Scientific Papers (www.scientificpapers.org)
Journal of Knowledge Management, Economics and Information Technology

Issue 7
December 2011

Forecasting Sales in a Sugar Factory

Authors: **Sofia-ira KTENA, Fotios PETROPOULOS**[1], **Polychronis KOUTSOLIAKOS, Dimitrios MICHOS, Vassilios ASSIMAKOPOULOS**, Forecasting & Strategy Unit, School of Electrical and Computer Engineering, National Technical University of Athens, Heroon Polytechniou 9, 15780, Zografou, Greece, ira@fsu.gr; fotis@fsu.gr; michos@fsu.gr; koutsoliakos@fsu.gr; vassim@fsu.gr

Beets' cultivation and sugar production represent one of the most important parts of Greek agricultural economy. A careful and well-organized planning of the production as well as the determination of an accurate safety stock is important for sugar industry, as for many other companies and organizations, in order to define the production quantity which leads to maximum revenues and profits. Forecasting, and especially widely used statistical forecasting techniques, is the best way for policymakers to organize their activities and company's production and make the appropriate adjustments. Apparently, management information systems and forecasting support packages play a leading role in this area, since the amount of data under process is usually quite large and demands an automated procedure to effectively produce and evaluate forecasts. In this case study, "Pythia", an expert forecasting platform developed by the Forecasting and Strategy Unit of the National Technical University of Athens, was implemented on a monthly data series regarding sugar sales of a Greek sugar factory for the years 2000-2005, bringing theory and practice together. Additionally, the methods or combinations of methods which are well suited for this time series are highlighted based on three error indices. Finally, the results of the study and

[1] Corresponding Author

conclusions are considered and perspectives of progress and development in the field of forecasting are contemplated.

Keywords: *Sales forecasting; Time series; Forecasting support systems; Statistical forecasting methods; Agricultural forecasting*

Introduction

Sugar Industry is an active and ever growing field of Greek agriculture. In many countries it is a matter of major importance to ensure a sufficient and satisfactory production of sugar, since thousands of tones are consumed and traded every day all over the world. According to Higgins and Muchow (2003) the cultivation, harvest, transfer, processing and marketing of sugar have to be treated as a single problem. This attempt may be too complicated, especially in countries, where harvesting units and farms belong to private companies and are separated from factories, where the processing takes place. Forecasting is without doubt essential for companies and industries in order to achieve their goals and maximize their profits (Armstrong, 1985). Since models implemented in other countries cannot be utilized in Greece due to the different environmental conditions and soil fertility, the development of algorithms in order to predict annual sugar production and demand in Greece has become a necessity. For this reason the present study applies the most commonly used and up-to-date statistical forecasting methods as well as combinations of multiple methods on one time series: sugar sales of a Greek factory for the period 2000-2005.

New technologies play a crucial role in the simplification of the forecasting process, so an efficient and expert software package, "Pythia", was implemented in this case. All forecasting methods chosen and tested for the specific type of data are described below. Furthermore, "Pythia" along with the results of the study and the smoothing method applied in this case study are presented. Finally, the most appropriate methods are indicated, based on various error indices.

Statistical tools and methods

Statistical forecasts refer to the application of statistical time series' models or deterministic models on data series with a view to a systematic and automated forecast production. Statistical forecasting methods can be directly used by business managers lacking any technical or statistical knowledge via expert forecasting information systems like "Pythia". In the present study the following widely known statistical methods are taken into consideration and are briefly reviewed below: Linear Trend, Simple

Exponential Smoothing, Holt Exponential Smoothing, Damped Exponential Smoothing, Holt-Winters Model and the Theta Model. The formulae of the aforementioned methods can be found in any forecasting textbook (e.g. Makridakis, Wheelwright & Hyndman, 1998; Brockwell & Davis, 1987).

In statistics, regression analysis examines the relation of a dependent variable (response variable) to specified independent variables (explanatory variables). In case of time series' analysis the index of each period is used as the independent variable.

Exponential Smoothing methods were developed in the early 1950s. Since then they've become very popular among operators, primarily due to the fact that they are easily implemented, require minimal computing time and a relatively small number of observations in order to extract a forecast. Smoothing methods are mainly suited for short and intermediate-term batch forecasting. Optimal performance is observed when these techniques are applied on stationary data series.

Simple Exponential Smoothing (SES) assumes that time series have an almost constant average and the forecast results from the extension of a constant-level line.

Holt Exponential Smoothing can additionally handle the trend component, which is usually present in business data.

Despite its popularity, empirical evidence has shown that the Holt linear forecast function tends to overestimate. Taking this into account, Gardner and McKenzie (1985) described how a dampening parameter, ϕ, can be used within Holt's method to provide more control over trend extrapolation. Gardner and McKenzie explain that if $0 < \phi < 1$, the trend is damped.

The most commonly used procedure to calculate the optimal values of the smoothing factors is the minimization of the in-sample Mean Squared Error (MSE).

The Holt-Winters model, which is a multiplicative seasonal model, is appropriate for time series in which the amplitude of the seasonal pattern is proportional to the average level of the series. The model introduces a seasonal factor I and a ratio and like in all smoothing methods mentioned above, every constant ranges from 0 to 1.

The Theta model (Assimakopoulos & Nikolopoulos, 2000) is based on the concept of modifying the local curvatures of the time series. This change is obtained from a coefficient, called Theta-coefficient (θ), which is applied directly to the second differences of the time series. The smaller the value of the theta coefficient, the larger is the degree of deflation. In the extreme case where $\theta=0$ the time series is transformed to a linear regression line. The progressive decrease of the fluctuations diminishes the absolute differences between successive terms in the derived series and is related, in qualitative terms, to the emergence of long-term trends in the data (Assimakopoulos, 1995). Conversely, if the local curvature is increased ($\theta>1$), then the time series is dilated, magnifying the short-term behavior.

Following this procedure, a set of new time series, the so-called Theta-lines, is constructed. Generally, the initial time series is decomposed into two or more Theta-lines. Each of the Theta-lines is extrapolated separately and the forecasts are then combined. Any forecasting method can be used for the extrapolation of a Theta-line according to existing experience (Fildes et al., 1998). A different combination of Theta-lines can be employed for each forecast horizon.

Organizing the forecasting process

It is a matter of fact that in many organizations successful fulfillment of the forecasting process is often obstructed by a gap between theoreticians and practical users (Mahmud et al., 1992). Especially, De Roeck (1991) states that a gap between forecasting theory and practice actually exists. Wheelwright & Clarke (1976) have come to the conclusion that, although practitioners support theoreticians in terms of technical competence and skills, theoreticians still think little of practical users who, according to them, lack judgmental ability to choose optimal techniques and produce cost effective forecasts. This case study is an attempt to bridge this gap between theory and practice in the field of forecasting, through the examination of data provided by Greek sugar industry and the implementation of the forecasting methods mentioned in the previous section. The original data concerning monthly sales of sugar in kilograms for the years 2000-2005 are studied in this case. We should note that sales take place every month of the year, whereas production occurs only five months of each year (campaign period). Thus, 72 monthly observations about sales for 6 consecutive years are available.

"Pythia" software (Makridakis et al., 2008), utilized to produce forecasts for the above data series, has been developed by the Forecasting and Strategy Unit of the National Technical University of Athens and designed in a way that it can also serve managers without any statistical/technical background. Furthermore, Pythia gives users the opportunity to incorporate human judgment in the forecast aiming to increase its accuracy and provides them with comparative statistical information, in order to point out systematic biases and rule them out in the future. "Pythia" has been applied in various areas, such as real estate (Pagourtzi et al., 2008a) and mortgage loans (Pagourtzi et al., 2008b) and its main features include: data analysis, data processing, statistical forecast, import of special events and actions, bottom-up and top-down forecasts, monitoring and reporting, graphical and numerical data presentation.

After mining the data, we observed that outliers were present in the time series and decided to follow the smoothing method proposed by Fildes et al. (1998):

- First, the differences $Zt = Xt - Xt\text{-}1$ are calculated, where $X1, X2,\ldots, XN$ is the raw data series.
- The observations of the resulting time series Zt are placed in ascending order.
- The upper and lower smoothing limit are defined as follows:

$$U_z = B \cdot \frac{75 \cdot (n-1)}{100} \text{ and } L_z = B \cdot \frac{25 \cdot (n-1)}{100}$$

where B is the number of observations for the Zt series and 75, 25 are the selected smoothing parameters. In the present study two more sets of values for the smoothing parameters (65, 35 and 70, 30) are put under the microscope.

An observation is defined as an outlier if:

$$Z_t < L_z - 1{,}5 \cdot (U_z - L_z) \text{ or } Z_t > U_z + 1{,}5 \cdot (U_z - L_z)$$

A random outlier XK is replaced by:

$$X'_K = X_K - [L_Z - 1{,}5 \cdot (U_z - L_z)], \text{ if } Z_t < L_z - 1{,}5 \cdot (U_z - L_z)$$
$$X'_K = X_K + [U_Z + 1{,}5 \cdot (U_z - L_z)], \text{ if } Z_t > U_z + 1{,}5 \cdot (U_z - L_z)$$

Results

Three accuracy measures (Mean Absolute Error, Mean Squared Error and Root Mean Squared Error) were used to analyze the performance of the aforementioned methods. In this section we summarize the results, after the implementation of these statistical techniques on the sugar sales series via the forecasting software “Pythia”. In addition, five combinations of multiple methods with various weights are tested here, since it has been observed that in some cases, combinations of methods tend to outperform the individual methods being combined (Makridakis & Hibon, 2000).

As far as the Mean Absolute Error is concerned, it is obvious that the Damped method produces the most accurate forecasts, followed by the combination SES-Holt-Damped with weights 70-15-15 respectively. It is also worth to notice that this combination actually outperforms SES, Holt and Damped methods, since the weighted mean of their errors is larger than the MAE of their combination. On the other hand, Winters method has the worst performance which is depicted in all three errors used in this analysis.

Taking into account the MSE and RMSE, Holt, Linear Trend and their combination perform better than any other method or combination of methods.

For this set of smoothing factors the relative ranking of the methods is analogous to the previous ranking, although the calculated in-sample errors are generally smaller than those for the previous set of parameters. Based on the MAE, Damped method and SES-Holt-Damped are best suited for this data series, whereas Holt, Linear Trend and Holt-Linear Trend are the most appropriate based on the MSE and RMSE measures.

Time series with smoothing factors 25-75:

Table 1: MAE, MSE and RMSE of statistical methods for smoothing factors 25-75

Method	**MAE**	**MSE**	**RMSE**
SES	974534	2.13×10^{12}	1458092
Holt	977860	2.12×10^{12}	1457198
Winters	2086027	8.10×10^{12}	2846885
Damped	971391	2.14×10^{12}	1462242
Linear Trend	977860	2.12×10^{12}	1457198
Theta	1281329	3.12×10^{12}	1765455
Holt (50%) – Trend (50%)	977860	2.12×10^{12}	1457198
Holt (50%) – Theta (50%)	1041801	2.39×10^{12}	1544863
SES (60%) – Holt (20%) – Trend (20%)	975863	2.12×10^{12}	1457551
Theta (50%) – Damped (20%) – Trend (30%)	1046685	2.40×10^{12}	1550637
SES (70%) – Holt (15%) – Damped (15%)	974320	2.13×10^{12}	1458182

Time series with smoothing factors 30-70

Table 2: MAE, MSE and RMSE of statistical methods for smoothing factors 30-70

Method	**MAE**	**MSE**	**RMSE**
SES	943804	2.08 × 1012	1441599
Holt	948276	2.07 × 1012	1438774
Winters	2024279	7.61 × 1012	2757785
Damped	924869	2.10 × 1012	1450145
Linear Trend	948276	2.07 × 1012	1438774
Theta	1220200	2.92 × 1012	1709461
Holt (50%) – Trend (50%)	948276	2.07 × 1012	1438774
Holt (50%) – Theta (50%)	1002419	2.29 × 1012	1515265
SES (60%) – Holt (20%) – Trend (20%)	944686	2.07 × 1012	1440010
Theta (50%) – Damped (20%) – Trend (30%)	1010603	2.32 × 1012	1524148
SES (70%) – Holt (15%) – Damped (15%)	940542	2.08 × 1012	1441464

Time series with smoothing factors 35-65

Table 3: MAE, MSE and RMSE of statistical methods for smoothing factors 35-65

Method	**MAE**	**MSE**	**RMSE**
SES	994952	2.33 × 1012	1527468
Holt	1013216	2.31 × 1012	1521166
Winters	2024208	7.66 × 1012	2767465
Damped	981909	2.39 × 1012	1546641
Linear Trend	1013216	2.31 × 1012	1521166
Theta	1253867	3.20 × 1012	1790235
Holt (50%) – Trend (50%)	1013216	2.31 × 1012	1521166
Holt (50%) – Theta (50%)	1044235	2.55 × 1012	1597226
SES (60%) – Holt (20%) – Trend (20%)	1001993	2.32 × 1012	1523798
Theta (50%) – Damped (20%) – Trend (30%)	1052204	2.59 × 1012	1611697
SES (70%) – Holt (15%) – Damped (15%)	1388197	3.67 × 1012	1916617

As we can see in table 3, Holt and Linear Trend as well as the combination Holt-Linear Trend are the most suitable methods to predict sugar sales, taking into account the Mean Squared Error, which is the most commonly used index to evaluate the accuracy of the forecasts.

Apparently, for all three sets of smoothing factors, Holt, Linear Trend and their combination provide the most accurate forecasts and the lowest values of the MSE. We evaluate the results considering this specific error, because the MSE is an accuracy measure of the forecast, which, due to squaring each term, weights large errors more heavily than small ones. However, every statistical technique utilized in this study presents relatively lower error values in the case of smoothing factors 30-70 than in the other two cases. Winters' significant deviation of error values from those of the other methods shows that the model is not suitable for this kind of data.

Conclusions

This study addressed a specific gap in the field of Greek agriculture by implementing commonly used forecasting techniques on the demand-side rather than the supply-side of the sugar industry, in order to facilitate the design of the production policy, which is a complicated problem to many countries. This is particularly important for the Greek sugar industry, since production doesn't take place every month of the year, but only during the campaign period which lasts five months, so the amount of production has to be meticulously predicted and organized taking into account annual demand for sugar and its side products.

The results indicate that Holt, Linear Trend and the combination Holt-Linear trend (with weights 50-50) offer the most accurate forecasts, while the Holt-Winters model is inappropriate for the specific time series. Apart from that, the best choice of smoothing factors has been identified to be 30-70, whereas the worst set of parameters is 35-65, for which the largest errors emerge. It is, however, worth to notice that the values of the error measures appearing throughout this study are relatively large due to unpredictable factors, such as weather conditions of the current year or the value of sugar in Greece compared to those of other countries, and the small number of available observations, and prove that there is a long way of improvement in the area of sugar demand forecasting.

Future research will involve examining other statistical methods for better performance or modifying already existing methods to fit this type of data series and investigating whether the incorporation of expert judgmental estimates could significantly improve the accuracy of the forecast. The methods which are proven to perform well in this case study can be also tested on other agricultural data series. Forecasting support systems can be very helpful in these procedures, minimizing the processing time, handling a great amount of data simultaneously and opening up new horizons. It is also essential to overcome the difficulties mentioned above which hinder accurate forecasts. This could be achieved by the expansion of the current time series and the integration of special events, such as intense competition or possible natural disasters, in the forecasting process.

References

[1] Armstrong, J.S. (1985), "*Long-Range Forecasting: From Crystal Ball to Computer*", New York: John Wiley and Sons

[2] Assimakopoulos V. (1995), "*A Successive Filtering Technique for Identifying Long-term Trends*", Journal of Forecasting, Vol.14, pp.35-43

[3] Assimakopoulos V. & Nikolopoulos K. (2000), "*The Theta Model: A Decomposition Approach to Forecasting*", International Journal of Forecasting, Vol.16, pp.521-530

[4] Brockwell, P.J. & Davis, R.A. (1987), "*Time Series: Theory and Methods*", New York: Springer Verlag

[5] De Roeck, R. (1991), "Is there a gap between forecasting theory and practice? A personal view", International Journal of Forecasting, Vol.7, pp.1-2

[6] Fildes, R., Hibon, M., Makridakis, S. & Meade, N. (1998), "*Generalizing about univariate forecasting methods: further empirical evidence*", International Journal of Forecasting, Vol.14, pp.339-358

[7] Gardner, E.S., Jr. & McKenzie, E. (1985), "*Forecasting trends in time series*", Management Science, Vol.31, pp.1237-1246

[8] Higgins, A.J. & Muchow, R.C. (2003), "*Assessing the potential benefits of alternative cane supply arrangements in the Australian sugar industry*", Agricultural systems, Vol.76, pp.623-638

[9] Mahmud, E., De Roeck, R., Brown, R. & Rice, G. (1992), "*Bridging the gap between theory and practice in forecasting*", International Journal of Forecasting, Vol.8, pp.251-267

[10] Makridakis, S., Assimakopoulos, V., Bougioukos, N., Nikolopoulos, K., Petropoulos, F., Pagourtzi, E. (2008), "*Pythia: an intelligent*

forecasting support system", 28th International Symposium on Forecasting ISF 2008, June 22-25 2008. Nice, France

[11] Makridakis, S. & Hibon, M. (2000), "*The M3-Competition: results, conclusion and implications",* International Journal of Forecasting, Vol.16, pp.451-476

[12] Makridakis, S., Wheelwright, S.C. & Hyndman, R.J. (1998), "*Forecasting Methods and Applications"*, New York: John Wiley and Sons

[13] Pagourtzi, E., Assimakopoulos, V., Litsa, A. & Petropoulos, F. (2008b), "*The advanced Forecasting Information System PYTHIA: an application in time series of mortgage loans in U.K.*", Pacific Rim Real Estate Society Conference 2008, Proceedings, January 20-23 2008, Kuala Lumpur, Malaysia

[14] Pagourtzi, E., Makridakis, S., Assimakopoulos, V. & Litsa, A. (2008a), "*The advanced Forecasting Information System PYTHIA: an application in Real Estate time series"*, Journal of European Real Estate Research, Vol.1, pp.114-138

[15] Wheelwright, S.C. & Clarke D.G. (1976), "*Corporate forecasting: Promise and reality"*, Harvard Business Review, Vol.54, pp.40–42