

Examination of industry production index in Turkey with time series method

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Abstract

In this paper, the time series analysis is conducted to the monthly industrial production index data calculated between 2005 and 2017 by TURKSTAT. The aim of the study is to define the industrial production index with the time series chart, to find the suitable time series model for the index and to forecast the future values of the index. For this purpose, we make the series stationary by taking both the first difference and the second seasonal difference of the series to perform the Box-Jenkins models. As a result of the analysis, SARIMA(1,1,1)(3,2,0)₁₂ model is determined as the most suitable model for the series. Using this model, the forecast values for the months of 2018 of the index series are calculated.

Keywords: Time series, industrial production index, ARIMA method.

Türkiye’de sanayi üretim endeksinin zaman serileri yöntemi ile incelenmesi

Özet

Bu çalışmada, TÜİK tarafından 2005-2017 yılları arasında hesaplanan aylık sanayi üretim endeksi verilerine zaman serisi analizi uygulanmıştır. Çalışmanın amacı, sanayi üretim endeksinin zaman serileri grafiği ile tanımlamak, endekse uygun zaman serisi modelini bulmak ve endeksin gelecek değerlerini tahmin etmektir. Bu amaçla, Box-Jenkins modellerinin uygulanabilmesi için serinin 1. dereceden fark ve 2. dereceden mevsimsel farkı alınarak seri durağan hale gelmiştir. Yapılan analizler sonucunda seriye en uygun model olarak SARIMA(1,1,1)(3,2,0)₁₂ modeli belirlenmiştir. Bu model kullanılarak endeks serisinin 2018 yılı için aylık öngörü değerleri hesaplanmıştır.

Anahtar kelimeler: Zaman serileri, sanayi üretim endeksi, ARIMA yöntemi.

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1. Introduction

The economic data are needed to see the short-term changes in the industry sector. Particularly, industrial countries form the industrial production index (IPI) in order to evaluate these changes correctly. In this way, the index becomes the most observed index by economists. In Turkey, this index value is obtained from the manufacturing industry trend survey, which is organized by TURKSTAT [1].

Industrialization is seen as the greatest support for the development of the countries. For this reason, one of the most important variables of policymakers is IPI and there are many studies on IPI in the literature. In the study of Moody et al. [2], authors have fitted industrial production forecasts with the help of two-layer neural network regression models. Marchetti and Parigi [3] have compared energy consumptions, survey data and industrial production forecasts to combine them with different models. Hassani et al. [4] have examined the industrial production of European countries with time series methods, such as the singular spectrum analysis, the ARIMA and the Holt-Winters. Manzur [5] has considered the density forecast performance of Dynamic Conditional Score models for the Polish industrial production. Ulbrich et al. [6] have made predictions of German industrial production using the media data.

In this paper, we study the forecasting short-term changes on the IPI by developing the most suitable version of seasonal ARIMA model for Turkey. Since the information of the IPI is influenced by economic policy decisions, the forecasting values might be very helpful for the policymakers.

2. Methods

The time-related observations are obtained in many areas such as business, agriculture, meteorology, biological sciences and ecology. The Time Series Analysis for examining these data is a highly preferred method. The main purpose of the analysis is to understand or model the series and to make a forecast based on past observations of the series. One of the basic methods in the Time Series Analysis is ARIMA. Although the ARIMA method was first used by Box and Jenkins in 1970 [7], it still maintains its importance today [8]. The studies of Bodo et al. [9], Bulligan et al. [10], Zhigljavsky et al. [11], Cekim et al. [12] and Guarnaccia et al. [13] have used the ARIMA method for modeling the series in various areas.

ARIMA model, which is a univariate forecasting method, is a process for calculating forecasts from past and present observation values. Indeed, it may augment forecasts by finding a suitable model for given data. Reliable forecasting depends on determining a fit model and thus ARIMA model includes a repeated process of formulating, fitting, checking, and if it is essential adjusting [14].

In order to be able to analyze with ARIMA method, the following assumptions are required:

i) The series must be stationary, i.e. the series must be the seasonal and trend waves should be adjusted,

- ii) The coefficients of the selected appropriate model should be statistically significant,
- iii) There should be no relationship between the errors of the forecast series, i.e the error series of the forecast model should be a white noise series [15]. In this study, we have examined in practice whether the assumptions are provided.

The ARIMA models are divided into two groups as the seasonal and non-seasonal models. If the series has only the trend, then it becomes stationary by taking the difference of the series and the non-seasonal ARIMA model is used. The general equation of the $ARIMA(p, d, q)$ model is given by

$$\lambda(B)(1-B)^d Y_t = \psi(B)\varepsilon_t, \tag{2.1}$$

where $\lambda(B) = 1 - \lambda_1 B - \lambda_2 B^2 - \dots - \lambda_p B^p$, $\psi(B) = 1 - \psi_1 B - \psi_2 B^2 - \dots - \psi_q B^q$,

Y_t is the time series, d is the number of difference to make the series stationary, ε_t is the error term and B is the backshift operator as $B^i Y_t = Y_{t-i}$.

If the series has both the trend and the seasonality, then it becomes stationary by taking both the difference and the seasonal difference of the series and in this case, the seasonal ARIMA model (also called the SARIMA) is used. The general equation of the $SARIMA(p, d, q)(P, D, Q)_s$ model is given by

$$\lambda(B)\Lambda(B)(1-B)^d (1-B^s)^D Y_t = \psi(B)\Psi(B)\varepsilon_t \tag{2.2}$$

where $\Lambda(B) = 1 - \Lambda_1 B^{12} - \Lambda_2 B^{24} - \dots - \Lambda_p B^{ps}$, $\Psi(B) = 1 - \Psi_1 B^{12} - \Psi_2 B^{24} - \dots - \Psi_q B^{qs}$, s is the period and D is the number of seasonal difference to make the series stationary.

3. Results

Today, we can reach the best ARIMA model or Exponential Smoothing Method by computer programs without knowing the theoretical knowledge in detail. However, these programs do not analyze the error terms of the models in terms of statistical assumptions; whereas, we obtain the best forecasting model by considering the statistical assumptions for the models in this article. In this way, we find that the additive and multiplicative models of the Winters Exponential Smoothing Method for the IPI index series do not satisfy the statistical assumptions; therefore, their results are not included in the article. As a result, we apply a SARIMA model to forecast the IPI series in Turkey using the data from January 2005 to September 2017. We first examine the time series plot, the autocorrelation function (ACF) and the partial autocorrelation function (PACF) graphs to evaluate the presence of trend and seasonality in the series.

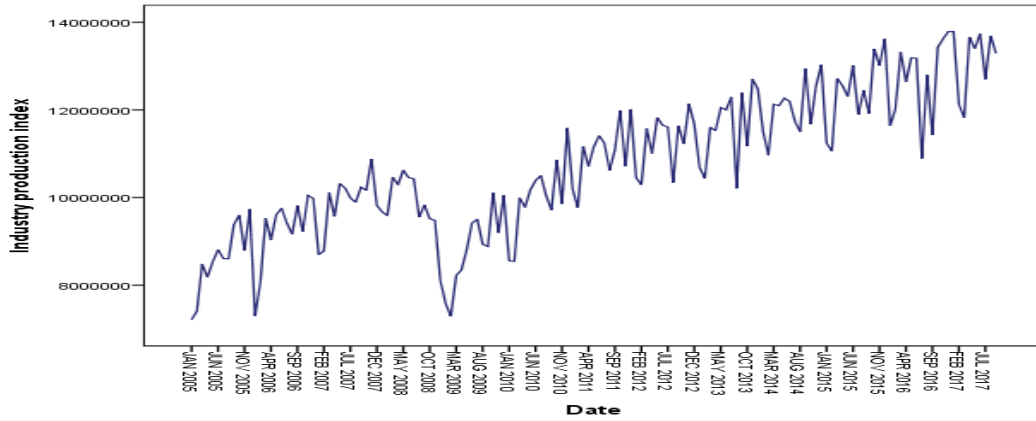


Figure 1. The Plot of Turkey Industry Production Index from 2005 to September 2017.

When the time series graph of the IPI in Figure 1 is analyzed, the index value in February 2009 takes place as an unexpected fall. It is clearly seen that the indicator steadily increases after March 2009. This increase could be regarded as the reason of the non-stationary series. The ACF and PACF charts should be consulted to arrive at an exact decision.

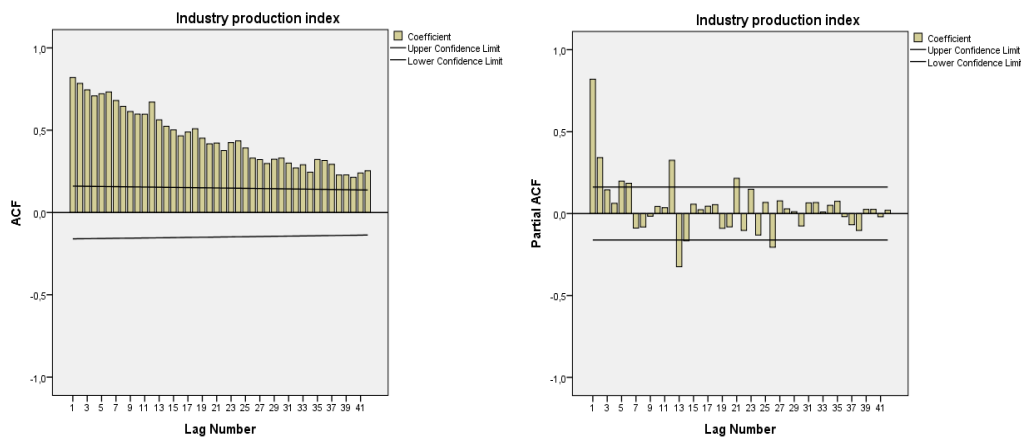


Figure 2. The ACF and PACF Graphs of the IPI.

Due to the ACF graph in Figure 2, IPI series has a trend and therefore it is non-stationary.

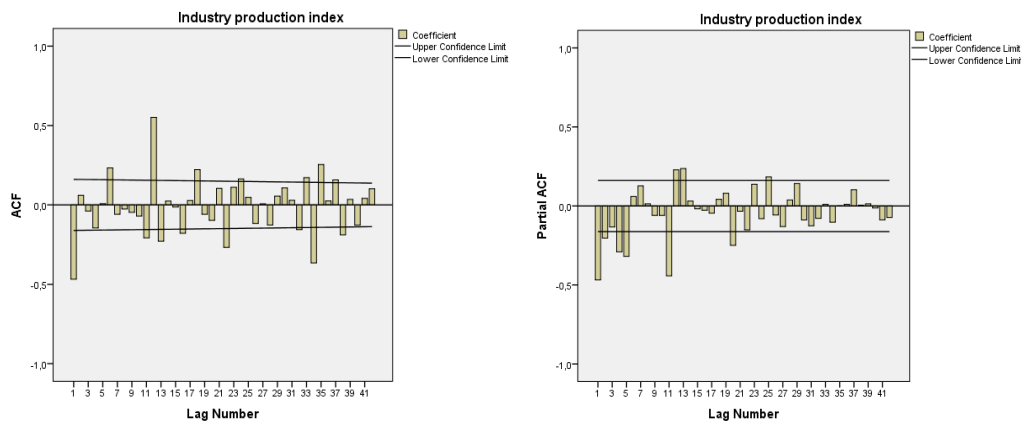


Figure 3. The ACF and PACF Graphs of the first differenced IPI.

After taking the first difference of the series, we observe from ACF graph in Figure 3 that there is a periodic movement and the period of the series is 12. After taking the first seasonal difference of the series, we see from ACF graph in Figure 4 that the series still has a periodic movement and therefore we take the second seasonal difference of the series whose ACF and PACF graphs are given in Figure 5. From ACF graph in Figure 5, it is clear that the series is stationary now.

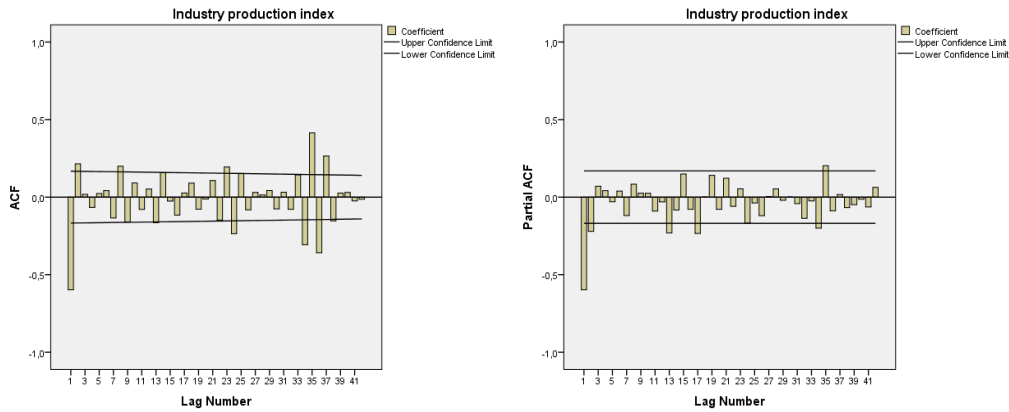


Figure 4. The ACF and PACF Graphs of the first differenced and first seasonal differenced IPI.

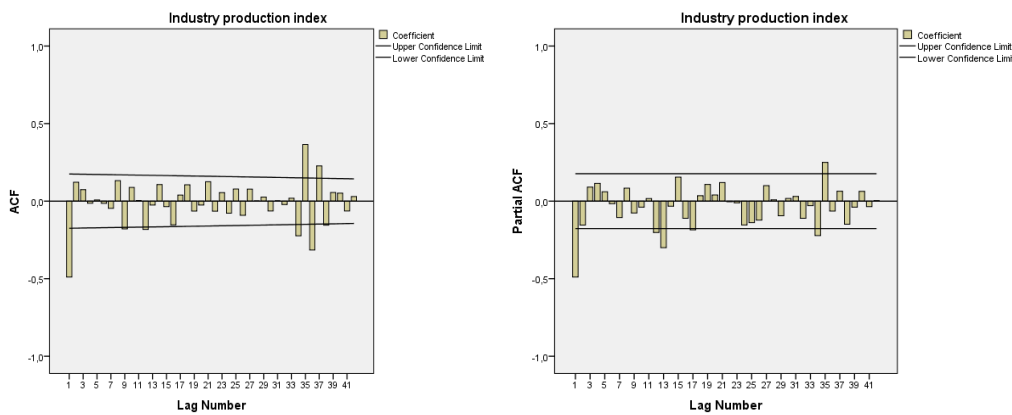


Figure 5. The ACF and PACF Graphs of the first differenced and second seasonal differenced IPI.

When we model the IPI series with the aid of ACF and PACF graphs in Figure 5, we can determine $p=1$, $q=1$ and from the number of differences, we can specify $d=1$, $D=2$ of $SARIMA(p,d,q)(P,D,Q)_s$. After trials of the models according to the significance of the parameters in Table 1 and the Schwarz Bayesian Criterion (BIC) value, we obtain the most suitable model as $SARIMA(1,1,1)(3,2,0)_{12}$ whose equation can be written as follows:

$$(1 - \phi_1 B)(1 - \Phi_1 B^{12} - \Phi_2 B^{24} - \Phi_3 B^{36})(1 - B)(1 - B^{12})^2 Z_t = (1 - \theta_1 B) \varepsilon_t,$$

and

$$(1 + 0.519B)(1 + 0.861B^{12} + 0.726B^{24} + 0.491B^{36})(1 - B)(1 - B^{12})^2 Z_t = (1 - 0.269B) \varepsilon_t.$$

Table 1. The results of the SARIMA model parameters.

Parameters	Estimate	t value	Sig. value
AR(1)	-0.519	-4.494	0.000
MA(1)	0.269	2.100	0.038
SAR(1)	-0.861	-8.457	0.000
SAR(2)	-0.726	-6.240	0.000
SAR(3)	-0.491	-4.783	0.000

Figure 6 shows that there is no relationship, in other words, the error series of the model is a white noise series. Note that Box-Ljung test statistics for each lag are also considered and it is seen that there is no autocorrelation in the error series.

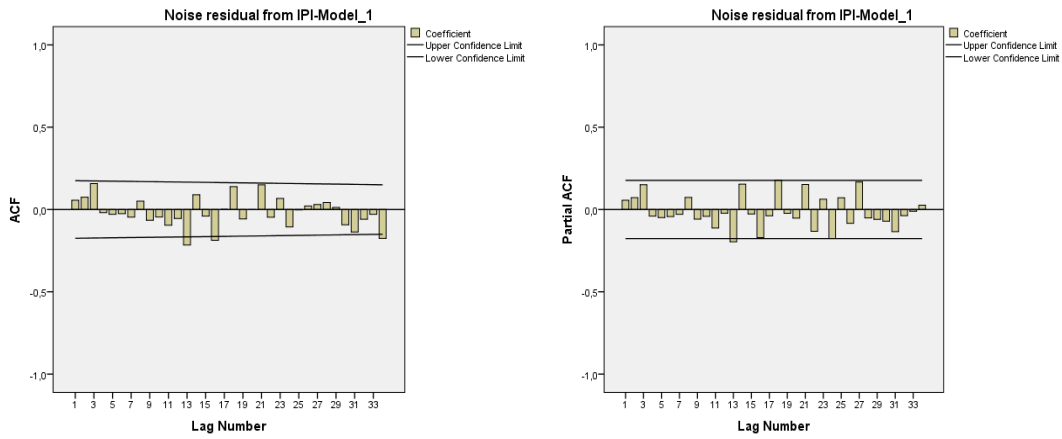


Figure 6. The ACF and PACF Graphs of the error series of the forecast model.

We compute forecasting values of the series with the help of this model until September 2018. These values are given in Table 2 and shown in Figure 7 at the end of line graph with green color.

Table 2. The forecast values of the IPI between October 2017 and September 2018.

Months	The forecast value	Months	The forecast value
October	14665347	April	15407635
November	15276343	May	14890460
December	15518960	June	15365682
January	15686268	July	13831933
February	13726200	August	15980045
March	13297013	September	14787171

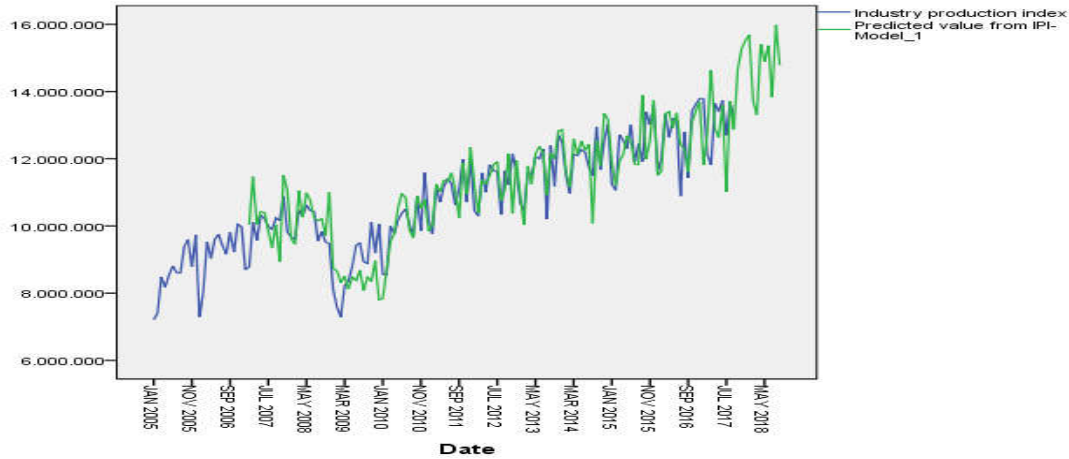


Figure 7. The graph of the IPI with the forecast values.

Furthermore, the time series graph of the IPI with confidence intervals obtained by using the mentioned model is shown in Figure 8.

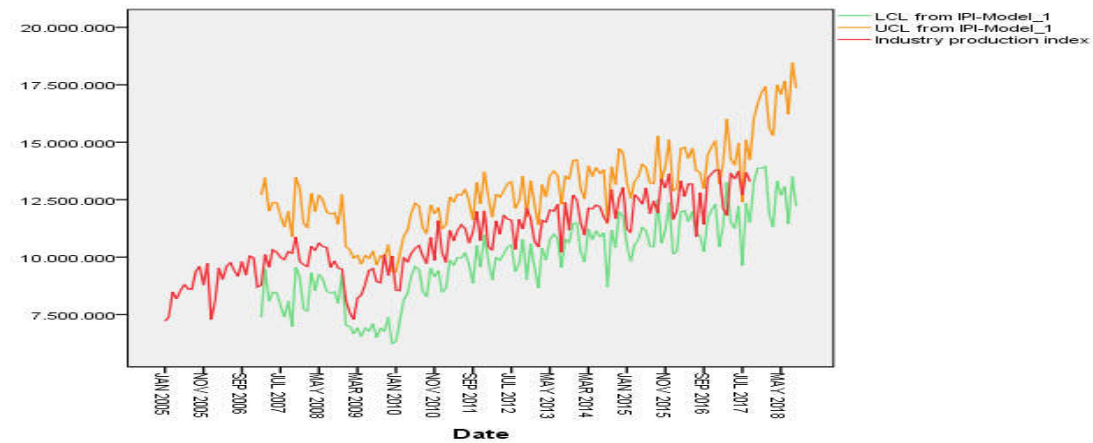


Figure 8. The graph of the IPI with confidence intervals.

4. Conclusion

The countries make plans for determining their policy according to the developments in the future. Thus, the politicians need the scientific reliable information of the related indicators in the country. Time Series Analysis is a suitable method that provides us to reach this information [16]. In this article, we forecast the monthly data of the IPI series that is one of the most important economic indicators in Turkey. The forecast values and the confidence intervals are calculated for last three months in 2017 and until September 2018, by using the model of $SARIMA(1,1,1)(3,2,0)_{12}$. Figure 7 shows a good fit between the original series and the forecast series. Since the original series remains in between the confidence intervals, as shown in Figure 8 and the error series of the model is a white noise series determined by performing Box-Ljung Test to each lag, we can infer that this model is a statistically suitable model for the series. According to this reliable model, as seen from Figure 7, the forecast values show that the IPI series will have continued to rise with fluctuations by the end of 2018.

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