Economics Letters 158 (2017) 41–46

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Application of wavelet decomposition in time-series forecasting

Keyi Zhang [a], Ramazan Gençay [a,*], M. Ege Yazgan [b]

[a] Department of Economics, Simon Fraser University, Burnaby, BC, V5A 1S6, Canada
[b] Department of Economics, Istanbul Bilgi University, Istanbul, Turkey

HIGHLIGHTS

- Wavelet-based multiresolution decomposes a time series into a set of constitutive series with an explicitly defined hierarchical structure.
- We show that this decomposition method can improve the accuracy of forecasts of original times series data.

ARTICLE INFO

Article history:
Received 29 March 2017
Received in revised form 7 June 2017
Accepted 8 June 2017
Available online 21 June 2017

JEL classification:
C53
G17

Keywords:
Wavelet decomposition
Combining forecasts
Reconciling forecasts
Hierarchical time series

ABSTRACT

Observed time series data can exhibit different components, such as trends, seasonality, and jumps, which are characterized by different coefficients in their respective data generating processes. Therefore, fitting a given time series model to aggregated data can be time consuming and may lead to a loss of forecasting accuracy. In this paper, coefficients for variable components in estimations are generated based on wavelet-based multiresolution analyses. Thus, the accuracy of forecasts based on aggregate data should be improved because the constraint of equality among the model coefficients for all data components is relaxed.

Wavelet-based multiresolution analyses can decompose a time series into a set of constitutive series with an explicitly defined hierarchical structure. In this paper, we show that this decomposition method can improve the accuracy of forecasts of original times series data.

A hierarchical time series includes multiple times series in which the high-level observations are aggregated according to low-level data. Economic data often have this hierarchical structure. For example, GDP data for a country, state, and city are a group of hierarchical time series based on geography. Conventional approaches to performing forecasts using such hierarchical data involve either a top-down or bottom-up method or a combination of the two. The top-level data could be forecast first, and then these forecasts could be disaggregated based on historical proportions (top-down approach); alternatively, the bottom-level data could be forecast first, and then additional data could be included to obtain the top-level forecasts (bottom-up approach).[1] Thus, when performing forecasts, the value of the data and the structure is important.

Ignoring the hierarchical structure of the data and forecasting all series at all levels independently will usually lead to the undesirable consequence in which higher-level forecasts are not equal to the sum of the directly related lower-level forecasts. To address this issue, Hyndman et al. (2011) presents a framework to ensure that forecasts are added appropriately by adjusting the independent forecasts. That is, given multiple times series that are hierarchically organized, an unbiased and efficient forecast can be achieved without losing the hierarchical structure.

In this paper, we extend the application of Hyndman et al. (2011) to any univariate times series data. We apply wavelet-based multiresolution analyses to expand univariate time series data into a group of hierarchical series in a meaningful manner. This application provides the opportunity to study and apply the structure of the data when forecasting.

To examine whether the wavelet decomposition can improve forecasting accuracy, we compare the forecast accuracy obtained by different methods. The accuracy benchmarks are forecasts performed using conventional univariate models, which are applied to the wavelet-decomposed hierarchical series, and the forecasts

* Corresponding author.
E-mail address: rgencay@sfu.ca (R. Gençay).

[1] The examples of combination forecasts include Claeskens et al. (2016), Del Negro et al. (2016), Chen et al. (2014), Zellner and Tobias (2000), Rapach et al. (2010), Fliedner (1999), Kohn (1982), Tiao and Guttman (1980).

http://dx.doi.org/10.1016/j.econlet.2017.06.010
0165-1765/

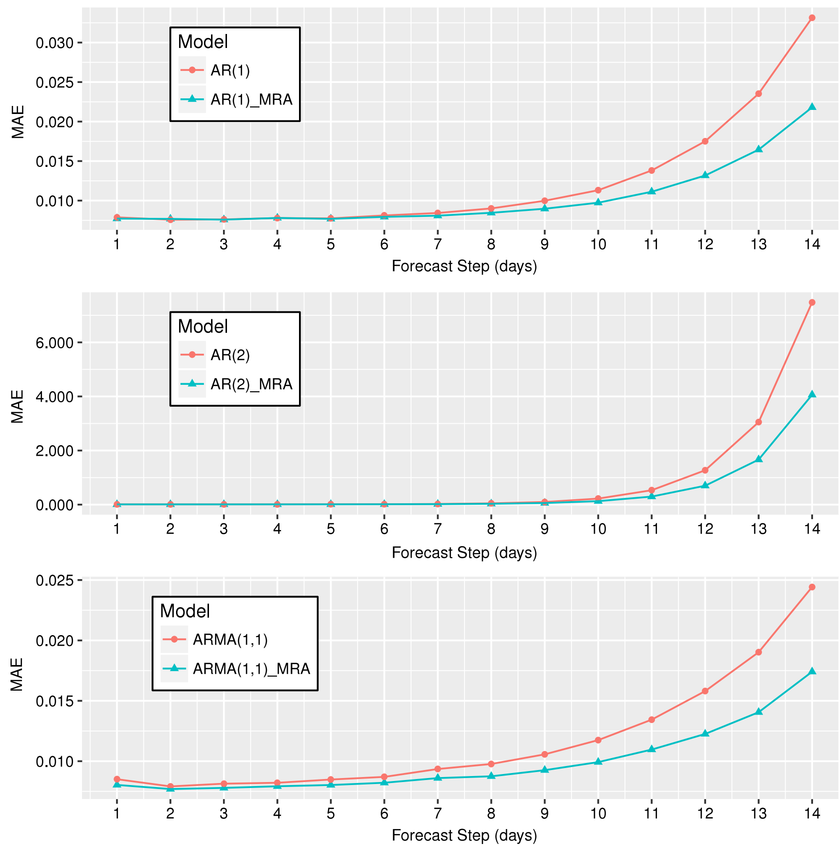

Fig. 1. Forecast improvement (MAE) with different horizons. The results correspond to the ones in the panel of 10-day rolling window in Table 1.

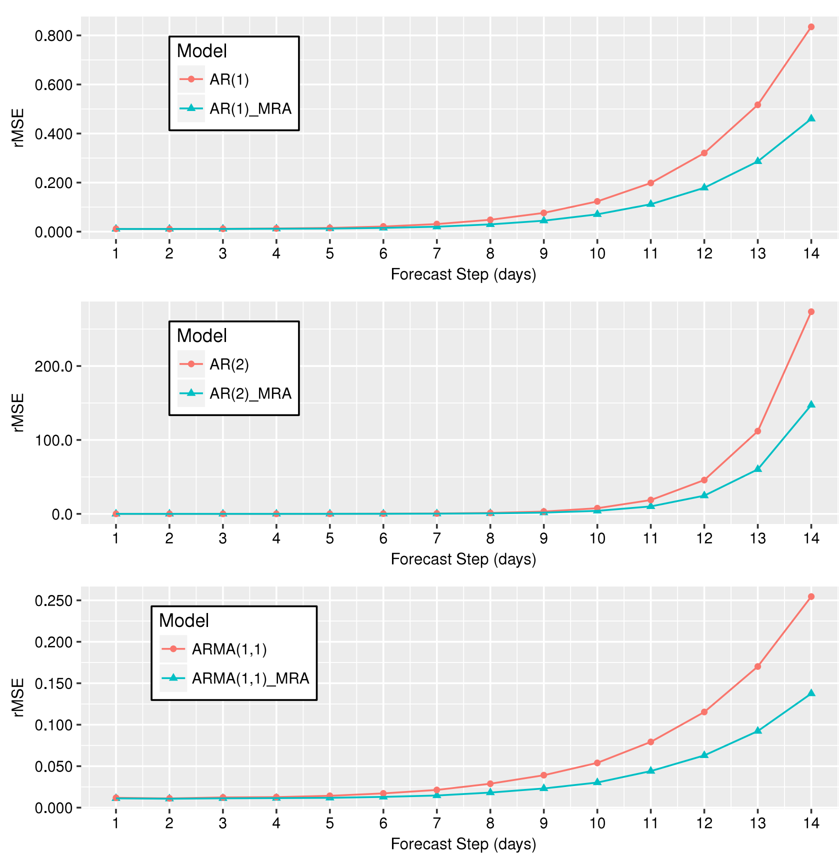

Fig. 2. Forecast improvement (rMSE) with different horizons. The results correspond to the ones in the panel of 10-day rolling window in Table 2.