ECONOMICS

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ADAPTIVE MODELS FOR FORECASTING PRICES FOR SHARES IN THE OIL AND GAS INDUSTRY

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Abstract

The article deals with the construction of Holtas-Winters adaptive models for constructing an adequate forecast of prices for Gazprom shares.

The oil and gas industry is the fastest growing branch of the fuel industry, and in Russia more than 30% of the world's explored reserves of natural gas and 8% of oil reserves are dispersed. Nowadays, PJSC "Gazprom" is one of the leading companies in this industry.

Keywords: Gazprom,spectral analysis,statistica,spectogram

Introduction

PJSC Gazprom is a global energy company. The main activities are geological exploration, production, transportation, storage, processing and sale of gas, gas condensate and oil, sale of gas as motor fuel, as well as production and sale of heat and electricity. In addition, Gazprom is of interest as well as the largest joint-stock company. The shares of Gazprom represent an interesting object for sale and, therefore, require the most accurate and current forecast.

Main part

Adaptive methods of forecasting (or models of exponential smoothing) are methods that allow you to build self-correcting EMMs that take into account the result of the realization of the forecast made in the previous step and build a forecast taking into account the results obtained. Consider the data on the highest monthly price of the Gazprom stock within 60 months. The graph of such a series of data will look like this:

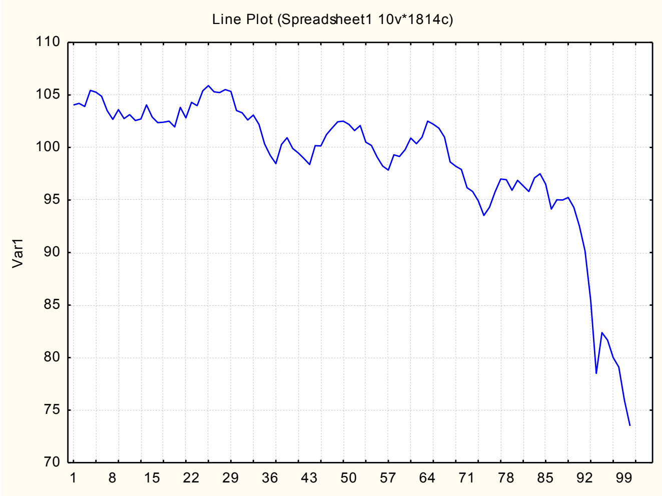


Figure 1. The schedule of the initial time series of shares of Gazprom

Based on the visual analysis of the time series presented in Figure 1, one can not unambiguously determine the presence of a trend, since the stock price changes its value, both in the direction of increase, and in the direction of decline.

Analysis of the series for the presence of a trend and seasonality with the help of correlograms and Fourier spectral analysis.

We constructed a periodogram in frequency to determine the trend (shown in Figure 2).

At the next stage, we perform a spectral analysis of a number of cleansing from the trend. Figure 3 shows a spectrogram of this series.

Identify the availability of seasonality, you can also on the basis of an analysis of correlated autocorrelation and private autocorrelation functions.

As can be seen from the correlograms AKF and CHAKF (Figures 4 and 5), the most significant coefficient of autocorrelation and the partial coefficient of autocorrelation corresponds to the first lag. From this we can conclude that there is no seasonality, there is a deterministic trend in the structure of the series. Also, the correlogram of ACF clearly shows the presence of the trend: the coefficients of the ACF decrease slowly with increasing lag length.

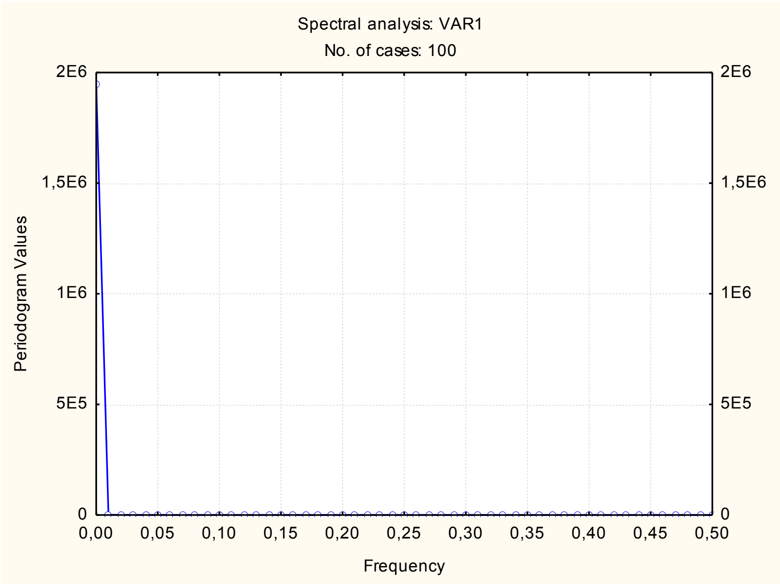


Figure 2. The spectrogram of the original series

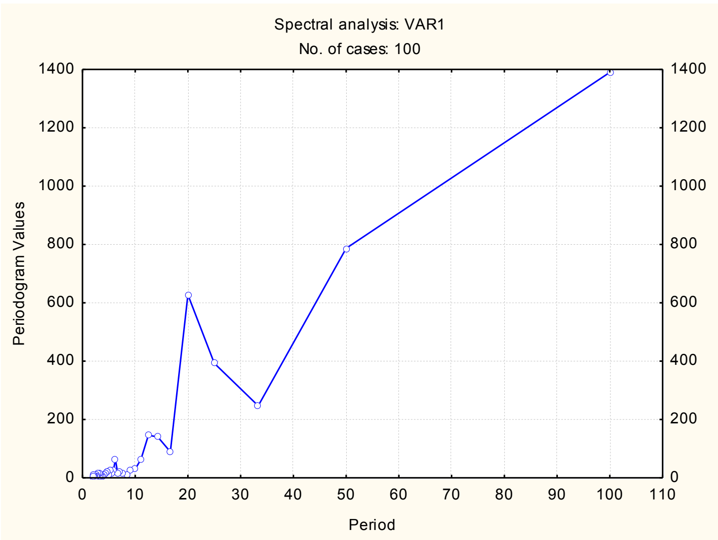


Figure 3. Spectrogram of the trend-free series by period

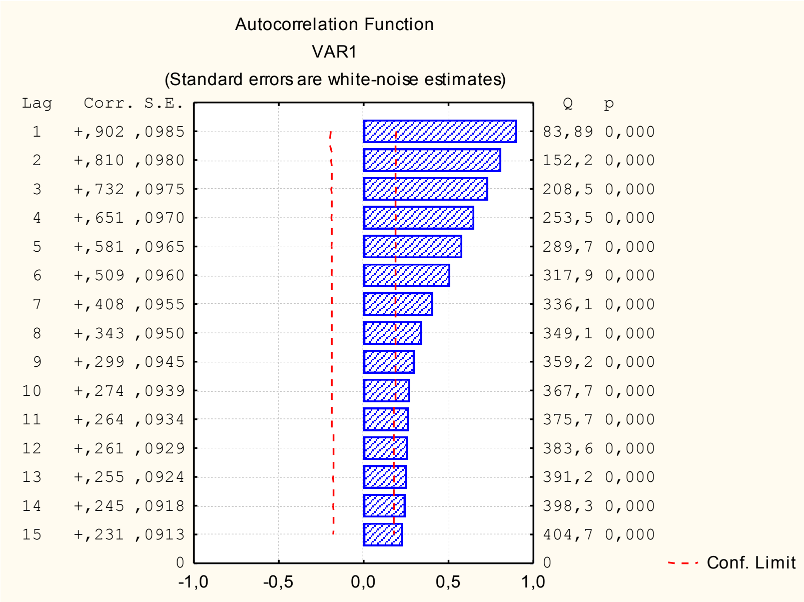


Figure 4. Correlogram of the ACF of the original series

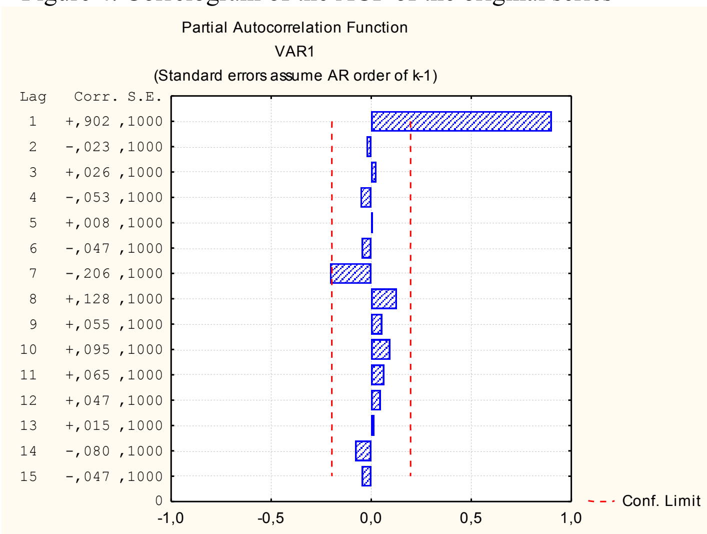


Figure 5. Corellogram of the CACF of the original series

With the help of Auto-search in the program STATISTICA it is possible to build a formally optimal model. Formally optimal is the model with the lowest error value. The search is performed by minimizing the error value using the quasi-Newtonian method.

Linear trend::

Workbook4* - Exp. smoothing: Multipl. season (12) S0=113,7 T0=-1,64 (Spreadsheet1)

Workbook4*
Time Series/Fc
Time Serie
Exp. sn
Exp. sn
Exp. sn
Exp. sn
Exp. sn
Exp. sn
Exp. sn
Exp. sn
Exp. sn
Param
Exp. sn
Exp. sn
Exp. sn

Exp. smoothing: Multipl. season (12) S0=113,7 T0=-1,64 (Spreadsheet1)
Damped trend,mult.season; Alpha= ,900 Delta=,100 Phi=,100
VAR1

Case	VAR1	Smoothed Series	Resids	Seasonal Factors
1	104,0500	113,6228	-9,57278	100,1113
2	104,2000	102,4696	1,73036	100,0050
3	103,9100	104,6704	-0,76037	100,3539
4	105,4400	104,0348	1,40520	100,5743
5	105,2600	105,7726	-0,51256	100,6981
6	104,8800	104,7828	0,09715	100,2952
7	103,5100	104,2398	-0,72977	99,6748
8	102,6800	103,4946	-0,81463	99,7660
9	103,6000	102,0877	1,51228	99,3216
10	102,7500	104,2138	-1,46377	99,7026
11	103,1300	102,3227	0,80725	99,4810
12	102,5700	103,7864	-1,21644	100,0159
13	102,7200	102,4843	0,23567	
14	104,0600	102,6393	1,42073	
15	102,9000	104,6392	-1,73921	
16	102,3700	102,8865	-0,51649	

Mean error	0,000960303521

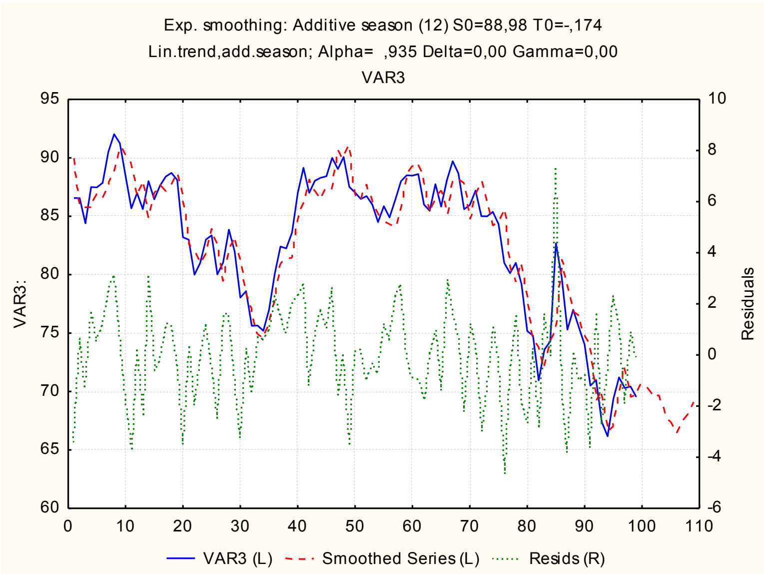
Exponential trend with additive seasonality:

Exp. smoothing: Additive season (12) S0=89,3
Expon.trend,add.season; Alpha= ,945 Delta=0
VAR3

Summary of error	Error
Mean error	0,016199347365
Mean absolute error	1,550438682760
Sums of squares	382,076986773778
Mean square	3,859363502765
Mean percentage error	-0,022545715607
Mean abs. perc. error	1,887468776418

Power trend with additive seasonality:

Summary of error	Exp. smoothing: Additive season Damped trend,add.season; Alpha VAR1 Error
Mean error	0,00012300
Mean absolute error	1,01567789
Sums of squares	356,09777705
Mean square	22011,82590648
Mean percentage error	0,36574890
Mean abs. perc. error	1,78864355



Conclusion

Based on the automatic search, it was revealed that the best model - with a power trend and additive seasonality and parameters **α=0.5, γ=0.1 и φ=0.3.**