IMPROVE CAPACITY UTILIZATION FOR MARUTI BY FORECASTING FUTURE DEMAND

Forecasting Analytics – Project Report

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Executive summary

Problem description

Improve capacity utilization of Maruti's Manesar and Gurgaon plants by forecasting future demand of Maruti cars and hence scheduling production.

Maruti has 2 manufacturing plants at Manesar and Gurgaon. Manesar plant has a capacity of 550k and Gurgaon plant has a capacity of 900k as of 2016. The production numbers for 2016 shows that Manesar plant produced 630k cars suggesting overtime at the plant, whereas Gurgaon plant produced 678k cars only suggesting underutilization.

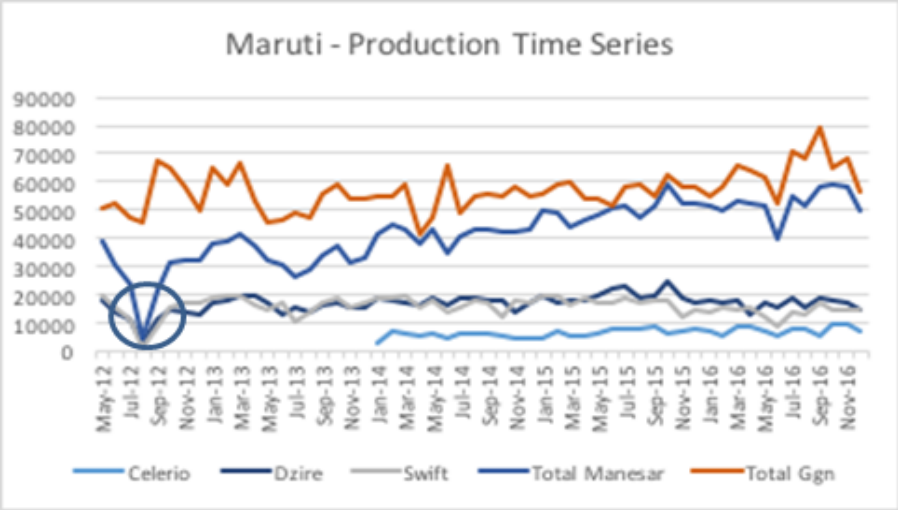
The problem that we are trying to solve is to figure out where capacity augmentation can be done to optimize the capacity utilization based on forecasts for various models.

Data Description

Source: Sales Data obtained from annual report

We collected data for 56 months starting from May 2012 for 18 models of Maruti cars and aggregated them based on the manufacturing plant they are being produced at, to get Manesar and Gurgaon plant data. Some models were discontinued in between and some were launched in between this period.

Original Data



Key Characteristics of the Data

Trend – Linear trend can be observed in the production at Manesar plant, whereas Gurgaon has a quadratic trend and the models (Dzire, Swift and Celerio) have varying trends. In case of Dzire and Swift, a downward trend can be observed in the last 12months of the data.

Seasonality – No observable seasonality in all the data that we have.

Level and noise are always there.

Other – The month of August 2012, has a significant dip across both the plants because of a agitation in the plants. While considering data for forecasting we have used the average of the other August months for August 2012 since this data was an anomaly. This period is circled in the graph above and going forward.

Methodology

- Forecast demand for next 12 months at Gurgaon and Manesar plant

- Forecast individual demand of Dzire (Monthly and Quarterly) and Swift models which contribute to 80% of cars produced in Manesar plant
- Forecast demand of a 3rd model which can be shifted to Gurgaon plant to accommodate Manesar's production plant for next 12 months
- Models used
    - Naïve forecasts (Lag 1, Lag 3 and Lag 12)
    - Multiple Linear Regression
    - Holts Winter
    - Double exponential smoothing, data deseasonalized using CMA of 12 and seasonality indices

Conclusion and Recommendations

Based on our forecasts, capacity at Manesar plant will be extremely strained over the next year

	Projected Demand	Capacity
Manesar	762,526	550,000
Gurgaon	845,632	900,000

- While **Swift demand is 185,936 over the next year, Dzire demand is 225,124**. These two combined capture 74% of regular capacity at Manesar plant
- Celerio demand is 90,481 cars out of which 54,368 can be accommodated in regular capacity of Gurgaon plant while rest can be managed at OT. This would enable Maruti to maintain OT level in 2017 at Manesar plant similar to 2016 level

Recommendations

1. Shift complete production of Celerio to Gurgaon plant since shifting production of Swift or Dzire (both produced in high volume) partially will have impact on economies of scale achieved in sourcing
2. Initiate capacity augmentation at both plants, at Manesar to deal with demand in Swift, Dzire and in Gurgaon for other models.

Technical Summary

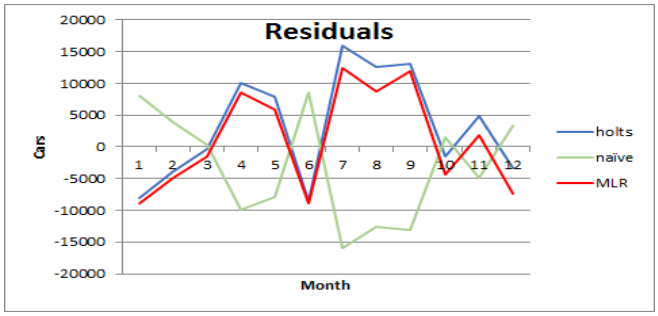
Since Maruti has flexible manufacturing, we looked at forecasting the models being produced at Manesar (Dzire, Swift, Celerio) along with forecasting the total production of Manesar and Gurgaon facility to figure out ways to better optimize the capacity based on the number of units that need to be produced. We have taken a 12 month forecast horizon for all five-time series.

Gurgaon

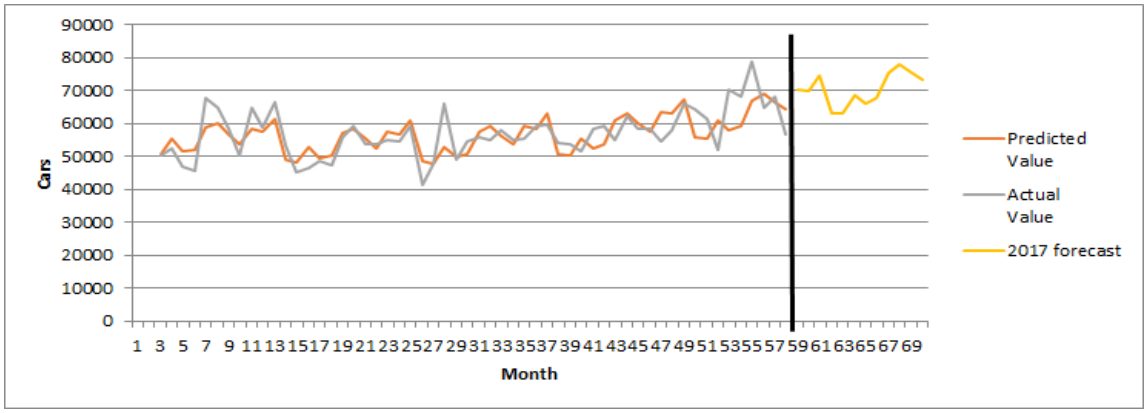
The data for Gurgaon was gathered by aggregating the production of all car models of the company being produced at Gurgaon. For Gurgaon, which has a quadratic trend we went ahead with Multiple Linear Regression. We benchmarked it with the seasonal naïve Forecast. We decided to use the seasonal naive as it was performing better than using the last month of available data as the naive for all the months. Here are the results for the same.

MLR	Training MAPE	Validation MAPE	Trend Order

	6.05%	11.27%	2
Holt's Winter	7.05%	12.63%	
Seasonal Naïve	10.16%	10.36%	



We notice from the plot of residuals above that the **seasonal Naïve model is constantly under-predicting and hence rejected.** We decided to select a model that over predicts and under predicts fairly equally. However, if we had data about cost of over prediction vs cost of under prediction, we could make a better judgement call as to which model to choose.

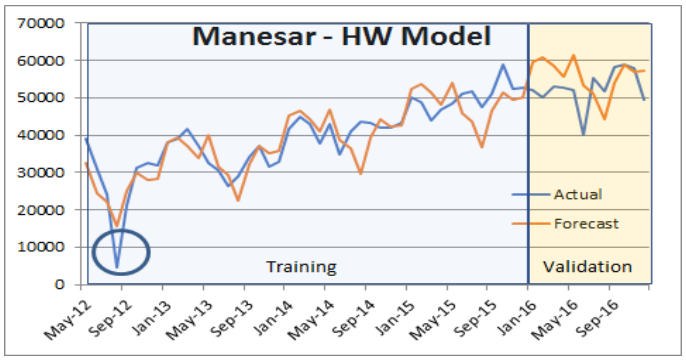


Prediction for 2017 :
8,45,632 Cars
95% Interval [-10329, +10329]

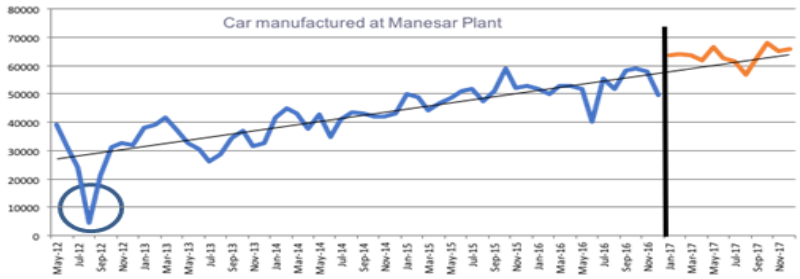
<u>Manesar</u>

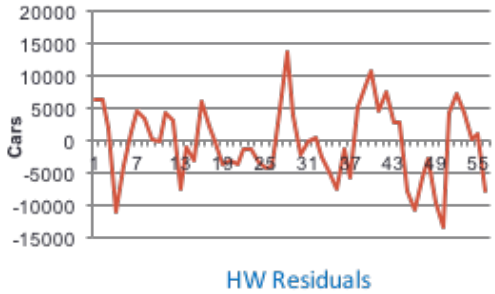
Similarly for Manesar, we aggregated demand of all cars being produced at Manesar to come up with the total number of cars produced at Manesar. As can be seen from the time series for Manesar, the data has a linear trend without an observable seasonality. We used Holt's Winter method to capture trend with a 12 month period. Here is the result for the same.

HW (12)	Training MAPE	Validation MAPE	Trend
	15.36%	12.61%	Linear
Naive (Lag 1)	21.72%	8.9%	



Naïve data showed strong indication of overfitting with training MAPE as 21.72% and validation MAPE as 8.9% and hence was rejected





Prediction for 2017 :
7,62,526 Cars
95% Interval [-8880, +2640]

<u>Dzire (Monthly and Quarterly)</u>

Initial method employed was Holt's Winter and even double exponential smoothening method was employed to come up with relevant forecasts. However the results were not satisfactory. We also tried Naive forecast with lag 1, 3 and 12. The best Naive MAPE came out to be 17.8% for validation period.

The vehicle shipped time series does not show any apparent trend or seasonality (Trendline fitted is polynomial of 5th order). (See Appendix 1)

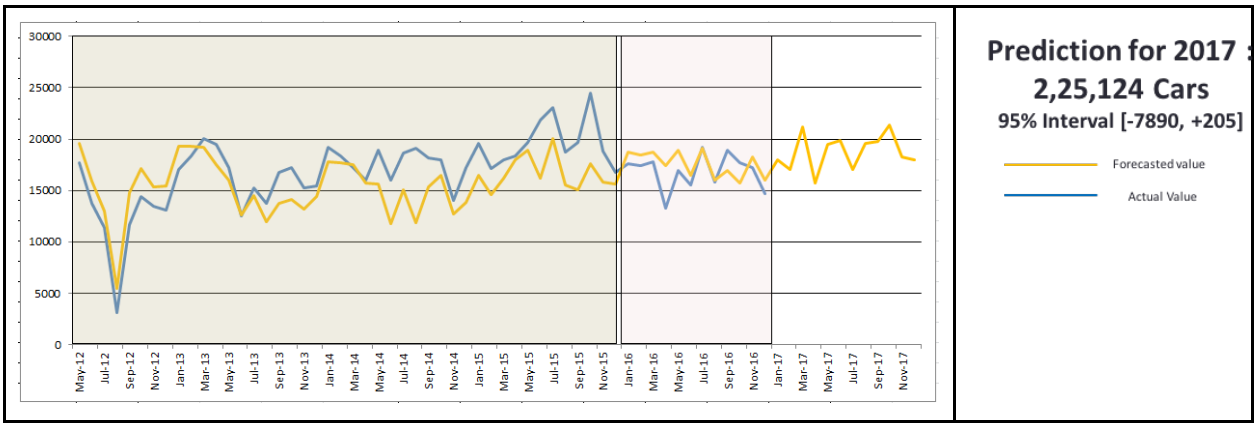
We also tried to use quarterly data instead of monthly data to see if forecasted results could be any better. (See Appendix 2). However the predictions were way off with consistent over-prediction. The training MAPE was 5.53 but validation MAPE was 24.83 indicating over-fitting. Hence in order to get better forecasts for the year 2017 (12 month forecast), we tried to forecast sale of Dzire as a percentage of the overall market for compact sedan. Procedure followed:

1) Dzire sales converted to percentage of total compact sedan sales.
2) Seasonality indices calculated for each month between January and December using *Centered Moving Average* method.
3) The percentage data is then de-seasonalized and data forecasted using *Double*

Exponential Smoothing.

4) The forecasts are then re-seasonalized and MAPE and residuals calculated for both *Validated* and *Forecast* periods.
5) The line graphs for both forecasted data and residuals is shown below.
6) August 2012 data was averaged out for the next 4 years as there was an abnormal disruption in August 2012 (Labor strikes in this period).

	Training MAPE	Validation MAPE	Trend
Double Exponential	**11.33%**	**7.68%**	**Varying**
Quaterly using Double Exponential	**5.53%**	**24.83%**	
Naive (lag 12)		**17.8%**	



Dzire Validation Residual (Check Appendix 4)

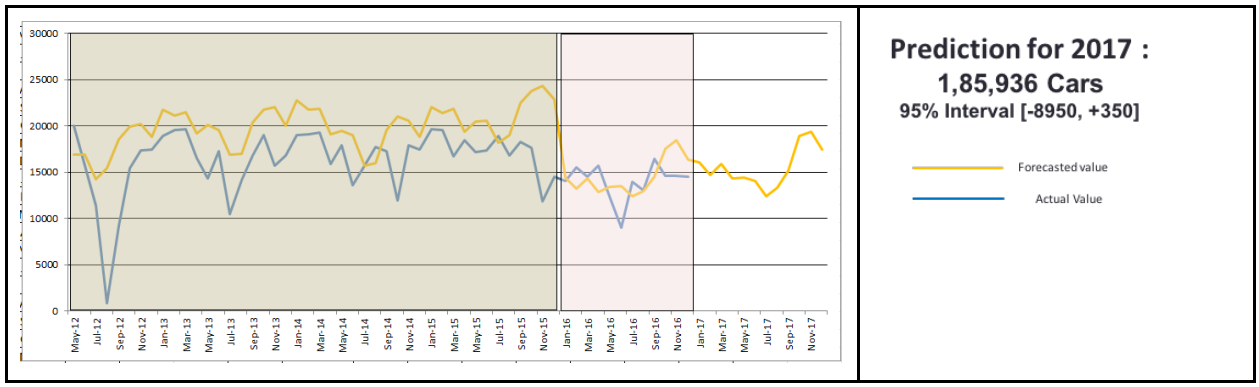
<u>Swift</u>

Swift data shows a regular product life cycle trend with growth from introduction and then plateauing out in 2015 and finally a downward trend in 2016 in the time series data. The same procedure and methods were employed to reach the forecasts for this model as Dzire model.

	Training MAPE	Validation MAPE	Trend
Double Exponential	**11.35%**	**3.65%**	**Varying**
Naive	**14.52%**	**44.29%**	

The data so obtained is show in Appendix 3

Naïve data showed strong indication of overfitting with training MAPE as 14.52% and validation MAPE as 44.29%



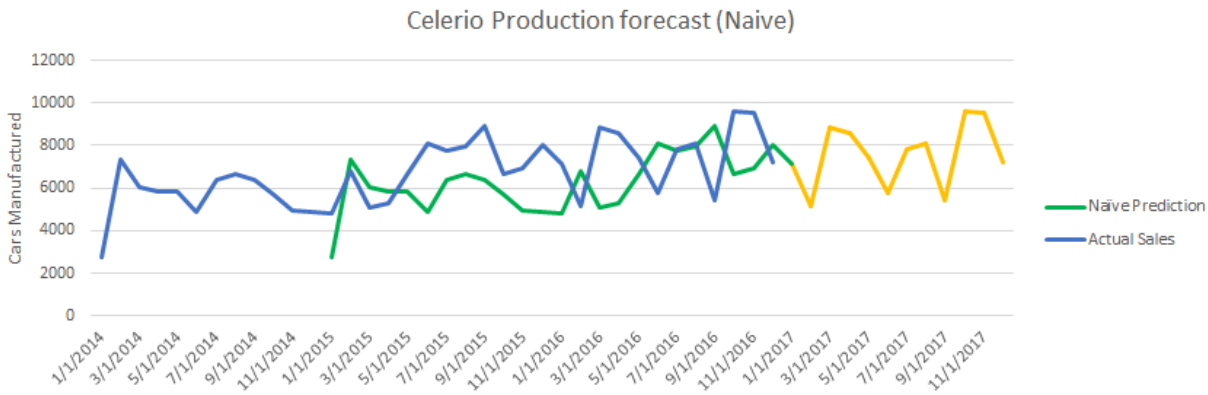
For Swift Residual please check appendix 5

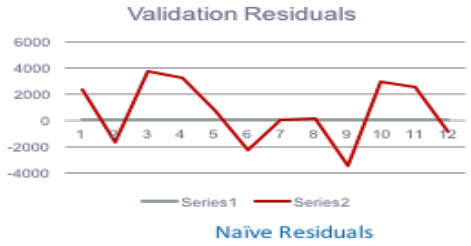
Celerio

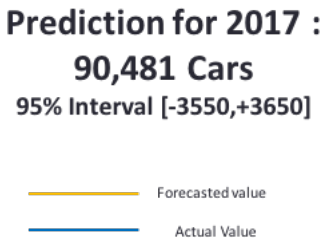
For Celerio, no apparent seasonality in the training data set, there is a slight upward trend.

- HW(12) provided a MAPE of 32.9%
- MLR with quadratic trend gives a RMSE of 4055.631
- Naïve provides best prediction for the next 12 month sales and hence we went ahead with Naive of lag 12 for the forecasts.

	Training MAPE	Validation MAPE	Validation RMSE
Naïve Lag 12	23.02%	27.35%	2352.19
HW (12)	**11.72%**	**32.90%**	**2491**
MLR			**4055.63**

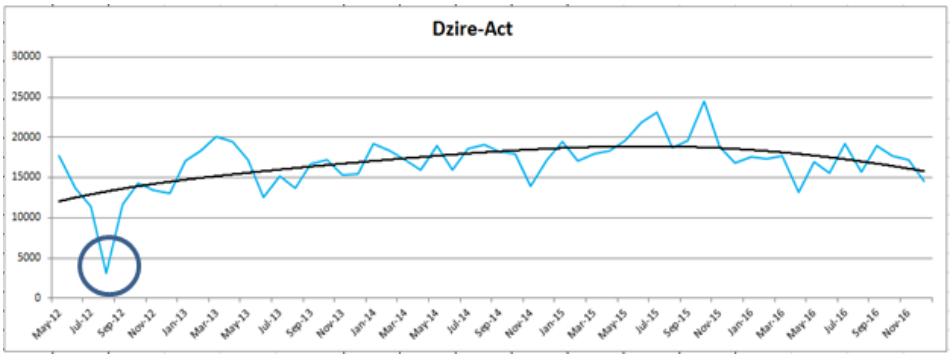




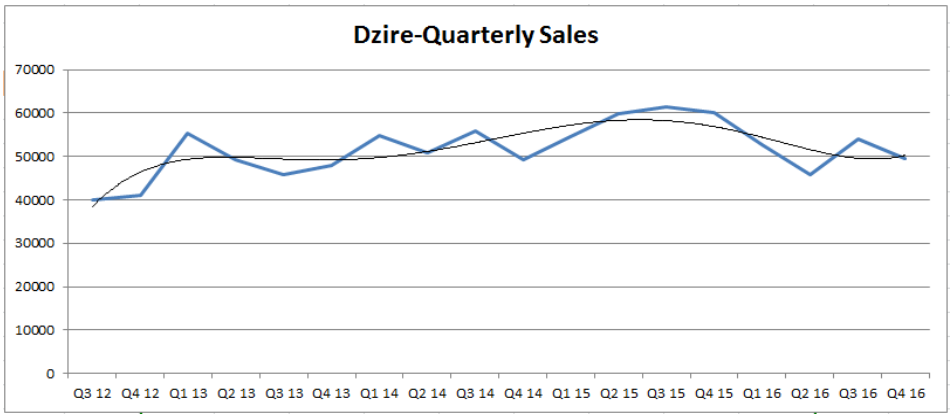


Appendix

1. Dzire Actual

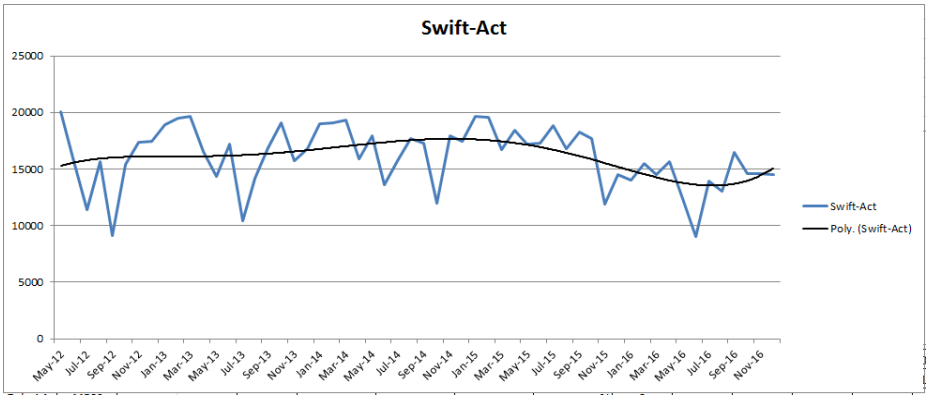


2. **Dzire Quarterly**



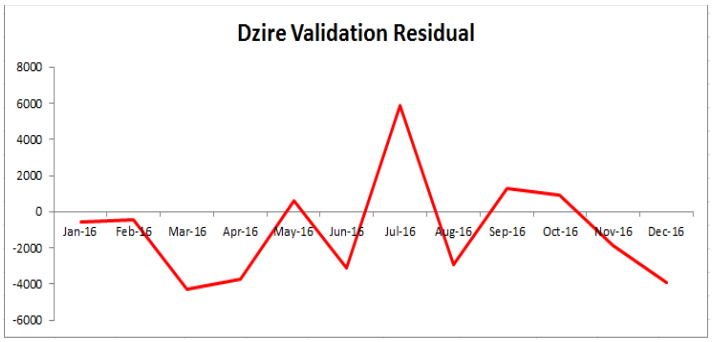
(Trendline fitted is polynomial of 5th order).

3. Swift Actual

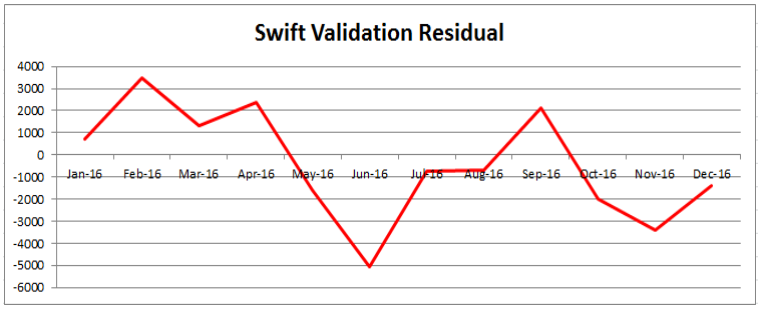


(Trendline fitted is polynomial of 5th order)

4. Validation Residual for Dzire



5. Swift Residual



5. Calculations for Dzire

	Demand						
Actual	Predicted	PredSeason	Dzire Act	Dzire Pred	Error	AbsError	%AbsError
33981	36430	36387	17851	18440	-589	589.057	1.73%
32453	34800	36089	17052	17517	-464	464.201	1.43%
36695	38870	37220	17194	21480	-4286	4285.89	11.68%
26142	34606	35936	13232	16985	-3752	3752.21	14.35%
32143	36043	34415	18377	17753	625	624.543	1.94%
31894	33848	33709	14922	18035	-3113	3113.43	9.76%
34220	34176	34398	21382	15540	5842	5842.16	17.07%
32525	33151	32139	15122	18042	-2921	2920.86	8.98%
38241	34314	33304	19059	17777	1282	1282.19	3.35%
41713	37206	33256	19717	18800	917	917.114	2.20%
29667	31673	35086	14832	16697	-1866	1865.55	6.29%
29202	31995	35595	12710	16615	-3905	3904.58	13.37%
37054	17999					**MAPE**	**7.68%**
35319	17079						
39824	21166						
33190	15685						
40991	19462						
38707	19904						
38766	17031						
37175	19571						
39344	19740						
43561	21341						
35596	18215						
35532	17932						
	225124						

6. Calculations for Swift

		Demand						
Jan-16	Act	Predicted	**Predseaon**	**SwAct**	**SwPredSea**	Error	AbsError	%AbsError
Feb-16	57780.323	61760.2	57244.93	15165.77	14445.91	719.864	719.864	1.17%
Mar-16	58523.496	60382.6	56017.74	16680.81	13183.82	3496.99	3496.99	5.79%
Apr-16	59982.464	61501.7	57164.04	15626.08	14314.98	1311.1	1311.1	2.13%
May-16	57338.043	51775.1	53269.51	15221.65	12845.93	2375.72	2375.72	4.59%
Jun-16	56351.803	53086.5	55420.14	11834.75	13417.39	-1582.6	1582.64	2.98%
Jul-16	48912.306	51753	55523.63	8419.561	13497.55	-5078	5077.99	9.81%
Aug-16	46981.654	43597.7	52240.19	11628.78	12364.14	-735.36	735.36	1.69%
Sep-16	52847.891	49419.7	52360.84	12295.28	12983.71	-688.43	688.429	1.39%
Oct-16	61159.382	59014.3	58572.04	16600.42	14473.11	2127.31	2127.31	3.60%
Nov-16	64921.935	65109.7	61401.1	15493.51	17497.97	-2004.5	2004.47	3.08%
Dec-16	54913.34	64162.5	62321.82	15025.03	18435.87	-3410.8	3410.83	5.32%
Jan-17	52890.439	61562.4	59797.33	14967.13	16359.6	-1392.5	1392.47	2.26%
Feb-17	60504.635	16049.1					**MAPE**	**3.65%**
Mar-17	59140.699	14658.9						
Apr-17	60171.771	15899.8						
May-17	56167.584	14319.6						
Jun-17	56124.826	14392.2						
Jul-17	54388.579	14030.2						
Aug-17	49151.98	12367.3						
Sep-17	50563.039	13353.2						
Oct-17	57533.979	15168.3						
Nov-17	62121.986	18922						
Dec-17	61159.689	19371.3						
	59313.398	17404.7						
		185936						