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# Suzuki Swift Marketing Data Comparative Study of Different Forecasting Methods

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**Abstract:** Sincere approaches to practical forecasts in organisations have been accomplished through operative research (OR) since its inception. Scientists have affected forecasts in other disciplines. Forecasting has an enormous social, economic and environmental impact and has a very important aspect of every business. Several prediction models have been developed to help people decide correctly against future uncertainties. However, there are distinct advantages and limitations for every prediction model. It is important to succeed in selecting correct forecasting methods from other alternatives. This paper aims to analyse predictive techniques to forecast car sales results, Ford Mustang. Companies depend on precise projected data to make the right decisions and to predict the business results over a long and short time. Predictions are usually based on historical results, industry comparisons and developments in the sector. Different model time series foresees were used in this phase, for example the moving average, exponential smoothing, the Holt double exponential smoothing, winter's three times exponential smoothing and ARIMA. The predictions were made on the basis of the annual (non-seasonal) data and the cumulative annual data (seasonal) in the ARIMA model. For both the threefold exponential smoothing system of winter and the ARIMA model, Minitab was used to produce forecast. In addition, the best prediction method for this given set of data was found to be the double-exponential smoothing process used by Holt when calculating the mean absolute deviation.

**Keywords:** ARIMA, forecasting, moving average, Management, supply chain Management.

## INTRODUCTION

In challenging environments, modern companies have to deal with various issues. The effective organizations are more flexible and follow up on new or revamped business management principles easily. Such methods are slowly being extended to functions. Provisioning chain management (SCM) was one of Bangladesh 's latest ideas from the late 1991s in the corporate sector. At first Supply Chain Management was integrated into the multinationals (MNC), and later other private and regional conglomerates followed the principles. Since the beginning of the purchasing and management of materials, SCM has played the major role but SCM has taken the integrated form, i.e. the procurement, management of materials, support for production and management of distribution services. Taking into account the competitive market scenario, SCM is the main area for companies to work[1].

The SCM deals with consumers as finished goods of primary, indirect and origin services (as input materials). The Supply Chain is a network between vendors, producers, retailers, distributors, transport operators and other supply chain partners. Since the beginning of the purchasing and management of materials, SCM has played the major role but SCM has taken the integrated form, i.e. the procurement, management of materials, support for production and management of distribution services[2]. Taking into account the competitive market scenario, SCM is the main area for companies to work. The SCM deals with consumers as finished goods of primary, indirect and origin services (as input materials). The Supply Chain is a network between vendors, producers, retailers, distributors, transport operators and other supply chain partners.

For most early SCM activities are expected to initiate all other SCM actions. Forecasting, however, plays a significant role both internally and externally. Forecasting is the primary component of both SCM and strategic strategy and decision-making. Companies are highly dependent on the real numerical value of forecasts, in real professional practice, to take significant decisions such as building capacity, allocating money, extending and further or backstream integrations etc[1].

Provision is an integral part of any enterprise. The practice is to forecast future trends on the basis of past knowledge. In our daily lives, many things are forecast. Data prediction helps an economy to see and prepare for the future. It also helps to develop prediction techniques which best fit current data. Projections of revenue, developments, demand patterns, economic revolutions, downturns and so on enable every company to prepare

its company. Companies are dependent on reliable forecasts to schedule programs, manufacturing, produce, revenue, profit margins, back-up plans, shop, funds, results, places, and mitigate vulnerability[3].
The methods of forecasting are primarily qualitative and quantitative. Historical data are not available, or qualitative approaches are used when there are inadequate data available. These predictions are based on assumptions, opinions, intuitions, expectations and are therefore subjective[4]. For example, a survey of the appropriate group of participants for the use of the product may be necessary to test the demand for a new product on the market. Some qualitative approaches may be used in the prediction process, such as: a) an opinion from an expert; b) a basic analysis, c) estimated estimation, d) Delphi.
At the other hand, quantitative approaches are based on existing statistical models and are empirical in nature. They forecast data based on historical or past evidence. In order to create a forecasted database, for example, rising consumption patterns can be easily explored. For these predictions there are no assumptions or opinions required[5]. This approach is used whenever a current trend is expected to occur again in future. In quantitative forecasting, the only challenge is to evaluate which forecast model better matches current data and which model is most reliable. A) Univarious or Times-Series forecasting and b) Multivariate forecasting are the specific forms of quantitative prediction process.
Time series forecasts are carried out if a pattern or trend is necessary in a number of previous data values. If the trend is observed, this type of projection predicts future values based on trend extrapolation[6]. This technique can only be used if a normal pattern is present in the data set and no significant fluctuations occur. This method is also useful for a single data set. The time series forecast is also known as: a) Moving average; b) Exponential trend and seasonal smoothing; c) ARMA / ARIMA models
For the purpose of predicting values for one single variable, a multivariate prediction method is useful. The explanation is that the different variables are related in these scenarios. Such correlations are the basis for the forecasts. It forms of prediction technology helps determine the effect of changes in certain variables. However, the detection, selection and estimation of these associated variables may be challenging[7].
Forecasts may be made on the basis either of qualitative empirical analysis or quantitative mathematical analysis. The prediction models can therefore be widely based on qualitative methods and quantitative methods. Fig.1 shows the flow diagram of a standard predictive modelling method[6]. Lusk and Files argued that the 'true' tool of numerous prediction competitions may not be a forecaster. There are obvious advantages and drawbacks of all prediction approaches. Therefore, it is important for all decision makers to choose an appropriate forecasting process. This paper discusses the most important predictive models briefly.

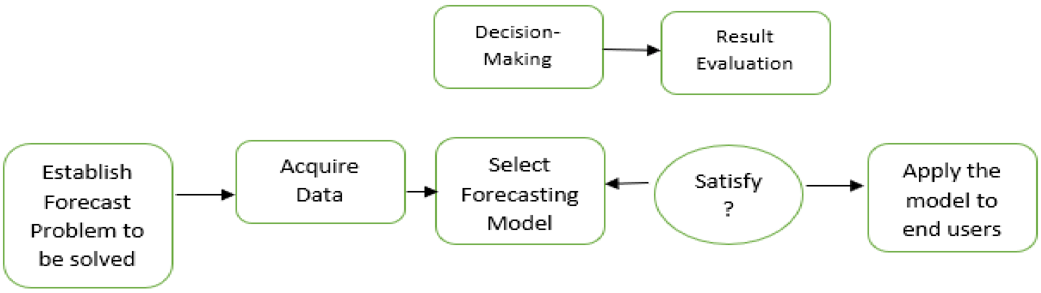


**Fig.1: Illustration of a Typical Forecasting Modelling Method**

## RESEARCH QUESTIONS

Question1: What are the different methods of forecasting?
Question2: What are quantitative Forecasting technique?

## LITERATURE REVIEW

Across many sectors, including food, energy and automobiles, numerous attempts have been made to forecast patterns. The aim of this paper section is to provide a brief overview of past research, adapting, updating, simulating and implementing various forecasting models. Moveable average models have historically been given more focus relative to the other models of forecasting sales data listed previously (Kahn, 2002).Since plain, shifting, average models are not very accurate, efforts have been made to develop complex models for improved prediction accuracy, such as cumulative, weighted shifting and exponential moving averages. For instance, Holt (2004) established an average moving model exponentially weighted and examined no pattern and pattern. Researchers have used other methods including basic exponential smoothing, exponential trend smoothing, winter model and ARIMA[5].
The forecast can be used as part of the planning method in both individual and business sectors. The primary area of application of the forecast is SCM, inventory management, government budgeting, and personal investment. Currently, forecasting in other untapped areas has become the growing concern. Forecasting activities are identified as inputs in the humanitarian and supply chain humanitarian disaster relief model and

forecasting is identified as supply chain management, which is known as a capability-building capacity creation in affected communities[8].

For the provision of sales data for some 45 retail shops, Walmart, Djukanovic, Milic, & Vuckovic (2014) compared the performance of exponential smoothing with seasonality, shifting average with seasonality, linear regression and others. The effectiveness of ARIMA models and state space models has been compared between Ramos, Santos and Rebelo (2015). The retail sales in five different categories of footwear are taken into account, for example boots, booti, apartments, sandals and schedules. Models have been tested based on the RMSE, the MAE, and the MAPE (Mean Absolute Percent Error). Methods were evaluated based on RMSE[9]. The tests have shown that both models have also changed. Researchers have also created new hybrid models, incorporating two or more different methods or a whole new model that fits a specific application.

Cachon and Fisher (2000) noted that supply chain partners should create joint strategies and forecasts to coordinate their production and shipping schedules in order to minimize costs, lead times as well as safety equipment and inventories, through inventory turnarounds, sales and profit margins and enhance operational efficiency through alignment of their process and promotion of knowledge sharing. Integration is characterized as the combining of parts into a whole and supply chain integration refers to the adoption and implementation of cooperation and collaboration systems, procedures, technologies and practices by supply chain partners for the development and maintenance of a seamless conduit to ensure that knowledge, materials and finished products can flow precisely and promptly[10].

Choi, Hui, Liu, Ng, & Yu (2014) created a new hybrid model to forecast fashion sales data in real time using a minimum amount of time and previously available data. Literature therefore suggests multiple models to research the prediction patterns of different developments in a wide range of industries, such as textiles, cars and utilities. Although not one of the best models suits all the various scenarios and industries, a specific approach can be chosen provided some simple parameters like business size, seasonal variations and data available.

Competition is commonly argued, not between firms today, but between supply chains. Active supply chain management (SCM) has become a potential useful way to maintain competitive competitiveness and boost organizational performance. Companies are starting to understand that enhancing efficiencies within an enterprise is not enough. Moberg et al (2002) have pointed out that understanding and practicing supply chain management (SCM) have become a fundamental condition for remaining competitive and profitable global race. Jones (1998) claimed that a number of organizations have started realizing that SCM is necessary for the creation in an increasingly crowded place of a sustainable competitive edge of its goods and services.

The literature offers no evidence of effective implementation despite increased attention paid to SCM and the SCM anticipations. Boddy et al. (1998) found that more than half of the survey respondents considered that their organisations' supply chain partnerships have not been successful. Speakman et al. (1998) noted that 60% of the alliances between the supply chain have failed. Many investigators have stressed the importance of sharing information in SCM practices. Lalonde (1998) sees knowledge sharing as one of five components of a good supply chain connection. The supply chain partners who exchange information regularly can work as a single entity, according to Stein and Sweat (1998). Together, they can better understand the end customer's needs and can therefore react more quickly to market changes[11]S.

In automatic forecasting systems, exponential smoothing is widely used. But when only limited historic details can be used in future demands, unintended outcomes can be obtained by the ad hoc startup approaches used in exponential smoothing. An exponentially smooth average weighs the data implicitly, like discounting, by large data sets. This pattern is important as it minimizes a prediction error as demonstrated by John McClain (1981). This is significant. Adjustment had little impact when statistical forecasts were almost perfect. When the predictions are less accurate, the adaptive accuracy increases. These findings indicate the graphical evaluation interest, as stated by Thomas R. Wille main (1989), and an adaptation of statistical forecasts.

Time series software forecasting tools typically include a number of techniques, some of which give users the ability to define parameters automatically. However, it is necessary to provide the decision-maker with specialized systems in real business circumstances where it could be necessary to forecast thousands of time series that are either automatic prediction parameters of certain prediction models or a prediction model selection from a set of models. Time series software forecasting tools typically include a number of techniques, some of which give users the ability to define parameters automatically. However, it is necessary to provide the decision-maker with specialized systems in real business circumstances where it could be necessary to forecast thousands of time series that are either automatic prediction parameters of certain prediction models or a prediction model selection from a set of models.

Improved accuracy does not automatically contribute to more reliable predictions. Predictions are of little value; no matter how precise, if not used. Most planners are not sure about forecasting. For predictions to be used, forecasters must decide the kind of predictions required[12]. Documents on forecasts should be clear and easy to understand. For ideas for addressing future issues before the final presentation, a draft report will be circulated. Following the distribution of the forecast numbers, forecasters should monitor how forecasts are used. Such community efforts in the production of projections usually boost both accuracy and acceptability, so Chaman L. Jain clarified the importance of the projections.

**METHODOLOGY**

For the forecasting of data for 2017, the predictions were based on time series techniques, namely 3 and 5 period average moving methodologies, simple, double and triple exponential smoothing techniques and ARIMA models. For average, basic and dual exponential flushing strategies, it was used in Microsoft Excel to calculate forecast values. For these forecast models all data were used up to 2010 until 2016. Minitab was used in Holt and Winter models to estimate values. Only data from the past three years, 2014 to 3 years, were used to estimate the Holt Model for the seasonal factor and the non-seasonal ARIMA Model; however, all data from 2010–16 used the ARIMA seasonal model to predict values.

**Design:**

In the estimation of car (Ford Mustang) sales data for 2017, this study aims to use various prediction techniques in time series. A) moving 3 and 5-period average, b) quick, exponential smoothing, d) exponential smoothing with inclination, d) pattern and seasonality triple exponential smoothing in Winter and e) non-seasonal and seasonal factors like ARIMA via Microsoft Excel and Minitab, respectively. The techniques used are a) moveable process. A contrast was made of the forecasting techniques and an interpretation of the best fit for the data set was considered to be an absolute mean deviation (MAD).

**Sample:**

A) α = 0.1, b) F (2) = A (1) for simple exponential smoothing. A) α = 0.1 b) β = 0.2, F (1) = A (1) For Double Exponential Smoothing: A) α = 0.1, b) β = 0.2, c) α = 0.3. In the case of three different exponential smoothing. Current car sales in July – December 2017 are expected to be the same in all linear smoothing as existing car sales in July – December 2016. Three sets of data were anticipated using all data for the ARIMA model taking into account seasonality between 2010 and 2016. ARIMA (1,1,0,0), ARIMA (1,1,1,0) (1,1,1,1,0) and ARIMA (1,1,1,1) (1,1,1) were the scenarios of three scenarios.

**Instrument:**

It is one of the simplest techniques to predict the future value using the average of previous periods. The arithmetic mean for the last 'p' observations is a p-period, moving average form. The prediction for the p+1 duration will be: this model is very useful for data that is almost constant over time and for data that has a more or less linear pattern, which does not swing.

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

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

If no time series pattern exists and the same weights have to be assigned to the last p observations. During the computation of forecasts using that method, the task is to choose the correct length of time. More random trend elements are smoothed the longer the average time period is moving. Furthermore, if a data set has a trend pattern, a moving average estimate leads to a lag. A number of limitations can occur in this model such as (a) All observations have equal weight although the latest data are most relevant to existing situations, (b) no data beyond the specified average and (c) forecast data can be misleading should the data have a seasonal tendency.

Another popular forecast is the simple exponential smoothing method by combining the actual value of the latter period with the expected value of the latter period to create the predicted forecast for the desired duration. The smoothing element is Alpha, which has a value from 0 to 1.

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

Even the latest findings are taken into account in this process, unlike the modified average. Therefore, for some types of data where the recent observations are very significant, this approach appears to be more precise. The most recent data are more likely to suggest potential patterns / trends in the majority of scenarios. This method of forecasting best suits these results. This is called exponential smoothing, as the word (1-α) declined through observation of the past.

This approach has already been developed using the basic exponential smoothing procedure, also known as the trend-oriented exponential smoothing technique, to display a linear trend or pattern in data series. In this procedure, 2 values are combined to achieve the expected value, the smooth estimate and the trend. The equations that make up the model are below.

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

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

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

The alpha and beta constants apply respectively to the smoothing constant and the trend element. The smoothing constant alpha was used by simple exponential smoothing to calculate the weight that was to be assigned to the predicted value. In this process, the amount of smoothing to be done on the trend constant has been specified by another betel smoothing parameter. The alpha and beta values must vary from 0 to 1. They must be selected to generate the most accurate predictions. The first values for F1 and T1 must also be carefully chosen.

Data collection:

For the years 2010-2017, sales data for Suzuki Swiftwas obtained in the United States (Table 1, Figure 1). This data set was applied to all time series forecasting techniques.

**Table 1: US Sales (Cain, 2017) Suzuki Swift Sales**

| | | SUZUKI SWIFT SALES DATA (Sum of cars) | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **2010** | **2011** | **2012** | **2013** | **2014** | **2015** | **2016** | **2017** |
| **January** | 4738 | 3124 | 3715 | 3617 | 3810 | 8683 | 7549 | 5065 |
| **February** | 5114 | 3694 | 7350 | 6023 | 649 | 8453 | 9992 | 8297 |
| **March** | 5839 | 8547 | 9036 | 7658 | 9315 | 12163 | 12263 | 9220 |
| **April** | 5245 | 8280 | 7701 | 7451 | 7143 | 13844 | 12126 | 8163 |
| **May** | 10,125 | 6107 | 10,327 | 8697 | 9861 | 12616 | 11327 | 7795 |
| **June** | 8914 | 8735 | 10,163 | 9543 | 7431 | 12719 | 9476 | 6286 |
| **July** | 7189 | 6205 | 7171 | 5468 | 6264 | 8782 | 9165 | NA |
| **August** | 5670 | 5418 | 6487 | 5466 | 5478 | 9497 | 8199 | NA |
| **September** | 5460 | 5154 | 4339 | 4320 | 3258 | 9356 | 6329 | NA |
| **October** | 5417 | 4798 | 5428 | 6818 | 4465 | 10086 | 5314 | NA |
| **November** | 4193 | 3765 | 5409 | 5476 | 8828 | 7386 | 6296 | NA |
| **December** | 5352 | 5157 | 5437 | 5827 | 9411 | 8842 | 7054 | NA |
| **Total** | 73256 | 68984 | 82563 | 76367 | 75913 | 122427 | 105090 | 44826 |

**Data analysis:**

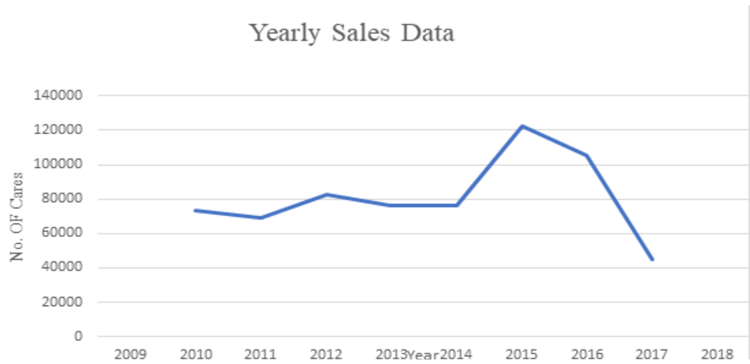


**Fig.2: Suzuki Swift U.S. sales data last year**

## RESULTS AND DISCUSSION

Tables 2 and 3 below summarize the results. Table 2 covers all estimates using the average moving and plain, double or triple exponential smoothing methods. The predictions in Table 3 are based on the ARIMA model.

**Table 2: Predicted values using the models MA, SES, DES and winter**

| | 2017 (Actual sales) | Moving Average | | SES | DES | Winter's model from years: | | |
|---|---|---|---|---|---|---|---|---|
| | | (3) | (5) | | | 2014 | 2015 | 2016 |
| **Jan** | 5146 | 6618 | 5400 | 5254 | 5110 | 4251 | 7173 | 4175 |
| **Feb** | 8198 | 8186 | 7546 | 6329 | 6511 | 6763 | 7422 | 6190 |
| **Mar** | 9220 | 12510 | 11253 | 7783 | 8708 | 9775 | 11440 | 7288 |
| **Apr** | 8263 | 12038 | 9833 | 7148 | 8458 | 7875 | 12751 | 7299 |
| **May** | 7295 | 12235 | 11586 | 12160 | 11012 | 12496 | 1202 | 5496 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Jun** | 6286 | 9509 | 9426 | 8786 | 9522 | 8421 | 9115 | 5150 |
| **Jul** | 9465 | 8104 | 7450 | 7477 | 7227 | 7188 | 6246 | 4281 |
| **Aug** | 8399 | 8458 | 7485 | 6437 | 6751 | 6463 | 7462 | 3420 |
| **Sep** | 6329 | 6448 | 5480 | 5731 | 5450 | 3228 | 7247 | 2858 |
| **Oct** | 5314 | 6592 | 6764 | 5473 | 5888 | 4870 | 7641 | 2241 |
| **Nov** | 6296 | 7413 | 6519 | 5255 | 5619 | 9523 | 5517 | 2239 |
| **Dec** | 7044 | 8449 | 7326 | 6354 | 6477 | 11424 | 6515 | 2264 |

**Table 3: Forecasted values by means of 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** | 8038 | 8558 | 7350 | 6744 | 6111 | 6056 |
| **Feb** | 7323 | 8573 | 8420 | 7691 | 6294 | 7531 |
| **Mar** | 7111 | 8552 | 8416 | 8221 | 10366 | 10548 |
| **Apr** | 6950 | 8544 | 9364 | 8146 | 10321 | 10102 |
| **May** | 6941 | 8575 | 9482 | 6593 | 10354 | 12414 |
| **Jun** | 6845 | 8547 | 11081 | 6405 | 9149 | 11791 |
| **Jul** | 6843 | 8549 | 12467 | 6382 | 6173 | 8546 |
| **Aug** | 6848 | 8521 | 11845 | 5478 | 7457 | 8647 |
| **Sep** | 6826 | 8512 | 12218 | 4401 | 6846 | 7422 |
| **Oct** | 6845 | 8414 | 12588 | 4227 | 7348 | 8715 |
| **Nov** | 6814 | 8416 | 12956 | 4192 | 4817 | 8018 |
| **Dec** | 6863 | 8472 | 12122 | 4202 | 6314 | 8861 |

**Table 4: Absolute Mean Variance (MAD) for predicted 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** | | | |
| 1172 | 451 | 107 | 35 | 855 | 2327 | 271 | 3012 | 3512 | 2714 | 1278 | 1145 | 1030 |
| 13 | 651 | 1859 | 1687 | 1235 | 1376 | 2218 | 925 | 225 | 23 | 1017 | 2114 | 774 |
| 2290 | 1123 | 1247 | 222 | 825 | 1420 | 1722 | 2029 | 548 | 303 | 729 | 1146 | 1518 |
| 2875 | 1680 | 814 | 285 | 278 | 2588 | 865 | 1083 | 441 | 1221 | 123 | 2648 | 1949 |
| 3540 | 2681 | 2245 | 2217 | 2611 | 3247 | 2289 | 944 | 640 | 1777 | 912 | 3049 | 4329 |
| 3423 | 3550 | 2810 | 3234 | 2015 | 3129 | 1146 | 629 | 2371 | 385 | 429 | 2923 | 5315 |
| 1261 | 2025 | 1778 | 2135 | 2488 | 2219 | 4854 | 2592 | 1056 | 912 | 3283 | 3312 | 1069 |
| 251 | 1024 | 1752 | 1644 | 1926 | 417 | 4449 | 1331 | 222 | 2556 | 2221 | 833 | 307 |
| 82 | 845 | 591 | 877 | 3011 | 928 | 3651 | 427 | 2083 | 4799 | 1528 | 384 | 1053 |
| 1288 | 1040 | 354 | 575 | 424 | 2227 | 3243 | 1251 | 3070 | 6164 | 1387 | 1914 | 3371 |
| 1217 | 384 | 954 | 568 | 3437 | 649 | 3957 | 658 | 2280 | 5730 | 1704 | 1349 | 1832 |
| 1385 | 253 | 727 | 488 | 3460 | 549 | 4770 | 210 | 1424 | 5228 | 2462 | 851 | 1887 |
| **1611** | **1319** | **1283** | **1145** | **1789** | **1703** | **2788** | **1278** | **1483** | **2955** | **1366** | **1832** | **2043** |

From the table above, 115, as a result of predictions made using a double exponential smoothing method (Holt method), can be seen as the least observed Insane. A simple exponential smoothing and ARIMA (1,1,0) using the non-seasonal model to forecast data from 2014 to 2017 were the next best examples for this scenario. The ARIMA (11.0), which forecast data from 2016 to 2017, is the system with the highest MAD. The predicted values with MA (3) are yet another important observation in Table 4. The Insane was found to be at least 12 and 81 respectively for periods 2 and 9. It must however be remembered that the MADs were found to be quite deviant for the following times. This shows one of the inconveniences of the typical moving system, since data are excluded from the defined definition. In addition, the SES and DES MAD at the start of the data series appears to have fluctuated from Table 4, but the forecasts are stabilized in subsequent periods (e.g. 9-12). The predictions of the 2016 data have also increased dramatically following period 7 for non-seasonary ARIMA and winter models.

## CONCLUSION

The global effect in Supply Chain Management offers companies the chance to increase sales and reduce costs at the same time. There appears to be no ambiguity in the management of the global supply chain. A business has seen fluctuation in demand, costs, exchange rates and the competitive climate over the span of its supply chain network. If conditions change, a decision that looks really good in the current climate may be very bad. The benefit of building versatile production capacity in one plant is dictated by unsure demand and quality. Mature, stable demand products are generally more easily predicted. Provision and subsequent management decisions become extremely complicated because either the raw material supply or the demand is highly volatile for the finished product. For the design of the supply chain and its response, therefore an estimate of the forecast error is necessary. Different time-series models for automotive sales from 2010 – 2016, including average moving smoothing, single, double and triple exponential smoothing and the Ares model have been used and are analysed in order to achieve precision with the use of a mean absolute deviation. Sales forecast was rendered using Microsoft Excel and Minitab. Two models of exponential lining, followed by simple exponential lining, have been defined as being the best fit for the collected data taking into account the prediction parameters used. No one is the perfect way to forecast data as accuracy of predictions can be improved with the right parameters in all models. The advantages and disadvantages of all models in forecast results. The appropriate model must therefore be carefully chosen to match any data. Projection is a very difficult but fascinating job. It can take longer to find the correct model for each specific data set, but once the model has matched best, reliable results can be expected. Precise projections allow companies to prepare their businesses accordingly.

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