Comparative Analysis of Different Forecasting Techniques for Ford Mustang Sales Data

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Abstract

This paper explores different forecasting techniques to predict sales data for the automobile, Ford Mustang. Companies rely on accurate forecasted data to make the right business decisions and to foresee long-term and short-term market performances. Forecasting data like sales data, demand data and market trends helps companies better manage their resources like cash flow, project funds, project plans, workforce and inventory. Forecasts are usually based on past data, industry-comparisons and market trends. In this project, different time-series forecasting models such as moving average, exponential smoothing, Holt's double exponential smoothing method, Winter's triple exponential smoothing method and the ARIMA were utilized. Forecasts were made based on the individual yearly data (non-seasonal) and also on all the yearly data combined (seasonal) in the ARIMA model. Minitab was used to generate forecasts for both Winter's triple exponential smoothing method as well as the ARIMA model. Further, on computing the mean absolute deviation (MAD), it was found that the best forecasting method for this given set of data was found out to be Holt's double exponential smoothing method. This study may inspire companies to adopt accurate forecasting techniques for similar data and may also motivate future studies to develop further precise forecasting tools.

Keywords
Forecasting, moving average, single and double exponential smoothing, Winter's method, ARIMA

1. Introduction

Forecasting is an integral component of any economy. It is the practice of predicting future patterns based on past data. Many things are predicted in our day-to-day lives. Predicting data helps an economy to visualize and prepare itself to face future situations (SHJ Consulting, 2007). It also helps to establish forecasting techniques that best match the actual data already present. Forecasting sales, demand patterns, trends, economic upturns and downturns, etc help any business to plan their operations accordingly. Businesses depend on accurate forecasts in order to plan projects, workforce, production, sales, profit margins, back-up plans, resources, inventory, funds, performance, business locations and to minimize uncertainty (James D. Blocher, 2004).

Forecasting methods are mainly classified as qualitative and quantitative. Qualitative methods are used when the data available is insufficient or there is no historic data available at all. These forecasts are based on judgements, beliefs, instincts, perceptions and are often subjective (Mechanical, 2014). For example, in order to study a new product's demand in the market, it might be required to carry out a survey with the correct set of participants suited to use the product. There are many qualitative methods that can be used in forecasting, such as: a) An expert opinion, b) Simple survey, c) Approximate estimation, d) Delphi method (Mechanical, 2014).

Quantitative methods, on the other hand are developed on actual mathematical models and are objective in nature. They forecast data as a function of past or historic data. For example, common commodities consumption trends can be easily studied to generate a database for forecasting. There is no assumption or opinion necessary for such predictions. This method is used when it is sensible to assume that an existing pattern may occur in the future again. The only challenge in quantitative forecasting is analyzing which forecast model fits the existing data best and which model provides the most accurate predictions. The different types of quantitative forecasting methods are: a) Univariate or Time-Series forecasting and b) Multivariate forecasting (Yeung, 2017).

Time-series forecasting is done when there is a need for a pattern or trend to be known in a set of past data values. Assuming that the trend will be followed, this kind of forecasting will predict future values based on extrapolation of the trend. This method can only be used when there is a regular pattern in the data set and there are no extreme fluctuations. Also, this approach is useful for a single-variable data set. Time series forecasting is further categorized into: a) Moving average, b) Exponential smoothing with and without trend and seasonality, c) ARMA/ARIMA models (Mechanical, 2014).

A multivariate forecasting approach is useful when multiple variables are to be studied in order to forecast values for a single variable. This is because the different variables in such scenarios are related. Forecasts are made based on these associations. This type of forecasting technique helps to evaluate the effect of changes in other variables. However, it can get challenging to identify these related variables, collect historic data about them and make predictions based on them (Yeung, 2017).

In this project, sales data of Ford Mustang for years 2010 - 2016 has been collected. A few of the time-series forecasting approaches were used to forecast sales data for 2017. The various forecast methods used were a) moving average methods with periods 3 and 5, b) simple exponential smoothing, c) exponential smoothing with trend, d) Winter's triple exponential smoothing with trend and seasonality, and e) ARIMA model including the non-seasonal and seasonal factors. Mean absolute deviation (MAD) has been used to analyze the best fitting model for this data set.

2. Literature Review

Innumerable attempts were made to forecast trends in several industries such as food, merchandise and automotives. The objective of this section of the paper is to provide a brief summary of previous studies which adapted, modified, simulated, and implemented different forecasting models. Traditionally, moving average models received greater attention compared to the other aforementioned models for forecasting sales data (Kahn, 2002). Since simple moving average model is not very effective, attempts were made to develop complex models such as cumulative moving average, weighted moving average, and exponential moving average to improve the accuracy of the predictions. For example, Holt (2004) developed an exponentially weighted moving average model and examined no trend and multiplicative trend. In addition, researchers also resorted to other models such as simple exponential smoothing, exponential smoothing with trend, winters model, and ARIMA.

Brown (1959) initially developed exponential smoothing for managing the inventory. Eventually, Holt (1957) and Winters (1960) extended the approach for considering linear, additive, and multiplicative seasonality trends. The model when developed was mostly used as a heuristic model which need not necessarily guarantee optimality. However, this changed when Ord, Koehler , & Snyder (1997) developed Single Source of Error (SSOE) model. Göb, Lurz, & Pievatolo (2015) applied a variant of exponential smoothing model on electricity load data and its corresponding sales data. The results show that the model performed very well and the forecasting trends were close to optimality.

Box & Tiao (1975) first attempted to study the ARIMA with explanatory variable models. Later on, Wang (2006) proposed an exponential smoothing model with covariance namely ESCov which was very similar to that of ARIMA (Göb, Lurz, & Pievatolo, 2015). Several studies also compared the performance of two or more different models to determine the most effective one. For example, Frank, Garg, Raheja, & Sztandera (2003) used single exponential smoothing and winters model to forecast women's apparel sales data. The results show that winters model outperformed the single exponential smoothing in terms of forecasting the sales data and better explaining the seasonal trends in the sales data.

LEE & CHO (2015) compared the performance of exponential smoothing and ARIMA model to forecast sales data for semi-conductor industry in Taiwan. For this purpose, data from 1999 to 2014 was aggregated and used for prediction and analysis. The model is evaluated based on the alpha significance. In contrast to the previous study, exponential smoothing Holt's model performed better than the ARIMA model for this data. Puthran, H.C., K.S., & M. (2014) studied the Indian motor cycle industry sales data and suggested that holt-winters method outperformed ARIMA.

Djukanovic, Milic, & Vuckovic (2014) compared the performance of exponential smoothing with seasonality, moving average with seasonality, linear regression, and others for forecasting the sales data for about 45 stores of the retail business, Walmart. Ramos, Santos, & Rebelo (2015) compared the effectiveness of ARIMA models and state space models. This is done by considering the retail sales of five different categories of footwear such as boots, booties, flats, sandals, and shoes. Models were evaluated based on RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), and MAPE (Mean Absolute Percent Error). The results showed that both the type of models performed equally better. Furthermore, researchers also developed new hybrid models that are either combination of two or more existing approaches or a completely new model which suits a specific application.

Choi, Hui, Liu, Ng, & Yu (2014) developed a new hybrid model to forecast the sales data for fashion in real time with minimal time and previous available data. Thus, literature suggests several models to study the forecasting patterns of different trends in wide range of industries such as textiles, automobiles, and utilities. Though there is no one best model that fits all the scenarios and industries, given some basic parameters such as type of the industry, seasonal variations, and available data, a particular method can be chosen.

3. Study Statement and Objectives

This study aims to use different time-series forecasting techniques in predicting automotive (Ford Mustang) sales data for the year 2017. The techniques used are a) 3-period and 5-period moving average methods, b) simple exponential smoothing, c) exponential smoothing with trend, d) Winter's triple exponential smoothing with trend and seasonality, and e) ARIMA model including the non-seasonal and seasonal factors through Microsoft Excel and Minitab respectively. Mean absolute deviation (MAD) was considered to make a comparison of the forecast techniques and analyze the best fitting model for the available set of data. The main objectives of this study are: a) Understand the application of various time-series forecasting methods for forecasting automotive sales data, b) Compute MAD against the actual data, c) Determine the best forecasting model for the data.

4. PPC Techniques and Methodology Adopted

4.1 PPC tools used

4.1.1 Moving Average

It is one of the simplest forecasting techniques that uses the average of a set of previous periods' data to predict the future value. A p-period moving average method is merely the arithmetic mean of the latest 'p' observations. Assuming there is no trend in the time series and allocating equal weights to the last p observations, the forecast for period p+1 would be (Cengage, 2016):

$$F_t = \frac{1}{p}\sum_{i=t-p+1}^{t} A(i)$$

$$f_{(t+\tau)} = F_t, \qquad \tau = 1, 2, \ldots$$

This model is highly suitable for data that is almost constant over time, or data that has a more or less linear trend that doesn't fluctuate (James D. Blocher, 2004). The challenge that might be faced while computing forecasts with this method are selecting the right period length. The longer the period of moving average, more number of random elements in the trend are smoothed. However, if any data set is characterized by a trend pattern, then moving average forecasting results in a lag in trend (Gor, 2017).

There can be a number of limitations in this model such as a) Equal weight is given to all observations though the most recent data is more relevant to the existing situations, b) The moving average method does not consider any data that is outside the specified period of average and c) forecasts can be misleading in case the data has any seasonal trend (Gor, 2017).

4.1.2 Simple Exponential Smoothing (SES)

Another common forecasting technique is the simple exponential smoothing method in which the forecast for the desired period is generated by combining the actual value of the latest period with the forecasted value of the latest period. Alpha is the smoothing factor, holding a value between 0 and 1 (Gor, 2017).

$$F_t = \alpha A_{t-1} + (1 - \alpha)F_{t-1}$$

In this method, only the most recent observations are considered; unlike in moving average. Hence, this method tends to be more accurate for certain types of data where the latest observations are very relevant. For majority of scenarios, the most recent data is more likely to indicate the patterns/trends in the future. This forecasting method best fits such data in the easiest way. It's called exponential smoothing because each of the observations in the past are declined by the term (1-α). The value of alpha has to be strategically chosen, as higher the value of alpha, more sensitive the model will be towards the most recent observations; and lesser the value of alpha, more stabilized the forecast.

4.1.3 Double Exponential Smoothing (DES)

Also known as the trend-driven exponential smoothing method (Holt's method), this method had been developed from the simple exponential smoothing method, for data series displaying a linear trend or a pattern. In this method, two values, the smoothed estimated and the trend are combined together to generate the forecasted value. Below are the equations that constitute the model (James D. Blocher, 2004):

$$F_t = \alpha A_t + (1-\alpha)(F_{t-1} + T_{t-1})$$

$$T_t = \beta(F_t - F_{t-1}) + (1-\beta)T_{t-1}$$

$$f_{t+\tau} = F_t + \tau T_t$$

The constants alpha and beta refer to the smoothing constant and the trend factor respectively. In the simple exponential smoothing method, the smoothing constant alpha was present to determine the weight to be given to the previous forecasted value. In this method, another smoothing parameter beta is introduced to define the extent of smoothing to be done on the trend constant (Gor, 2017). Values of both alpha and beta have to be between 0 and 1. They have to be chosen in a way that they yield the most accurate forecasts. The initial values for F_1 and T_1 also have to be judiciously chosen.

4.1.4 Triple Exponential Smoothing

More commonly referred to as Winter's model, the model is the extension of the double exponential smoothing along with a seasonality factor. This method is best suited for data series that exhibit a prominent seasonal pattern. A third smoothing factor gamma is used. The equations of the model are as below (Trubetskoy, 2016):

$$F_t = \alpha\,(A_t / c\,(t - N)) + (1 - \alpha)\,(F_{t-1} + T_{t-1})$$

$$T_t = \beta\,(F_t - F_{t-1}) + (1 - \beta)\,T_{t-1}$$

$$c_t = \gamma\,(A_t / F_t) + (1 - \gamma)\,c_{(t-N)}$$

$$F_{t+\tau} = (F_t + \tau\,T_t)\,c_{(t+\tau-N)} \qquad t + \tau = N + 1, \ldots, 2N$$

The equations determine the following in the order they are mentioned: series, trend, seasonal factor and forecasted value. This model demands at least one set of complete seasonal data series for initiation. The seasonal length refers to the data points (periods) in one season. The seasonal component (c) repeats itself in every season.

4.1.5 ARIMA model

The autoregressive integrated moving average (ARIMA) model is an autoregressive moving average (ARMA) model fitted to a non-stationary data series, where an additional term 'integration' is applied to make the time series stationary. ARIMA model eradicates all residual correlation, incorporates long-term patterns and seasonality in data series, studies the lags in the series and decides if it has to be present in the forecast equation and checks the auto-correlation function (ACF) and the partial autocorrelation (PACF) plots (Nau, 2014). An ARIMA model with orders (p, d, q) is represented as follows in mathematical terms (Flandoli , 2017).

$$\left(1 - \sum_{k=1}^{p} \alpha_k L^k\right)(1 - L)^d X_t = \left(1 + \sum_{k=1}^{q} \beta_k L^k\right)\epsilon_t$$

Where,
p is the number of autoregressive terms,
d is the number of nonseasonal differences needed for stationarity
q is the number of lagged forecast errors in the prediction equation.
$\alpha_1, \alpha_2, \ldots\ldots \alpha_p$ are real numbers
L is an operator that matches the space of all sequences S
t is a non-negative integer
ϵ_t is an error term

As discussed, ARIMA is a special case of ARMA model. ARMA model can be represented as follows

$$\left(1 - \sum_{k=1}^{p} \alpha_k L^k\right) Y_t = \left(1 + \sum_{k=1}^{q} \beta_k L^k\right) \epsilon_t$$

Where X_t is obtained from Y_t by d successive integrations. The number d is thus the order of integration.

4.2 Methodology

Time-series forecasting techniques, namely, 3-period and 5-period moving average methods, simple, double and triple exponential smoothing techniques and ARIMA models were used to forecast data for 2017. Microsoft Excel was used to compute forecasted values for moving average, simple and double exponential smoothing approaches. All data through 2010 to 2016 was used for these forecast models. Minitab was used to forecast values using Holt's and Winter's models. For the Holt's model encompassing the seasonal factor and for the non-seasonal ARIMA model, only data from three recent years, 2014 – 2016 were used to forecast; however all data from 2010 – 2016 was used to forecast values using the ARIMA seasonal model.

The model parameters and assumptions made in the various forecasting techniques are as follows:

For simple exponential smoothing: a) $\alpha = 0.1$, b) F(2) = A(1). For double exponential smoothing: a) $\alpha = 0.1$, b) $\beta = 0.2$, F(1) = A(1). For triple exponential smoothing: a) $\alpha = 0.1$, b) $\beta = 0.2$, c) $\gamma = 0.3$. For all exponential smoothing, actual car sales for July – Dec 2017 are assumed to be same as actual car sales July – Dec 2016. For ARIMA model taking seasonality into account, three sets of data were forecasted using all data through 2010 to 2016. The three scenarios used were: ARIMA (1,1,0)(1,0,0), ARIMA (1,1,0)(1,1,0) and ARIMA (1,1,1)(1,1,1). For ARIMA model computing forecasts without seasonality, three sets of data were forecasted using data through three recent most years, 2014 – 2016 by using the ARIMA (1,1,0) non-seasonal model.

5. Data

Sales data for Ford Mustang in the US had been collected for the years 2010 – 2017 (Table 1, Figure 1). All time-series forecasting techniques were applied on this set of data.

Table 1. Ford Mustang US Sales (Cain, 2017)

FORD MUSTANG SALES DATA (Number of cars)								
	2010	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
January	4747	3165	3736	3608	3881	8694	7580	5046
February	5115	3697	7351	6024	6410	8454	9993	8298
March	5829	8557	9046	7688	9305	12663	12563	9120
April	5145	8180	7801	7751	7243	13144	12726	8063
May	10,225	6607	10,427	8797	9761	13616	10327	7895
June	8974	8835	10,263	9243	7631	11719	9776	6186
July	7489	6805	7371	5768	6564	8482	9565	NA
August	5570	5718	6387	5866	5878	9997	8299	NA
September	5760	5054	4439	4420	3158	9456	6429	NA
October	5317	4898	5328	6918	4565	10096	5414	NA
November	4093	3865	5309	5376	8728	7286	6196	NA
December	5452	5057	5537	5727	9511	8742	7064	NA
Total	73716	70438	82995	77186	82635	122349	105932	44608

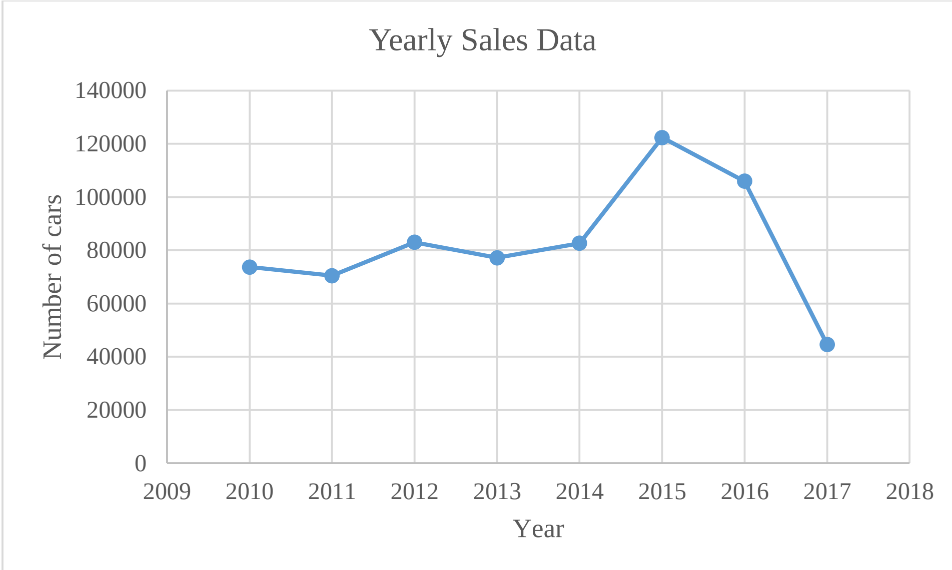

Figure 1. Yearly sales data - Ford Mustang US Sales
Note: 2017 data is only available until June

6. Results and Discussion

The results are summarized in the tables 2, 3 and 4 below. Table 2 encapsulates all the forecasts using the moving average and simple, double and triple exponential smoothing methods. Table 3 consists of forecasts made using the ARIMA model, and Table 4 contains the mean absolute deviation from the actual 2017 sales data.

Table 2. Forecasted values using MA, SES, DES and Winter's model

	2017 (Actual sales)	**Moving Average**		**SES**	**DES**	**Winter's model from years:**		
		(3)	**(5)**			**2014**	**2015**	**2016**
Jan	5046	6718	5500	5154	5010	4151	7273	4775
Feb	8298	8286	7646	6429	6511	6863	7022	6090
Mar	9120	11510	10253	7883	8908	9975	10440	7388
Apr	8063	11038	9733	7248	8358	7775	10751	7199
May	7895	11235	10586	10160	10012	10496	11042	5596
Jun	6186	9709	9726	8986	9422	8221	9415	5050
Jul	9565	8204	7550	7777	7427	7088	6746	4681
Aug	8299	8058	7285	6537	6651	6363	7862	3820
Sep	6429	6348	5580	5831	5550	3428	7347	2758
Oct	5414	6692	6464	5773	5988	4970	7741	2141
Nov	6196	7403	6579	5245	5629	9533	5507	2229
Dec	7064	8439	7316	6344	6577	10424	6505	2274

Table 3. Forecasted values using ARIMA

	(Non-seasonal) ARIMA (1,1,0) from years:			**(Seasonal) ARIMA (2010 - 2016)**		
	2014	**2015**	**2016**	(1,1,0)(1,0,0)	(1,1,0)(1,0,0)	(1,1,1)(1,1,1)
Jan	8048	8548	7750	6344	6211	6066
Feb	7393	8563	8320	7291	6194	7521
Mar	7101	8552	8816	8321	10266	10648
Apr	6970	8544	9264	8246	10721	10002
May	6911	8535	9682	6993	10954	12214
Jun	6885	8527	10081	6605	9169	11491
Jul	6873	8519	10467	6382	6183	8526
Aug	6868	8511	10845	5678	7467	8607
Sep	6866	8502	11218	4701	6816	7472
Oct	6865	8494	11588	4127	7318	8795
Nov	6864	8486	11956	4392	4807	8038
Dec	6864	8478	12322	4702	6214	8961

Table 4. Mean Absolute Deviation (MAD) for forecasted values

Mean Absolute Deviation (MAD)														
MA		**SES**	**DES**	**Winter's model**			**(Non-Seasonal) ARIMA**			**(Seasonal) ARIMA 2010-2016**		
(3)	**(5)**			**2014**	**2015**	**2016**	**2014**	**2015**	**2016**			
1672	454	108	36	895	2227	271	3002	3502	2704	1298	1165	1020
12	652	1869	1787	1435	1276	2208	905	265	22	1007	2104	777
2390	1133	1237	212	855	1320	1732	2019	568	304	799	1146	1528
2975	1670	815	295	288	2688	864	1093	481	1201	183	2658	1939
3340	2691	2265	2117	2601	3147	2299	984	640	1787	902	3059	4319
3523	3540	2800	3236	2035	3229	1136	699	2341	3895	419	2983	5305
1361	2015	1788	2138	2478	2819	4884	2692	1046	902	3183	3382	1039
241	1014	1762	1648	1936	437	4479	1431	212	2546	2621	832	308
81	849	598	879	3001	918	3671	437	2073	4789	1728	387	1043
1278	1050	359	574	444	2327	3273	1451	3080	6174	1287	1904	3381
1207	383	951	567	3337	689	3967	668	2290	5760	1804	1389	1842
1375	252	720	487	3360	559	4790	200	1414	5258	2362	850	1897
1621	**1309**	**1273**	**1165**	**1889**	**1803**	**2798**	**1298**	**1493**	**2945**	**1466**	**1822**	**2033**

From the above table, it can be seen that the least observed MAD is 1165, as a result of forecasts made using the double exponential smoothing method (Holt's method). The next best models in this scenario were found to be the simple exponential smoothing and ARIMA (1,1,0) using the non-seasonal model to forecast data from 2014 to 2017. The method with the highest MAD is the ARIMA (1,1,0), which had forecasted data from 2016 to 2017. One more interesting observation in Table 4 can be the forecasted values using MA (3). It is seen that for periods 2 and 9, the MAD was found to be the least with 12 and 81 respectively. However, it has to be noted that the MADs for the consecutive periods were found to be very deviant. This shows one of the disadvantages of the moving average method, as it does not consider data outside of its specified period. Furthermore, it can be seen from Table 4 that the MAD for SES and DES seems to fluctuate in the beginning of the data series, but the forecasts stabilize in the later periods (i.e. 9-12). It can be seen from Figure 2 that most of the models have their peak MADs in the middle of the year. It should also be noted that the MAD's for non-seasonal ARIMA and Winter's model, predicting data from 2016 have drastically increased after period 7.

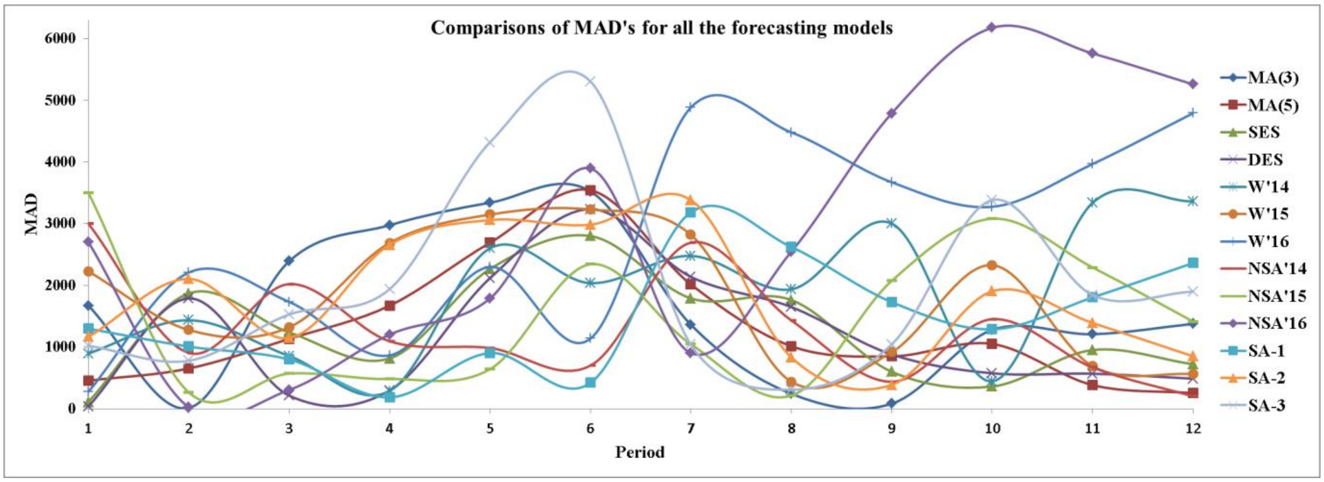

Figure 2. Comparison of MAD for all forecasting models
Note: SA-1, SA-2 and SA-3 refer to the three scenarios of the seasonal ARIMA model used.

7. Proposed Improvement

Accurate forecasts are a challenging task. However, they can be achieved by trial and error, or by seeking an expert advice on model parameters.

The ARIMA model was run with limited parameter changes. The AR, I and the MA (p,d,q) terms have been chosen in the combinations of 1 and 0. There could have been several other combinations to choose the p,d,q terms, both in the non-seasonal and seasonal scenarios, to achieve more accurate results.

Similarly, by changing the period length, alpha, beta, gamma values for the other models like moving average and exponential smoothing methods, there could have been better forecasted values. Future research can exhaust the various combinations of contributing factors to provide more accurate forecasts.

8. Conclusion

Various time-series forecasting models like moving average, simple, double and triple exponential smoothing, and the ARIMA model were applied to data series of automotive sales from 2010 – 2016 and were analyzed for accuracy using mean absolute deviation. Microsoft Excel and Minitab were used to forecast sales. Double exponential smoothing model, followed by the simple exponential smoothing was found to be the best fit for the data collected, considering the forecasting parameters used.

There is no single best method for forecasting any data, as accuracy of forecasts can be optimized in all models, given the right parameters. All models have their advantages and dis-advantages in forecasting data. Hence the right model to fit any given data has to be cautiously chosen.

Forecasting is a very tricky, yet interesting task. It might take long to arrive at the correct model for any given data set, but once the model is the best fit, it can help predict accurate data. Accurate forecasts immensely help businesses plan their operations accordingly.

9. Acknowledgments

I would like to thank my Professor, Dr. Ali, for having imparted his knowledge and expertise through his classes and for having given me this opportunity to practically implement the knowledge on real time data.

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Biography

Ayyagari Ramani is a research student at New York University, Abu Dhabi. She earned a B.E. (Hons) Chemical Engineering degree from BITS Pilani, Dubai, MSc. Renewable Energy Engineering from Heriot Watt University, Dubai and MSc Engineering Management from Lawrence Technological University, Michigan - USA. One of her significant career ventures is at Dubai Cable Company as a Process Engineer in the manufacturing department where she worked on multiple process improvement projects and waste-reduction projects as part of lean manufacturing. Her interdisciplinary research interests include lean and agile construction, consequences of 3D printing on supply chain, continuous improvement initiatives in production and latest process advancements in manufacturing and construction.