Decomposition with Seasonal Component for Time Series Forecast of the Macroeconomic Parameters of Russia

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Abstract.*Inthepaperweconsider two new non-parametricalgorithms for decomposition of time series including a significant seasonal component.We demonstratethe advantage of proposed algorithms on the example of short-term forecast for one of the macroeconomic parameters of Russia. Thequality of forecast proves to be essentially better that the existing methods provide. The proposed approach should be compared withthe GMDH, which is presented by series of parametric algorithms.*

1.Introduction

Time series analysis and forecast have their very long history. For example, in the paper [1] one can find more than 100 classes of possible models to be used for forecast of time series. Time series decomposition is one of the traditional approaches, where time series is presented in the form:

$$Y(t) = T(t) + S(t) + E(t),$$

whereT$(t)$is non-parametric trend, $S(t)$ is non-parametric seasonal component, and E(t) is noise. Each component of the equation is considered separately. The problem consists in determination of these components.

2.Algorithms of decomposition

2.1. Smoothing procedure

The first algorithm we used in the non-parametric procedure is the smoothing algorithm. It is based on local lineal regression (LLR) described in **[**2**]**.Here we weigh each point using exponential coefficients and then we use the WLS (weighted least squares) method. The exponential coefficients are calculated according the formula

$$w(i) = \lambda^{|t-i|},$$

where*t* – is the point, which the WLS is used for.The WLS method consists in minimization of the values:

$$\sum_{i=1}^{n} (Y(i) - A_t \cdot i - B_t)^2 \, w(i) \longrightarrow min.$$

Having received A_t andB_t we calculate$Z(i) = A_t \cdot i + B_t$for each point. It is easy to see that when weights are equal (an extreme case) then the local linear regression reduces to the ordinary lineal regression.Figure 1 demonstrates the results of smoothing time series by using LLR with different values of exogenous parameter λ.

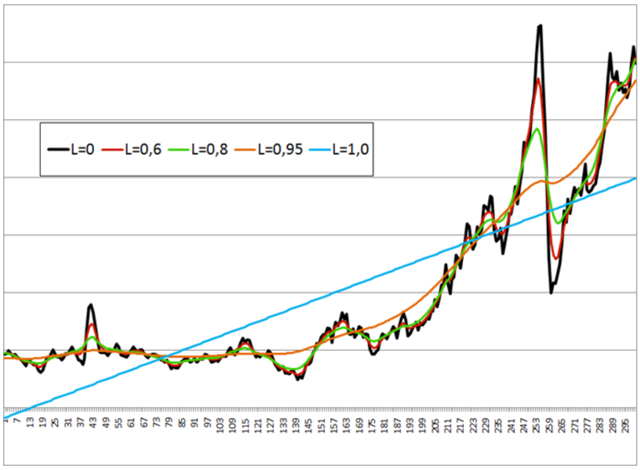

Fig. 1. Results of smoothing with the different values of exogenous parameter

2.2. Elimination of seasonal component

Firstly, we introduce the so-called curvature degree according the formula:

$$\sum_{i=2}^{n}\left(Y(i)-Y(i-1)\right)^{2}.$$

On the next step, we consider time series (TS) as a sum of trend and season function. The latter is a periodical function with the period p. So, the seasonal function is a set of p seasonal coefficients $k(i)$:

$$k(i) = k(i+p), i = [1, 2, \dots, n-p].$$

$$Y(i) = Y^{real}(i) + k(i).$$

To find these coefficients we minimize the degree of curvature for time series $Y^{real}(i)$ with respect to all $k(i)$ having in view the last equation. On figure 2 one can see how the seasonal component can be revealed from a given time series. This time series reflects the dynamics of employees working in the National Economy from 2006 to 2014.

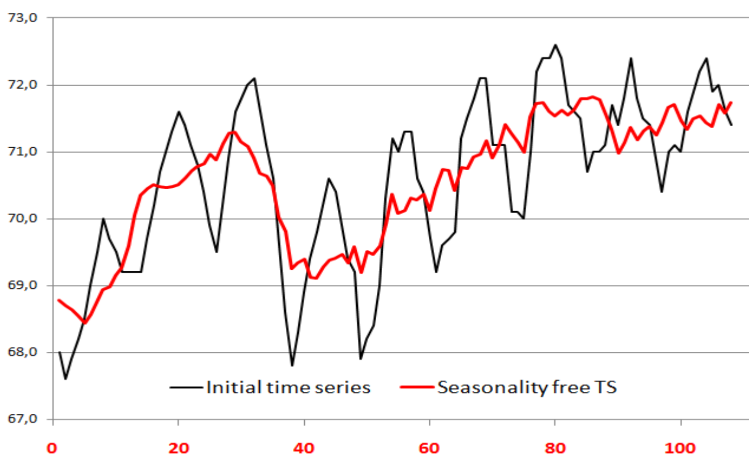

Fig. 2. Result of revealing seasonal component

3.Experiments

Gaydar Institute for Economic Policy (IEP) publishes monthly bulletin containing short-term forecasts of the most important macroeconomic parameters of Russia. For this,the specialists of IEP use two principal approaches the ARIMA models and structural econometric equations. The goal of our experiments was the comparison of forecasts based on our non-parametricdecomposition model and on the mentioned models. We evaluated the quality of results using the well-known MAPE = mean absolute percentage error. Figure 3 shows three graphics related to the dynamics of import to Russia: the real import, the forecast based on ARIMA and the forecast based on non-parametricdecomposition model. It is easy to see the advantage of the proposed algorithmsfor building decomposition model. The erroris 33% less.It should say that we obtained the similar results for other 7 macroeconomic parameters that were used in our full research.

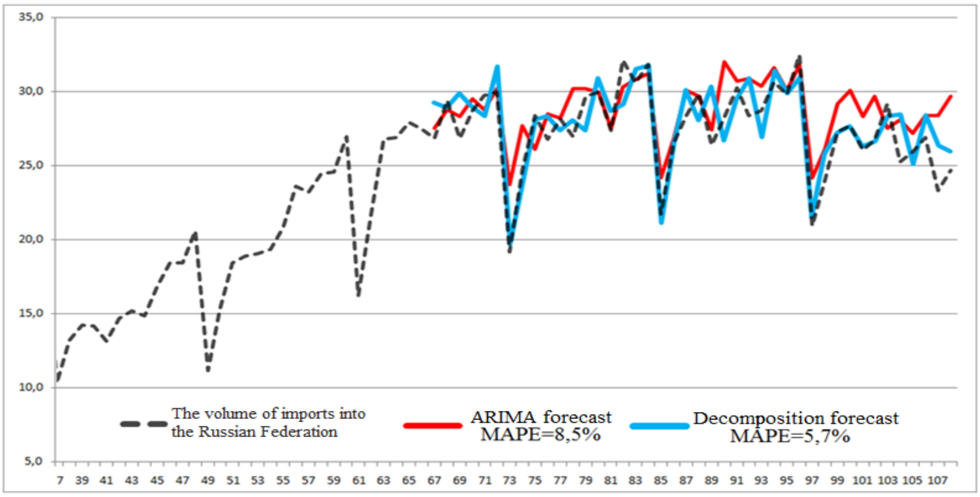

Fig. 3. The volume of imports into the Russian Federation.

4.Conclusion

In the paper weshortly describe two non-parametric algorithms for decomposition of time series with seasonal component. We demonstrate the advantage of the proposed algorithms on the realdatarelated to the forecast of one of the macroeconomic parameter of Russia. We also give our vision how to use GMDH for revealing the seasonal component. In future, we suppose to realize GMDH in the framework of our algorithms of decomposition

References

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