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ANALYSIS OF THE USE OF THE ARIMA MODEL IN FORECASTING ECONOMIC INDICATORS

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Abstract: This article examines the analysis and forecasting of wholesale trade volume in the Surkhandarya region using time series methodsthe ARIMA model was applied to predict future values of the wholesale trade indicator. The stationarity of the time series was tested using the Augmented Dickey–Fuller test The findings of the study can be effectively used in regional economic planning and trade development strategies

Keywords: wholesale trade, time series analysis, ARIMA model, forecasting, stationarity, Augmented Dickey–Fuller test, economic analysis.

Аннотация. В исследовании использованы статистические данные и применена модель ARIMA для прогнозирования будущих значений экономического показателя. Стационарность временного ряда была проверена с помощью расширенного теста Дики–Фуллера. Результаты исследования могут быть использованы при разработке региональных программ социально-экономического развития.

Ключевые слова: временные ряды, модель ARIMA, прогнозирование, стационарность, тест Дики–Фуллера, экономический анализ.

Autoregressive modeling (Autoregressive, AR) and moving average Modeling (Moving Average, MA) time rows forecast to do two kind ARIMA model exactly this two approach unites , therefore for him too name so Forecasting is mechanical of learning one direction It is time. of the row past to their behavior based on the future one or one how many values prophecy to do goal does . Imagination do it , you small the store filling for ice cream buy If the weather is warming with ice cream trade regular accordingly exceed going if you know , next per week order size this from the week a little more to be guess you do logically right will be . The order how much more to be and this of the week trade size past from the week how much difference to what he did related We will see the future . past with without comparison standing prophecy can We can't . This because of , in the past timely row data ARIMA model for , in general all forecast and timely rows analysis methods very much for important is considered .

"Autoregressive Integrated Moving Average" , used in the forecasting process is one of the widely used statistical methods for analyzing time series. Typically, this model consists of three main parameters, which are specified in the order (p, d, q). Here: p is the level of the autoregressive component, d is the level of integration or differentiation, and q is the level of the moving average component.

The ARIMA model is essentially an ARMA (Autoregressive Moving Average) model adapted to non-stationary time series. If the time series is not initially stationary, it can be made stationary by differentiating it to a certain order. The series obtained after this process are called differentiated or integrated stationary series. Thus, after the d-order differentiation is performed in the ARIMA(p,d,q) model, the remaining parts are adapted to the ARMA(p,q) model.

Various statistical tests are used to determine the stationarity of a time series. These tests determine the presence of unit roots and the degree of integration of the time series (usually 1st or 2nd degree). If the series has a unit root and its degree of integration is greater than zero, then the series can be made stationary by differentiating it. After that, an ARMA model can be built for the new series, since it now has a stationary property, which makes it possible to perform analysis and forecasting reliably.

non-stationary Y_t time series, the ARIMA(p, d, q) model has the following general form:

$$\Delta^d Y_t = c + \sum_{i=1}^{p} \varphi_i \, \Delta^d y_{t-i} + \sum_{j=1}^{q} \theta_j \Delta\varepsilon_{t-j} + \varepsilon(t) \qquad (1)$$

Δorder differences in sequence : first the original time series is differentiated, then the resulting first- order difference row , then second in order differences and etc. This in a way , time row stationary to the situation will be brought and analysis for adapts .

Determining the stationarity of a time series is very important for subsequent analysis processes. A stationary process is a stochastic process whose probability distribution remains unchanged over time and whose mean and variance are constant. Since many methods in time series analysis are based on stationary processes, non-stationary data are often brought to a stationary form using appropriate transformations. Stationarity violations are often caused by changes in the mean value over time, which can be associated with the presence of a trend or a unit root. It can also be seen from dynamic graphs that if a time series does not oscillate around a certain constant value, this indicates that it is non-stationary. The augmented Dickey-Fuller (ADF) test is widely used to determine whether a given time series is stationary or non-stationary. This test is one of the most effective and popular methods in statistics and serves to assess the stationarity of a time series.

The first step in constructing an ARIMA model is to determine the order of differentiation necessary to make the time series stationary. The ADF test is mainly designed to check statistical significance, and it calculates the test statistic and p-value by comparing the null and alternative hypotheses. Based on the test results, it is possible to conclude whether the series is stationary or not. In the next step, it is important to determine the autoregressive (p) and moving average (q) parameters. To do this, the correlogram of the time series (i.e., the ACF and PACF graphs) is analyzed. The autocorrelation (ACF) and partial autocorrelation (PACF) functions of the time series have a specific form for different ARIMA models. However, it is not always easy to accurately determine the parameters p and q based on the ACF alone, especially when q=0. To solve this problem, the PACF analysis of Y_t as a stationary process is very useful. The ACF function approaching zero after lag q indicates that the model is MA(q), while the PACF function approaching zero after lag p indicates that the model is AR(p). Therefore, ACF and PACF analyses help to more accurately identify ARIMA (p, d, q) models, especially when both p and q are non-zero.

The table below summarizes the ACF and PACF properties of popular ARIMA models for stationary time series.

Table 1.

Generalized properties of ACF and PACF functions for time series models[1]

Model	ASF	PSF
White Noise, MA (0)	When k ≠ 0, ρ(k) = 0	When $k \neq 0, \rho_{part}(k) = 0$
AR(1), $\boldsymbol{a_1 > 0}$	Exponential Decay: $\rho(k)=a_1^k$	$\rho_{part}(1) = a_1$, $\rho_{part}(k) = 0, k \geq 2$at
AR(1), $\boldsymbol{a_1 < 0}$	Vibration reduction: $\rho(k)=a_1^k$	$\rho_{part}(1) = a_1$, $\rho_{part}(k) = 0, k \geq 2$at
AR(p)	Zeroing in with probable fluctuations	$k \geq p$to zero in
MA(1), $\boldsymbol{b_1 > 0}$	positive peak at k=1, $k > 1$to zero in	Vibration reduction: $\rho_{part}(1) > 0$

[1] V.P. Nosko . Econometrics. Introduction to regression analysis of time series. Moscow 2002.40-41 ctr .

MA(1),$b_1 < 0$	negative peak at k=1, $k > 1$to zero in	Decrease in absolute value: $\rho_{part}(k) < 0, k \geq 1$at
MA(q)	$k \geq p$to zero in	

k is defined as the correlation coefficient between $\rho_{part}(k)$the value of the lag $Y_t$and $Y_{t+k}$the random variables, where the effect of the random variables Y_{t+1}, ..., $Y_{t+k-1}$is eliminated. This is$\rho_{part}(k)$ Y_{t-1}, ..., is the coefficient in the linear combination $Y_{t-k}$of random variables $Y_t$that best approximates the random variable Y_{t-k}. Here, $\rho_{part}(k)$the first k are defined as the solution of the system of Yule-Walker equations $a_k$with respect to .

r (s) = a_1r (s-1) + a_2r (s-2) +... + a_kr (sk), s = 1, 2, ..., k,

In order to forecast the volume of wholesale trade in the region, available statistical data was analyzed and based on them, an "ARIMA" model was developed.

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