

Advances in Manufacturing Technology XXX

The urgent need to keep pace with the accelerating globalization of manufacturing in the 21st century has produced rapid advancements in manufacturing technology, research and expertise.

This book presents the proceedings of the 14th International Conference on Manufacturing Research (ICMR 2016), entitled *Advances in Manufacturing Technology XXX*. The conference also incorporated the 31st National Conference on Manufacturing Research, and was held at Loughborough University, Loughborough, UK, in September 2016. The ICMR conference is renowned as a friendly and inclusive environment which brings together a broad community of researchers who share the common goal of developing and managing the technologies and operations key to sustaining the success of manufacturing businesses.

The proceedings is divided into 14 sections, including: Manufacturing Processes; Additive Manufacturing; Manufacturing Materials; Advanced Manufacturing Technology; Product Design and Development, as well as many other aspects of manufacturing management and innovation. It contains 92 papers, which represents an acceptance rate of 75%.

With its comprehensive overview of current developments, this book will be of interest to all those involved in manufacturing today.

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Advances in Manufacturing Technology XXX

Y.M. Goh and K. Case (Eds.)



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Advances in Manufacturing Technology XXX

Proceedings of the 14th International
Conference on Manufacturing Research,
incorporating the 31st National Conference
on Manufacturing Research,
September 6 – 8, 2016, Loughborough
University, UK

EDITED BY
Yee Mey Goh
Keith Case

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Part 1

Keynote

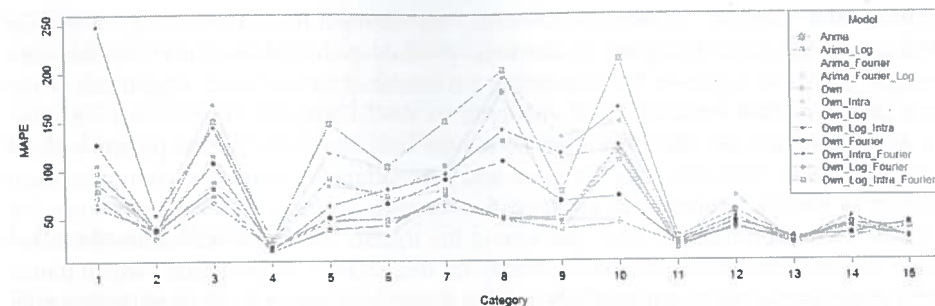


Figure 4. MAPE by category for all models.

5. Conclusions

Sales forecasting is a major challenge in retail industry particularly in the context of continuous promotional activity. In this work dynamic regression models based on price and promotional information of the focal product and its competitors, and Fourier terms to accommodate multiple seasonality, are used for sales forecasting. The forecasting models overall performance is analyzed for the full test period and for the periods with and without promotions. The results show that the dynamic regression models generate substantially more accurate forecasts than pure time series models for all periods studied.

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Evaluating the Forecasting Accuracy of Pure Time Series Models on Retail Data

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Abstract. Forecasting future sales is one of the most important issues that is beyond all strategic and planning decisions in effective operations of retail supply chains. For profitable retail businesses, accurate sales forecasting is crucial in organizing and planning purchasing, production, transportation and labor force. Retail sales series belong to a special type of time series that typically contain strong trend and seasonal patterns, presenting challenges in developing effective forecasting models. This paper compares the forecasting performance of state space models and ARIMA models. The forecasting performance is demonstrated through a case study of retail sales of five different categories of women footwear: Boots, Booties, Flats, Sandals and Shoes. An approach based on cross-validation is used to identify automatically appropriate state space and ARIMA models. The forecasting performance of these models is also compared by examining the out-of-sample forecasts. The results indicate that the overall out-of-sample forecasting performance of ARIMA models evaluated via RMSE, MAE and MAPE is better than state space models. The performance of both forecasting methodologies in producing forecast intervals was also evaluated and the results indicate that ARIMA produces slightly better coverage probabilities than state space models for the nominal 95% forecast intervals. For the nominal 80% forecast intervals the performance of state space models is slightly better.

Keywords. Pure time series models; forecasting accuracy; retailing; cross-validation

1. Introduction

Time series often exhibit strong trend and seasonal variations presenting challenges in developing effective forecasting models. How to effectively model time series in order to improve the quality of forecasts is still an outstanding question. State space and Autoregressive Integrated Moving Average (ARIMA) models are the two most widely-used approaches to time series forecasting, and provide complementary methodologies to the problem. While exponential smoothing methods are based on a description of trend and seasonality in the data [1], ARIMA models aim to describe the autocorrelations in the data [2]. The ARIMA forecasting framework originally developed by Box *et al.* [3] involves an iterative three-stage process of model selection, parameter estimation and model checking. A statistical framework for exponential

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smoothing methods was recently developed based on state space models called ETS models [4]. Identifying the proper autocorrelation structure of a time series is not an easy task in ARIMA modelling. Identifying an appropriate state space model for a time series can also be difficult. However, the usual forecast accuracy measures can be used for identifying a model provided the errors are computed from data in a test set and not from the same data that were used for model estimation. In this work, a cross-validation procedure is used to automatically identify an appropriate state space model and an appropriate ARIMA model for a time series. That is, the in-sample data are split into a training set and a testing set. The training set is used to estimate the models' parameters and the testing set is used to choose the final model. This approach is presented in the paper through a case study of retail sales time series of different categories of women's footwear from a Portuguese retailer that by exhibiting complex patterns present challenges in developing effective forecasting models. After identifying appropriate state space and ARIMA models, it is reasonable to compare the forecasting accuracy of both methodologies by examining the out-of-sample forecasts, which is also done in the paper. The remainder of the paper is organized as follows.

2. Data

The brand Foreva was born in September 1984. Since the beginning, the company is known for offering a wide range of footwear for all seasons. The geographical coverage of Foreva shops in Portugal is presently vast as it has around 70 stores opened to the public with most of them in Shopping Centers. In this study, monthly sales of the five categories of women's footwear of the brand Foreva: Boots, Booties, Flats, Sandals and Shoes, from January 2007 to April 2012 (64 observations), are analyzed. These time series are plotted in Figure 1. The Boots and Booties categories are sold primarily during the winter season while the Flats and Sandals categories are sold primarily during the summer season. The Shoes category is sold throughout the year. The winter season starts on September 30th of one year and ends on February 27th of the next year. The summer season starts on February 28th and ends on September 29th of each year. With the exception of Flats, the series of all the other footwear present a strong seasonal pattern and are obviously non-stationary. The Boots series remains almost constant in the first two seasons, decreases slightly in 2009-2010, then recovers in 2010-2011 and finally decreases again in 2011-2012. The Booties series also remains fairly constant in the first two seasons and then maintains an upward trend movement in the next three seasons. The Flats series seems more volatile than the other series and the seasonal fluctuations are not so visible. In 2007 the sales are clearly higher than the rest of the years. An exceptional increase of sales is observed in March and April of 2012. The Sandals series increases in 2008 remaining almost constant in the next season, then increases again in 2010 remaining almost constant in the last season. The Shoes series presents an upward trend in the first two years and then reverses to a downward movement in the last three years. The seasonal behavior of this series shows more variation than the seasonal behavior of the other series. In general there is a small variation in the variance with the level, and so it may be necessary to make a logarithmic transformation to stabilize the variance. In each case, the in-sample period for model fitting and selection was specified from January 2007 to October 2011 (first

58 observations), while the out-of-sample period for forecast evaluation was specified from November 2011 to April 2012 (last 6 observations). The last 6 observations of in-sample data (May-October 2011) were used as the validation and testing sample and the rest of observations were used for model estimation (January 2007 to April 2011). The model with the best performance in the testing sample was selected as the final model for further evaluation in the out-of-sample.

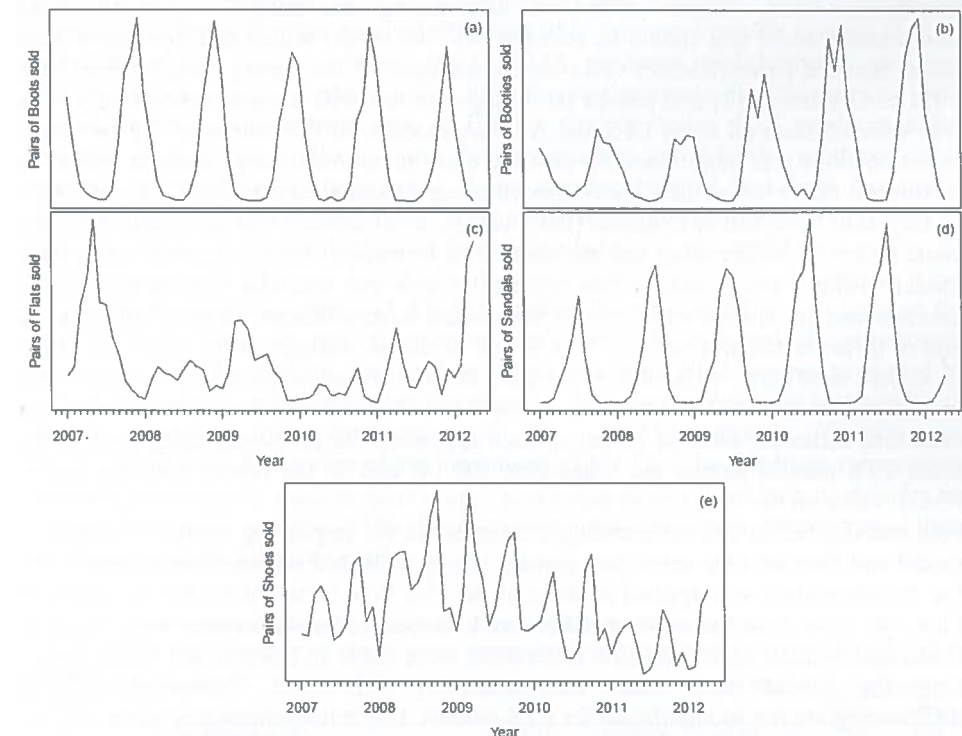


Figure 1. Monthly sales of the five footwear categories between January 2007 and April 2012.

3. Empirical study

To find appropriate ETS and ARIMA models for a time series is not an easy task. Both forecast methodologies are subjective and usually difficult to apply [5]. The challenge was to specify a procedure to automatically identify an appropriate ETS and an appropriate ARIMA model for a time series. We started by calculating the sample ACF and the sample PACF for the five time series (not shown). In general the sample ACFs decayed very slowly at regular lags and at multiples of seasonal period 12 and the sample PACFs had a large spike at lag 1 and cut off to zero after lag 2 or 3. This suggested a monthly seasonal difference and, if necessary, regular differences to achieve stationarity. To be fair and to be able to compare more accurately the forecasting performance of both modeling approaches, for each time series all possible ETS models and all ARIMA $(p,d,q) \times (P,D,Q)_m$ models where p and q could take

values from 0 to 5 and P and Q could take values from 0 to 2 were fitted using the training set from January 2007 to April 2011. Twelve types of data were considered on both cases: raw data ($d = D = 0$), first differenced data ($d = 1, D = 0$), second differenced data ($d = 2, D = 0$), seasonally differenced data ($d = 0, D = 1$), first and seasonally differenced data ($d = D = 1$), second and seasonally differenced data ($d = 2, D = 1$); the same orders of differencing were also applied to logarithm transformed data. Higher orders of differencing are unlikely to make much interpretable sense and should be avoided [4]. The model which had the lowest Root Mean Squared Error (RMSE) value on the forecasts of the testing sample (from May 2011 to October 2011) and passed the Ljung-Box test with a significance level of 5% was selected from all fitted ETS and ARIMA models. RMSE was used for the model selection since it is more sensitive than the other measures to large error. It should be mentioned that when models are compared using Akaike's Information Criterion (AIC) or Bayesian Information Criterion (BIC) values, it is essential that all models have the same orders of differencing and the same transformation. However, when comparing models using a testing set, it does not matter how the forecasts were produced, the comparisons are always valid even if the models have different orders of differencing and/or different transformations. This is one of the advantages of the cross-validation procedure used here – to be able to compare the forecasting performance of models that have different orders of differencing and/or different transformations. Table 1 gives for each time series the selected model on each approach. For the Shoes series none of the fitted ETS models passed the Ljung-Box test [4] and so the model with the lowest RMSE value on the forecasts of the testing sample was selected. It can be observed that both transformation and differencing are important for improving ARIMA's ability to model and forecast time series that contain strong trend and seasonal components. The log transformation was applied to three of the five time series. With the exception of Flats, all other time series were differenced: second-order differences were made in Boots and Sandals series and first differences were made in Booties and Shoes series. Only the Sandals time series was seasonally differenced. Transformation and differencing are not so significant for ETS models. Log transformation is made only on Boots series and none of the series is differenced. After identifying appropriate ETS and ARIMA models, it is reasonable to compare the forecasting accuracy of both approaches. Then, for each time series, both selected models were re-estimated using the in-sample data (January 2007 to October 2011) and then used to forecast on the out-of-sample period (from November 2011 to April 2012). The results of the forecast error measures (Root Mean Squared Error - RMSE, Mean Absolute Error - MAE, Mean Absolute Percentage Error - MAPE define in [6]) for this period are presented in Table 1. The results show that the overall out-of-sample forecasting performance of ARIMA models evaluated via RMSE, MAE and MAPE is better than ETS models. For Boots time series, the RMSE, MAE and MAPE are respectively 73%, 80% and 44% smaller. For Booties time series, the RMSE, MAE and MAPE are respectively 55%, 43% and 56% smaller. For Flats time series, the MAE and MAPE are respectively 2% and 7% smaller. The RMSE value of the ETS model is smaller than the RMSE value of the ARIMA model but only by 4%. For Sandals time series, the RMSE, MAE and MAPE are respectively 39%, 33% and 90% smaller. For Shoes time series, the RMSE and MAE are respectively 38% and 19% smaller. The MAPE value of ETS model is smaller than the MAPE value of ARIMA model but only by 11%. Another observation from Table 1 is that judging from MAPE, which does not vary with the magnitude of

the actual values of the time series, both the ARIMA and ETS models forecast Shoes series more accurately than the other time series (23.87% vs. 26.35%, 33.75%, 51.25%, 101.01% and 21.15% vs. 46.98%, 77.20%, 55.22%, 1013.69%) despite the variation present in its seasonal behavior. It is also interesting to observe that although the ETS model selected for the Shoes series have failed the Ljung-Box test, it gave better results than the ARIMA model in terms of MAPE (21.15% vs. 23.87%), which reinforces the robustness of our rule for model selection. The performance of both forecasting methodologies in producing forecast intervals was also evaluated. Table 1 shows the percentage of times that the nominal 80% and 95% forecast intervals contain the true observations. The results indicate that ARIMA produces slightly better coverage probabilities than ETS for the nominal 95% forecast intervals. For the nominal 80% forecast intervals, the performance of ETS is slightly better. ETS produces better coverage probabilities in Booties and Flats time series and ARIMA produces better coverage probabilities in Shoes series. It can also be observed that these forecasting methods slightly underestimate the coverage probabilities for the nominal 80% forecast intervals. To see the individual point forecasting behavior, the actual data versus the forecasts from both ETS and ARIMA models were plotted (Figure 2). In general, it can be seen that both state space and ARIMA models have the capability to forecast the trend movement and seasonal fluctuations fairly well. As expected, the exceptional increase in the sales of Flats observed in March and April 2012 was not predicted by both models which under-forecasted the situation. This fact explains the larger value of MAPE especially in the case of the ARIMA model (51.24% vs. 26.35%/33.75%/23.87%). One of the limitations of MAPE is having huge values when data may contain very small numbers. The large value of MAPE of both models for the Sandals time series is explained by this fact since during the out-of-sample period there are almost no sales (close to zero).

Table 1. Out-of-sample comparison between state space models and ARIMA models.

Time series	Model	RMSE	MAE	MAPE	Nominal coverage	
					80%	95%
Boots	Log ETS(A,A,A)	3077.71	2267.08	46.98	100	100
	Log ARIMA (2, 2, 5) \times (0, 0, 2) ₁₂	828.13	449.01	26.35	100	100
Booties	ETS(M,M,M)	954.10	654.59	77.20	83	100
	ARIMA (4, 1, 2) \times (0, 0, 1) ₁₂	429.19	371.44	33.75	67	100
Flats	ETS(A,A,A)	1194.47	881.57	55.22	67	67
	Log ARIMA (4, 0, 2) \times (0, 0, 1) ₁₂	1244.01	861.65	51.25	33	100
Sandals	ETS(M,N,M)	2832.59	1415.86	1013.69	83	100
	ARIMA (3, 2, 3) \times (0, 1, 0) ₁₂	1728.71	945.07	101.01	83	100
Shoes	ETS(M,A,M)	1279.73	878.08	21.15	50	67
	Log ARIMA (5, 1, 3) \times (0, 0, 0) ₁₂	791.62	712.53	23.87	67	100

4. Conclusions

In this work, a cross-validation procedure is used to automatically identify an appropriate ARIMA model and an appropriate ETS model for a time series. The modeling results indicate that both transformation and differencing are important for improving ARIMA's ability to model and forecast time series that contain strong trend and seasonal components. The out-of-sample forecasting results show that the overall

performance of ARIMA models evaluated via RMSE, MAE and MAPE is slightly better than state space models. The improvements in RMSE found were between 38% and 73%; in MAE were between 2% and 80%; and in MAPE were between 7% and 90%.

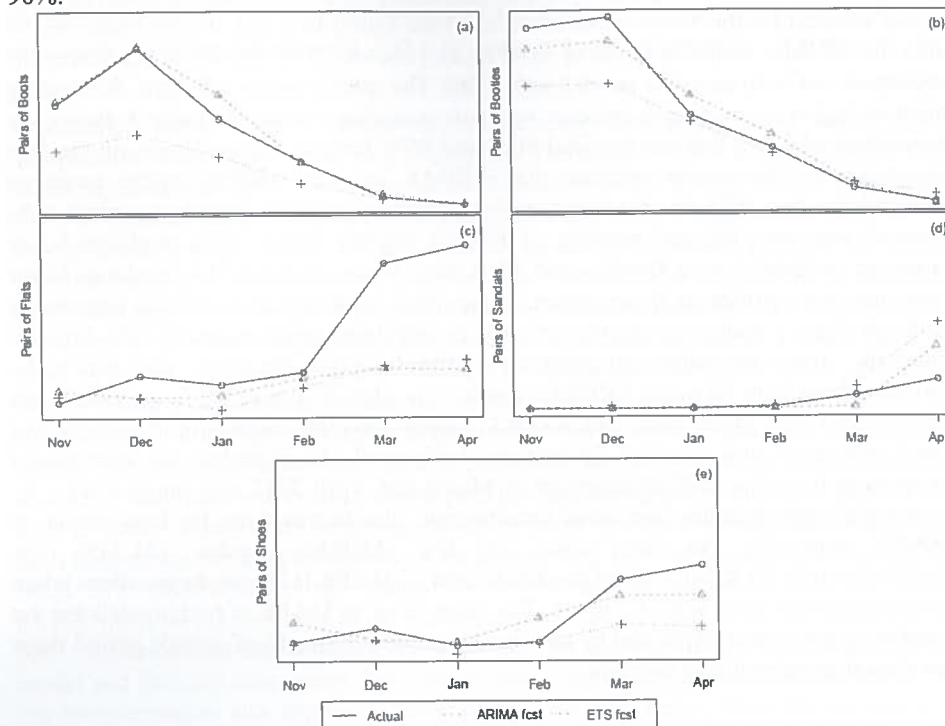


Figure 2. Out-of-sample forecasting comparison for the five footwear categories.

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Part 13

Lean and Quality Management