

## Research Article

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Dejan Mircetic\*, Svetlana Nikolicic, Marinko Maslaric, Nebojsa Ralevic, and Borna Debelic

# Development of S-ARIMA Model for Forecasting Demand in a Beverage Supply Chain

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**Abstract:** Demand forecasting is one of the key activities in planning the freight flows in supply chains, and accordingly it is essential for planning and scheduling of logistic activities within observed supply chain. Accurate demand forecasting models directly influence the decrease of logistics costs, since they provide an assessment of customer demand. Customer demand is a key component for planning all logistic processes in supply chain, and therefore determining levels of customer demand is of great interest for supply chain managers. In this paper we deal with exactly this kind of problem, and we develop the seasonal Autoregressive Integrated Moving Average (S-ARIMA) model for forecasting demand patterns of a major product of an observed beverage company. The model is easy to understand, flexible to use and appropriate for assisting the expert in decision making process about consumer demand in particular periods.

**Keywords:** consumer demand; time series; S-ARIMA

## 1 Introduction

Forecasting is the art and science of making projections about what future demand and conditions will be [1]. Demand forecasting is one of the key activities in planning the freight flows in supply chains, and accordingly it is es-

sential for planning and scheduling of logistic activities within observed supply chain. Demand forecasts form the basis of all supply chain planning [1]. Accurate demand forecasting models directly influence and can significantly decrease logistics costs, since they provide assessment of customer demand. Companies often use forecasts both on a tactical level to schedule production and on a strategic level to determine whether to build new plants or even whether to enter a new market [1–4].

In this paper we dealt with forecasting the demand for beverage products. First studies in the field started in 50s and 60s years of the last century in the United States. Among several, the paper by Hogarty and Elzinga [5] is interesting to study, since they dealt with the question of income influence on beverage consumption. Also, for forecasting beverage demand they proposed using ordinary least squares model, with the variables transformed in a logarithmic form. How economic conditions affect alcohol consumption is still a matter of debate [6]. Brenner and Mooney [7] produced evidence that a host of self and other destructive activities, including alcohol abuse and drunk driving, increased during periods of unemployment. Freeman [8] used monthly shipments data in the U.S. from 1955 through 1994 in an error-correction framework to test for the short-run response to economic factors such as unemployment, industrial production, and personal income. Although there does appear to be a long-run relationship between beer consumption levels and the economic variables, Freeman finds no evidence of short-run cyclical response of beer to economic variables.

In this paper we tried to extract the demand patterns, and extrapolate it to the future, using seasonal Autoregressive Integrated Moving Average (S-ARIMA). The remaining of the paper is organized as follows. Section 2 describes the data, with its seasonal, cyclical and trend components. In Section 3 the methodology steps for building forecasting models are presented. Section 4 describes how the models were created and evaluated. In last two Sections we discuss our findings and conclude paper with future research directions.


**\*Corresponding Author: Dejan Mircetic:** University of Novi Sad, Faculty of Technical Science/Traffic Department, Novi Sad, Serbia; Email: Dejan.Mircetic@uns.ac.rs

**Svetlana Nikolicic:** University of Novi Sad, Faculty of Technical Science/Traffic Department, Novi Sad, Serbia; Email: cecan@uns.ac.rs

**Marinko Maslaric:** University of Novi Sad, Faculty of Technical Science/Traffic Department, Novi Sad, Serbia; Email: marinko@uns.ac.rs

**Nebojsa Ralevic:** University of Novi Sad, Faculty of Technical Science/Traffic Department, Novi Sad, Serbia; Email: nravic@uns.ac.rs

**Borna Debelic:** University of Rijeka, Faculty of Maritime Studies, Rijeka, Croatia; Email: debelic@pfri.hr

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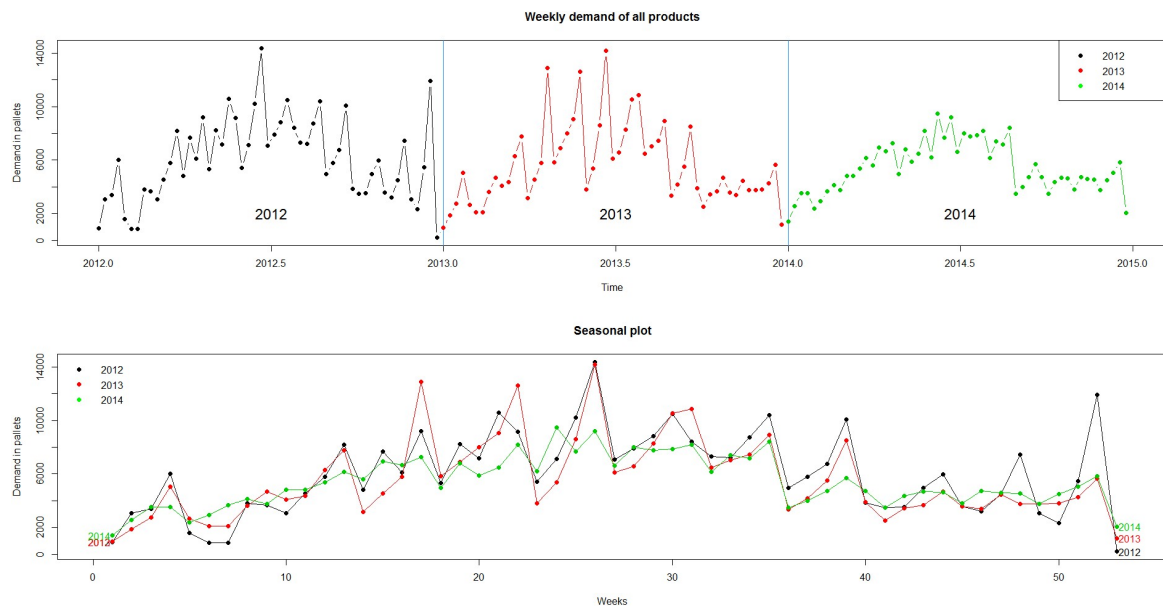


Figure 1: Weekly demand of beverage products [9].

## 2 Data description

Consumption data of all beverage products from observed company is represented in the form of weekly demand for the period from January of 2012 to the December of 2014 (Figure 1). Data is represented as weekly demand, since this the period in which the supply of final points of sale is performed. Therefore, management of the company is interested in forecasting weekly beverage consumption in the market.

From the Figure 1, it is evident that demand data is represented in a form of univariate time series. Also, data is seasonal, with cyclic period of one year and downturn of trend in the last year. In 2014, demand for beverage products was significantly lower than in previous years, and possible reasons for that will be discussed in the last two sections of the paper.

Using seasonal trend decomposition (STL) methodology presented in [10], a decomposition of the beverage time series is performed (Figure 2). Observed time series have an additive nature, i.e. fluctuations around the trend cycle curve do not have a notable increase with increasing the time scale in series. Therefore, raw time series did not require the Box-Cox transformations. Decomposition revealed that the seasonal component is dominant in observed series, with high fluctuations within a one year period. Bearing in mind that we do not have many years of observations, it is hard to conclude business cycle. Decomposition also revealed that the series trend is small, with a decreasing pattern from the middle of 2013.

## 3 Methodology

Obtaining forecasting information frequently means using sophisticated techniques to estimate future sales or market conditions [1]. Due to the data structure, which has seasonal, cyclic and trend components S-ARIMA model is used for fitting given data and forecasting captured patterns into the future. S-ARIMA is regarded as one of the best models for forecasting complicated seasonal time series, and it represents the combination of differencing with autoregression and a moving average model. On the other side, S-ARIMA extends the ARIMA concept, and allows application of the ARIMA concept on the problems of forecasting the time series with seasonal patterns. The seasonal ARIMA  $(p, d, q)(P, D, Q)_m$  process is given by:

$$\Phi(B^m)\varphi(B)(1-B^m)^D(1-B)^d y_t = c + \Theta(B^m)\theta(B)\varepsilon_t, \quad (1)$$

where  $\Phi(z)$  and  $\Theta(z)$  are polynomials of order  $P$  and  $Q$  respectively, each containing no roots inside the unit circle.  $B$  is the backshift operator used for describing the process of differencing, i.e.  $By_t = y_t - 1$ . If  $c \neq 0$ , there is an implied polynomial of order  $d + D$  in the forecast function. A common obstacle for many people in using ARIMA models for forecasting is that the order selection process is usually considered subjective and difficult to apply [11]. Key question in using S-ARIMA model is selection of an appropriate model order, that is the values  $p, q, P, Q, D, d$ . If  $d$  and  $D$  are known, we can select the orders  $p, q, P$  and  $Q$  via an information criterion such as the Akaike information cri-

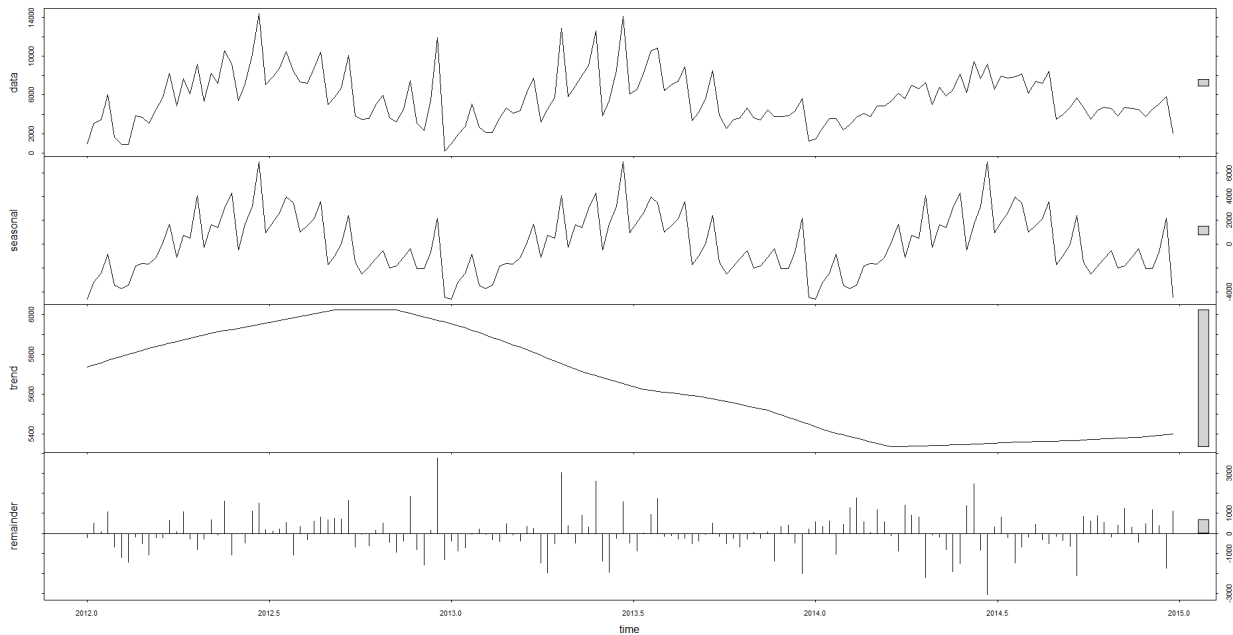


Figure 2: STL decomposition of the beverage time series.

Table 1: Comparative review of the different S-ARIMA models.

Models <sup>a</sup>	RMSE	MAPE	MASE	AIC	BIC
S-ARIMA (5, 0, 1)(1, 0, 0) <sub>52</sub> <sup>b</sup>	1023	14.18%	0.60%	86.62	110.5
S-ARIMA (4, 0, 0)(1, 0, 0) <sub>52</sub> <sup>c</sup>	1041	14.53%	0.62%	86.73	105.31
S-ARIMA (4, 0, 0)(0, 1, 1) <sub>52</sub> <sup>d</sup>	1882	22.12%	1.05%	41.74	53.56
S-ARIMA (4, 0, 1)(1, 0, 0) <sub>52</sub> <sup>e</sup>	1050	14.18%	0.60%	88.23	109.47
S-ARIMA (0, 0, 1)(0, 1, 0) <sub>52</sub> <sup>f</sup>	1797	21.42%	1.02%	36.52	40.46

<sup>a</sup> The model errors are calculated from the test data set.

<sup>b</sup> Details about S-ARIMA (5, 0, 1)(1, 0, 0)<sub>52</sub> model are given in 3.

<sup>c</sup>  $(1 - 0.39B + 0.06B^2 + 0.04B^3 - 0.46B^4)(1 - 0.65B^{52})y_t = 8.52$ .

<sup>d</sup>  $(1 - 0.29B + 0.19B^2 - 0.05B^3 - 0.19B^4)(1 - B^{52})y_t = (1 + 0.12B^{52})e_t$ .

<sup>e</sup>  $(1 - 0.29B + 0.01B^2 + 0.05B^3 - 0.48B^4)(1 - 0.65B^{52})y_t = 8.52 + (1 + 0.13B)e_t$ .

<sup>f</sup>  $(1 - B^{52})y_t = (1 + 0.3B)e_t$ .

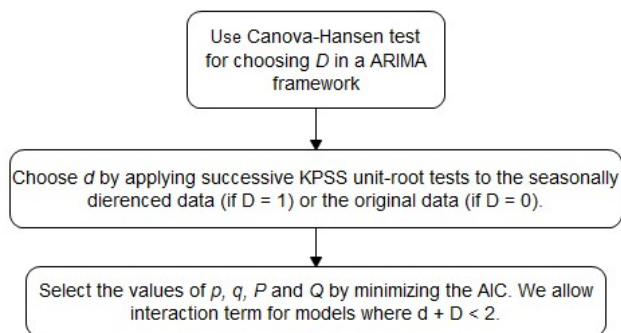


Figure 3: Algorithm for selecting the terms in S-ARIMA [11].

terion (AIC) or Bayesian information criterion (BIC):

$$AIC = -2 \log(L) + 2(p + q + P + Q + k); \quad (2)$$

$$BIC = N \log \left( \frac{SSE}{N} \right) + (k + 2) \log(N),$$

where  $k = 1$  if  $c \neq 0$  and 0 otherwise, and  $L$  is the maximized likelihood of the model fitted to the differenced data  $(1 - B^m)^D(1 - B)^d y_t$ . SSE is sum of squared errors.  $N$  is the number of observations used for estimation and  $k$  is the number of predictors in the model. For that purpose we used the algorithm briefly described in Figure 3.

## 4 Model building and evaluation

Following the steps in the proposed algorithm, as the model with smallest errors, S-ARIMA (5, 0, 1)(1, 0, 0)<sub>52</sub> emerged. The proposed S-ARIMA is defined as:

$$(1 - \varphi_1 B - \varphi_2 B - \varphi_3 B - \varphi_4 B - \varphi_5 B) (1 - \Phi_1 B^{52}) y_t \quad (3) \\ = c + (1 + \theta_1 B) e_t,$$

where  $\varphi_1 = -0.5421$ ,  $\varphi_2 = 0.2962$ ,  $\varphi_3 = -0.099$ ,  $\varphi_4 = 0.3974$ ,  $\varphi_5 = 0.4994$ ,  $\Phi_1 = 0.9558$ ,  $c = 8.523$ ,  $\theta_1 = 0.6345$ . In order to validate the proposed model, and determine whether it is the best model for a given beverage demand forecasting, we created several others, following the logic of a general forecasting process using ARIMA, given in Figure 4.

For evaluating the created models we used the root mean square error (RMSE), mean absolute percentage error (MAPE), mean absolute scaled error (MASE), AIC and BIC, as seen in Equations 2 and 4.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N e_i^2}; \quad MAPE = \frac{1}{N} \sum_{i=1}^N |e_i|; \quad (4) \\ MASE = \frac{1}{N} \sum_{i=1}^N |q_i|$$

where  $e_i$  are residuals and  $q_j = \frac{e_j}{\frac{1}{T-m} \sum_{t=m+1}^T |y_t - y_{t-m}|}$ .

A comparison of the different models is shown in Table 1.

From the Table 1 it is clear that S-ARIMA (5, 0, 1)(1, 0, 0)<sub>52</sub> outperformed its competing models, since it achieved the lowest RMSE, MAPE and MASE error. Similar results were achieved by S-ARIMA (4, 0, 0)(1, 0, 0)<sub>52</sub> and S-ARIMA (4, 0, 1)(1, 0, 0)<sub>52</sub>. The evaluation results in some way underline the initial questions and concerns regarding which terms to include in S-ARIMA model. Evaluation showed that model structures which include autoregressive ( $p$ ,  $P$ ) and moving average part ( $q$ ,  $Q$ ) are more successful in forecasting given beverage consumption, than models that include seasonal or non-seasonal differencing. The comparative model review has also shown some surprising results, *i.e.* models that include seasonal differencing (S-ARIMA (4, 0, 0)(0, 1, 1)<sub>52</sub> and S-ARIMA (0, 0, 1)(0, 1, 0)<sub>52</sub>), have worse forecasting accuracy than the simple average naive forecast model, since their MASE errors are greater than one.

The residuals test for S-ARIMA (5, 0, 1)(1, 0, 0)<sub>52</sub> showed that the model residuals can be regarded as “white noise”, given that they have a stationary shape,

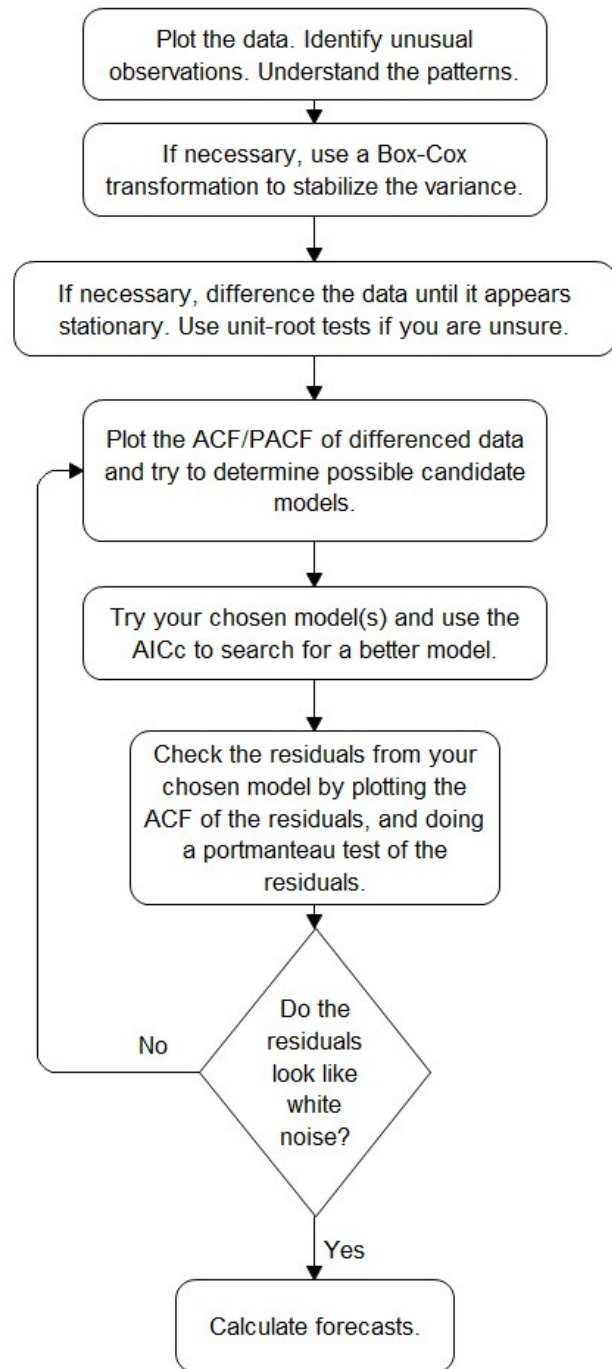


Figure 4: General process of forecasting using ARIMA models [12].

and the ACF/PACF plot doesn't have any significant Lag terms (Figure 5). These observations indicate that S-ARIMA (5, 0, 1)(1, 0, 0)<sub>52</sub> captured all the available information regarding behavioral patterns of a given beverage time series. Therefore, it can be efficiently used for future forecasting.

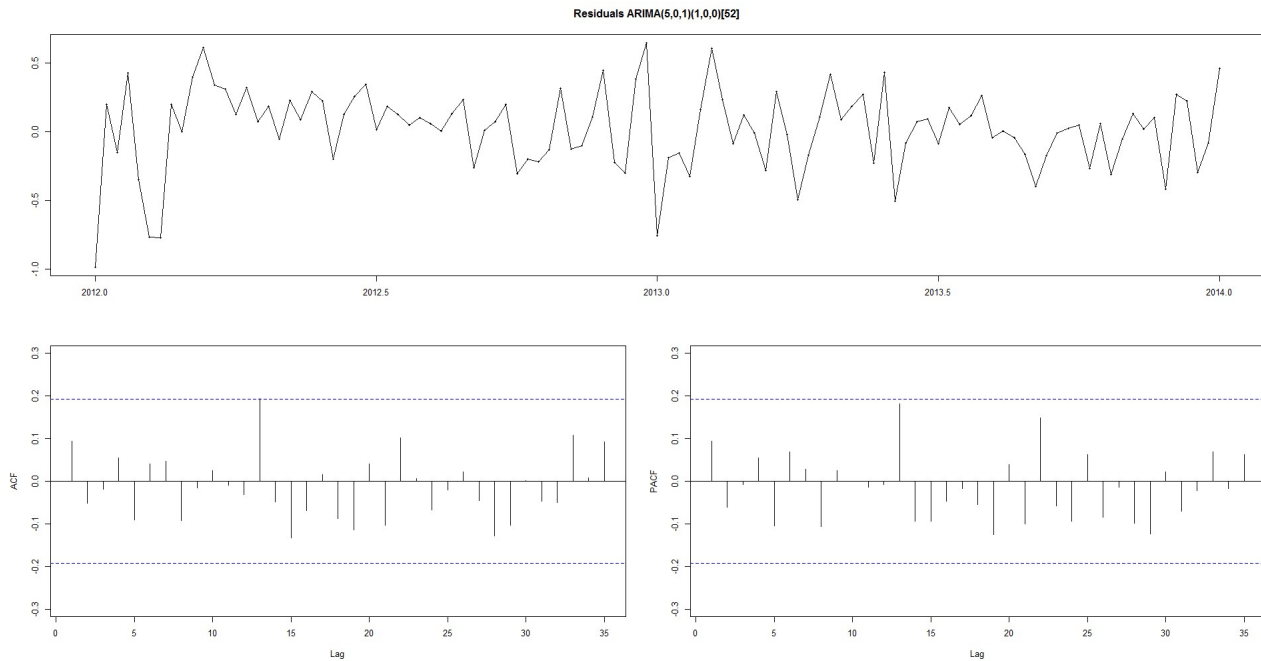


Figure 5: Residuals of S-ARIMA (5, 0, 1)(1, 0, 0)<sub>52</sub>.

## 5 Conclusion

In this paper we created several forecasting models for beverage consumption, for one of the market leaders in a region of South-East Europe. The models were tested and mutually compared (Table 1). As the best forecasting model on a weekly level, S-ARIMA (5, 0, 1)(1, 0, 0)<sub>52</sub> emerged. During the research, we have also discovered that S-ARIMA models that include seasonal components are worse than the simple average naive forecast model, which are regarded as one of the basic and simplest models in literature. This result should be tested on other beverage companies within the region, in order to determine if this result is coincidence and whether there is something that only relates on an observed company, or could it be extrapolated as a general rule for an observed industry.

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