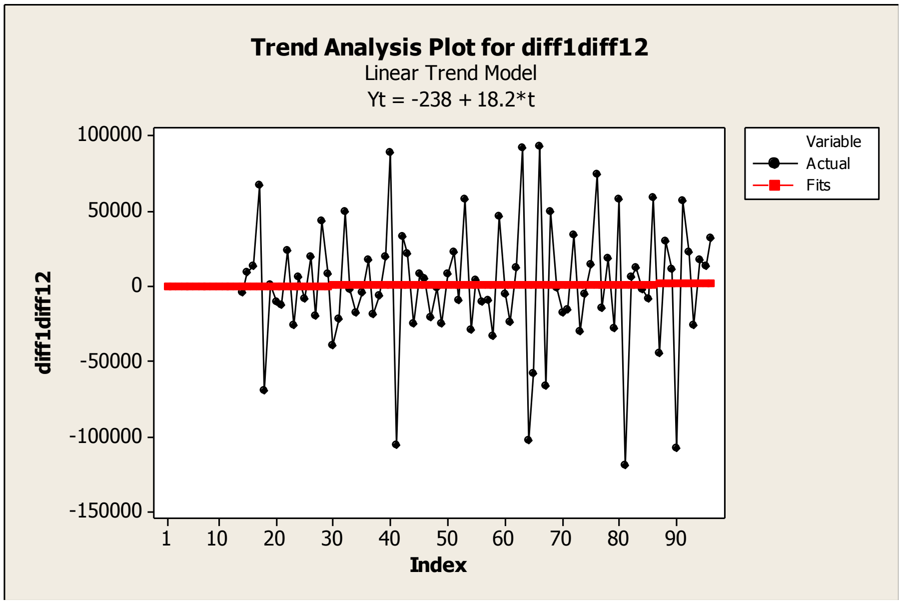

Fig.4 The time series data diff1diff12 after 1st difference of diff12

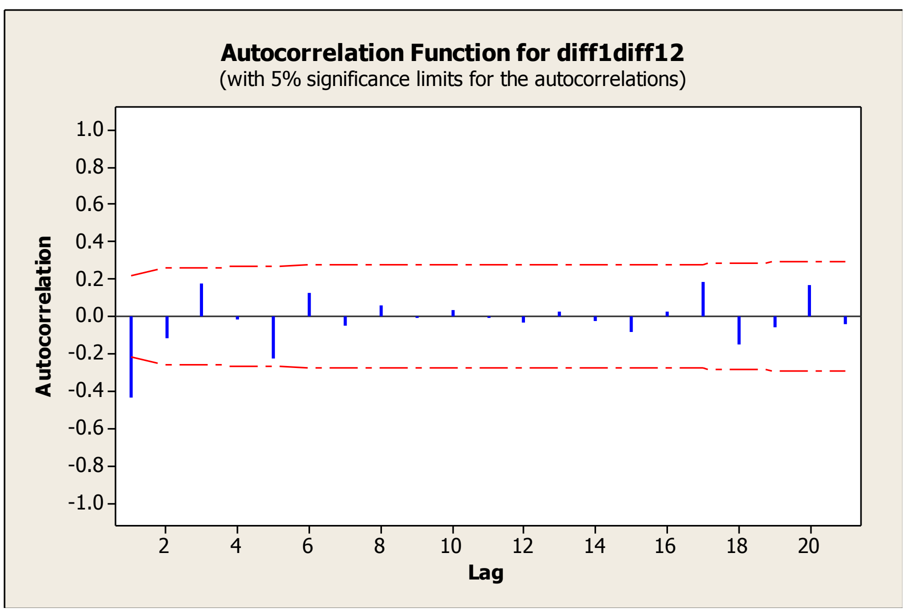

Fig.5 The autocorrelation of data diff1diff12

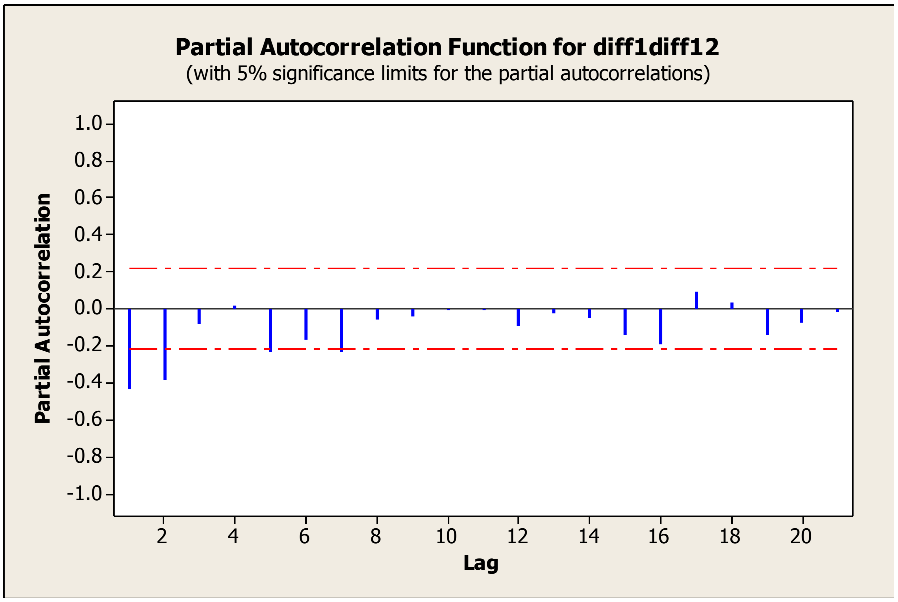

Fig.6 The partial autocorrelation of data diff1diff12

After that, we plot the correlograms for autocorrelation and partial autocorrelation in Fig.5 and Fig.6. By considering both results, we initially think that the time series diff1diff12 should model with ARMA(2,1).

Table.1 ARIMA (2,1,1) x $(0,1,0)_{12}$ result

```
Type          Coef  SE Coef      T      P
AR    1     0.1327   0.1213   1.09  0.278
AR    2     0.0054   0.1196   0.05  0.964
MA    1     0.9696   0.0736  13.17  0.000
Constant     177.2    179.4   0.99  0.326


Differencing: 1 regular, 1 seasonal of order 12
Number of observations:  Original series 96, after differencing 83
Residuals:    SS =  79925161034 (backforecasts excluded)
              MS =  1011710899  DF = 79


Modified Box-Pierce (Ljung-Box) Chi-Square statistic

Lag            12      24      36      48
Chi-Square    9.8    38.1    48.5    61.3
DF              8      20      32      44
P-Value     0.282   0.009   0.031   0.043
```

From Table.1, we observe that the P-value for AR-1, AR-2 and constant leads us to accept H_0 which is coefficient is equal to zero.

Then, we try another model ARIMA (0,1,1) x $(0,1,0)_{12}$, which idea is come from removing both AR coefficients.

Table.2 ARIMA (0,1,1) x $(0,1,0)_{12}$ result

```
Type         Coef  SE Coef      T      P
MA   1     1.0190   0.0266  38.35  0.000
Constant   271.86    72.53   3.75  0.000


Differencing: 1 regular, 1 seasonal of order 12
Number of observations:  Original series 96, after differencing 83
Residuals:    SS =  77085827647 (backforecasts excluded)
              MS =  951676885  DF = 81


Modified Box-Pierce (Ljung-Box) Chi-Square statistic

Lag            12      24      36      48
Chi-Square   11.4    36.3    48.9    58.3
DF             10      22      34      46
P-Value     0.327   0.028   0.047   0.105
```

From Table.2, we observe that the P-value for MA-1 and constant leads us to reject H_0 which we conclude the coefficient should not equal to zero with higher than 95% confident level. Moreover, with considering the result of ACF and PACF of residual in Fig.7 and Fig.8, the residual seems not to have the significant autocorrelation.

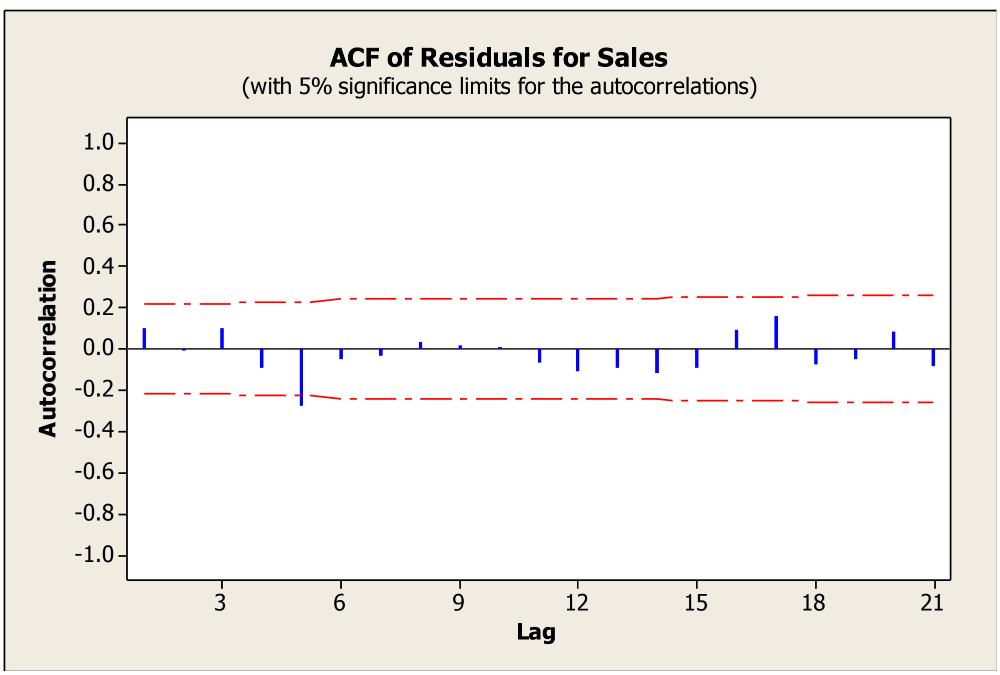

Fig.7 The autocorrelation function of residual for ARIMA(0,1,1)$(0,1,0)_{12}$ model

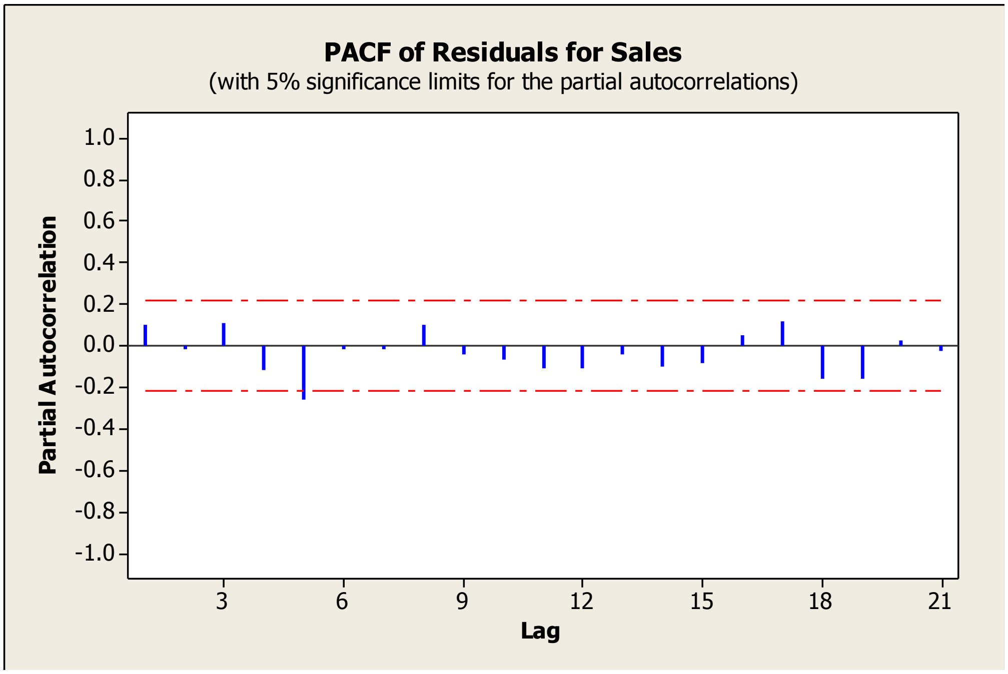

Fig.8 The partial autocorrelation function of residual for ARIMA(0,1,1)(0,1,0)$_{12}$ model

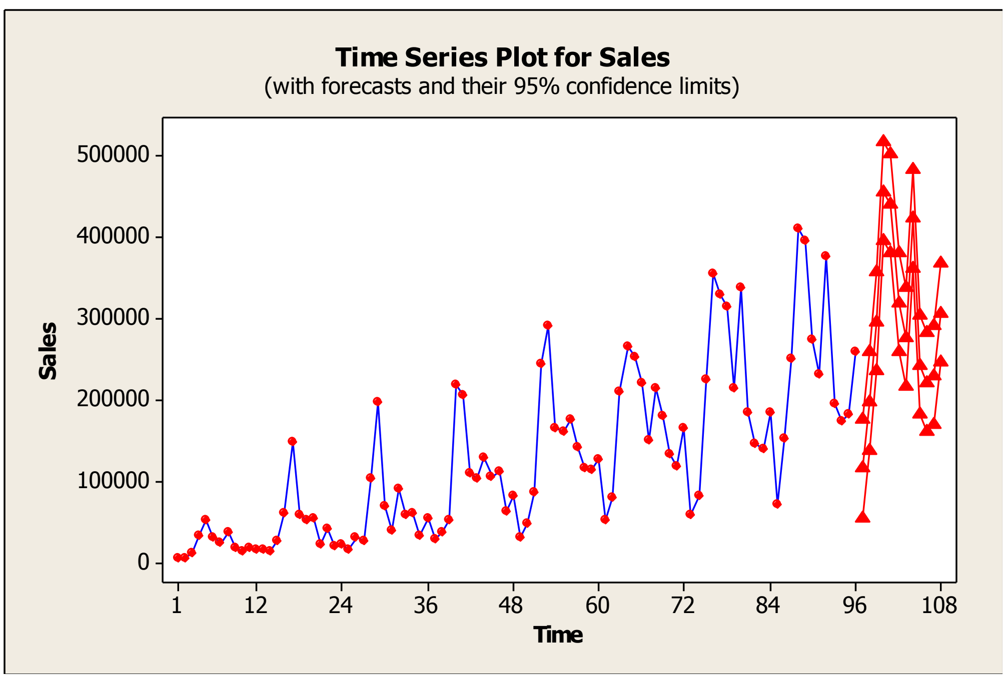

Fig.9 The forecast time series plot on sale volume for ARIMA(0,1,1)(0,1,0)$_{12}$ model

Summary

To forecast the sale volume in next 12 months, we believe that ARIMA(0,1,1)(0,1,0)$_{12}$ model can well forecast with theoretically statistical supports. In Fig.9, the forecast result on next 12 months is vary by seasonal and trend to growth. We can bring this report submit to financial institute to be evident supporting for capital approval.