Assessment of the Sales Forecast Technique Double-Weighted Moving Average vs Other Widely Used Forecasting Techniques

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Abstract

In order to improve the operations planning of two companies, whose main business is to be chemical products suppliers in Mexico, it was made the sales forecast of a fourth year of operations, using the monthly sales data information of the three previous years. The objective of the chemical suppliers forecast was to be in a better position to satisfy the multiple and varied needs of their clients, which demand different quantities of products and have different consumption patterns. The sales forecast was made by the next six techniques: Simple Moving Average (SMA), Weighted Moving Average (WMA), Trend Projection (TP), Exponential Smoothing (ES), Simple Linear Regression (SLR), and the recently proposed (Castillo, et al. 2016) technique called: Double-Weighted Moving Average (DWMA). The three years monthly sales data of 61 products, handled by the two companies, were processed in order to obtain the monthly forecast of the fourth year. After the fourth year, the forecasted data were compared with real monthly sales data. The analysis was made by the determination of the Symmetric Mean Absolute Percentage Error (SMAPE), which gave the next results: In the case of company 1, the average errors for the five reference techniques (SMA, WMA, TP, ES and SLR) was in the range 0.235 – 0.351] vs 0.249 for the DWMA. For company 2, the average error, of the same five reference techniques was in the range [0.292 – 0.467] vs 0.282 for the DWMA. WMA was the second technique in giving the least forecasting errors. In both companies, DWMA was the forecasting technique with one of the lowest average error and the lowest error in most of the products.

Keywords: forecasting techniques, least error, suppliers of chemical products, consumption patterns, operational planning

1. Introduction

The chemical products supplying companies are characterized by handling high numbers of products, which can vary between 20 and 500, and a large number of customers, which present different types and forms of business, like: hardware stores, pharmaceutical enterprises, automotive enterprises, inks and paints producers, and many more. All of them with different and changing consumption patterns and even with requirements for changes in their last-minute orders. These circumstances make the chemicals suppliers operations planning to be conducted in a climate of high uncertainty. So, the development of accurate sales forecasts is an easy and simple way for better operations planning.

Effective planning (Heizer & Render 2009), in the short and long term, depends on the information about the demand for products that the company has. Good forecasts are crucial for all aspects of the business: the forecast is the only estimate of demand until real demand is known. Therefore, demand forecasts guide decisions in the areas of human resources, capacity, inventory control and supply chain management.

It is interesting to realize that, by far, the most successful enterprises use the simplest methodology that also requires the least amount of data. For Chase and Jacobs (2014), forecasts are vital for any business organization, as well as, for any important management decision. Forecasts are the basis of long-term corporate planning. In the functional areas of finance and accounting, forecasts represent the basis for budgeting and controlling costs. With the forecasts, the marketing staff can make decisions such as, compensation for sales staff, planning of business with new products, etc. and production/operations staff can make regular decisions about: process selection, production planning, inventory

control of raw materials and final products, distribution methods, etc. For this reason, it is important to seek forecasting ́s techniques that are simple and easy to manage by the personnel involved in operations planning of these enterprises, and to get forecast results close to real sales values, in order to maintain appropriate inventories of each product, without reaching excessive levels that generate unnecessary financial costs or low levels that prevent the supply of customer orders.

According to the Pochteca census (Santacruz 2012, October 26), in the National Association of the Chemical Industry (ANIQ), there are registered 59 distributors of chemical products in Mexico, but in total there are about 300 distributors located in 450 locations, so there is a large number of small businesses not registered in the Association.

The distribution of Chemical Products in México is a key industry in the productive chains, since it acquires products from around 30 industrial branches and distributes them in around 40 industrial branches, and more accurate sales forecasts contribute to a more efficient operation in this industry.

2. Technical Concepts and Tools Used in the Present Development

2.1 Forecasting

Forecasting is the art and science of predicting future events (Heizer and Render 2009). It involves the use of historical data and its projection into the future through some type of mathematical model, also it can be an intuitive prediction; or it can be a combination of them, that is, a mathematical model adjusted by a good management judgment. Good forecasts are really important for all aspects of the business, as demand forecasts guide decisions in many areas.

When several forecasting techniques are analyzed, it can be concluded that there is not one best in all cases. What works better in an enterprise with a series of conditions can be a complete disaster in another one. In addition, it is observed that there are limits on what can be expected from the forecasts, since they are not perfect. Their monitoring and preparation are also expensive and time consuming. However, few businesses have the luxury of evading the forecasting process and only wait, to see what happens and then take actions. Effective planning in the short and long terms depends on the forecast of the demand for the enterprise ́s products.

2.2 Forecasting Techniques

In this paper there were used the same forecasting techniques as those applied by Castillo et al (2016)

Simple Moving Average (SMA).

$$SMA = \frac{\sum_{i=1}^{n} Demand\ of\ the\ n\ previous\ periods}{n} \tag{1}$$

Weighted Moving Average (WMA).

$$WMA = \frac{\sum_{i=1}^{n}(Weighting\ for\ period\ n * Demand\ in\ period\ n)}{\sum_{i=1}^{n} Weighting} \tag{2}$$

Simple exponential smoothing (ES).

$$F_t = F_{t-1} + \alpha * (Y_{t-1} - F_{t-1}) \tag{3}$$

Where: α = smoothing constant (0, 1), F_{t-1} = previous forecast, F_t = new forecast and Y_{t-1} = real demand in previous period.

Requires initialize, for example: In the case of $F_1 = Y_1$ it was used an α value of 0.3.

Trend Projection (TP).

$$Y = b_0 + b_1 * X \tag{4}$$

Where: Y = the predicted value, b_0 = ordinate to the origin, b_1 = the slope of the trend line, and X = month to which its sales are forecasted, on the base of last three months sales data.

Simple linear regression (SLR) method.

$$Y = b_0 + b_1 * X \tag{5}$$

Where: Y = the predicted value, b_0 is the ordinate at the origin, b_1 is the slope of the linear relationship, and X = month to which its sales are forecasted, considering all data of the previous three years.

Double-Weighted Moving Average (DWMA).

A technique that was proposed by Castillo et al. (2016), based on historical sales data; it considers the variations in sales values of the last three months and the seasonal behavior of the sales values in last three years, considering months like the month to be forecasted (for example, for predicting January, there are considered the data of the previous months of October, November and December and the data of January in the last three years).

DWMA was calculated in following way:

$$DWMA = (\, WMA(last\ three\ months) + WMA(the\ same\ month, of\ the\ previous\ three\ years)\,)/2 \quad (6)$$

Where: WMA = Weighted moving average.

2.3 Error Calculation

2.3.1 Classification

There are several ways to evaluate forecasting error; these will be described, following the classification stablished by Hyndman (2016):

There are four types of forecast-error metrics: scale-dependent metrics such as the Mean Absolute Error (MAE), or Mean Absolute Deviation (MAD); percentage-error metrics such as the Mean Absolute Percent Error (MAPE); relative-error metrics, which average the ratios of the errors from a designated method to the errors of a naive method; and scale-free error metrics, which express each error as a ratio to an average error from a baseline method.

For assessing accuracy on a single series, the MAE metric is preferred because it is easiest to understand and compute. However, it cannot be compared across series because it is scale dependent.

Percentage errors have the advantage of being scale independent, so they are frequently used to compare forecast performance between different data series. But measurements based on percentage errors have the disadvantage of being infinite or undefined if there are zero values in a series, as is frequent for intermittent data.

Relative-error metrics are also scale independent. However, when the errors are small, as they can be with intermittent series, use of the naïve method as a benchmark is no longer possible because it would involve division by zero.

The scale-free error metric called Mean Absolute Scaled Error (MASE) can be used to compare forecast methods on a single series and also to compare forecast accuracy between series. This metric is well suited to intermittent-demand series because it never gives infinite or undefined values.

The SMAPE, proposed by Makridakis in 1993, is a modified Mean Absolute Percentage error (MAPE), in which the divisor is half of the sum of the real and forecasted values. SMAPE can be applied when the demand is intermittent, since the error technique can handle the zero demand without approaching infinity.

2.3.2 Tried out Methods for Error Calculation

Due to the importance of error calculation for this work, different alternative methods were tried to measure the error of the predictions, starting by testing the MAPE which is defined as:

$$MAPE = \frac{\sum_{t=1}^{n} |A_t - F_t| / A_t}{n} \quad (7)$$

Where A_t and F_t denote the current and predicted values at data point t, respectively, and n is the number of data points.

We found calculation problems where the monthly sales values equal to zero or very close to zero, thatś why calculated errors would be infinite or extremely high numbers, this situation coincides with what was expressed by S. Kim and H. Kim (2016), and it is transcribed below:

The MAPE is one of the most popular measures of forecast accuracy. It is recommended in most textbooks for example, Bowerman, O'Connell and Koehler (2004), Hanke and Reitsch (1995), and was used as the main measure in the M competence (M is the name given to a competition of different forecasting techniques, because the organizer was Makridakis) (Makridakis et al., 1982). MAPE is the mean of Absolute Percentage Errors (APE).

It was tried to solve the problem of sales values equal to zero or very close to zero, by excluding outliers that have real values less than one, or APE values greater than the MAPE plus three standard deviations (Makridakis, 1993). However, this approach is only an arbitrary adjustment, and leads to another question, namely, how outliers can be eliminated. In addition, the exclusion of outliers can distort the information provided, particularly when the data involves numerous small real values. Several alternative measures have been proposed to address this problem. For example, the SMAPE, proposed by Makridakis (1993). It is a modified MAPE in which the divisor is half the sum of the actual and predicted values.

While S. Kim and H. Kim (2016), commented on other alternative methods, they proposed a new way to measure the errors in the prognoses called mean arc tangent absolute percentage error (MAAPE).

In the present research, for error calculation, it was used the SMAPE, defined in the next equation 8:

$$SMAPE = \frac{\sum_{t=1}^{n}|F_t - A_t|}{\sum_{t=1}^{n}(A_t + F_t)} \qquad (8)$$

Where: A_t is the real value, F_t is the predicted value.

2.4 Selecting Forecasting Methods

Armstrong (2001) examined six parameters to select forecasting methods: convenience, market popularity, structured judgment, statistical criteria, relative track records, and guidelines from prior research.

Convenience

In many situations, it is not worth spending a lot of time to select a forecasting method. Sometimes little change is expected, so different methods will yield similar forecasts. Or perhaps the economics of the situation indicate that forecast errors are of little consequence. These situations are common.

Convenience may lead to methods that are hard to understand. Statisticians, for example, sometimes use Box-Jenkins (2015) procedures to forecast because they have been trained in their use, although decision makers may be mystified. This methodology is applied in the analysis of time series, it uses the Auto Regressive Mobile Average (ARMA), models, or the Auto Regressive Integrated Mobile Average (ARIMA), models to find the best fit for a time series of values, so that the forecasts are more accurate.

Also, a method selected by convenience may lead to large errors in situations that involve large changes.

Market popularity

Market popularity involves determining what methods are used by other people or organizations. The assumptions are that (1) over time, people figure out what methods work best, and (2) what is best for others will be best for you. Surveys of usage, offer only indirect evidence of success.

Structured judgment

When a number of criteria are relevant and a number of methods are possible, structured judgment can help the forecaster to select the best methods. In structured judgment, the forecaster first develops explicit criteria and then rates the methods.

Statistical criteria

Statisticians rely heavily upon whether a method meets statistical criteria, such as the distribution of errors, statistical significance of relationships, or an autocorrelation test in the residuals of a statistical regression analysis, like the Durbin-Watson (DW), (1971) statistic.

Statistical criteria are not appropriate for making comparisons among substantially different methods. They would be of little use to someone trying to choose between judgmental and quantitative methods, or among role playing and expert forecasts. Statistical criteria are useful for selection only after the decision has been made about the general type of forecasting method, and even then, their use has been confined primarily to quantitative methods.

Relative track records

The relative track record is the comparative performance of various methods as assessed by procedures that are systematic, unbiased, and reliable. It does not have to do with forecasting methods being used for a long time or people's satisfaction with them.

Principles from published research

Assume that you need to forecast personal computer sales in China over the next ten years. To determine which forecasting methods to use, you might use methods that have worked well in similar situations in the past. Having decided on this approach, you must consider: (1) How similar were the previous situations to the current one? (You would be unlikely to find comparative studies of forecasts of computer sales, much less computer sales in China), (2) Were the leading methods compared in earlier studies? (3) Were the evaluations unbiased? (4) Were the findings reliable? (5) Did these researchers examine the types of situations that might be encountered in the future? and (6) Did they compare enough forecasts?

An extensive body of research is available for developing principles for selecting forecasting methods. The principles are relevant to the extent that the current situation is similar to those examined in the published research. Use of this approach is fairly simple and inexpensive.

General Principles

- Use structured rather than unstructured forecasting methods

- Use quantitative methods rather than judgmental methods if enough data exist.

- Use causal rather than naive methods, especially if changes are expected to be large.

- Use simple methods unless substantial evidence exists that complexity helps.

- Match the forecasting methods to the situation.

In this work, we focused in accuracy for selecting more suitable forecasting method.

3. Methodology

In this work, we look for demand patterns and try to find different demand components that could help us to establish a correlation between demand patterns and the lower error forecasting technique. Chase and Jacobs (2014), in relation to the components of the demand, state following. In most cases, the demand for products or services is divided into six components: average demand for the period, a trend, seasonal elements, cyclical elements, random variation and autocorrelation.

It is more difficult to determine the factors because perhaps the time is unknown or the cause of the cycle is not considered. The cyclical influence on demand can come from events such as political elections, wars, economic conditions or sociological pressures.

Random variations are caused by fortuitous events. Statistically by subtracting all known causes of demand (average, trends, seasonal, cyclical and autocorrelation) from total demand, what remains is the inexplicable part of demand. If the cause of the remainder cannot be identified, it is assumed to be random.

The autocorrelation indicates the persistence of the fact. More specifically, the expected value at one time has a very high correlation with its own previous values. In the theory of the waiting line, the length of a waiting line has a very high autocorrelation. That is, if a line is too long at a certain time, shortly after that time it would be expected that the line would remain long.

The software "System for predicting sales for suppliers of chemicals", developed by Abascal, et al. (2016), was used for evaluating different forecasting techniques on the basis of historical sales of Chemical Products Supplying Enterprises, comparing forecasting results with actual sales. The software only requires historical sales information of three years to make the forecast and sales information of a fourth year. To assess the accuracy of the forecast, both the most popular method for calculating errors, the mean absolute percentage error (MAPE), as well as the symmetric mean absolute percentage error (SMAPE), were used. The first one was discarded because it gave error values to high when real sales were close to zero, and infinite error values when real sales were zero. On the contrary the second method results indicated that it is more appropriate to assess the characteristics of historical sales data.

The program was used with the sales data (fifty products of the company 1 and eleven products of the company 2, which represented about 80% of total sales volume in both cases) of the first three years, the graphs of monthly sales vs months were generated, in order to be able to analyze the type of pattern presented by the sales in each case. Then, sales forecast calculations were performed using the techniques SMA, WMA, TP, ES, SLR and DWMA. Subsequently, errors were calculated for each technique, each product and each company, comparing forecasted values vs real sales data. Error results were analyzed to establish which techniques presented the least error in most of the products. The sales graphs of each product were analyzed in order to find the relationship between the sales patterns and the forecasts calculated with the lower error technique.

4. Research Results

The errors for each product, each forecasting technique and each of the two companies are shown in Tables 1 and 2.

Table 1. Forecasting error for Company 1 products

Product	DWMA	SMA	WMA	TP	ES	SRL
1	0.0575	0.0776	0.0709	0.0910	0.0816	0.0659
2	0.2303	0.2322	0.2184	0.3024	0.2451	0.3963
3	0.3374	0.3550	0.3600	0.6115	0.3249	0.3684
4	0.2748	0.2990	0.2927	0.4831	0.3002	0.4904
5	0.3662	0.3439	0.3273	0.3545	0.3378	0.5106
6	0.2542	0.3159	0.2945	0.3594	0.3098	0.2668
7	0.7074	0.6796	0.6075	1.4414	0.7366	0.8046
8	0.0957	0.0842	0.0850	0.1301	0.0921	0.1291
9	0.2596	0.1715	0.1649	0.2339	0.1759	0.6107
10	0.1286	0.1323	0.1350	0.1669	0.1212	0.1146
11	0.2513	0.2858	0.2722	0.3755	0.2443	0.2409
12	0.2140	0.2444	0.2570	0.5434	0.2539	0.2986
13	0.1406	0.0986	0.0975	0.1409	0.1005	0.1784
14	0.2350	0.1987	0.1906	0.2656	0.1886	0.1597
15	0.1523	0.1537	0.1531	0.2250	0.1369	0.8043
16	0.2840	0.2002	0.1885	0.2034	0.1970	0.7559
17	0.2036	0.1620	0.1560	0.2089	0.1743	0.1159
18	0.4083	0.3425	0.3165	0.3849	0.3704	0.8292
19	0.2204	0.0756	0.0855	0.2043	0.0836	0.2682
20	0.3135	0.1983	0.1827	0.2118	0.2166	0.6214
21	0.2794	0.3122	0.2960	0.3226	0.3352	0.3073
22	0.1688	0.1062	0.1028	0.1373	0.1077	1.0703
23	0.4555	0.5857	0.5061	0.7089	0.6016	1.0116
24	0.1322	0.0978	0.0982	0.1846	0.1031	0.1319
25	0.1347	0.1709	0.1530	0.1463	0.1782	0.1857
26	0.2279	0.1697	0.1904	0.3746	0.1797	0.4038
27	0.3538	0.3864	0.3484	0.5349	0.3515	0.3334
28	0.0943	0.1298	0.1279	0.1662	0.1339	0.1242
29	0.3813	0.4062	0.4480	0.8884	0.4015	0.5275
30	0.1743	0.1516	0.1395	0.1859	0.1614	-8.1482
31	0.1293	0.1365	0.1348	0.1823	0.1287	0.2035
32	0.2145	0.1657	0.1612	0.3091	0.1688	0.2723
33	0.2761	0.2846	0.2858	0.4969	0.2778	0.2379
34	0.2110	0.1526	0.1476	0.1696	0.1422	0.2578
35	0.1719	0.1979	0.1965	0.2468	0.1954	0.1540
36	0.3237	0.3528	0.3316	0.4593	0.3666	0.2940
37	0.2165	0.2188	0.2293	0.3600	0.1844	0.1291
38	0.3811	0.2828	0.2783	0.3815	0.2757	0.3849

39	0.2969	0.2345	0.2167	0.4605	0.2522	0.5730
40	0.3291	0.1923	0.1753	0.2195	0.2090	0.5138
41	0.2444	0.2816	0.2813	0.3626	0.2985	3.1235
42	0.1790	0.1784	0.1746	0.2425	0.1723	0.5371
43	0.3087	0.3992	0.3935	0.5486	0.3905	0.2943
44	0.3540	0.5387	0.5148	0.6661	0.5288	0.4775
45	0.0869	0.1146	0.1245	0.2173	0.1174	0.1135
46	0.2075	0.2672	0.2790	0.3645	0.2848	0.2983
47	0.2376	0.1460	0.1473	0.2017	0.1651	0.4829
48	0.2888	0.3631	0.3604	0.4767	0.3553	0.3419
49	0.1499	0.2050	0.1923	0.2389	0.2024	0.2905
50	0.3330	0.3125	0.2975	0.3701	0.3350	0.6903
Average	**0.2495**	**0.2438**	**0.2358**	**0.3512**	**0.2459**	**0.2729**

Table 2. Forecasting error for Company 1 products

Product	DWMA	SMA	WMA	TP	ES	SLR
1	0.0665	0.0696	0.0704	0.1033	0.0659	0.0705
2	0.1870	0.2719	0.2649	0.3751	0.2528	0.3756
3	0.0803	0.0914	0.0948	0.1803	0.1029	0.0843
4	0.0941	0.1121	0.1044	0.1105	0.1162	0.1187
5	0.1112	0.0761	0.0746	0.0978	0.0721	0.1591
6	0.1493	0.1561	0.1617	0.3453	0.1575	0.1657
7	0.7262	0.7646	0.7629	1.0745	0.7462	0.6240
8	0.5903	0.5709	0.5608	0.8574	0.5904	0.5450
9	0.5227	0.6158	0.6615	1.0760	0.6342	0.5647
10	0.3201	0.2478	0.2629	0.4383	0.2558	0.4586
Average	**0.2825**	**0.2925**	**0.2997**	**0.4673**	**0.2979**	**0.3143**

The analysis of the SMAPE average errors for the different forecasting techniques, for all the products of each company, allowed locating the DWMA as the technique in which, for the greatest number of products, it was obtained the smallest prediction error: Fifteen of fifty products for company 1 and five of eleven products for company 2. The DWMA technique presents not only the lower error levels, but also the lower dispersion of the error values, as it is shown in Figures 1 and 2.
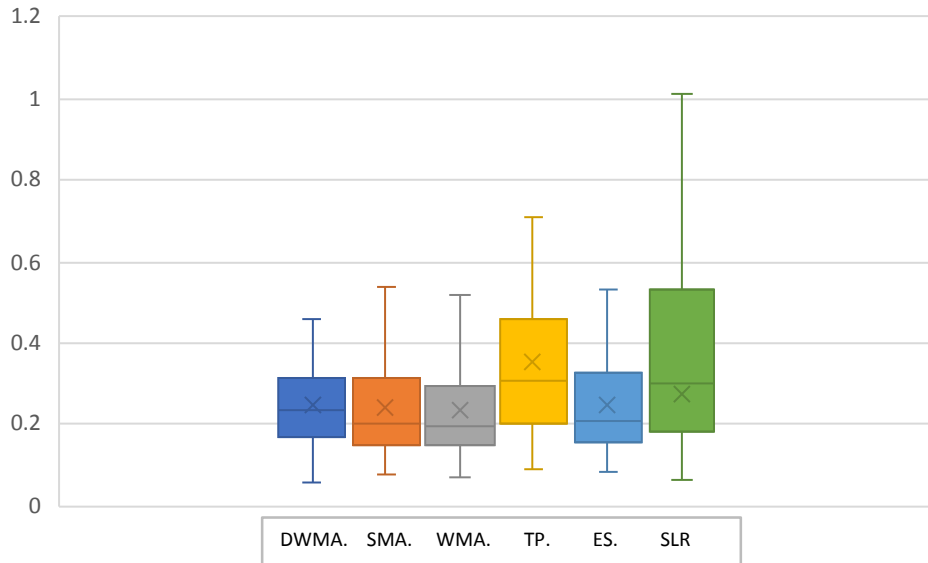
Figure 1. Chart for company 1 showing SMAPE error levels and dispersion for each forecasting technique, considering fifty products
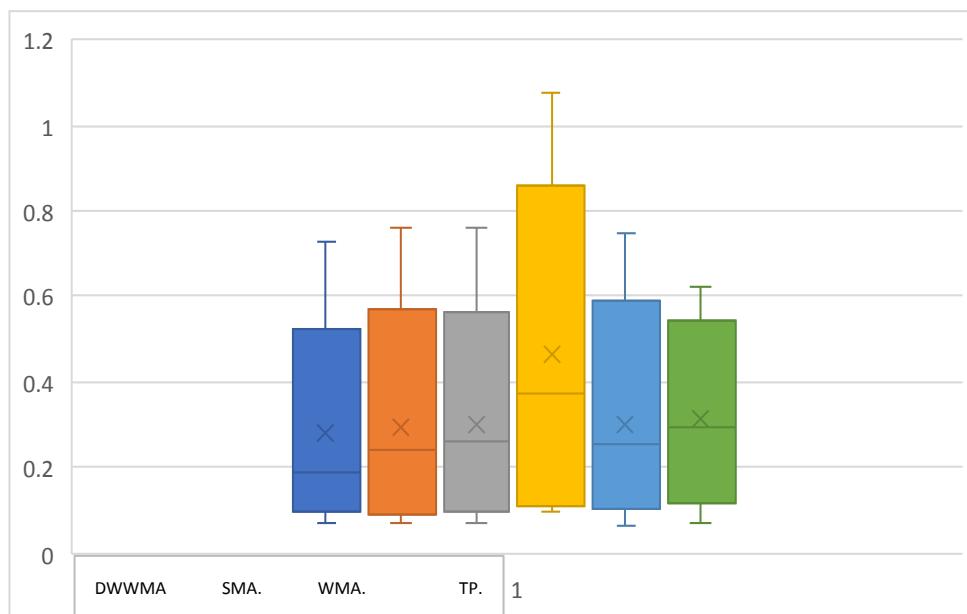

Figure 2. Chart for company 2 showing SMAPE error levels and dispersion for each forecasting technique, considering eleven products

For products in which the DWMA technique was obtained as a minor error technique, demand patterns exhibited during the previous three years were analyzed, and it was found that sales show a combined pattern of trend and cyclicity. Figure 3 with sales values of product 1, company 1 is an example of a combined pattern of trend and cyclicity, it has a series of maximum sales peaks uniformly distributed during each year, combined with a tendency to reduce the volume of sales i.e. in the last two years a slightly decreasing trend has been presented, with peaks of higher sales in the first and third quarters of each year. Figure 5, shows the demand of product 28, company 1. In here the seasonal peaks are not so clear but it can be observed a tendency for reducing sales level and again some peaks of higher sales. In this second case, the lower error forecasting technique, was also DWMA. Figures 4 and 6 show a comparison between actual sales and forecasted sales for the fourth year, based on the data shown in Figures 3 and 5 respectively.
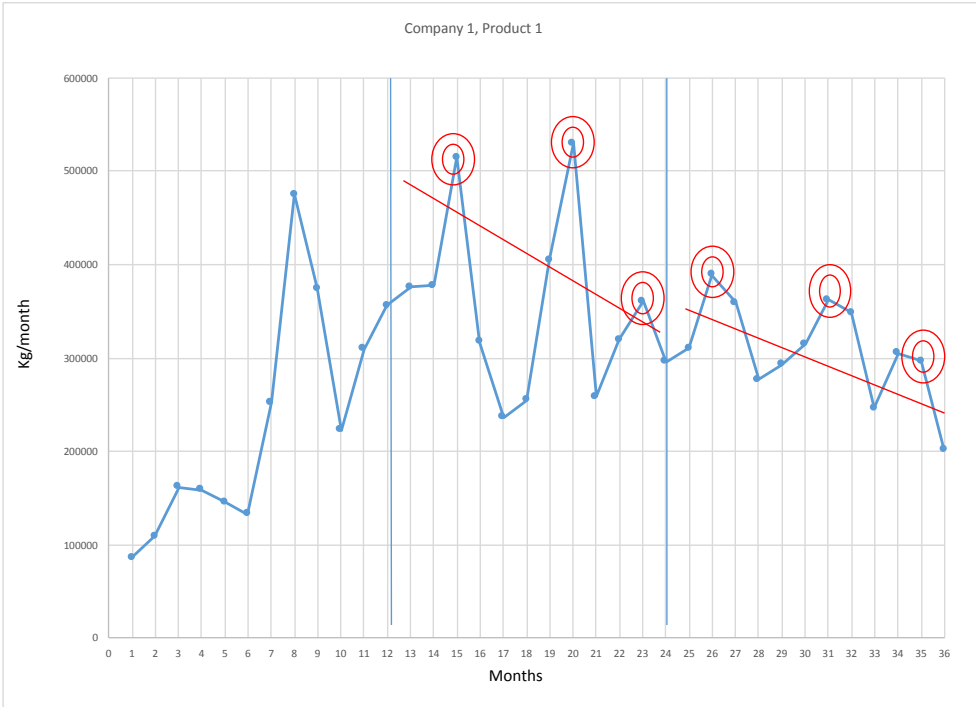
Figure 3. Monthly sales data of three years for company 1 and product 1
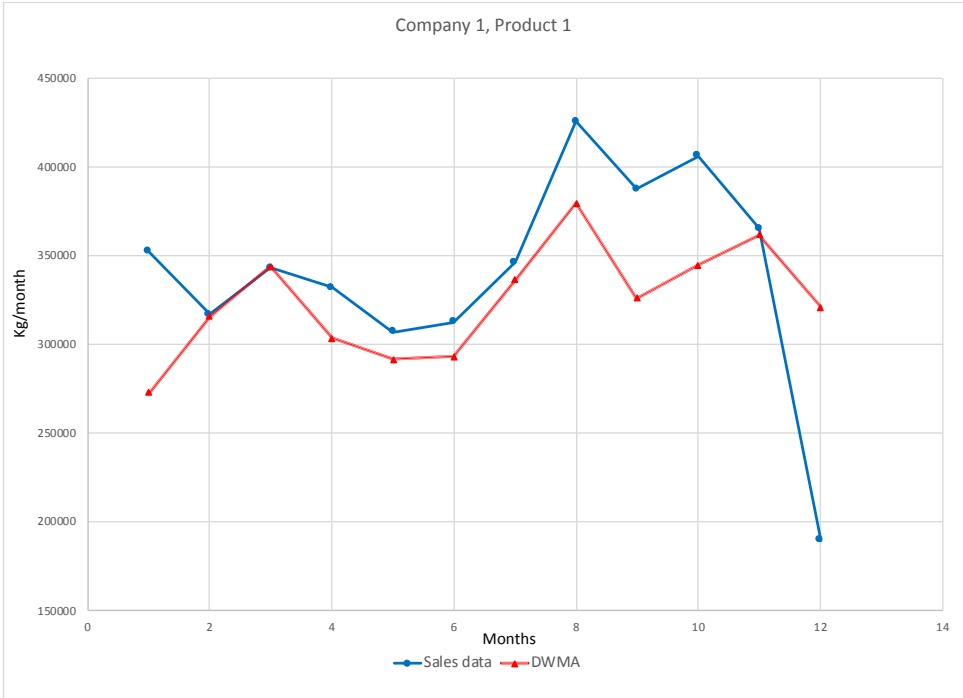
Figure 4. Comparison between actual sales and forecasted sales in fourth year; company 1, product 1
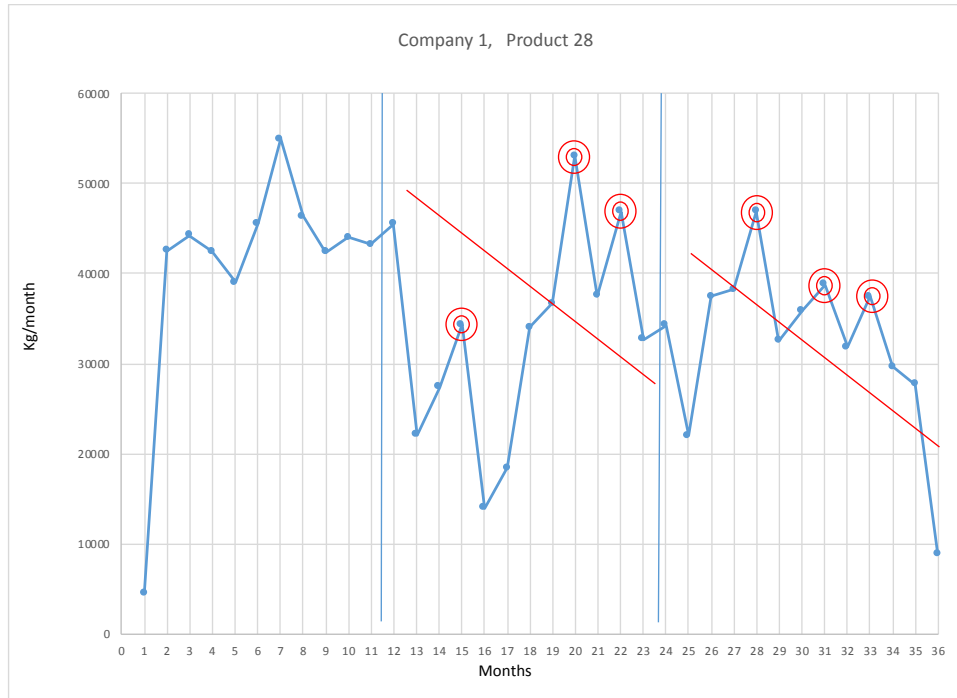
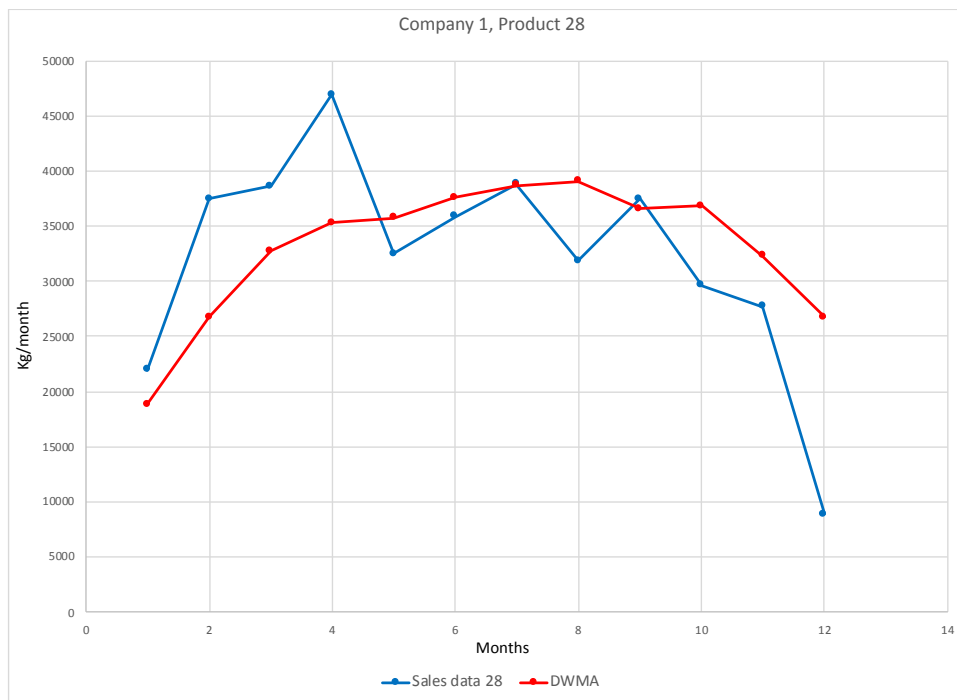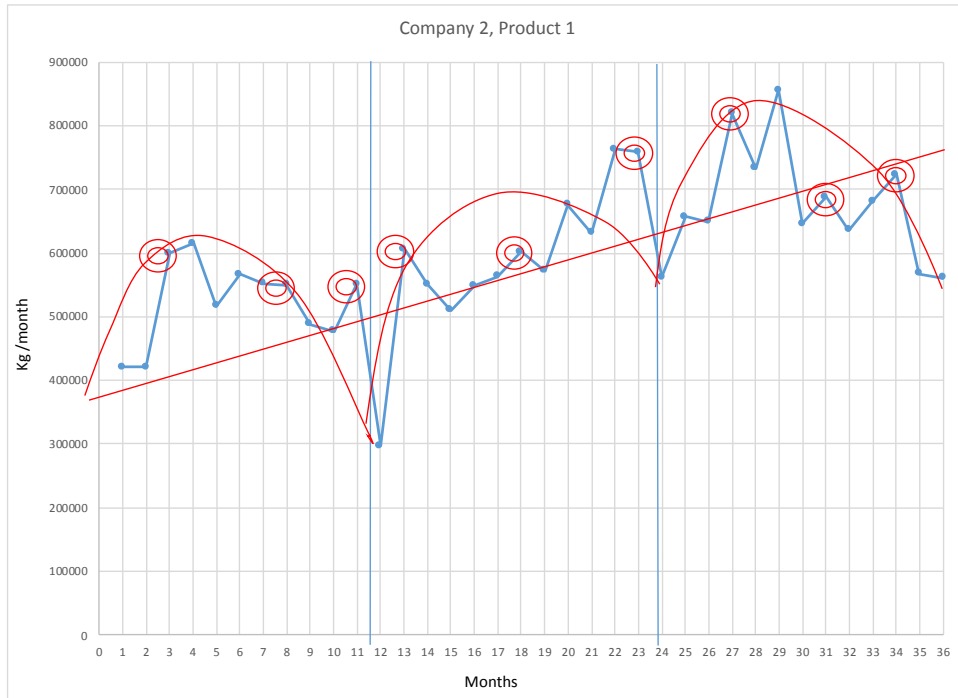Figure 5. Monthly sales data of three years for company 1 and product 28

Figure 6. Comparison between actual sales and forecasted sales in fourth year; company 1, product 28

For the analysis of the second enterprise in 5 of 11 products, in which a combined trend pattern and uniformly distributed sales peaks are also evident during the year, the lowest error technique was also DWMA. Two typical cases are presented in what follows. For company 2, product 1, the tendency was to increase sales in about a hundred thousand kg/year, combined with sales peaks evenly distributed through the year, see Figure 7 for monthly sales data of three years, and Figure 8 for the forecasted and real sales of the fourth year. This forecast did not give a further increase

of an extra hundred thousand kg/year for the fourth year, that a SLR technique will predict. The DWMA prediction was closer to the real sales. In the case of company 2, product 3, the tendency was to maintain a constant sales level, combined with peak sales at the beginning and end of the year, see Figure 9 for monthly sales data of three years and Figure 10 for the forecasted and real sales of the fourth year.

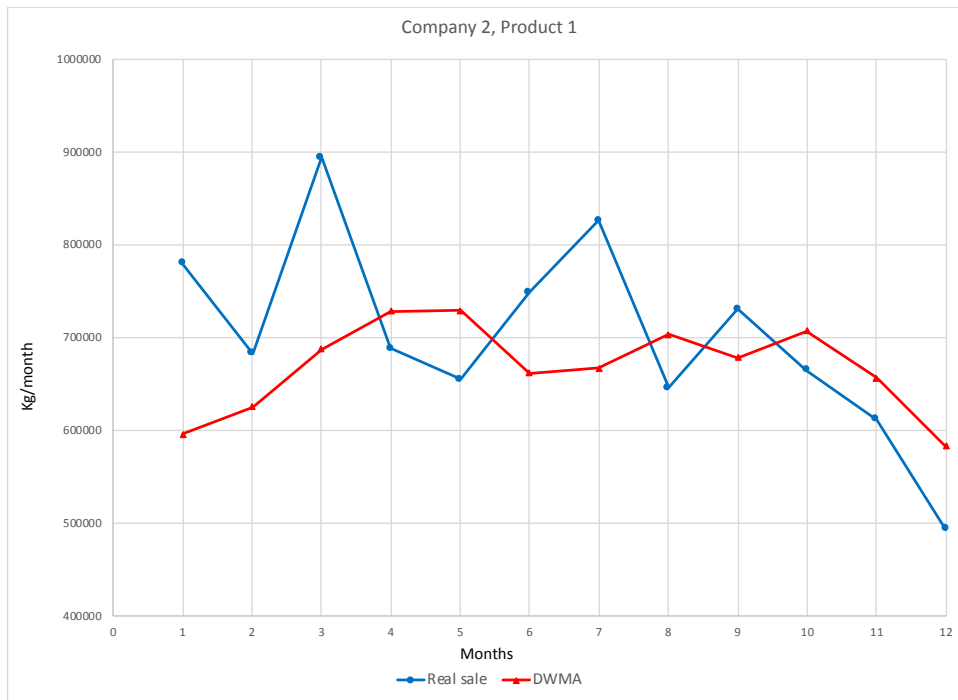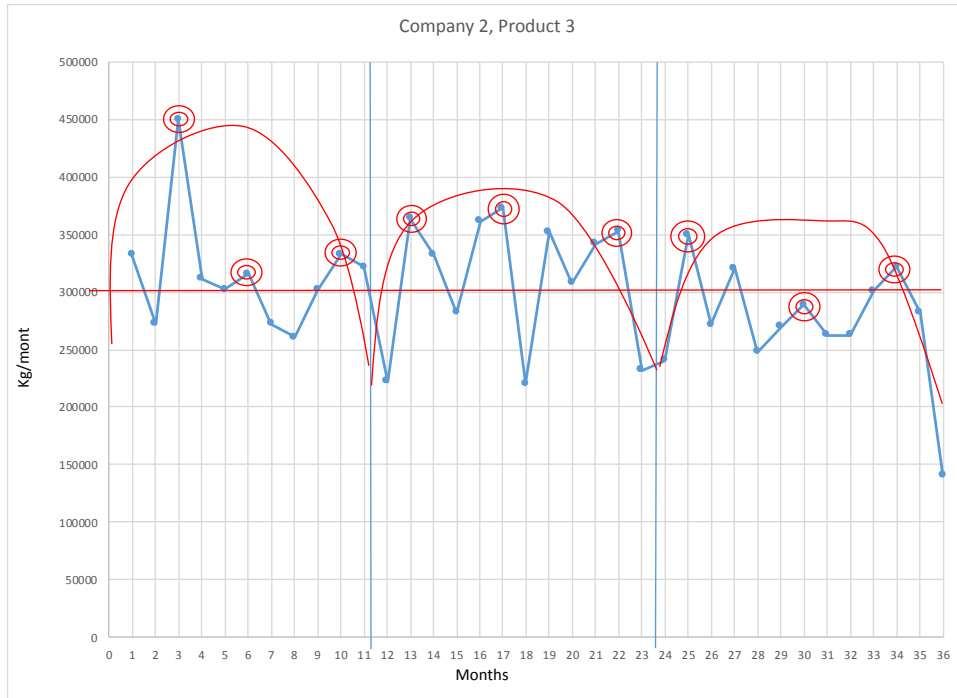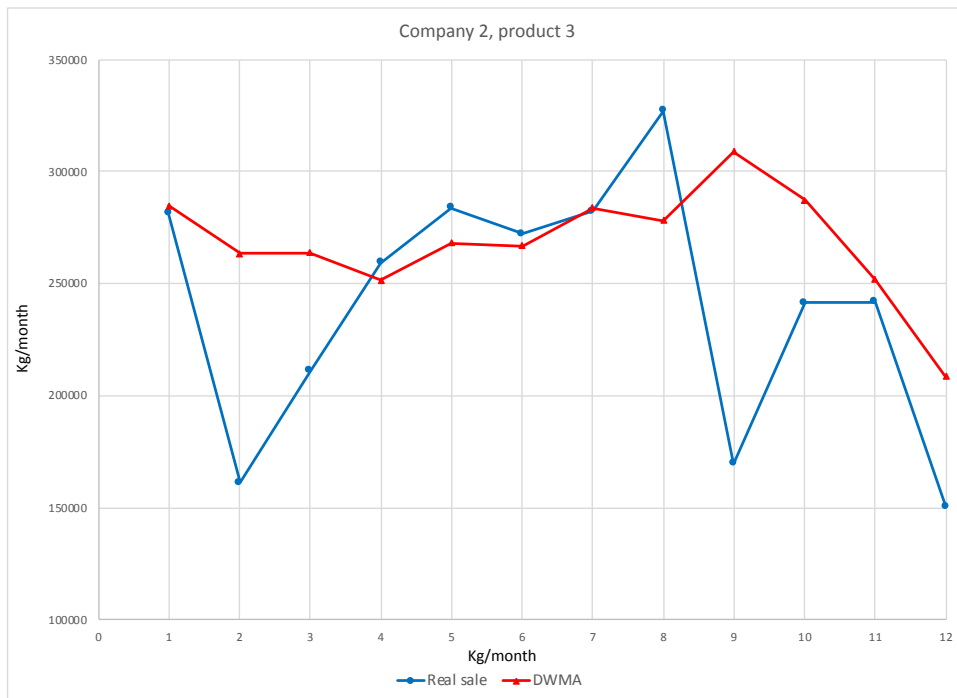Figure 7. Monthly sales data of three years for company 2 and product 1

Figure 8. Comparison between actual sales and forecasted sales in fourth year; company 2, product 1

Figure 9. Monthly sales data of three years for company 2 and product 3

Figure 10. Comparison between actual sales and forecasted sales for the fourth year of company 2, product 3

The monthly sales data for three years, showed in Figures 11 and 13, are examples of a decreasing or increasing tendency, but higher sales peaks cannot be clearly identified. In this case was the WMA technique that gave the forecasts with closer to real sales values. Figures 12 and 14 show the comparisons between actual sales, and expected sales based on data from the previous two figures. In the same company 1 other products presented trend, but no sales peaks with some frequency, in all these cases the WMA technique gave the forecasts with closer to real sales values.
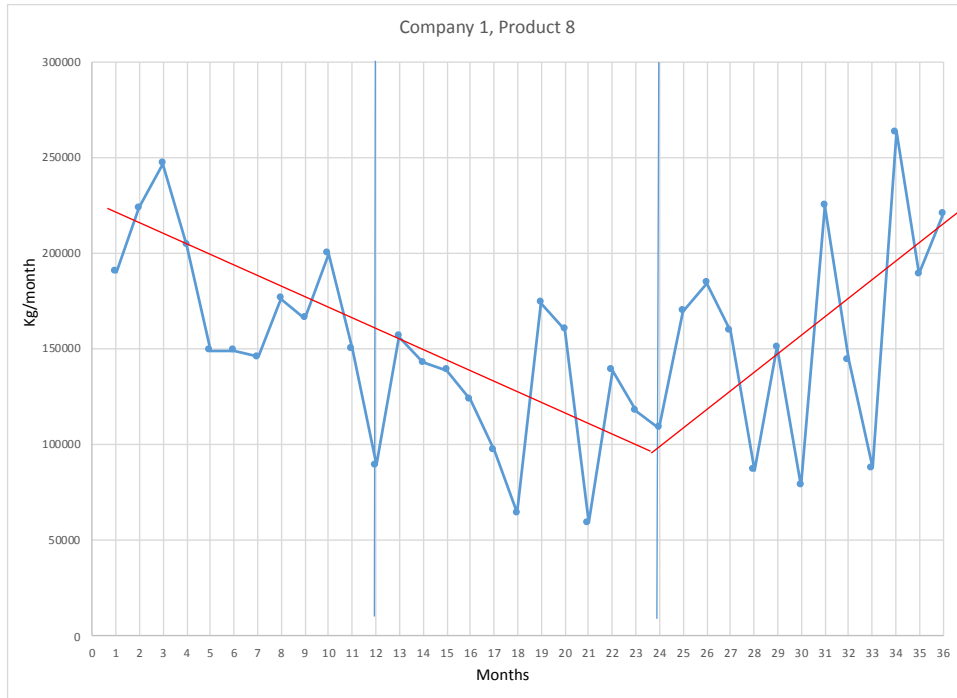
Figure 11. Monthly sales data of three years for company 1 and product 8
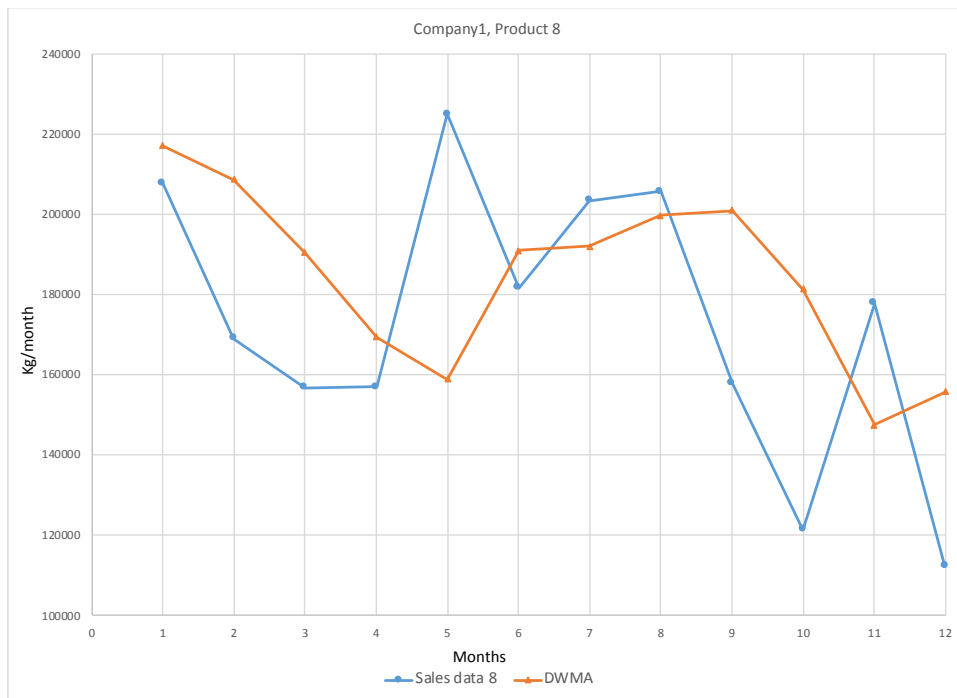

Figure 12. Comparison between actual sales and forecasted sales in fourth year; company 1, product 8
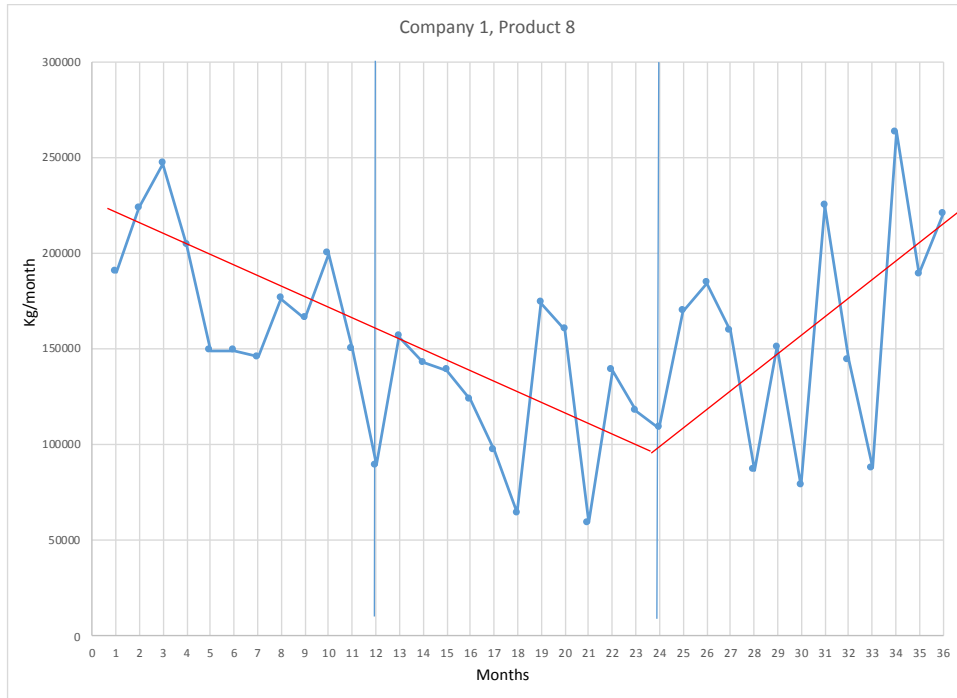
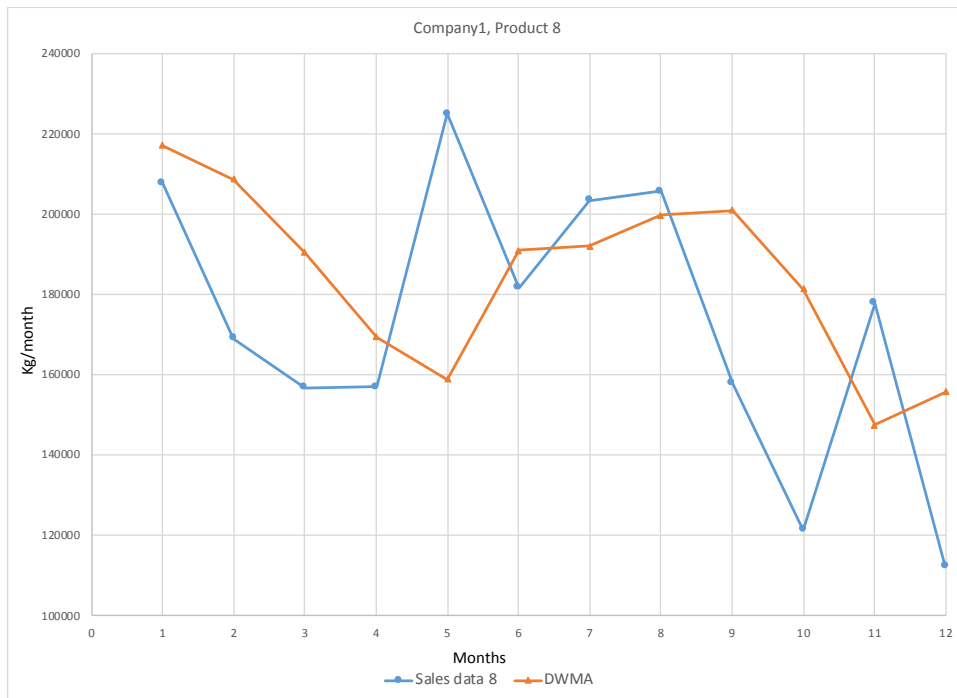Figure 13. Monthly sales data of three years for company 1 and product 13

Figure 14. Comparison between actual sales and forecasted sales in fourth year; company 1, product 13

By doing the sales forecast with the six techniques described in this paper and calculating the average error for each forecast of all the 50 chemical products, of company 1, it was made an assessment of the relative usefulness of each technique. DWMA was the first and WMA was the second technique in giving the least forecasting errors. In figure 15, it is shown how with DWMA and WMA in 29 of 50 company 1 products, it is obtained the least farecasting error. With respect to the products (14 of 50 in company 1) in which the WMA technique was obtained as the least error technique,

the analysis of the demand, exhibited by the three-year monthly sales data, shows only a trend pattern. In Figure 16 are shown, for company 2 products, the number of products that gave for each forecasting technique the least errors. With the DWMA technique it was obtained in 5 of the 11 products the least farecasting error.
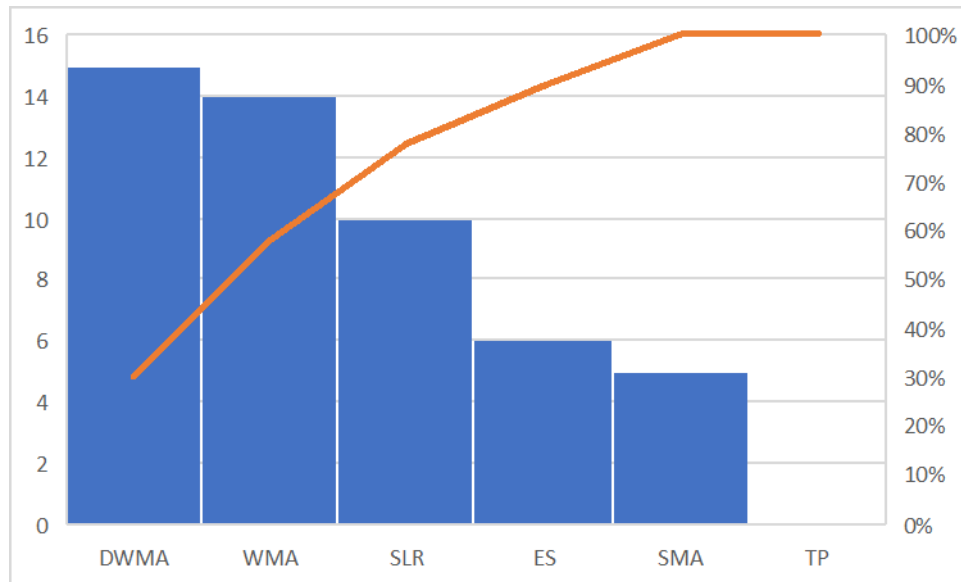

Figure 15. Chart for Company 1 showing forecasting techniques with lowest error in fifty products
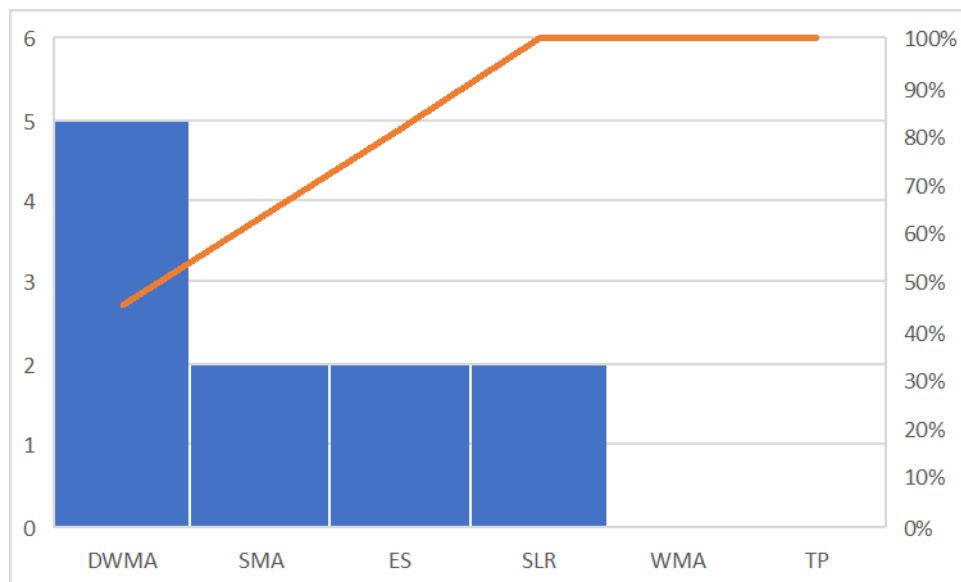

Figure 16. Chart for Company 2 showing forecasting techniques with lowest error in eleven products

In summary, with the two forecasting methods: The DWMA and the WMA, in 56% of the products, distributed in the two companies, the smallest forecast errors are obtained. In addition, by using the already mentioned software, it is possible to select the forecasting technique with less error, for all products in a simple and fast way, and establish a relationship between the demand pattern and the most appropriate forecasting technique.

5. Discussion

For selecting a suitable forecasting method, Chase and Jacobs, (2014) proposed the guide summarized on Table 3.

Table 3. Guide for selecting a suitable forecasting method

Forecasting method	Quantity of historical data	Data pattern	Forecast horizon
Linear regression	From ten to twenty observations for temporality, at least five observations per season	Stationary, trend and temporality	Short to medium
Simple moving average	Six to twelve months, weekly data is often used	The data must be stationary (i.e. without trend or temporality)	Short
Weighted moving average and Simple exponential smoothing	To begin with, five to ten observations are needed	The data must be stationary	Short
Exponential smoothing with trend	To begin with, five to ten observations are needed	Stationery and trends	Short

Although the guide mentions that in order to select the WMA method the data pattern should be seasonal, in our case this technique was adequate in trend patterns.

The guide does not mention the DWMA because this technique was proposed in 2016, two years after the Chase and Jacobs paper, however, it mentions linear regression as adequate for stationary, trends and temporality data patterns, in this work the DWMA was found to be more adequate than linear regression, for seasonal and trend type data patterns.

Establishing the best forecasting method for the sales, of a sector of the Economy as broad and changing as that of the distribution of chemical products, is not an easy job, and in addition, a method selected as the least error in a specific year, it may not be the most appropriate in another period of time. That is why, it is important to repeat the data analysis at least annually to verify if sales patterns are maintained, and if there are variations, to determine again which is the best forecasting method to be used for each product in the new scenario.

For selecting forecasting methods, regarding six ways analyzed by Amstrong (2001), in this work we made the following considerations:

Convenience

When examining the forecasts that companies have already made, it was found that company 1 uses the SMA technique, and company 2 uses the TP technique, for all their respective products. Although, it could be convenient to use the forecasting methods selected by each company to take advantage of personnel experience, for this research, it was decided to compare the two mentioned methods with the other four, looking for the more suitable one in each company. By using the appropriate software and making the graphic evaluation of the forecasted values it is easy to define the best method to use. This exercise also helps the decision makers in the development of their work.

Market popularity

In this work there were used 5 popular methods, that many companies use because they are easy to understand and to handle, and the DWMA method.

Structured judgment

With respect to the criteria used for selecting the more suitable forecasting methods, it was chosen the forecasting with least error for one-year period, and then it was compared in a graphic way the real sales data vs forecasted data by the selected method.

Statistical criteria

The forecasting techniques that have the least error in the largest number of products were selected, and the results reflected in a Pareto Chart as in Figures 1 and 2. By considering all products in both companies and using Boxplot Charts, as in Figures 15 and 16, it was found that DWMA technique presented the lowest error level.

Relative track records

The comparative performance of the six methods was evaluated by analyzing, the demand patterns of each product over a period of three years; with the data it was made the sales forecast for a fourth year, using six methods. These

forecasts were compared with the actual sales data for the fourth year, and the SMAPE error was calculated in each case.

Principles from published research

We did not find a published research for selecting forecasting methods specifically applied to Chemicals suppliers, but we found different papers talking about selecting or evaluating forecasting methods in other economic activities.

According to Chase and Jacobs (2014) the forecast model that an enterprise must choose depends on:

1. The time horizon that is going to be forecasted.

In the present research there were made monthly forecasts for an annual sales period, for each product, and each enterprise.

2. The availability of data.

It was available the monthly sales data of products sold by two companies that supply chemical products, corresponding to four annual periods.

3. The required precision.

It was established the objective of identifying the most accurate forecasting method (s) in each case, through the use of the software already mention in this paper.

4. As for the budget for forecasts.

Only a relatively small budget is required to make the forecasts, by the use of the above-mentioned software that can be run in any operating system (Windows, Mac or Unix).

5. The availability of qualified personnel

With respect to the availability of qualified personnel, the use of the aforementioned software is simple and fast, and specialized personnel in statistics, models or computing are not required. It carries out both the analysis of sales patterns of chemical suppliers based on historical data from three years prior to the desired one, as well as the selection of the predictive method that may have the least error in each product; and after the fourth year it is possible to make the comparison of the forecasted values against the actual sales data, and the calculation of the monthly errors. By annually doing this exercise, it is possible to notice any change in the demand patterns of the products, and make a new selection of the best forecasting technique.

6. Conclusions

The obtained results allow us to conclude that; although each product has a forecasting method with the lowest error compared to real sales, this method of forecasting least error can change with time. Also, it was observed that two of the six compared methods, DWMA and WMA gave the results of the lowest error in 57% of the products. In other words, the sales of most products in this sector of the economy, present patterns with increasing or decreasing trends and at the same time seasonal peaks (each year in the same quarter) of higher or lower sales. For this type of patterns, the two methods mentioned above offer the closest forecast to real sales values.

We also must say that we found that the DWMA forecast technique, gave good results in about 34.5% of all analyzed products and that the demand patterns of these products tended to increase or decrease the level of sales or even to remain at a constant level, but presenting peaks of repetitive sales in any particular month or quarter of each year.

Taking into consideration that most of the companies supplying chemical products in Mexico, are small companies that need to make forecasts of their sales as accurate as possible for planning their operations, but usually these companies do not have specialized personnel, the evaluation of simple forecasting methods, looking for the least error depending on the type of demand patterns of each product, represents a viable option.

Finally, it is clear that the more products a company manages, the more calculations will be necessary, so the use of software such as the one used in this work will be useful for the calculation and analysis process to be carried out in a relatively short time.

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