Modeling and Forecasting CPI in Serbia Using the SARIMA Model

KATARINA NIKOLIĆ & DRAGANA RADOJIČIĆ

Abstract To develop the most appropriate economic strategies in a country, policymakers need to have a reliable forecast of the rate of inflation. This is achieved is by using the appropriate model that possesses high predictive accuracy. This paper analyzes the efficacy of Seasonal Autoregressive Integrated Moving Average (SARIMA) models to anticipate the CPI rates in Serbia. The model is developed using the monthly CPI (2010=100) in Serbia in the period 1995- first half of 2022 obtained from the International Monetary Fund. The paper aims to demonstrate the importance of modeling seasonal series, the structure of the SARIMA model, and possibilities of application in the field of economics, specifically related to the analysis of CPI, but also the importance of seasonal influences in general. The qualities, as well as shortcomings of the model, serve to provide breadth in the observation of economic phenomena.

Keywords: • time series modeling • seasonality • CPI • forecasting • SARIMA

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1 Introduction

Time series arise in a wide range of areas, from marketing to oceanography, and they apply to any variable that changes over time. Time series analysis often has two goals: to understand or model the stochastic mechanism that generates an observed series and to predict or forecast the future values of a series based on the performance of that series in the past, and potentially also of other related series or factors (Springer, 2008). Analyzing such a series may raise several problems of both a theoretical and practical nature (Chatfield, 2013).

A time series is defined as a set of quantitative observations arranged in chronological order (Kirchgässner et al., 2012). In economics, there are much different time series that can be observed, including such series as share prices on successive days, export totals in executive months, average incomes in successive months, company profits in successive years, etc. (Chatfield, 2013). Thus, studying the time series allows us to better understand the variations of variables over time, so they can be better described, interpreted, predicted, and controlled by the appropriate economic policies.

According to Webster's definition of inflation from 2000, inflation is an ongoing rise in consumer price levels or an ongoing loss of money's purchasing power. The Consumer Price Index measures the overall change in consumer prices based on a representative basket of goods and services over time. As such, it is important to analyze it and draw appropriate conclusions, to implement specific economic policies in the country. As a reasonably persistent process that inflation tends to be, current and historical values should be useful in predicting future inflation (Brent and Mehmet, 2010).

This paper consists of two parts, theoretical and practical. The theoretical part discusses time series components, SARIMA models, model layout, components, and characteristics. The practical chapter of the paper will work to use the appropriate modeling and apply it to the CPI in Serbia.

2 Literature Review

The ARIMA and regression with ARIMA errors were introduced (Mohamed, J,2020) to model CPI and forecast its future CPI values in Somaliland. In order to forecast Jordan's GDP and CPI for the 2020, 2021 and 2022, the Box-Jenkins model, was used (Ghazo A., 2021). After examining the consumer price index's movement between January 2010 and September 2020, inflation in the Ukraine was forecasted using ARIMA models (Shinkarenko V. et al, 2021). This approach yields an appropriate ARIMA model for forecasting Indonesia's CPI data (Ahmar A. S. et al., 2018).

3 Methodology

ARIMA is a Box-Jenkins method that breaks down time series data into the following categories: the Autoregressive (AR) process and Moving Average (MA) process. Denote by $\Delta_k X_t$ the difference operator of order k of time series $\{X_t\}_{t\in T}$, so for $k \in N$ we have $\Delta_k X_t = X_t - X_{t-k}$. Especially, within series with seasonality component is the most significant use of the seasonal difference, expressed as $\Delta_s X_t = X_t - X_{t-s} = (1\text{-}Ls)\ X_t$, where L is the delay operator (most often s=4 or s=12). The SARIMA model can be useful when time series data exhibit seasonality-periodic variations that repeat with roughly the same intensity regularly, such as quarterly (Martinez et al., 2011). Thus, the SARIMA model is suitable for research involving monthly inflation rate data and it will be used in this paper concerning inflation rates in Serbia.

3.1 SARIMA models

SARIMA is an extension of the ARIMA model, enabling additional modeling of seasonal time series components. SARIMA is an easy-to-use but effective model. It makes the supposition that current behavior is dictated by historical values. Additionally, it presumes that the data is steady and devoid of anomalies and that the model's parameters and error terms are constant. Though SARIMA does not account for the stresses in market data, economic and political conditions, or correlations of all risk factors to forecast inflation rates, the process can help predict inflation movements under normal circumstances where past behavior dictates present values (Shumway, 2000).

Multiple movements can be recognized in time series, which can be categorized into trends, seasonal variations, cyclical fluctuations, calendar variations, and irregular movements. Since data observations are collected periodically, the time variable is discrete in this case (Kirchgässner et al., 2012).

The trend represents the long-term trajectory of the time series, i.e. the general tendency of growth or decline. It is usually observed utilizing a graphical representation of a time series against the flow of time (Chatfield, 1995: 10). Calendar influence occurs due to calendar changes from year to year. The main reasons for this are the change in the number of working days and weekends in a month/quarter, the change in the number of each specific day in a month/quarter (trading days), leap years and "moving holidays", where certain holidays can fall on a different day every year.

Irregular movements represent factors that affect the movement of the time series, and cannot be predicted or controlled, such as strikes or the current covid-19 virus pandemic. It can occur in several forms:

- Structural break that occurs only in one period that can easily be observed on the chart,
- Lasting for several periods and then returning to the original trend,

- Completely changing the level of the series,
- Taking more values only in certain months/years and the like.

In the absence of structural breaks, the irregular component will be white noise, a set of normally distributed random variables with a constant variance that is uncorrelated.

Seasonal and cyclical variations belong to short-term movements. Cyclical, as opposed to seasonal, occurs over a period of more than a year, usually several years. They are also called business cycles. It represents dips and rises in movement, which are usually associated with phases in the economy (prosperity, recession, depression, recovery) and occur every few years. It is usually viewed in conjunction with the time series trend and together forms the trend-cyclical component.

The seasonal component represents regular and periodic movements of the time series within one calendar year. This means that every previous and following year we can observe a certain type of similarity in movement, usually over quarters or months. Additionally, the term "moving seasonality” marks the gradual seasonal changes over time.[2] In certain activities, the effect of seasonal fluctuations is much more pronounced than in others. The causes differ from social, religious, climatic, and such. For instance, the sale of certain kinds of products in our region increases during Easter and Christmas, in the winter months the electricity bills are higher, etc. The season period is denoted by s - the number of periods that pass until the cycle is repeated, which is 4 for the quarterly time series, while for the monthly time series it is 12.

The role of the SARIMA model is to describe the data movement of one variable in the most precise measure, to explain its movement in the past, as well as to successfully forecast the future. In practice, the largest number of time series is non-stationary, therefore the use of the mentioned model is extremely important.

The SARIMA model can be labeled *ARIMA(p, d, q)+(P, D, Q)s or ARIMA(p, d, q)x(P, D, Q)s*, which represents an additive and a multiplicative model respectively. They are used when there is stochastic seasonal variation. If it is about the deterministic nature of the season, it will be modeled simply by adding seasonal artificial variables. Therefore, if the movement of the season cannot be predicted, it will be considered stochastic and SARIMA models will be used. Even intuitively, it can be concluded that with the additive model, seasonal variations are added to the existing ones, while with the multiplicative model, the interactivity of variations and the inclusion of the product of standard and seasonal components are implied (Mladenović et al., 2012: 205). The multiplicative form of the SARIMA model can be represented as follows:

$$\phi_p(L)\Phi_P(L^S)\Delta^d \Delta D\ s\ X_t = \theta_q(L)\Theta_Q(L^S)e_t$$

where applicable,

$\phi_p(L) = 1 - \phi_1 L - \phi_2 L^2 - \phi_3 L^3 - \cdots - \phi_p L^p$
$\Phi P(L^S) = 1 - \Phi 1 L^S - \Phi 2 L^{2S} - \Phi 3 L^{3S} \ldots - \Phi P L^{PS}$
$\Theta_Q(L^S) = 1 - \Theta_1 L^S - \Theta_2 L^{2S} - \Theta_3 L^{3S} - \cdots - \Theta_Q L^{QS}$
$\theta_q(L) = 1 - \theta_1 L - \theta_2 L^2 - \theta_3 L^3 - \cdots - \theta_q L^q$
$\Delta^d \Delta D\ s\ \ X_t = (1 - L)^d (1 - L^S)^D X_t$

where X_t is the time series,
S period of the season,
$\Phi_1, \Phi_2, \ldots, \Phi_P$ parameters of the seasonal autoregression components of the series of order P,
$\phi_1, \phi_2, \ldots, \phi_p$ autoregression parameters of the series of order p,
$\theta_1, \theta_2, \ldots, \theta_q$ parameters of the component of moving average of order q,
$\Theta_1, \Theta_2, \ldots, \Theta_Q$ parameters of the seasonal component of moving averages of order Q,
d the level of integration of the series,
D the level of seasonal integration of the series.

3.2 Box-Jenkins modeling strategy

The Box-Jenkins approach consists of three steps:
1. model identification,
2. model parameter estimation, and
3. model adequacy verification.

Model identification involves the determination of several pieces of information. First, through the graphic representation of the series, it is observed whether there is a need to stabilize the variance of the time series.

Further, the degree of integration (*d*) and seasonal integration (*D*) of the series is determined, which can be done in several ways: analysis of the variance score, unit root tests, and analysis of the ordinary autocorrelation function score. Variance score analysis involves observing time series Xt, $(1\text{-}L)X_t$, $(1\text{-}Ls)X_t$ and $(1\text{-}L)(1\text{-}Ls)X_t$. It is necessary to check which of the series has the minimum variance score and give an adequate conclusion. For X_t the conclusion is $D=d=0$, for $(1\text{-}L)X_t$ the conclusion is $D=0$ and $d=1$, for $(1\text{-}Ls)X_t$ the conclusion is $D=1$ and $d=0$, for $(1\text{-}L)(1\text{-}Ls)X_t$ conclusion is $D=d=1$. The results obtained by this method should be taken with a grain of salt and used only as a preliminary analysis, as it is unreliable.

Unit root tests include the Dickey-Fuller test, the KPSS test (Kwiatkowski–Phillips–Schmidt–Shin), and seasonal unit root tests. The Dickey-Fuller (DF) test asserts the existence of a unit root in the null hypothesis, while the alternative hypothesis asserts the stationarity of the time series. If the null hypothesis is not rejected, it is necessary to test the existence of two unit roots by testing the stationarity of the first difference (Bachurewicz, 2017). The process needs to be repeated until the null hypothesis is rejected and stationarity is established. Critical values obtained by certain formulas are used for rejection and hypothesis. In case the DF statistic is greater than the critical one, the null hypothesis is not rejected, otherwise, it is rejected. The DF test can differ depending on whether there is a deterministic component and autocorrelation in the model. In the case of the existence of a linear deterministic trend, the dependence of the time series is evaluated as a function of the constant, the linear trend, and the value of the variable with a delay of the first order. Otherwise, the variable is evaluated depending on the constant and the value of the variable with the delay of the first order. It is necessary to pay attention to the statistical significance of the mean value of the first difference of the series, which is checked by the Stock-Watson test (SW) which tests the null hypothesis of its insignificance. The SW test is intended to help determine the appropriate form of the Dickey-Fuller test (with or without a trend component). The presence of autocorrelation must be observed for at least a 2s delay (Mladenović et al., 2012: 216). If the existence of autocorrelation is determined in the model, it is necessary to add corrective factors that will be able to include dynamic relationships. They are defined as the values of the dependent variable on arrears. In that case, the Augmented Dickey-Fuller statistic (ADF) is in question. When choosing the number of corrective factors, the strategy from "specific to general", "general to specific" and the strategy based on information criteria are used. Information criteria include Schwarz-SC, Akaikeov-AIC, Hana-Kvinov-HQC (Mladenović et al., 2012: 17).

The KPSS test is fundamentally different from the DF test and its null hypothesis speaks of the stationarity of the time series, based on the observation of the variance of the random component of the series (νt). If by testing it is determined to be greater than zero, the null hypothesis is rejected and the alternative hypothesis about the existence of a unit root is accepted. If the KPSS statistic is greater than its critical value, the null hypothesis is rejected. To test the existence of a seasonal unit root, the following can be used: DHF test (Dickey, Hasza, Fuller), HEGY test (Hylleberg, Engle, Granger, Yoo), CH test (Canova, Hansen) (Rodrigues et al., 2006). If the existence of two unit roots is established, we will observe the case D=1 and d=1, or d=2 and D=0, in the case of one unit root it will be D=1 and d=0, or d=1 and D=0.

The third way of determining the existence of a unit root involves observing the ordinary and partially autocorrelated function of the initial time series. If a gradual decrease from a value close to unity can be observed, the existence of a unit root is to be suspected. It follows that the time series is dominated by the long-term stochastic component. By eliminating the unit root, we can further determine whether there is also a seasonal unit root. If the values on the correlogram decrease slowly at lags *s, 2s, 3s*, etc., where the value of the delay s is close to unity, it can be said that there is also seasonal non-stationarity (*D=1* and *d=1*). If this is not the case, the time series has only one unit root (*d=1*). When the coefficients of the autocorrelation function do not gradually decrease from a value close to one, there is probably no common unit root. In that case, it is necessary to pay attention to the values of coefficients according to seasonal delays s, 2s, 3s, etc. If there is a decrease from a value close to unity, it can be concluded that there is seasonal non-stationarity in the series (*D=1* and *d=0*). Otherwise, it is a stationary series (*D=d=0*) (Mladenović et al., 2012: 214).

After determining the degree of integration of the series, it is necessary to determine the values of the rows of autoregressive (p), seasonal autoregressive (P), components of moving averages (q), and seasonal components of moving averages (Q). It is necessary to observe the ordinary and partial function of the series which has been transformed according to the number of unit roots. When observing the correlogram, it should be kept in mind that the first q coefficients are determined by the parameters of the AR and MA components, while for the later ones greater than q, the coefficients behave as in the case of the AR model. While in the case of a partial correlogram, the first p coefficients are determined by the effect of the AR and MA components, while the lags greater than p follows a movement similar to MA models (Mladenović et al., 2012: 190). The P component can be said to exist if there is a noticeable decline in the autocorrelation coefficients gradually by seasonal lags, from a value that is not close to unity. The Q component exists if there is a significant autocorrelation coefficient only on the seasonal lag s. When statistical significance is observed on seasonal arrears and arrears around it, it is a multiplicative model.

In the model specification, it will rarely happen that D is greater than one, especially for monthly series, and the rows P and Q will also not so often need to be greater than one. Especially if the database is not large enough to justify having P and Q greater than one (Box et al., 1994: 378).

The second step of the Box-Jenkins strategy is to estimate the parameters of the ARIMA model. The Nonlinear Least Squares (NLS) method is used, while the Ordinary Least Squares (OLS) model is available only for the AR model. The last stage is checking the adequacy of the model, which includes checking the agreement of the model and checking the optimality of the selection of model components.

If the unexplained part of the movement of the time series approximated by the SARIMA model is a completely random component, the model agrees with the data. The residuals should be normally distributed and not autocorrelated, to meet the agreement condition. Normality testing is performed using the Jarque-Bera test-JB, while autocorrelation is checked using the Box-Pierce-BP statistic, Box-Ljung-Q Statistic, and Box-Leung-Q2. The optimality of the choice of model components represents the choice of the simplest ARIMA model and takes into account economy, which implies that the minimum required parameters for evaluation will be included. Information criteria can be used to check the relationship between precision and economy.

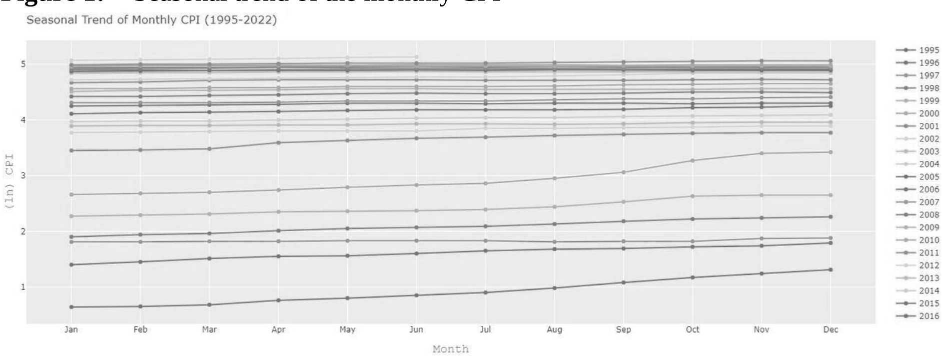
Additional methods used to check model adequacy are a subsequent extension of the ARIMA model to check its stability, a comparison of different models based on prediction accuracy, and a comparison of model forecast accuracy. When comparing models, the one with the smaller forecast error variance will be selected. The accuracy of the forecast is observed by comparing the root mean square error of the forecast, the mean absolute error of the forecast, and the mean absolute percentage error of the forecast. A model with a lower value of the mentioned parameters is considered more accurate for the given time series (Mladenović et al.,2012: 195).

4 Results and observations

The chapter is devoted to the practical application of the SARIMA model. Model creation, as well as obtaining all attached images, will be done in the Python programming language. This research is based on the dataset (open data, downloaded from: https://data.imf.org/regular.aspx?key=61545849) that represents the monthly Consumer Price Index (hereinafter CPI), where the base year is 2010 (2010= 100). The period observed is from 1995 to the last available data in 2022 (June). The data was transformed with the ln function before the analysis itself (which is a standard procedure for this type of data).

Firstly, it is necessary to see if there is a characteristic seasonality for the time series. The graph (Figure 1) shows the individual monthly movement of the CPI yearly, for the period 1995-2022.

Figure 1: Seasonal trend of the monthly CPI



Source: Python programming language (project-ml.ipynb in annex).

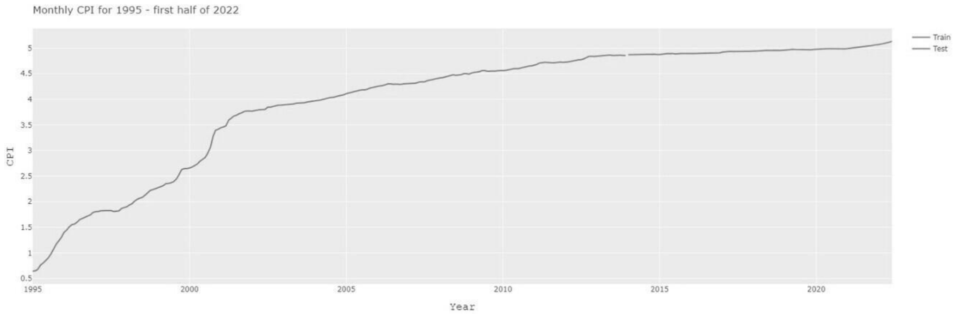
It is noticeable that there is no strong pronounced seasonality, however, there is a possibility that it is present. In further analysis, it will be determined whether the ARIMA or SARIMA model should be used.

From now on the data will be divided into 2 types: Train and Test

The model will be "trained" on past data using the Training data set, and then predict CPI, which we will subsequently compare with the actual Test data set. The usual split ratio of training and test data is 70%:30%. In our case, the data will be divided as follows: the period 1995-2013 is included in the training data, and the period 2014-2022 is included in the test data. Graph 2 shows the movement of the entire series. Training data are marked in blue and the test data in red.

Graph 2 –

Figure 2: Display of test and train data (1995-2022)

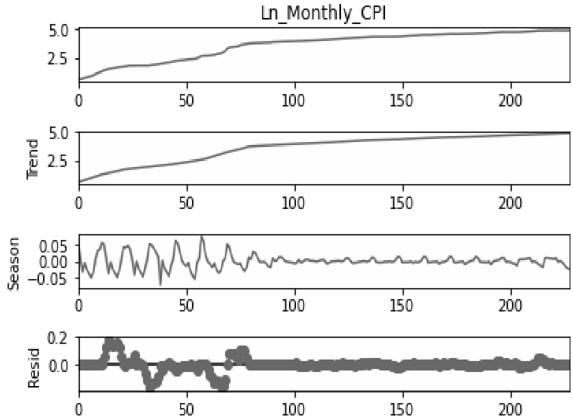


Source: Python programming language.

What we can observe is that the CPI series in Serbia (graph 2) has an increasing trend at the beginning of the period (which is confirmed with the Mann-Kendall trend test) and seems to be stochastic, followed by stagnation with a slight growth tendency. Eliminating the stochastic trend is achieved by using the first difference operator.

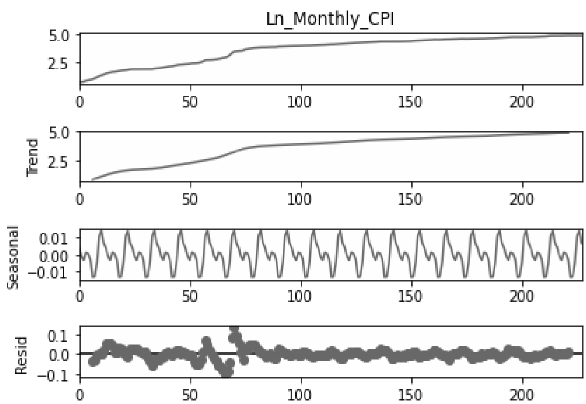
Graph 3 shows the components of the series obtained by STL decomposition, which is often used in economic analyses. Graph 4 presents classic decomposition. A noticeable difference between these two methods can be seen in the seasonal component. STL allows the season to change over time, while in the classic season this is not the case. Additionally, there is a difference in the residuals. This is the result of the robustness of the STL method towards outliers (it will be more noticeable in the continuation of the study), which eliminates their influence on the seasonal and trend components, but leaves an impact on the remainder component (Hyndman et al., 2018).

Figure 3: STL decomposition on Train data



Source: Python programming language.

Figure 4: Classical decomposition on Train data



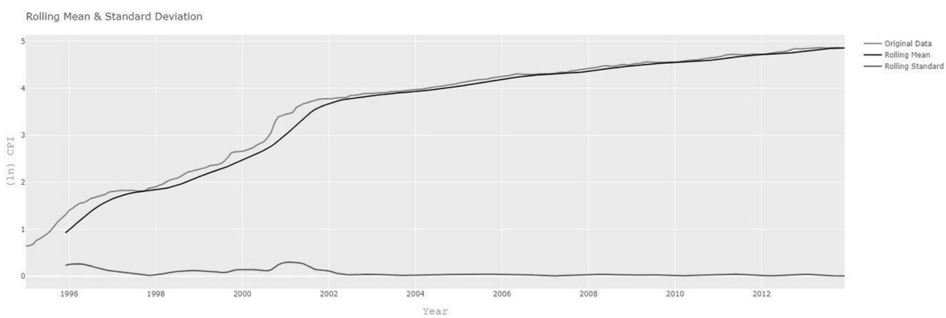
Source: Python programming language.

Apart from the above-mentioned differences, through both methods we can see that the series 'Observed', 'Trend', and 'Residual' are fluctuating randomly and that there is no specific systematic pattern that they follow. The "Seasonal" series, to a lesser or greater extent, shows that there are probably cyclical movements that indicate the existence of seasonality in the data set. For this reason, it is necessary to remove this seasonality to obtain the most optimal final model.

Stationarity can be checked in several ways:

1) Plotting data along with Rolling Average and Rolling Standard Deviation (time series is stationary if it remains steady with time)
2) Augmented Dickey-Fuller Test (time series is considered stationary if the p-value is low (<0.05) and the Test Statistic is lower than the critical values at a 5% level of significance)
3) By observing the correlogram of the series (if the values fall gradually from a value close to unity, there is a high probability that there is a unit root in the series)
4) KPSS test (time series is considered stationary if the p-value is high (>0.05) and the Test Statistic is lower than the critical values at a 5% level of significance)
5) Analysis of standard deviation (looking for the smallest standard deviation of the following series X_t, $(1-L)X_t$, $(1-L^2)X_t$, $(1-L^S)X_t$, $(1-L)(1-L^S)X_t$; the most imprecise method and is used only as a means of preliminary analysis).

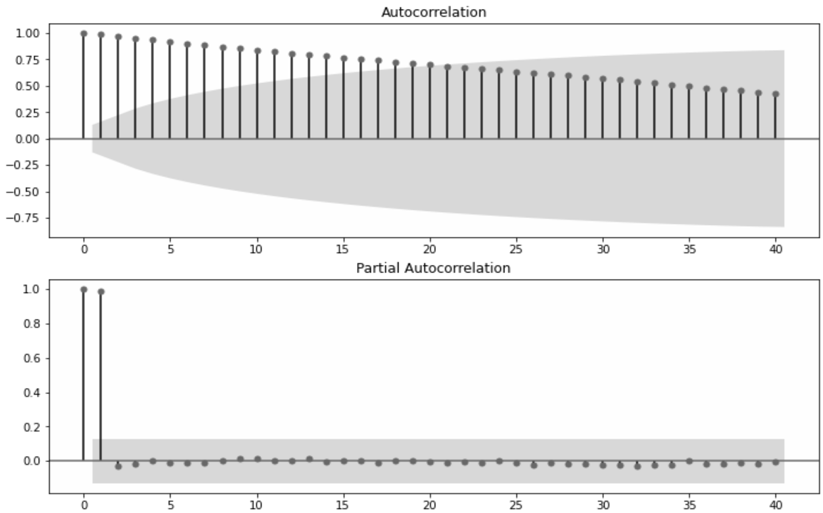
Figure 5: Rolling Mean and Standard Deviation for Train data set



Source: Python programming language.

Observing graph 5, we can see that the rolling mean largely deviates from the steady movement, which is the first indicator that differentiation of the series is necessary. The KPSS test resulted in the rejection of the null hypothesis and the conclusion that the X_t series has one unit root. Analyzing the standard deviations of the series, it is observed that the smallest values, in order, have the 2nd-order difference series, the 1st-order difference series, and the ordinary and seasonally differentiated series. This means that the series potentially has one, two, or one common and one seasonal unit root. The ADF test leads to failure to reject the null hypothesis, which asserts that there is at least one unit root in the series. The last check before concluding that the series is non-stationary is to observe the correlogram of the series. Graph 6 shows a characteristic gradual decline of the autocorrelation function, which is statistically significant (outside of the blue zone), and indicates the existence of a unit root.

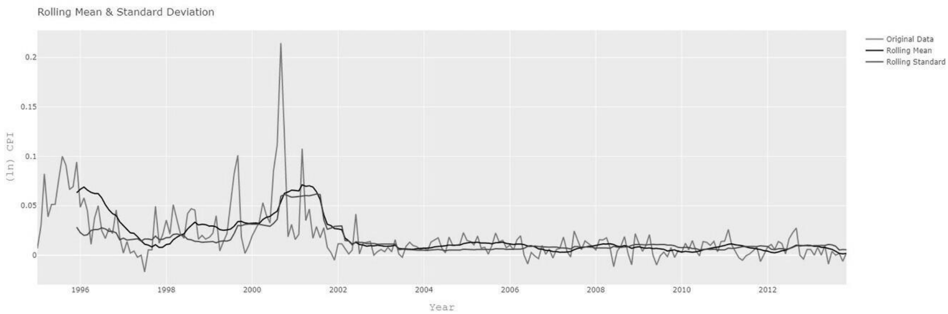
Figure 6: Correlogram for Train data set



Source: Python programming language.

After several analyses and tests, differentiation of the first order is applied, in an attempt to obtain a stationary series. Also, with this transformation, the gained series represents the inflation rate in Serbia for the same period (graph 7). It is noticeable that there has been an improvement in the appearance of the rolling mean because it is now steadier than in the original series, but there could still be room for improvement. There are a lot of outliers (one-time structural breaks), at the beginning of the observed period, which we can say that they have a hyperinflationary character. This can affect the further course of testing the series and forming the model. Therefore, further modeling should be approached with caution.

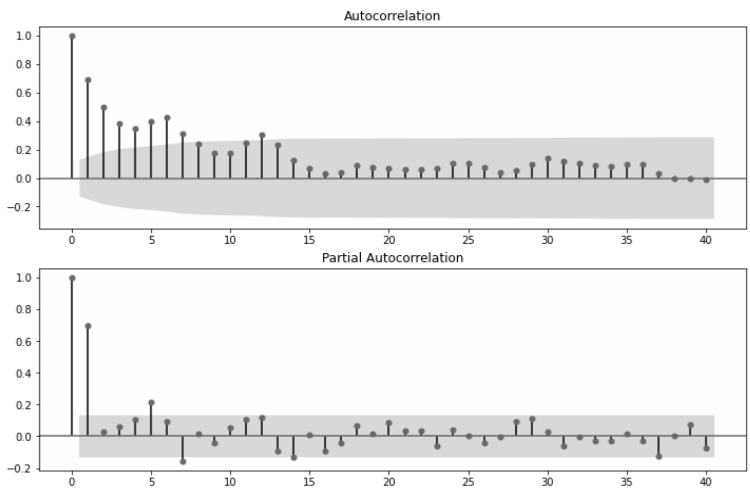
Figure 7: Rolling Mean and Standard Deviation for First difference of Train dataset



Source: Python programming language.

By examining the ADF test, it can be concluded that the null hypothesis should be rejected, that it is a stationary series. While the KPSS test claims the opposite, that this series also has a unit root. It should be remembered that the presence of one-time structural breaks affects both the tests and the appearance of the correlogram. It has the possibility of making the ADF test unreliable, that is, it is biased in the direction of rejecting the hypothesis of the presence of a unit root. It can also lead to an underestimation of the order of the AR and MA components (Mladenović et al., 2012: 224).

Figure 8: Correlogram for First difference of Train dataset

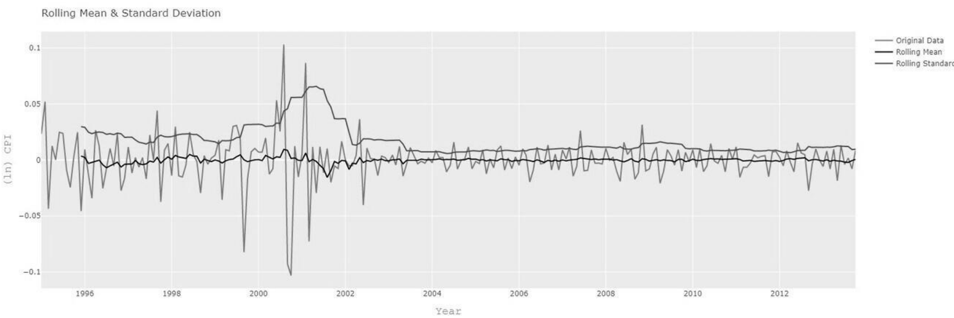


Source: Python programming language.

Looking at graph 8, where the correlogram is shown, it can be noted that there are statistically significant coefficients on seasonal delays, which indicates that there is probably a seasonal component in the series. Based on the previously mentioned arguments, we can choose whether or not to apply another differentiation to the series, or create a model based on the first differentiation of the series.

In this stage of research, there will always be a degree of subjectivity in selecting which differences to apply. A researcher has the option of choosing a different path, based on his experience (Hyndman et al., 2018).

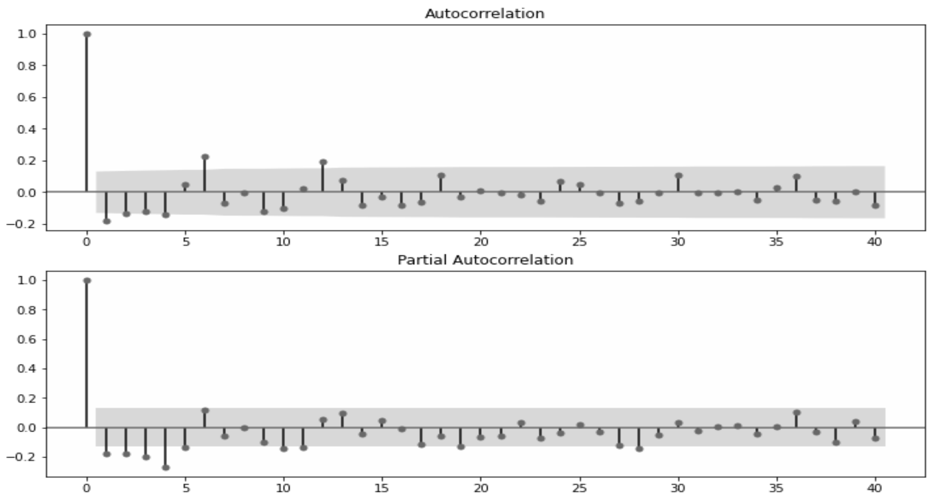
Figure 9: Rolling Mean and Standard Deviation for Second difference of Train dataset



Source: Python programming language.

After applying the second-order difference, there was an improvement in the rolling mean, which at this point stably and weakly oscillates around 0. The KPSS and the ADF test bring us to the same conclusion, that it is now a stationary series. The correlogram on graph 10 does not show the characteristics of a non-stationary series. Therefore, a proper foundation is built for further model-making.

Figure 10: Correlogram for Second difference of Train dataset



Source: Python programming language.

Model construction

To determine the elements of the SARIMA model, it is necessary to determine the values of the following arguments: *p, d, q, P, D, Q, s.* The observation of the autocorrelation function, as well as the partial autocorrelation function, shown in the previous graphs, can help with this. During the modeling, a dummy variable was included, which takes the value 1 for the periods of one-time structural breaks that were observed on the graph of the first difference of the series, and the value 0 for the other periods.

In the following, two models will be presented, which may be adequate for predicting the monthly CPI in Serbia.

The first model:
SARIMA (1, 2, 1)x(1, 0, 0)$_{12}$

Table 1: Estimation of the second difference equation of the monthly CPI in Serbia

Variable	Estimate	z score
V	-0.0118	-5.269
AR(1)	0.5577	9.588
MA(1)	-0.9355	-30.776
AR(12)	0.1613	2.596
Q=0.01 (0.93) JB=1431.4 (0.00) H=0.09 (0.00) AIC=-1101.648 alpha 3=1.16 alpha4=15.49		

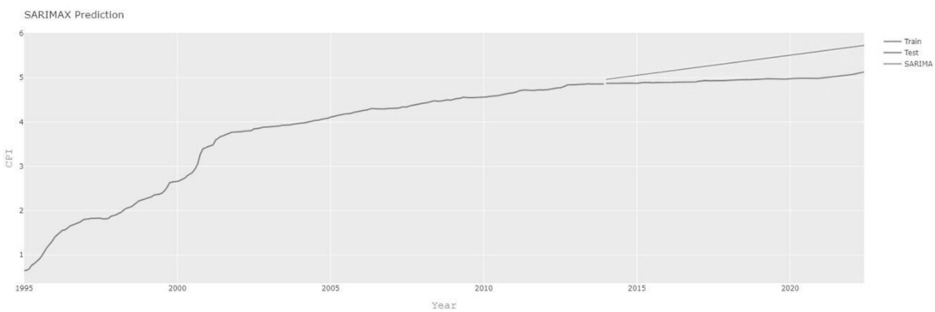
Source: Python programming language.

Root mean squared error of the predicted CPI in the Test data set = 0.43
The standard deviation of the CPI in the Test data set = 0.0607

Error in model's prediction = 0.3693%
Dummy variable V takes values:
V=
$\{1, t = 1999M09\ 1, t = 2000M08\ 1, t = 2000M09\ 1, t = 2000M11\ 1, t = 2001M02\ 1, t = 2001M03\ 0,\ otherwise$

Graph 11 shows the prediction that the model makes on the test data. It can be noted that it is an overestimated movement of the series which has an upward trend, while the real test data has almost no rising trend and is stagnating.

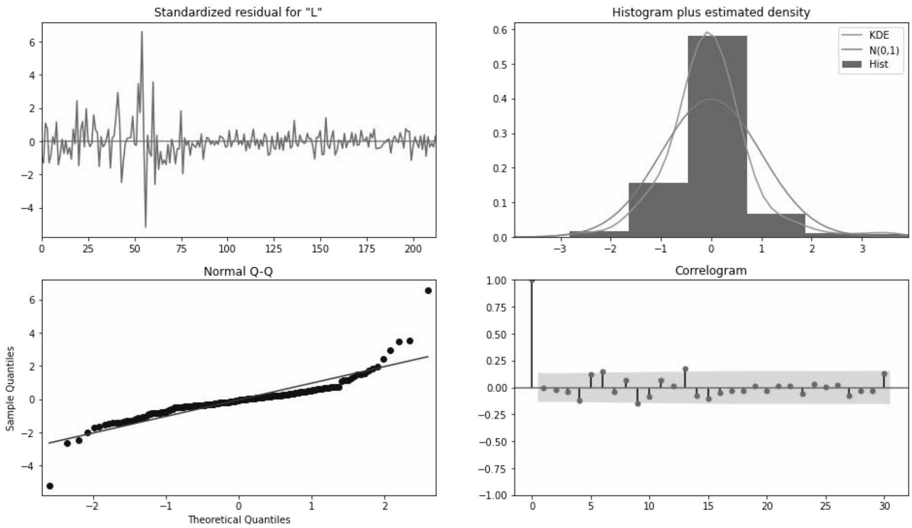
Figure 11: Prediction of model for Test data (SARIMA (1, 2, 1)x(1, 0, 0)12)



Source: Python programming language.

A model that was obtained violates certain assumptions that it should fulfill for the sake of greater credibility. Box Lung's statistic Q is not statistically significant, which means that the null hypothesis claiming that there is an autocorrelation between the residuals is rejected. Thus, the assumption that there is no autocorrelation between the residuals is satisfied. In graph 12 (lower right sub-graph), the correlogram shows the autocorrelation of the residuals, where the area marked in blue is the zone of statistically significant coefficients.

Figure 12: Plots for residuals (SARIMA (1, 2, 1)x(1, 0, 0)$_{12}$)

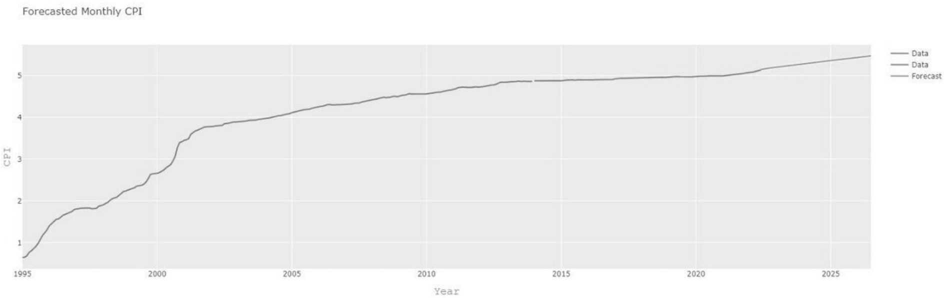


Source: Python programming language.

The JB statistic in the model shows that the normality of the residuals does not apply because the null hypothesis is rejected. The same can be noticed in graph 12, on the lower left sub-graph. There is a "Normal Q-Q plot" which shows whether the residuals are normally distributed. The blue dots should not deviate much from the red line if there is normality. In the case of this model, there are "heavy tails", which means it is more likely to see extreme values than to be expected if the data was truly normally distributed. Additionally, on "Histogram plus estimated density" you can see KDE (kernel density estimation), which shows that the distribution has heavy tails (which are caused by the extreme values in the series that we have already stated) and therefore deviates from normal.

Heteroskedasticity is also present in the model. It occurs more frequently in datasets with a broad spread between the highest and lowest reported values. In a time-series model, heteroscedasticity can happen when the dependent variable drastically changes from the start to the end of the series.

Figure 13: Forecasted monthly CPI (SARIMA (1, 2, 1)x(1, 0, 0)$_{12}$)



Source: Python programming language.

Graph 13 shows the forecast for the future produced by the SARIMA (1, 2, 1)x(1, 0, 0)12 model, and it predicts an upward trend of the series.

Second model:
SARIMA (1, 1, 0)x(1, 0, 0)$_{12}$

Table 2: Estimation of the first difference equation of the monthly CPI in Serbia

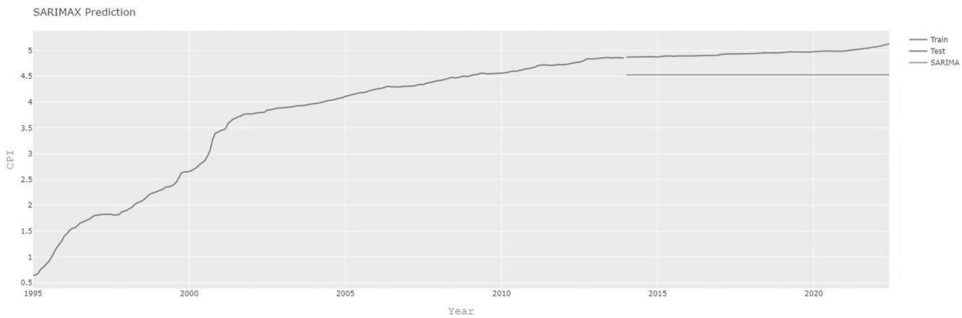
Variable	Estimate	z score
V	-0.0105	-5.026
AR(1)	0.6934	24.638
AR(12)	0.2412	3.720
Q=2.16 (0.14) JB=1363.24 (0.00) H=0.09 (0.00) AIC=-1103.007 alpha3=1.44 alpha4=15.02		

Source: Python programming language.

Root mean squared error of the predicted CPI in the Test data set = 0.4257
The standard deviation of the CPI in the Test data set = 0.0607

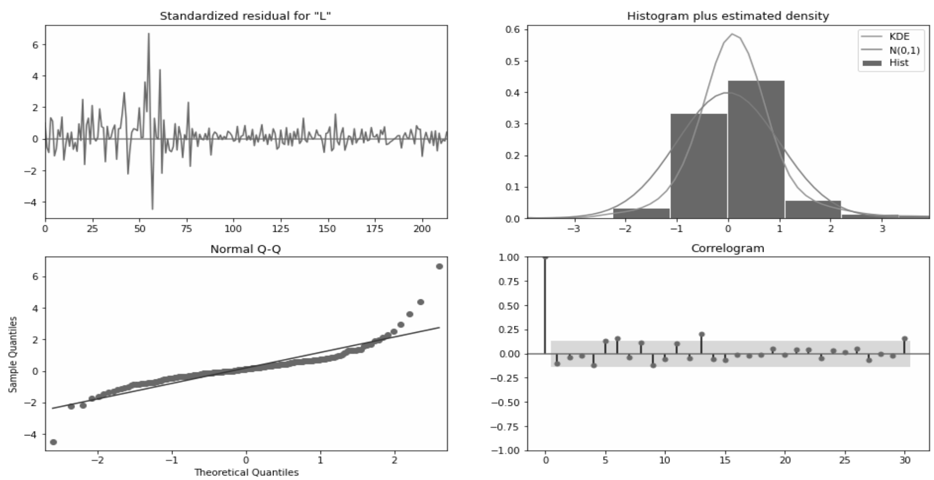
Error in model's prediction = 0.365%
Dummy variable V takes the same values as in the first model.
It is noticed that both models have very similar parameters and statistics, with minimal differences in their values, so the conclusions and shortcomings will be the same as in the first model.
Graph 14 shows the predicted values for the test period, and they are underestimated compared to the original series.

Figure 14: Prediction of model for Test data (SARIMA (1, 1, 0)x(1, 0, 0)$_{12}$)



Source: Python programming language.

Figure 15: Plots for residuals (SARIMA (1, 1, 0)x(1, 0, 0)$_{12}$)

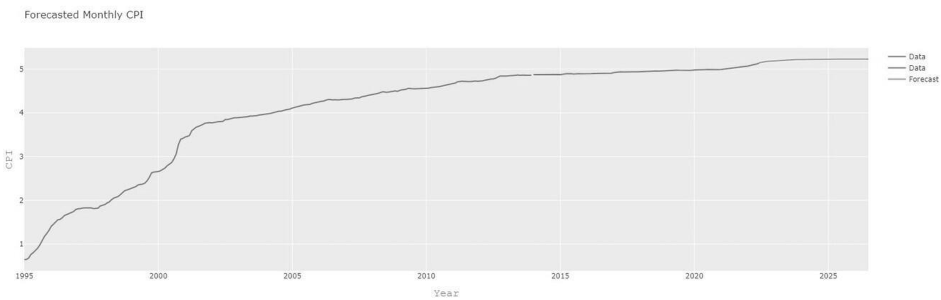


Source: Python programming language.

The main differences between models are in the graphs of prediction on test data and forecast for the future (graphs 11, 13, 14, 16). The second model may seem more appropriate for use in the forecast of the future (graph 16) because it does not have a weak upward trend like the first model. Therefore it may be concluded that only one differencing of the series would be enough for proper model building.

However, there are many obstacles due to which we cannot claim that this model predicts the movement of the series to the best extent. Since many of the assumptions that condition the model are violated, the results should be taken with precaution and consider this model a robust one.

Figure 16: Forecasted monthly CPI (SARIMA (1, 1, 0)x(1, 0, 0)$_{12}$)



Source: Python programming language.

5 Discussion and conclusion

In this paper, an appropriate SARIMA model was used to model the CPI of Serbia. The model has not been proven to be the best fitting for forecasting the inflation rate in Serbia according to assumptions of the model that are violated.

The methodology of the SARIMA model as well as its background has been investigated. We have implemented the said model in the practical portion of the paper and noted the difference in the conclusions concerning CPI that were to be drawn from the modeling phases.

Through analyzing and modeling the series, we encountered several obstacles. The original series tend to be of greater difficulty to interpret, and often the tendency of the data is not seen. Seasonality was revealed in the series, which was treated in the right way. Also, it was established that it is a non-stationary series that needs to be transformed. The biggest problem that affects the series, and the making of the model itself, is the existence of a large number of structural breaks. In this sense, the results of the study are very limited because they need to be carefully interpreted and modified. The work can be improved by more detailed analysis and treatment of extreme values that are problematic. Further research can be conducted in the direction of applying additional types of machine learning models, such as neural networks, which go beyond the scope of the study. Even though SARIMA does not account for the stresses in market data, economic and political conditions, or correlations of all risk factors to forecast inflation rates, the procedure illustrated above can be helpful for roughly predicting inflation movements under normal circumstances where past behavior dictates present values.

As for the choice of the appropriate model, it will depend on the needs of the analysis and should be left to the researcher. In the future, the field of time series modeling is certain to progress. Software programs that help faster and more accurate analyses are in rapid development and will help eliminate a large dose of subjectivism, as well as improve the precision of the drawn conclusions.

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