# Statistical Forecasting Modeling to Predict Inventory Demand in Motorcycle Industry: Case Study

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Industrial Engineering & Management
ISSN: 2169-0316

Chen, Ind Eng Manage 2018, 7:4
DOI: 10.4172/2169-0316.1000270

Case Report Open Access

# Statistical Forecasting Modeling to Predict Inventory Demand in Motorcycle Industry: Case Study

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## Abstract

A comprehensive method of finding seasonal patterns of demand and the accurate prediction of future demands are still critical elements for different industries especially in manufacturing companies as it contributes to effective planning and operation. In this paper, a statistical forecasting model has been proposed and implemented in a motorcycle accessories manufacturing company in the USA. Dataset for a 7-year timeframe of historical sales data has been mined, cleaned, and compiled using Python programming. Results have been compared to the conventional forecasting model used by the company. Based on this comparison, using the proposed statistical forecasting model can improve the Mean Absolute Deviation (MAD) by almost 61% and the mean squared error (MSE) by 82%. These improvements will drastically improve the chance of consistently maintaining the right levels of inventory in the right place and at the right time. It also provides the opportunity of ensuring the safety stock of its inventory is sized correctly to avoid inflated carrying costs and lost sales orders due to stock outs.

**Keywords:** Demand forecast; Python programming; Statistical forecasting model; Forecasting model comparison

## Introduction

Forecasting is a process of building assumptions and estimates about future events that are generally unknown and uncertain [1]. A demand forecast is an estimated demand of what will be required to fulfill customer request over a defined future period [2]. Many organizations rely on demand forecasting as of the most important entities in keeping the right amount of stock on hand. An applicable forecasting model is a necessity of a viable supply chain system. It can easily provide better opportunity to allow firms to cope with the ever-changing shifts in demands for their products and resources. The ultimate goal is to have the optimized level of inventory to meet customers' demands while it is minimizing the cost of buying and holding the inventory.

Knowledge of how demand will fluctuate enables a company to keep the right amount of stock on hand. If demand is underestimated, sales can be lost due to the lack of products in stock and if the demand is overestimated, the business is left with a surplus that can be a financial drain on working capital. There are two main reasons for forecasting: (1). There is always a lead time between the ordering time and the delivery time, and (2). Due to ordering cost, it is often necessary to order in batches instead of item by item. This simply means that businesses need to frequently be looking ahead and forecasting for future demand to stay in front of these two variables. However, it is not enough to just forecast your demand. Understanding demand forecast accuracy is equally important in order to determine how uncertain the forecast will be for a given business period. Moreover, by calculating and understanding the forecast error, it can be always ensured that safety stock of the inventory is sized correctly to avoid inflated carrying cost and lost sales orders due to stock outs.

There have been several attempts to perform demand forecasting over last decades. Ozsaglam [3] tried to use data mining techniques to forecast sales of company products. Carson et al. [4] attempted to analyze whether it is better to forecast air travel demand using aggregate data at a national level, or to aggregate the forecasts derived for individual airports using airport-specific data. Song et al. [5] strived to propose a model which can forecast future tourism demand accurately by developing the causal structural time series model (STSM) further and introducing the time-varying parameter (TVP) estimation of the explanatory variable coefficients, and therefore combines the merits of the STSM and TVP models. Inaba and Kato [6] tried to analyze the potential impacts of motorcycle demand management and its contribution to the transportation market in Yangon, Myanmar, where motorcycles have been banned since 2003. Cam et al. [7] presented the application of the process of KDD (knowledge discovery in databases) for the forecasting of the electrical power demand of a supply fan of an AHU (air handling unit). Recently, Rabiei Hosseinabad and Moraga [8] proposed a novel method of forecasting using system dynamics approach to predict energy demand. By the comparison that they have conducted, their system dynamics method happened to be a reliable method for prediction which can be applied to different fields.

Finding out the most suitable demand forecasting method is a challenging task due to different reasons that prove uncertainty. Distributers and manufacturers are always looking for ways to improve their inventory management processes. Many companies are still struggling finding the balance between overstocking inventory with increases costs versus under stocking inventory which results in lost sales opportunities. The common reason for this struggle is that most ERP systems and inventory management solutions fall short in three areas when it comes to forecasting: (1) They assume that all demand is normally distributed; (2) They cannot dynamically follow the product life-cycle, and 3. They assume that the safety stock is normally distributed or just simplified with a coverage period.

Demands can change throughout a year due to a lot of reasons that the seasonality factor is one of the most crucial factors. To be

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**Received** August 17, 2018; **Accepted** November 07, 2018; **Published** November 13, 2018

**Citation:** Chen L (2018) Statistical Forecasting Modeling to Predict Inventory Demand in Motorcycle Industry: Case Study. Ind Eng Manage 7: 270. doi:10.4172/2169-0316.1000270

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able to meet customers' needs, appropriate forecasting model is vital. There are many forecasting methods available which are applicable to certain product life-cycles and businesses. In this paper, we attempted to propose a practical statistical demand forecasting model which can provide the most accurate demand forecast with the least amount of error. In the same way, historical sales data of a product at a motorcycle accessory manufacturing company has been analyzed. Consequently, proposed model and conventional forecasting model have been compared to prove that the proposed forecasting model is just practical with the least amount of error possible.

## Case Study and Discussion

In this article, we propose a practical forecasting model in predicting future demand for a motorcycle accessory. Historical sales data of 7 years has been considered for this analysis. Data has been retrieved by data mining techniques and have been cleaned and complied by using Python programming. Python programming was very useful in this study since it ensured data accuracy and reliability in the analysis stage. To elaborate, in the cleaning stage, detection and removal (or correction) of errors and inconsistencies in a data set or database due to the corruption or inaccurate entry of the data has been performed. Incomplete, inaccurate or irrelevant data was identified and then either replaced, modified or deleted. One important example of type of data that has been eliminated from study was outlier demand which was due to sales promotions in a specific period in the past.

The company used demand history to predict future demand. The data saved in the monthly demand history, x(1),……,x(N) where the x(t) is demand in month t, t=1 the oldest month in history and t=N, the most current month[D/p11].

Seasonal forecasts are used when the demand over a year has a cyclical flow [9]. The company considered in this paper is a motorcycle accessories manufacturer. These products have various demands in each season. The demand for each of the products in this company fluctuates throughout the year. As a result, the demand does not have a pattern and because it is seasonal, demand prediction has been found very challenging. The company use to predict demands by using demand history and it has been running into various problems such as lack of raw material or semi-finished products since the demand has not being forecasted in the way it has been supposed to which resulted in lost sales.

In this article, a model similar to moving average forecasting has been implemented by using the multiplicative model. Seasonal multiplicative model is used when demand follows a cyclical pattern from year to year.

A static method assumes that the estimates of level, trend, and seasonality within the systematic component do not vary as new demand is observed. This point needs to be noted that different forecasting methods can be applied in a variety of fields. The accuracy and reliability of one forecasting method can only be tested by comparing with other forecasting methods. Recently, Rabiei Hosseinabad and Moraga [10] worked on a novel forecasting model using system dynamics method in air quality prediction that showed a promising results in terms of accuracy because of the fact that it can be utilized both in fitting historical data and predicting values with low percentage error. Therefore, it is crucial that the proposed model is able to fit historical data and accurately predict for future. In this case, we estimated each of these parameters based on historical data and then used the same values for all future forecasts.

L=estimate of level at t=0 (the deseasonalized demand estimate during Period t=0)

T=estimate of trend (increase or decrease in demand per period)

$S_t$=estimate of seasonal factor for period t

$D_t$=actual demand observed in period t

$F_t$=forecast of demand for period t.

Deseasonalized demand has been formulated and computed by the following mathematical model:

Deseasonalized demand represents the demand that would have been observed in the absence of seasonal fluctuations. The periodicity (p) is the number of periods after which the seasonal cycle repeats.

$$\bar{D}_t = \begin{cases} \left[ D_{T-(p/2)} + D_{T+(p/2)} + \sum_{i=t+1-(p/2)}^{t-1+(p/2)} 2Di \right] \Big/ (2p) \text{ for } p \text{ even} \\ \sum_{i=t+1-(p/2)}^{t+[(p-1)/2]} Di/p \text{ for } p \text{ odd} \end{cases} \quad (1)$$

Estimating Seasonal Factors:

The seasonal factor $S_t$ for Period t is the ratio of actual demand $D_t$ to deseasonalized demand $D_t$ and is given as:

$$\bar{S}_t = \frac{D_t}{\bar{D}_t} \quad (2)$$

The seasonal factor for these periods is obtained as the average of the four seasonal factors. Given r seasonal cycles in the data, for all periods of the form $p_t$ + i, 1 … i … $p$, we obtained the seasonal factor as:

$$S_i = \frac{\sum_{j=0}^{r-1} \bar{S}_{jp+i}}{r} \quad (3)$$

We have quarterly sales data for the motorcycle accessory from 2010 to 2016. We used data of six years to test the accuracy of our prediction in 2016. The first four columns of the table present the historical time series data. Due to the fact that future demand was intended to be forecasted, sales quantities in the last six years have been considered [11]. This way, we could understand how the amount of sales moves through the time and then we could predict future's demand. Figure 1 shows the visualized historical sales data for the product over 6 years.

In Figure 1, it is obvious that a pattern that repeats itself more or less every year exists which seems to be a cycle or seasonal. In the proposed demand forecasting, the number of most recent monthly demands to forecast the future demands have been considered. The model gives equal weight to each of sales quantity. One cycle in the data has four quarters so moving average of four periods have been labels as CMA and shown in Figure 2. In order to obtain moving average of four periods, the average of the first four sales quantities from the time series should be calculated [12,13]. The center of moving average (CMA) has been calculated.

Seasonal component ($S_t$), irregular component($I_t$), and trend component ($T_t$) have been also calculated. $Y_t$ is the real time series demand $S_t$ * $I_t$ has been computed based on the formula below.

$$S_t{*}I_t = Y_t/CMA \quad (4)$$

$Y_t$ is basically the classical multiplicative model. This combination is known as a model, mathematic approximation of time series. Four components have been calculated in multiplicative and additive time series model including seasonal, irregular variation, trend, and cyclical

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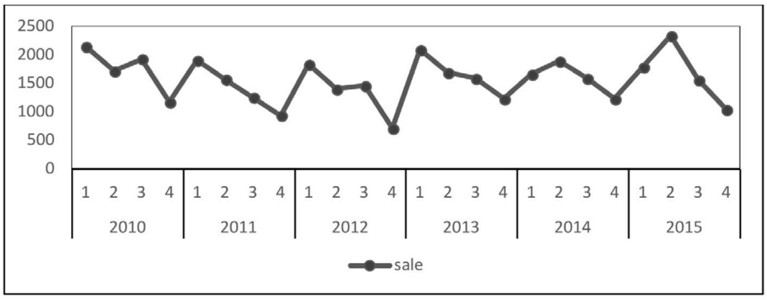


**Figure 1:** Visualized historical sales data over 6 years.

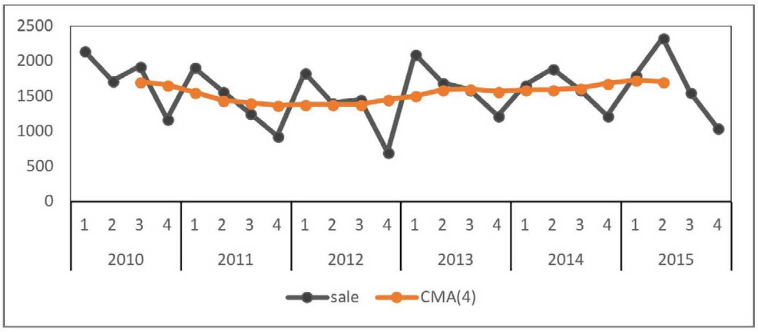


**Figure 2:** Center of moving average (CMA) in time series plot of sales.

for all years. Results have been seasonalized by formula below.

$$\text{Seasonalize}=Y_t/S_t \qquad (5)$$

After seasonalizing, trend components have been computed. For doing it, simple linear regression has been obtained as shown in Figure 3. The simple linear regression is a well-known method used by many authors for forecasting and estimation [14-16].

SUMMARY OUTPUT

| Regression Statistics | |
|---|---|
| Multiple R | 0.209022657 |
| R Square | 0.043690471 |
| Adjusted R Square | -0.001848078 |
| Standard Error | 229.4782632 |
| Observations | 23 |

ANOVA

| | df | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 1 | 50523.1764 | 50523.18 | 0.959417 | 0.338483994 |
| Residual | 21 | 1105865.739 | 52660.27 | | |
| Total | 22 | 1156388.915 | | | |

| | Coefficients | Standard Error | t Stat | P-value | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|
| Intercept | 1463.120208 | 105.2788421 | 13.89757 | 4.64E-12 | 1244.18087 | 1682.059546 |
| 1 | 7.065697938 | 7.2135874 | 0.979498 | 0.338484 | -7.935778288 | 22.06717416 |

**Figure 3:** Simple linear regression.

Based on the simple linear regression and trend component, predictions can be done. As a result, all four components introduced above have been multiplied by each other. Consequently, forecast has been calculated and shown in Figure 4.

In addition to forecasting, error has been also calculated to testify forecasting accuracy [17-30]. In the same way, the evaluation of model fit with the mean absolute deviation and mean square error which are two of the most popular goodness-of-fit have been considered.

Mean Absolute Deviation (MAD) has been calculated by using formula below.

$$\frac{1}{n}\sum_{i=1}^{n}|xi-m(X)| \qquad (6)$$

Mean squared error (MSE) has been also computed by using formula below.

$$\frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i-Y_i\right)^2 \qquad (7)$$

In the below Table 1, summary of calculated error based on both conventional and proposed forecasting model have been listed.

A=the real amount of demand

$F_c$=the forecast amount of demand by company

$F_i$=the forecast amount of demand by (MA) method

As it is shown in the figure above, the propose model has been able to improve the demand accuracy by lowering the forecasting error substantially. The most improvement refers to the years 2014, 2011, 2015, respectively. It is also obvious that using the proposed statistical forecasting model compared to the conventional forecasting method the company uses can improve the MAD by almost 61% and MSE by 82%.

## Conclusion

Accurate demand forecasting has been one of the major concerns for companies who are dealing with supplying products. Since demand is not always the same and it most of the time fluctuates based on different factors including weather, competitors, and

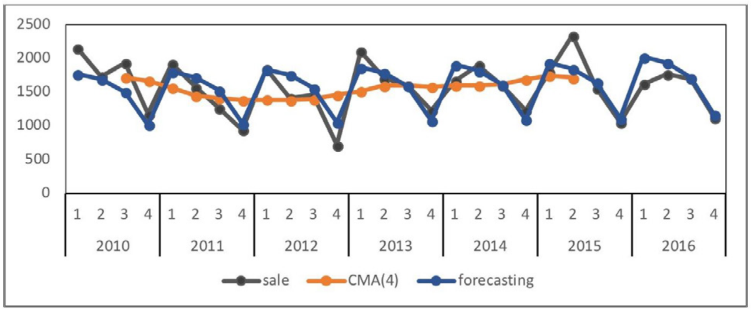


**Figure 4:** Actual sales, CMA, and forecasting trend.

| Year | $\lvert A - F_c \rvert$(Current Model) | $\lvert A - F_i \rvert$(Proposed model) |
|---|---|---|
| 2010 | 498 | 355 |
| 2011 | 677 | 81 |
| 2012 | 216 | 56 |
| 2013 | 698 | 402 |
| 2014 | 1158 | 163 |
| 2015 | 339 | 19 |
| 2016 | 134 | 44 |
| MAD | 450.375 | 174.625 |
| MSE | 324091 | 58265 |

**Table 1:** Summary of calculated error based on both conventional and proposed forecasting model.

market, a practical forecasting model needs to be proposed and implemented based on the product lifecycle. In this paper, a practical statistical forecasting model has been adapted and implemented in a motorcycle accessory manufacturing company in the US market which suffers from seasonality. Numerical comparison between current and proposed forecasting model results indicates that the proposed model is more reliable and accurate. Proposed model was able to improve the MAD by almost 61% and MSE by 82% which are great achievement in demand forecasting improvements. This model is able to help this manufacturing company to forecast demand for their products effectively. This efficient demand forecasting method will assist this manufacturer in projecting their production and operations management to implement production strategies in an optimized way. It also provides the opportunity of understanding their demand patterns which will make the company much more competitive in the marketplace and drives higher profits.

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