Leveraging the Application of Forecasting Methods to Analyze the Scrap Data of a Tire Industry

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Abstract

Forecasting methods are being used during the planning phase in different departments in several companies, helping managers on their decision-making process. The aim of this paper is to analyze which forecast method fits better for the scrap rate of a tire industry based on historical data analysis. The scrap rate is a very important key performance indicator for the observed company, having a high weight on strategic decisions. Using past data, a comparison is made between trend-based methods: regression analysis and double exponential smoothing, and the currently in use by the company, a subjective method. By having a set KPI established for the tire scrap allows companies to allocate the proper funding and resources to this process. This also allows companies to have a standardized selection method on different factors that is accurate. In doing so there is no exact better or worse method to forecast the data however each company needs to evaluate which method is right for them.

Keywords
Forecast, Scrap, Tires and Forecast Analysis

1. Introduction

In a competitive market, every type of decision made can have a big impact in a company's performance and the usage of forecast techniques can be a strong ally on these situations. According to Wood (2020), tire sales are expected to reach a value around $154 billion by 2027, which shows how big this market is.

The company observed on this study is a tire plant and the data that is going be analyzed is the scrap ratio. The scrap is a very important key performance indicator (KPI) for the plants because it represents quality and cost in one single indicator. It's calculated based between the cost of non-conform material - like a subcomponent produced out of tolerances or an out of spec rubber - over the total cost of production.

$$Scrap\ Ratio\ (\%) = \frac{Total\ cost\ of\ non-conform\ produced\ material}{Total\ cost\ of\ production}$$

The scrap ratio is a KPI over the Quality Department responsibility. Among tasks of control and scrap reduction, Quality Department needs to provide to the Controlling Department a scrap forecast for the whole year by month in every beginning of the year. Currently the scrap forecast is performed with a mix between objective and subjective methods, where the past data is used as a reference but without any specific calculation together with expert's opinion on the topic.

The current method to forecast scrap used by the company is not proven to be the best one since no analysis on which method to use have been done until the present moment. The purpose of this research is to apply some of the most common methods of forecast to the company scrap data and analyze which of the methods, including the company one, has the smallest error.

2. Literature Review

The material being observed on this study is scrap. The data that is going be analyzed is the scrap ratio. Scrap is such an important key performance indicator because it represents all the wasted time and money in the process. Scrap is the output of a production process that is not finished goods or WIP. It is critical to forecast scrap ratio because it is very meaningful to understanding the amount of money or time lost in the production process. Scrap ratio can be calculated by each step or the overall process. The scrap can also be broken into the basic scrap categories. The use of scrap from tires is very useful since it cannot be exactly recycled into other tires (Memon, et al., 2012). Not only is it not possible to recycle an old tire back into a new tire the efficiency of recycling tires is significantly lower than most processes (Semenok, et al., 2014). It is also easy for tire recycling to utilize multiple different industries that use tires such as the aerospace industry because all tires are build in the same method and can be recycled in the same method (Kuruppu &Hettiarachchi, 2018). Every year roughly 1.2 billion tires are scraped (Moghaddamzadeh & Rodrigue, 2018). Because of the large amount of waste from worn tires and the need for recycling it is easy for industries to utilize these methods for KPIs on scrap. Even if not for scrap the carbon footprint of tire manufacturing is a big concern to most governments and recycling tires can ultimately reduce the carbon footprint (Saxena, Jain, & Sharma, 2018).

The basic scrap categories include rework time, energy, handling, disposal cost, and quality assurance cost. Scrap usually costs money and time. Scrap can be a waste of materials because it usually cannot be recycled. Scrap also contributes to non-productive time in the form of rework time. "The scrap that is being produced takes the machine time that produces the goods. For example, if a machine produces 80% goods and 20% scrap, by reducing the scrap to 12% we can get 10% more goods output at the same operating cost" (Meron 2018) When scrap is produced, energy is wasted as well. When scrap is attempted to be recycled then twice the energy is wasted. When scrap needs to be removed then it will require a disposal cost. The handling of scrap requires a lot of time. Scrap will need to be moved around, possible recycled, and then disposed of. According to Meron (2018), "If the production process creates a lot of scrap, then the quality assurance process should be tighter and that means more manpower and resources. For example, if your process produces 1% scrap, you need much less quality assurance resource than if you have 30% scrap if you want the customer to have the same positive experience." Aside from the prior categories of scrap, there are three major categories.

The major scrap categories include bad products, rework, and first material. If a material or WIP has been converted into a product but is not up to par on quality standards it is considered a bad product. Some bad products will only need a minor adjustment to become good products, so rework time will be dedicated to fixing the error. At the beginning of a process when the tools first begin it can consume some materials. The results of the initial unadjusted parameters are off spec materials. This is considered first material because according to Meron (2018), "The first material "cleans" the machine, and so on." Studying these categories of scrap and forecasting the scrap ratio for the future will be used to calculate the cost of scrap. To calculate these impending costs beforehand multiple forecasting methods will be used. For the data in this study the forecasting methods being compared will be the Regression Analysis, the Double Exponential Smoothing method, and the subjective method currently used by the company the data was obtained from.

Regression analysis and Double Exponential Smoothing are both objective methods of forecasting, that by definition according to Nahamias and Olsen (2015): "Objective forecasting methods are those which the forecast is derived from an analysis of data". They are considered Trend-Based methods because the forecast is a result of analyzing past trends to predict futures ones. Regression analysis is a reliable method of forecasting. The Regression analysis will result in a best fit line through all the data to give a general estimation of the how the dependent variable will react to the independent variable. The process of performing a regression will determine how these factors influence each other. The Regression analysis method relies on the belief that there is a linear relationship existing between a dependent variable and an independent variable. The equation of the slope lines is derived from the following equation. Regression analysis is a good option for forecasting because there is no initial identification of any variables. There is also no required tuning of parameters. Regression analysis can be inconvenient, though, because it is complicated to incorporate new observations into the data series. Any time a new data point needs to be added to the analysis the entire model needs to be updated and recalculated.

Double Exponential Smoothing is another method to analyze the scrap ratio data. The Double smoothing is required for this study because the single exponential smoothing is not able to analyze data containing trends. Two smoothing constants need to be identified prior to the calculations being made. Alpha (α) is associated with the intercept of the series, and Beta (β) is associated with the slope of the series. Tau (τ) represents the time horizon of the forecast. Double Exponential Smoothing also requires the initial identification of G and S values. G represents the value of the slope at time τ. S represents the value of the intercept at time τ. The initial values of G and S will be the value of data at time $\tau = 0$. The Double Exponential Smoothing method is convenient because it is easy to incorporate new observations.

Subjective methods can also be used to forecast data. Subjective Methods can be based on human judgment, sales, force composites, customer surveys, jury of executive opinion, and by the Delphi method. The Company method used to forecast the data in this study is an example of a subjective method even though is not an official method.

Any method of forecasting will yield results that can be used as KPI's. These results can also be used to identify the cost of scrap and possible opportunities to decrease these costs. It is important to understand how these results will be used in the calculation of cost of scrap.

There are multiple ways that the cost of scrap could be calculated. If the previously discussed wastes are used in the calculation of actual cost, then many assumptions will be used. This calculation is important, though, because it is used to understand the resources lacking in quality assurance and further will be input for several decisions. The cost of finished goods can also be calculated. Meron (2018) gives the following example, "If finished product XXX has a value of $100 per unit/ton to be produced, and produces 1,000 products and 200 pieces of scrap, then $100,000 of goods and $20,000 of scrap were produced." From those values it is simple to calculate the cost of scrap ratio using this method. It also allows the use percent of scrap from the total batch produced. Even now more and more governmental organizations are being proactive in tire recycling by investing money into the process. The Ontario Government decided in 2010 to provide two million dollars to and experimental tire recycling facility (Ontario, 2010). Even if companies and government choose not to recycle, recycling still has a better life cycle cost when dealing with waste, energy, and water usage (Maulina, et al., 2015).

3. Methods Case Study

In this paper, we chose our case study to be about the scrap data of a tire industry. The tire industry is a fast-growing industry, reported by Research and Markets, where they stated, "the Tires market worldwide is projected to grow by 731.6 million units, driven by a compounded growth of 4.6%" (Wood 2020). Being such a fast-growing industry, you want to cut out your losses from defective products as much as possible. A tire is essentially made up of 10 components. These components are shown in figure 1: ": 1 – rubber (inner) liner, 2 – carcass ply, 3 – bead core, 4 – bead filler, 5 – bead reinforcement, 6 – flange cushion, 7 – sidewall, 8 – belts, 9 – cap ply, 10 – tread" (Weyssenhoff et al. 2019). Tire productions is seen as a "multi-stage complex process" leaving plenty of room for error. "Defects may be visible in the tire from the moment of purchase or may occur during use... properly detected manufacturing defects allow eliminating tires not suitable for use" (Weyssenhoff et al. 2019).

By forecasting the defect ratio, we will be able to measure our quality of production and see if we are producing well or not. Our defects that lead to our scrap come from the rubber being burned at the wrong temperature, having a cured tire that had a pressure issue on the press during processing, or a subcomponent produced in the wrong size that will not fit. Based on recent data, we assume and know there will be scrap, but we will be forecasting the scrap ratio to try to determine ways to cut the ratio down to raise our quality of production and income from production.

Figure 1. Cross section of a passenger car tire (Beczkowska et al., 2020).

The real scrap ratio can be seen on the figure 2 where the scrap data was plotted on the Y coordinate and time in months on the X coordinate. For the present study, the group chose to incorporate a regression analysis and double exponential smoothing forecast and compare with the forecast already provided by the company, subjective method, to see which trend-based forecasting method is more accurate to utilize for our company. A trend-based method was chosen since the data provides a clear trend to reduce, also in accordance with the worldwide trend from other facilities, the more mature a plant is the lower the scrap ratio tends to be.

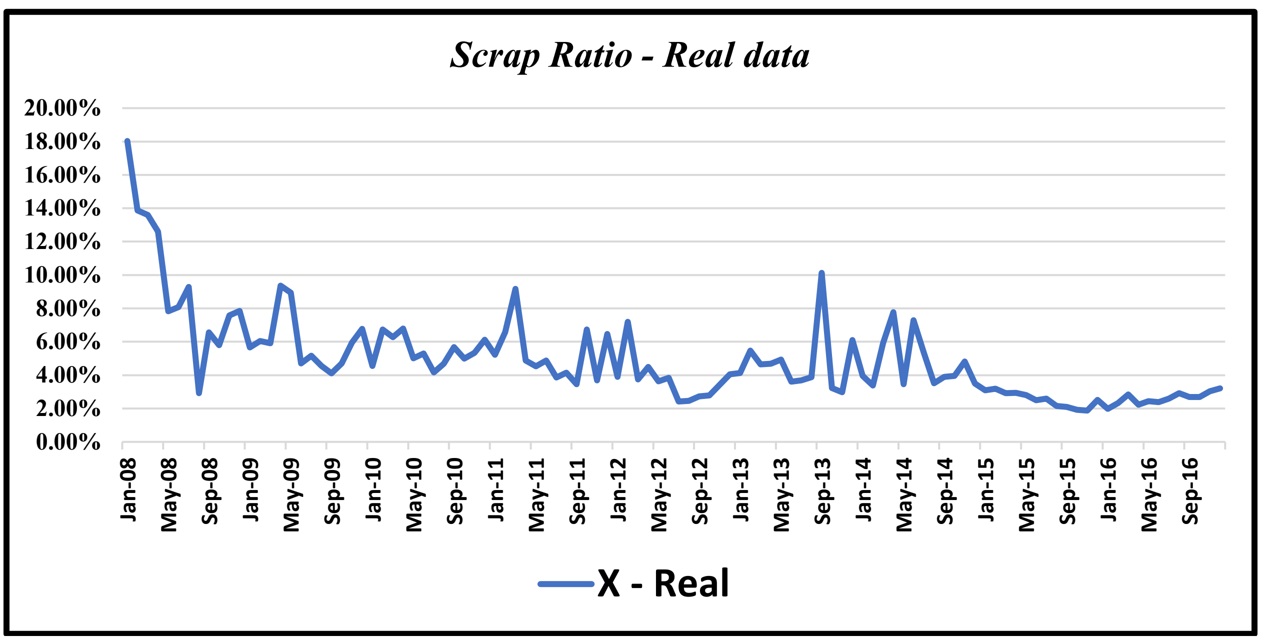

Figure 2. Scrap Ratio Graph

4. Data Collection

In finding our data for the forecast in scrap percentage, we took data from January in 2008 until December 2016 percentages. We utilized formulas into excel to find new forecast values utilizing double exponential smoothing and regression analysis methods. Then we found the errors from each of those methods utilizing mean absolute deviation (MAD), mean squared error (MSE), and mean absolute percentage error (MAPE). Utilizing Excel functions to compute these calculations helped with limiting error in calculations and presenting the data in an efficient way.

"Competition has forced automakers and other manufacturers of mass-produced products to achieve extremely low defect rates" to maximize production and stay ahead of their competitors (Barkan and Hinckley 1993). Having these new forecasts can help us predict our scrap ratio for the future to help plan for actions to minimize and prepare for these percentages of scrap. Adding in these errors are important to show that we are forecasting accurately for our company, so we are not projecting the wrong amount of loss of productions. By finding the forecasts of scrap percentage in the past has helped make the business more proficient as they have cut the percentage from 18% in 2008 to around 2-3% in 2016. Knowing that forecasts are not always right, we have still been able to increase our accuracy through our calculations of errors to minimize the percentages for the future.

In our calculations, we incorporated the following formulas:

- For Double Exponential Smoothing method:

$$S_t = \alpha D_t + (1-\alpha)(S_{t-1} + G_{t-1})$$
$$G_t = \beta(S_t - S_{t-1}) + (1-\beta)G_{t-1}$$
$$F_{t,t+\tau} = S_t + \tau G_\tau$$

- For Regression Analysis with time the independent variable:

$$Y = \alpha + bX$$
$$b = \frac{S_{xy}}{S_{xx}}$$
$$S_{xy} = n\sum_{i=1}^{n} iD_i - \frac{n(n+1)}{2}\sum_{i=1}^{n} D_i$$
$$S_{xx} = \frac{n^2(n+1)(2n+1)}{6} - \frac{n^2(n+1)^2}{4}$$

5. Results and Discussion
5.1. Graphical Results

By applying the objective forecast methods chosen on this study and plotting the results on a graph together with the current forecast method used by the company and the real scrap, we have the following results for:

- Regression Analysis where $\mathbf{Y = 0.081 - 0.001X}$

From figure 3 it is possible to analyze that the Regression Analysis - as it is represented by the regression line which expresses the relationship between scrap and time. The line that represents the Regression analysis is not the best option to represent the scrap variation that occurs between the months because it's not sensitive for this variation within small periods. Regression analysis results in a constant slope, so any outlier months will not be represented in the forecast. On the other hand, regression analysis presents a view of the long-term horizon for the data because it follows the general trend as the other calculation methods.

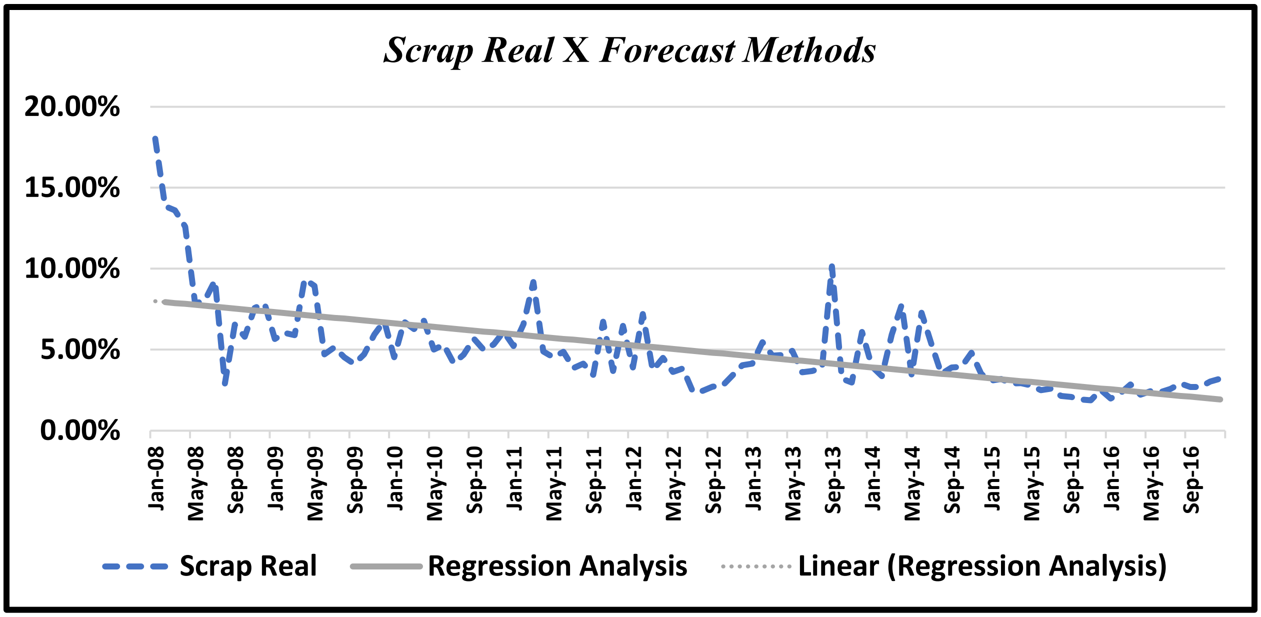

Figure 3. Scrap Ratio Real x Regression Analysis Graph

- Company Method (subjective):

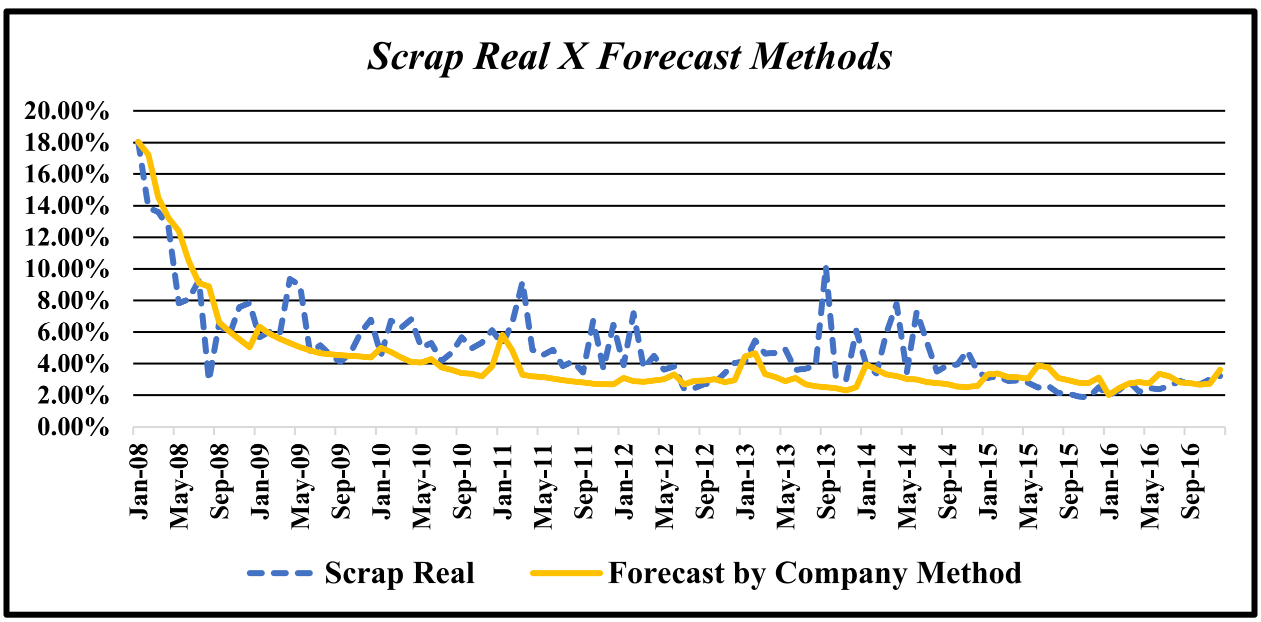

Figure 4. Scrap Ratio Real x Company Forecast Method Graph

It is possible to analyze that the subjective method used by the company in most of the times tends to forecast a smaller value than the real scrap as shown in figure 4. This behavior can be explained that since a scrap ratio is a KPI that the goal is to be as low as possible, then management tends to pull to the performance side indicating that the plant is going to have a better result on the following month.

- Double Exponential Smoothing where $\alpha = 0.568$ and $\beta = 0.156$

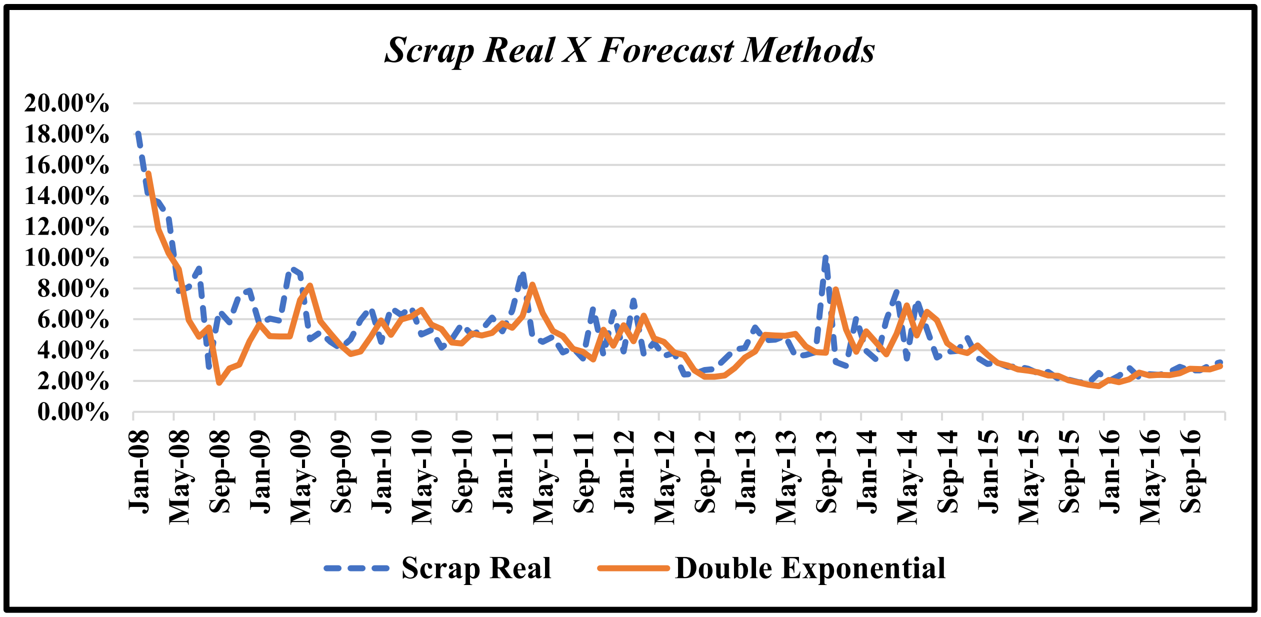

Figure 5. Scrap Ratio Real X Double Exponential Graph

The Double Exponential Smoothing method as shown in figure 5 is represented by the solid orange line. The line expresses the variation of the scrap within the months and has a similar pattern as the real scrap, but it lags in one time period to react to change. The Double Exponential Smoothing line is the most accurate line when compared to the real scrap data obtained from the tire company.

5.3. Proposed Improvements

The usage of forecast methods plays a very important role on the organizations and maintain an accurate set of data to generate a good forecast can be a great support on the decision-making process. The aim of this paper is to compare the current subjective forecast method used by the studied company with other two objective forecast methods.

A good manner to evaluate forecast methods is through measurement of its errors which is shown on table 1. “Three common measures of forecast error are MAD (average of absolute errors over n periods), MSE (the average of the sum of the squared errors over n periods), and MAPE (the average of the percentage errors over n periods).” (Nahamias and Olsen 2015). To evaluate the results of this paper we’re using those three errors measurements applied to the calculated and collected data.

Table 1. Error Analysis Comparison table

	Error Analysis Table		
	Double Exponential	**Regression Analysis**	**Company Method**
MAD	0.0128	0.0125	0.0137
MSE	0.0003	0.0003	0.0004
MAPE	24.98%	26.56%	26.69%

	Bigger Error
	Medium Error
	Small Error

Comparing the errors between the methods, we can see that the company’s method is the one with the biggest error in the three different error types. The Regression Analysis and the Double Exponential Smoothing have similar values for the MSE and one is slightly more accurate than the other in MAD and MAPE.

6. Conclusion

According to Chambers et al. (1997), “The selection of a method depends on many factors—the context of the forecast, the relevance and availability of historical data, the degree of accuracy desirable, the time period to be forecast, the cost/ benefit (or value) of the forecast to the company, and the time available for making the analysis.” The company currently uses a method that is not a stablished one and even with higher errors than other methods compared on the paper, it’s not a forecast with a complete inaccuracy or irrational values, which shows how expert information can be very useful when forecasting.

So, it is important to highlight that there’s no better or worse forecast method, there’s the most suitable one that will fit according to the company scenario, to the type of organization, to the current software’s available etc.

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Biography

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