Economics Bulletin

Volume 34, Issue 1

A comparison of different forecasting models of the international trade in India

Aviral Kumar Tiwari
ICFAI University Tripura

Claudiu T Albulescu
Politehnica University of Timisoara

Phouphet Kyophilavong
National University of Laos

Abstract

We assess the out-of-sample forecasting performance of eight models on Indian real exports and imports. The results, in large part show only a slight increase or no clear increase in India's international trade. However, the results are very robust when comparing the predictions in terms of exports and imports. In both the cases, the ARIMA and ETS models perform better in terms of the accuracy fit.

Citation: Aviral Kumar Tiwari and Claudiu T Albulescu and Phouphet Kyophilavong, (2014) ''A comparison of different forecasting models of the international trade in India'', *Economics Bulletin*, Vol. 34 No. 1 pp. 420-429.
Contact: Aviral Kumar Tiwari - aviral.eco@gmail.com, Claudiu T Albulescu - claudiual@yahoo.com, Phouphet Kyophilavong - phouphetkyophilavong@gmail.com.
Submitted: January 09, 2014. **Published:** March 04, 2014.

1. Introduction

National central banks and governments are all concerned with estimating the impact of international trade on their specific objectives. The volume of exports and imports not only influences the trade deficit, the exchange rate, and inflation but also the employment in different sectors. Furthermore, forecasting international trade is crucial for the private players who are active on the international markets and who construct their strategies based on their forecast or the official one. In this paper, we use a battery of forecasting models to examine their performance. We start with the ARIMA model (Hyndman and Khandakar, 2008) and continue with a double-seasonal Holt-Winters model (Taylor, 2003), an exponential smoothing state space model (Hyndman *et al*. 2002; Hyndman and Khandakar, 2008), a BATS model (DeLivera *et al*., 2011), and a Theta model (Assimakopoulos and Nikolopoulos, 2000; Hyndman and Billah, 2003).

Our approach is in contrast to the classical forecasting literature regarding the international trade. For example, Co and Boosarawongse (2007) compare the performances of artificial neural networks with exponential smoothing and Autoregressive Integrated Moving Average (ARIMA) models to forecast the international trade in rice for Thailand. Along the same line, Wang (2011) does a comparison study between fuzzy time series models and ARIMA models to forecast Taiwan's exports. Both studies highlight the performance of the ARIMA models. Wong *et al*. (2010) find similar results that show that the ARIMA models generate smaller forecasting errors over a longer time period. Lin and Wang (2012) examine the forecasting of natural gas imports in China, and Chou *et al*. (2008) propose a regression model for forecasting the volume of Taiwan's import containers. Only a few studies (Arora, 2013) compare several forecasting models at once, but do so in relation to energy consumption.Our study also contributes to the forecasting literature by analyzing the particular case of India. India has a poor transport infrastructure that constrains cross-border trade unlike its main commercial partners – the United Arab Emirates and U.S.. However, India has established a five year plan that started in 2013 to encourage infrastructure investments. This plan hopefully will contribute to higher trade openness in the context of a highly growing population. But, a severe contraction in the demand of India's main trade partners could be a menace to export activities. Against this background, the accuracy of forecasting the international trade of India is of great importance. In this paper, we use IMF monthly data from January 1957 to December 2011 to examine this accuracy.

The rest of this paper is organized as follows: Section 2 describes the methodology. Section 3 presents the forecasting results. The last section concludes.

2. Methodology

2.1. ARFIMA and AUTO-ARIMA models

ARIMA models are very common in forecasting macroeconomic variables, but the order selection process for these models is subjective. However, unit root tests can make that process less subjective.

Usually the ARIMA model is specified as an ARIMA(p,1,0). Nevertheless, a distinction should be made between seasonal and non-seasonal series. For a non-seasonal series, Hyndman and Khandakar (2008) show that an ARIMA(p,d,q) process is given by:

$$\emptyset(B)(1-B^{d})y_t = c + \theta(B)\varepsilon_t \qquad (1a)$$

where $y_t$is the time series, $\{\varepsilon_t\}$ is a white-noise process with 0 mean and σ^2 variance, B is the backshift operator, d is difference parameter, and $\emptyset(z)$ and $\theta(z)$ are polynomials of order p and q respectively.

For a seasonal ARIMA (p,d,q)(P,D,Q)$_m$ process, we have:

$$\Phi(B^m)\phi(B)(1-B^m)^D(1-B)^d y_t = c + \Theta(B^m)\theta(B)\varepsilon_t \tag{1b}$$

where $\Phi(z)$ and $\Theta(z)$ are polynomials of orders P and Q, respectively, with no roots inside the unit circle. If $c \neq 0$, then there is an implied polynomial of order $d + D$ in the forecast function.

An Autoregressive Fractionally Integrated Moving Average (ARFIMA) model shares the same form of representation as the ARIMA(p,d,q) process. However, in contrast to the ordinary ARIMA process, d is allowed to take non-integer values.

Hyndman and Khandakar (2008) also propose an automatic forecasting approach (AUTO-ARIMA) in which the appropriate model order (the values p, q, P, Q, D, d) is selected based on AIC information criteria:

$$AIC = -2\log(l) + 2(p + q + P + Q + k) \tag{1c}$$

where $k = 1$ if $c \neq 0$ and zero otherwise.

2.2. Taylor's (2003) Double-Seasonal Holt-Winters model

Another popular automatic forecasting framework is based on exponential smoothing. The robustness and accuracy of exponential smoothing methods have led to their extensive use in applications with a large number of series. Exponential smoothing methods have developed progressively, but Taylor's (2003) extension is noteworthy. Taylor extends the Holt-Winters exponential smoothing formulation to accommodate a second seasonality. Thus, if m_1 and m_2 are the periods of the seasonal cycles, and d_t is a white-noise random variable representing the prediction error; then while the components l_t and $b_t$represent the level and the trend of the y series at time t, the seasonal components $s_t^{(i)}$ become:

$$s_t^{(1)} = s_{t-m_1}^{(1)} + \gamma_1 d_t \tag{2a}$$

$$s_t^{(2)} = s_{t-m_2}^{(2)} + \gamma_2 d_t \tag{2b}$$

and

$$y_t = l_{t-1} + b_{t-1} + s_t^{(1)} + s_t^{(2)} + d_t \tag{2c}$$

$$l_t = l_{t-1} + b_{t-1} + \alpha d_t \tag{2d}$$

$$b_t = b_{t-1} + \beta d_t \tag{2e}$$

where the coefficients $\alpha, \beta, \gamma_1, \gamma_2$ are the soothing parameters; and $l_0, b_0, \left\{s_{1-m_1}^{(1)}, \dots, s_0^{(1)}\right\}$ and $\left\{s_{1-m_2}^{(2)}, \dots, s_0^{(2)}\right\}$ are the initial state variables.

The seasonal equations are given by:

$$s_t^{(1)} + y_t = \left(s_{t-m_1}^{(1)} + y_t\right) + \gamma_1 d_t \tag{2f}$$

$$s_t^{(2)} - y_t = \left(s_{t-m_2}^{(2)} - y_t\right) + \gamma_2 d_t \tag{2g}$$

where y_t is a time series consisting of repeated sequences for each season in the smaller cycle.

2.3. Exponential smoothing state space (ETS) model

Hyndman *et al*. (2002) and Hyndman and Khandakar (2008) propose a different approach to automatic forecasting based on an extended range of exponential smoothing, namely the exponential smoothing state space models for additive and multiplicative errors. The so-called ETS model refers to three components: the error, trend, and seasonality.

For additive errors, the state space model is:

$$y_t = l_{t-1} + \emptyset b_{t-1} + \varepsilon_t \tag{3a}$$
$$l_t = l_{t-1} + \emptyset b_{t-1} + \alpha\varepsilon_t \tag{3b}$$
$$b_t = \phi b_{t-1} + \beta^*(l_t - l_{t-1} - \emptyset b_{t-1}) = \emptyset b_{t-1} + \alpha\beta^*\varepsilon_t \tag{3c}$$

where $\mu_t = \widehat{y_t} = l_{t-1} + b_{t-1}$ denotes the one-step forecast of y_t when the values of all of the parameters are known, and $\varepsilon_t = y_t - \mu_t$ is the one-step forecast error in time t.

For multiplicative errors, the state space model becomes:

$$y_t = (l_{t-1} + \phi b_{t-1})(1 + \varepsilon_t) \tag{3d}$$
$$l_t = (l_{t-1} + \phi b_{t-1})(1 + \alpha\varepsilon_t) \tag{3e}$$
$$b_t = \phi b_{t-1} + \beta(l_{t-1} + \phi b_{t-1})\varepsilon_t \tag{3f}$$

where $\varepsilon_t = (y_t - \mu_t)/\mu_t$, so that ε_t is the relative error.

2.4. BATS and TBATS models

De Livera *et al*. (2011) discover a series of issues related to the exponential smoothing techniques, such as a large number of initial seasonal values that remain to be estimated when some of the seasonal patterns have long periods. In addition, the models used for exponential smoothing assume that the error process $\{d_t\}$ is serially uncorrelated.

Consequently, they extend Taylor's (2003) model to include a Box–Cox transformation, ARMA errors, and T seasonal patterns (called the BATS model). The notation $y_t^{(\omega)}$ is used to represent the Box–Cox transformed observations with the parameter ω as follows:

$$y_t^{(\omega)} = \frac{y_t^{\omega}-1}{\omega}\ , if\ \omega \neq 0, or\ log y_t, if\ \omega = 0 \tag{4a}$$
$$y_t^{(w)} = l_{t-1} + \emptyset b_{t-1} + \sum_{i=1}^{T} s_{t-m_i}^{(i)} + d_t \tag{4b}$$
$$l_t = l_{t-1} + \emptyset b_{t-1} + \alpha d_t \tag{4c}$$
$$b_t = (1 - \emptyset)b + \emptyset b_{t-1} + \beta d_t \tag{4d}$$
$$s_t^{(i)} = s_{t-m_i}^{(i)} + \gamma_i d_t \tag{4e}$$
$$d_t = \sum_{i=1}^{p} \varphi_i d_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{4f}$$

where $m_1, \ldots., m_T$ denote the seasonal periods; l_t is the local level in period t; b is the long-run trend; b_t is the short-run trend in the period t; $s_t^{(i)}$ is the i^{th} seasonal component at time t; d_t represents an ARMA(p,q) process; ε_t denotes a Gaussian white-noise process with zero mean and constant σ^2 variance; and α, β, γ_i are smoothing parameters.

The trigonometric seasonal models proposed by De Livera *et al*. (2011) and derived from the BATS is called TBATS. A TBATS model requires the estimation of $2(k_1 + k_2 + \cdots k_T)$ initial seasonal values, a number that is likely to be much smaller than the number of seasonal seed parameters in a BATS model. Because the TBATS relies on trigonometric functions, it can be used to model non-integer seasonal frequencies:

$$s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t}^{(i)} \tag{4g}$$
$$s_{j,t}^{(i)} = s_{j,t-1}^{(i)} cos\lambda_j^{(i)} + s_{j,t-1}^{*(i)} sin\lambda_j^{(i)} + \gamma_1^{(i)} d_t \tag{4h}$$
$$s_{j,t}^{*(i)} = -s_{j,t-1} sin\lambda_j^{(i)} + s_{j,t-1}^{*(i)} cos\lambda_j^{(i)} + \gamma_2^{(i)} d_t \tag{4h}$$

where $\gamma_1^{(i)}$ and $\gamma_2^{(i)}$ are smoothing parameters, and $\lambda_j^{(i)} = 2\pi j/m_i$.

2.5. Theta forecast

The “Theta method” of forecasting was introduced by Assimakopoulos and Nikolopoulos (2000) and simplified by Hyndman and Billah (2003). The proposed method decomposes the original time series into two or more different Theta-lines that are extrapolated separately while the subsequent forecasts are combined.

Assimakopoulos and Nikolopoulos (2000) construct from a $\{X_1, \dots, X_n\}$ observed univariate time series, a new series $\{Y_1(\theta), \dots, Y_n(\theta)\}$ such that:

$$Y_t^{''}(\theta) = \theta X_t^{''} \quad (5a)$$

where $X_t^{''}$ denotes the second difference of X_t, and $Y_t^{''}(\theta)$ is the second difference of $Y_t(\theta)$.

The above equation is a second-order difference equation and has the solution:

$$Y_t(\theta) = a_\theta + b_\theta(t-1) + \theta X_t \quad (5b)$$

where a_θ and b_θ are constants, and $Y_t(\theta)$ is the Theta line.

The forecasts from the Theta methodfor $\theta = 0$ and $\theta = 2$ are obtained through the weighted average of $Y_t(\theta)$ forecasts for different values of θ. Therefore:

$$\hat{X}_{n+h} = \frac{1}{2}\left[\hat{Y}_{n+h}(0) + \hat{Y}_{n+h}(2)\right] \quad (5c)$$

Hyndman and Billah (2003) generalize these results and show that for large n, we have:

$$\hat{X}_{n+h} = \tilde{X}_{n+h} + \frac{1}{2}\hat{b}_{0,n}(h - 1 + 1/\alpha) \quad (5d)$$

where $\tilde{X}_{n+h}$ is the simple exponential smoothing of the series $\{X_t\}$.

3. Forecasting results

The forecasting performance of each model is evaluated based on standard metrics: the mean error (ME), the root mean squared error (RMSE), the mean absolute error (MAE), the mean percentage error (MPE), the mean absolute percentage error (MAPE), and the mean absolute scaled error (MASE).

The results for the accuracy fit are differentiated for exports (Table 1) and imports (Table 2).[1] In the case of the Indian exports, Appendix B shows that only the ARFIMA model predicts a decrease in the real level of the exports.[2] All the others models forecast an increase in the exports (ARIMA, Holt, Holt-Winters) or no clear up or down trend (ETS, BATS, TBATS, Theta).

We notice that only the ARIMA model forecasts a decrease in international trade for India. This result can be associated with a possible misspecification of the difference parameter d, based on information criteria. For ARFIMA models, d can take a non-integer value. Thus, the forecasts based on ARFIMA for a $d > 0.5$ can be problematic (Ray, 1993; Doornik and Ooms, 2004).

Moreover, in terms of the accuracy fit, Table 1 shows that the ARFIMA does not perform well. The ARIMA model presents the lowest ME and RMSE values, while the ETS is supported by the MAE and MASE. We conclude that the most accurate models predict a slight increase in the level of the real exports for India.

[1] The plots for exports are presented in Appendix A, while the plots for the imports are presented in Appendix B.
[2] The real level of exports and imports (Appendix C) is obtained by dividing the nominal value to the Wholesale Price Index (WPI).

Table 1. Comparison of the Accuracy Fit of Models Forecasting the Real Exports

	ME	RMSE	MAE	MPE	MAPE	MASE
ARFIMA	0.2613	0.8958	0.5387	-77.600	102.80	4.4608
ARIMA	0.0101	0.1995	0.0915	-0.2589	8.6753	0.7579
Holt	0.0132	0.2463	0.1062	-0.5481	9.3308	0.8795
Holt-Winters	0.0104	0.2072	0.0907	-0.3580	9.2949	0.7517
ETS	0.0269	0.2136	0.0892	0.5188	7.7235	0.7387
BATS	-	-	-	-	-	-
TBATS	-	-	-	-	-	-
Theta	0.0243	0.2486	0.1062	0.0356	9.2639	0.8794

Similar results are obtained in the case of real imports (Table 2).

Table 2. Comparison of the Accuracy Fit of Models Forecasting the Real Imports

	ME	RMSE	MAE	MPE	MAPE	MASE
ARFIMA	0.1491	0.5828	0.2970	-27.712	37.512	1.8656
ARIMA	0.0156	0.3277	0.1429	-0.6320	9.9993	0.8977
Holt	0.0169	0.3338	0.1442	-0.7091	9.8455	0.9061
Holt-Winters	0.0162	0.3291	0.1516	-0.3595	14.8069	0.9528
ETS	0.0396	0.3452	0.1407	0.1709	9.1956	0.8838
BATS	-	-	-	-	-	-
TBATS	-	-	-	-	-	-
Theta	0.0295	0.3361	0.1452	-0.2456	9.8409	0.9121

The strength of the ARIMA model in forecasting real imports is considerable, as both the ME and the RMSE metrics show the lowest forecast errors for this model. All of the other metrics support the ETS model because this model performs better in terms of the accuracy fit. In general, the forecasting errors for the imports are bigger than those for the real exports, except in the ARFIMA model.

4. Conclusions

We evaluate the out-of-sample forecasting performance of eight models on India's real exports and imports. There is no clear evidence regarding an increase or a stagnation in India's international trade. All in all, the models provide mixed results. However, the ARIMA and ETS models present smaller forecasting errors and thus better accuracy.

These two models are supported by the standard metrics chosen for assessing their performance, both for real exports and imports. The ARIMA performs well in terms of accuracy; these results confirm the main findings in the literature regarding trade forecasting. Obtaining accurate forecasts is important both for the Indian authorities, as well as for the investors.

More precisely, if we consider the results provided by the models with the best accuracy, we notice an increase of the international trade for India. This evidence has several policy implications. First, the dominant view is that the trade openness will fasten the economic growth. Second, an increase in international trade can influence the inflationary process, trough the Balassa-Samuelson effect. Third, as both exports and imports increase, the current account deficit in India will deepen, as the imports' level exceeds the exports. Finally, based on the last observation, an increase in international trade will put additional pressure on the domestic currency.

References

Arora, V. (2013) “Comparisons of Chinese and Indian Energy Consumption Forecasting Models” *Economics Bulletin* **33**, 2110–2121.

Assimakopoulos, V. and K. Nikolopoulos (2000) “The Theta Model: A Decomposition Approach to Forecasting“ *International Journal of Forecasting* **16**, 521–530.

Chou, C-C., Chub, C-W. and G-S Liang (2008) “A Modified Regression Model for Forecasting the Volumes of Taiwan’s Import Containers” *Mathematical and Computer Modelling* **47**, 797–807.

Co, H.C. and R. Boosarawongse (2007) “Forecasting Thailand’s Rice Export: Statistical Techniquesvs, Artificial Neural Networks” *Computers & Industrial Engineering* **53**, 610–627.

De Livera, A.M., Hyndman, R.J. and R.D. Snyder (2011) “Forecasting Time Series with Complexseasonal Patterns using Exponential Smoothing” *Journal of the American Statistical Association* **106**, 1513–1527.

Doornik, J.A. and Ooms, M. (2004) “Inference and Forecasting for ARFIMA Models with an Application to US and UK Inflation” *Studies in Nonlinear Dynamics & Econometrics* **8**, Article 14.

Hyndman, R.J. and B. Billah (2003) “Unmasking the Theta Method” *International Journal of Forecasting* **19**, 287–290.

Hyndman, R.J. and Y. Khandakar (2008) “Automatic Time Series Forecasting: The Forecast Package for R. *Journal of Statistical Software* **27**, 1–22.

Hyndman, R.J, Koehler, A.B., Snyder, R.D. and S. Grose (2002) “A State Space Framework for Automatic Forecasting using Exponential Smoothing Methods” *International Journal of Forecasting* **18**, 439–454.

Lin, B. and T. Wang (2012) “Forecasting Natural Gas Supply in China: Production Peak and Import Trends. *Energy Policy* **49**, 225–233.

Ray, B.K. (1993) “Modeling long memory processes for optimal long-range prediction” *Journal of Time Series Analysis* **14**, 511–525.

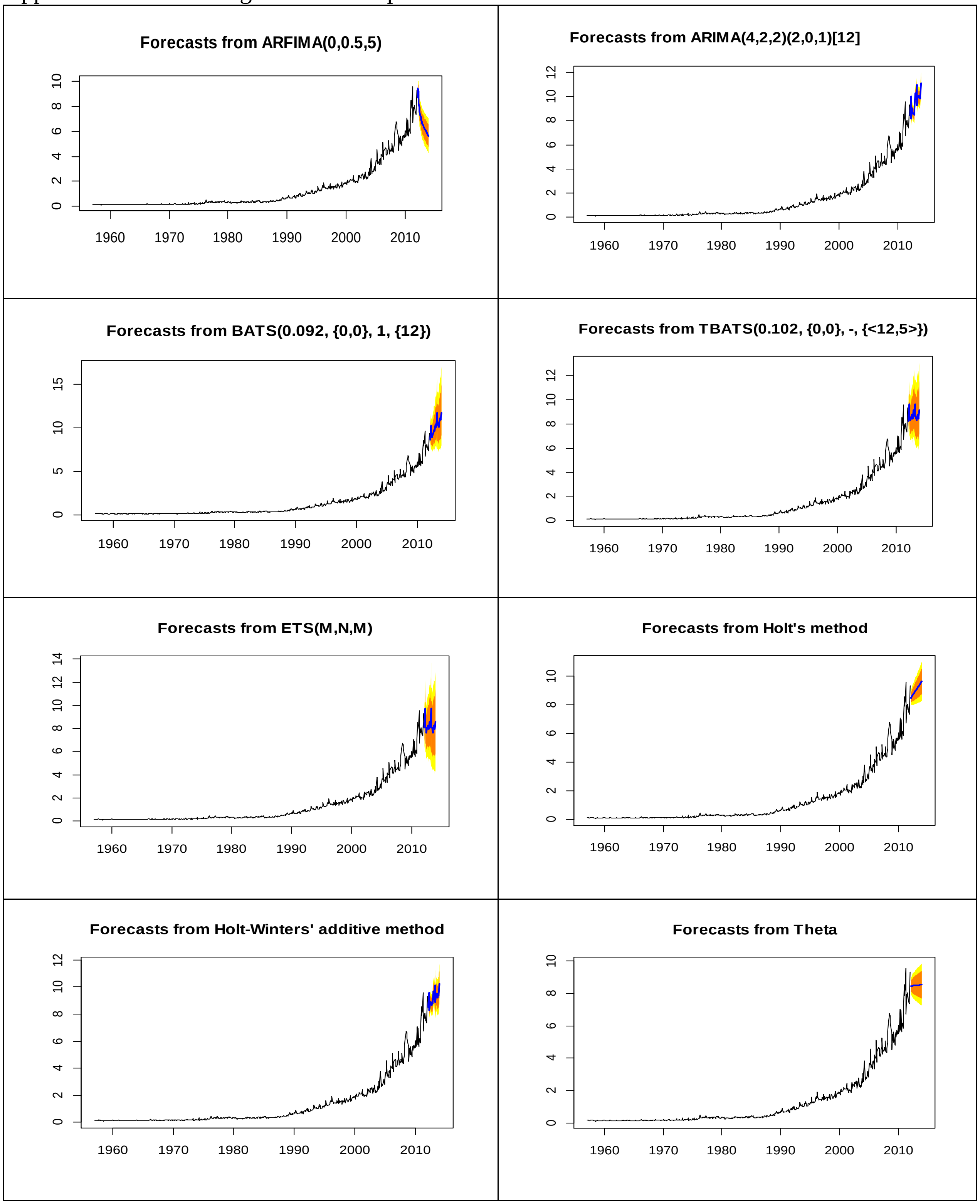
Taylor, J.W. (2003) “Short-term Electricity Demand Forecasting using Double Seasonal Exponential Smoothing” *Journal of the Operational Research Society* **54**, 799–805.

Wang, C-C. (2011) “A Comparison Study Between Fuzzy Time Series Model and ARIMA Model for Forecasting Taiwan Export“ *Expert Systems with Applications* **38**, 9296–9304.

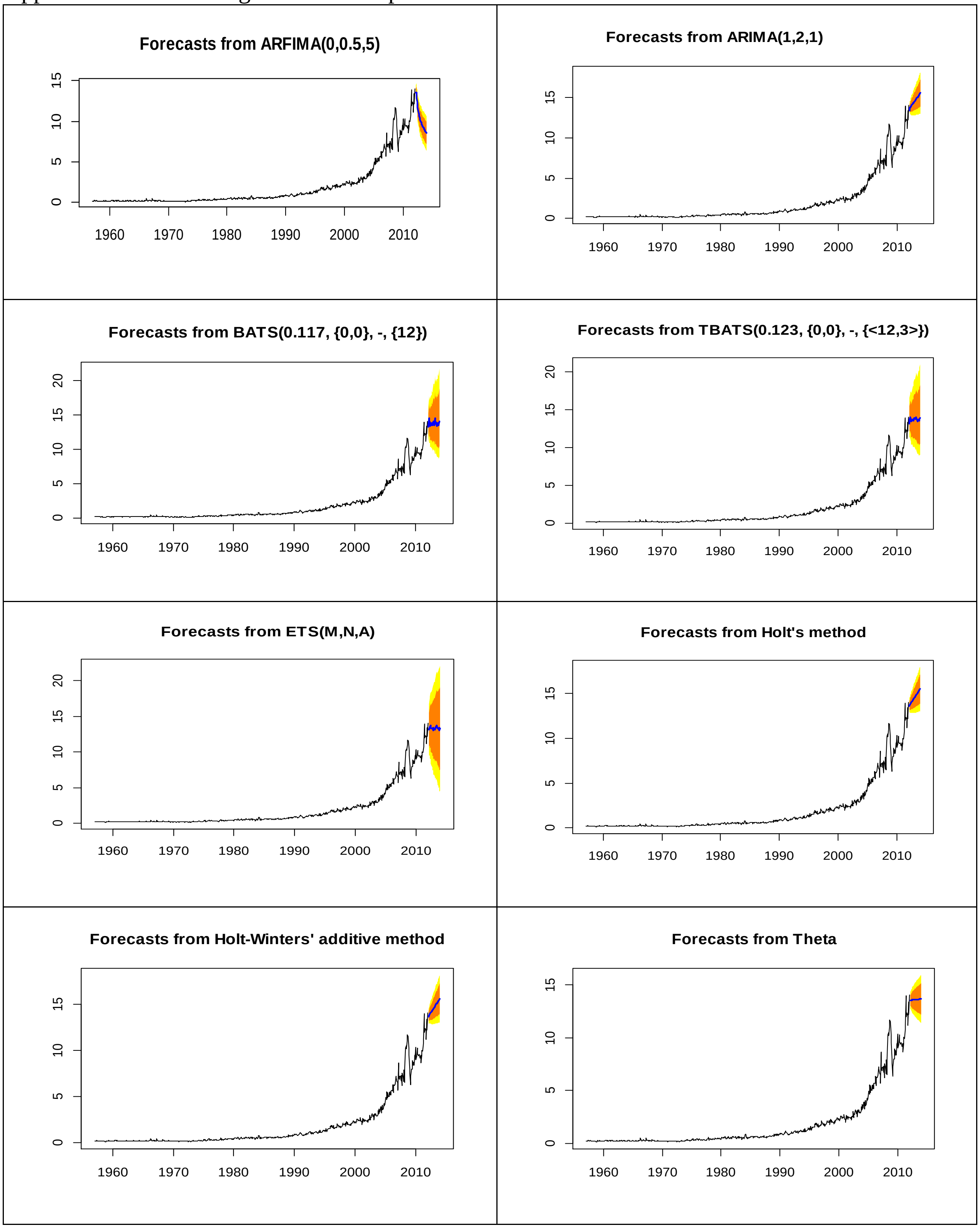
Wong, H-L., Tu, I-H. and C-C. Wang (2010) “Application of Fuzzy Time Series Models for Forecasting the Amount of Taiwan Export“ *Expert Systems with Applications* **37**, 1465–1470.

Appendices

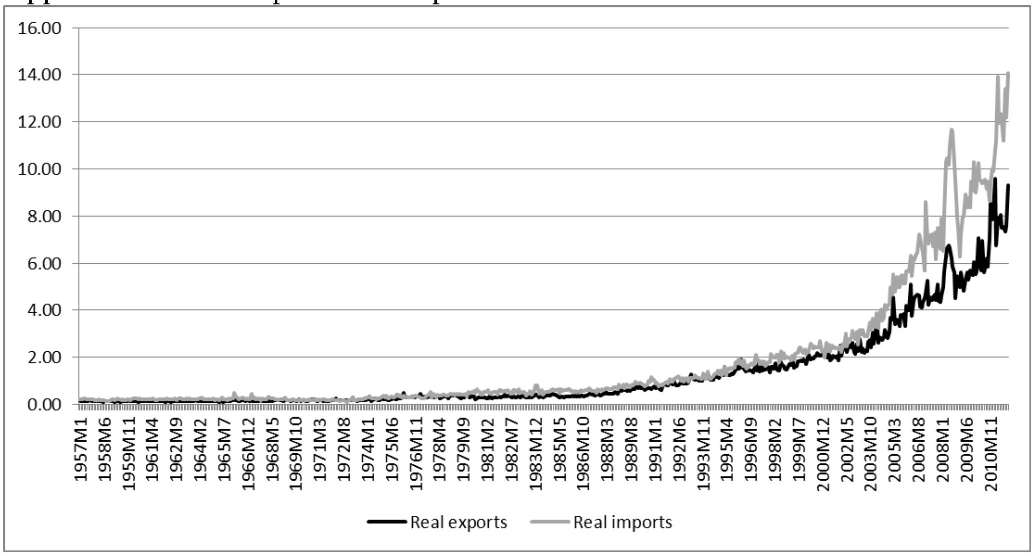
Appendix A. Forecasting results for exports



Appendix B. Forecasting results for imports



Appendix C. Real exports and imports for India



Source: IMF database