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ARIMA vs. ETS for RMG Export Forecasting of Bangladesh: A Comparative Study on Model Accuracy

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Abstract

This study conducts a comparative analysis of ARIMA and ETS models to forecast Bangladesh RMG export trends. Utilizing annual RMG export data from 1983 to 2023, sourced from BGMEA's website, the research applies a logarithmic transformation to stabilize variance, with differencing exclusively for ARIMA to address non-stationarity. Automated model selection via R's functions – auto.arima() for ARIMA and ets() for ETS – was implemented to optimize parameter configurations. The optimal ARIMA (2,2,0) and ETS (A, Ad, N) models was trained on data from 1983 to 2015 and validated on the 2016-2023 testing subset. Accuracy metrics, revealed ETS's superior performance, yielding a lower MAPE (8.47% vs 19.74%) and RMSE (3794.72 vs 8334.12) compared to ARIMA's. The Diebold-Mariano test confirmed ETS's statistical superiority at a 15% significance level. The ETS's adaptability to non-linear trends and damped volatility in RMG underscore its efficacy, while ARIMA's reliance on linear assumptions limited its applicability. Forecast for 2024-2028 project sustained RMG export growth, emphasizing sector's economic resilience. These findings advocate for policymakers to inform strategic planning, while highlighting the need for future research integrating external factors through hybrid or machine learning models

Keywords: ARIMA, ETS, RMG, MAPE, RMSE

I. Introduction

Forecasting is critical for time series analysis, requiring appropriate model selection to enhance accuracy. Diverse techniques exist for capturing data patterns, selecting models, and generating forecasts across economic and operational contexts.[1] Among these, Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing (ETS) frameworks are widely used. ARIMA excels at modeling linear, stationary univariate series, whereas ETS is adept at capturing non-linear patterns with trends and seasonal variations.

The ARIMA methodology, developed by Box and Jenkins in the 1970s, established a systematic framework for analyzing stationary time series data.[2] Their approach revolutionized forecasting practices by emphasizing an iterative cycle of model selection, parameter estimation, and diagnostic validation.[3] The Box-Jenkins method remains foundational for analyzing stationary data and generating reliable predictions. The auto.arima() function from the forecast package in R streamlines ARIMA modeling by automating parameter selection, optimizing information criteria such as AIC and BIC to identify best-fit model.[4]

ETS, on the other hand, decomposes time series data into three core components: errors, trends, and seasonality. This framework dynamically captures interactions among these elements through smoothing equations, and adjusts parameters iteratively to minimize prediction errors. This characteristic makes ETS effective for forecasting non-stationary data with complex trends or seasonal shifts.[5] The ets() function from the forecast package in R automates ETS model selection by evaluating component combinations, optimizing information criteria like AIC to identify the most statistically robust model.[6]

Several studies have compared ARIMA and ETS forecasting performance. For example, an analysis of monthly rice production data (1990-2020) from Bangladesh Bureau of Statistics (BBS) found ARIMA superior to ETS.[6] Similarly, studies on annual tea production in Bangladesh,[7] and quarterly U.S. retail sales from the M3 competition[8] concluded that ARIMA outperformed ETS, likely due to dataset's linear trends and minimal seasonality. Conversely, research on monthly electricity demand in Bangladesh[9] and Australian domestic tourism data[10] demonstrated ETS's superiority over ARIMA, due to dataset's non-linear trends and seasonality.

Bangladesh's Ready-Made Garment (RMG) sector, contributing 85% of total export earnings and employing 4.2 million workers, is pivotal to the national economy.[11] Forecasting RMG export trends is thus essential for economic planning. Previous studies have explored this using methods like ARIMA[12] and Semi-Log Parabolic Regression[13], yet a comparative analysis of ARIMA and ETS for annual RMG export data remains absent in existing literature.

This study evaluates ARIMA and ETS models to forecast Bangladesh's annual RMG exports, addressing this research gap. Section II outlines the methodological frameworks. Section III describes the dataset. Section IV presents results with supporting tables and figures. Section V discusses key findings, and Section VI offers recommendations and conclusions.

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II. Methodology

This study employs two widely recognized time series forecasting frameworks: The Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing (ETS) to analyze and forecast Bangladesh's annual Ready-Made Garment (RMG) export data. Both methodologies are grounded in distinct theoretical and operational principles, as outlined below.

ARIMA Framework

The ARIMA methodology, developed by Box and Jenkins[2], is designed to model linear trends in stationary time series data. The framework integrates three key components: The autoregressive (AR) term, which captures dependency of current values on past observations; the differencing (I) term, which transform non-stationary data into a stationary series; and the moving average (MA), which accounts for the relationship between current values and past forecast errors. The model is formally denoted as ARIMA (p, d, q) where, p, d, and q represent the order of AR, differencing, and MA components, respectively.

The Box-Jenkins approach follows an iterative cycle beginning with stationarity assessment. Stationarity is evaluated through Graphical Analysis and the Augmented Dickey-Fuller (ADF) test. If non-stationarity is detected, differencing is applied until the series stabilizes. Model identification then proceeds using autocorrelation (ACF) and partial autocorrelation function (PACF) plots to tentatively determine p and q values. The automated auto.arima() function from forecast package in R[4] streamlines this process by systematically evaluating combination of p, d, and q, and selecting the appropriate model based on minimized Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Parameter estimation employs maximum likelihood estimation (MLE), followed by diagnostic validation to ensure residuals exhibit white noise properties. These includes checks for zero mean, constant variance, and absence of autocorrelation using Ljung-Box test.[2]

ETS Framework

The ETS framework decomposes time series into three components: error (E), trend (T), and seasonality (S), with additive (A) or multiplicative (M) configuration for each. This flexibility enables ETS to model non-linear trends, dampen random errors, and incorporate seasonal variation, making it particularly suited for non-stationary data. The general form ETS (E, T, S) accommodates combinations such as additive errors (A), dampen trends (Ad) or multiplicative seasonality (M).

ETS employs weighted averages of past observations, where weights decay exponentially over time, assigning less influence to older data. Smoothing equations iteratively adjust parameters: alpha (level), beta (trend), phi (damping factor), and gamma (seasonality) to minimize prediction errors. The automated ets() function from the forecast package in R evaluates all possible ETS configurations and select the optimal model based on the lowest AIC[5]

Model Comparison and Validation

To compare the forecasting performance, two error metrics are employed: The Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). MAPE quantifies the average absolute percentage deviation between predicted (f_t) and actual (A_t) value[13], calculated as,

$$MAPE = \frac{\frac{1}{n}\sum_{t=1}^{n}|f_t - A_t|}{A_t}$$

RMSE measures the square root of the average squared errors[13], defined as, $RMSE = \sqrt{E(f_t - A_t)^2}$

Lower values for both metrics indicate superior predictive accuracy. Models are trained on historical data spanning from 1983 to 2015 and validated on a testing subset (2016-2023). Final forecasts are generated using the model with the lowest error scores.

Data Preprocessing

A logarithmic transformation is applied to the raw RMG export series to stabilize variance and address heteroscedasticity. Both methodologies utilize automated functions: auto. arima() and ets() from the forecast package in R[4,5], to ensure methodological consistency and reproducibility. This systematic approach aligns with established practices in time series forecasting literature[1,2,4,5], providing a robust foundation for model selection and validation.

III. Data and Variables

The foundation of this study is the annual RMG export data spanning four decades (1983 to 2023), sourced directly from the Bangladesh Garment Manufacturers and Exporters Association (BGMEA) in its "Export Performance" report (2025). To simplify temporal analysis, fiscal years has been transformed into single-year notations (e.g., fiscal year 2008-09 transformed into year 2008).

The primary variable of interest is RMG export values, represented as a univariate time series. This dataset captures annual export performance in monetary terms, serving as the sole input for modeling and forecasting with ARIMA and ETS frameworks.

IV. Results

Stationarity Check

The dataset (1983-2023) was divided into training (1983-2015) and testing (2016-2023) subsets for train and test the models. A logarithmic transformation stabilized the variance of RMG export series. Graphical Analysis and the Augmented Dickey-Fuller (ADF) test confirmed non-stationarity in the original series. Second order differencing (d=2) achieved stationarity (ADF p-value < 0.05).

ARIMA Model Development

The auto.arima() function[4] selected the optimal ARIMA (2,2,0) model based on minimized AIC and BIC values. The model incorporated second-order differencing (d=2) to address non-stationarity, with autoregressive terms p=2, and no moving average component (q=0). Parameter estimates are summarized in Table 1.

Table 1. Estimated parameters of ARIMA (2,2,0)

	ARIMA (2,2,0)
AR(1)	-1.1771
AR(2)	-0.4675
σ^2 (Estimated)	0.03987
Log-likelihood	6.23
AIC	-6.46
BIC	-2.15

Forecasts for the year 2016 to 2023 (Table 2) yielded a mean absolute percentage error (MAPE) of 19.74%, indicating a moderate predictive accuracy (MAPE > 10%).[13]

Table 2. ARIMA (2,2,0) Forecasting Performance (2016-2023)

Year	Actual Value	Predicted Value	Error	MAPE
2016	28149.84	30183.36	2033.52	
2017	30614.76	32533.74	1918.98	
2018	34133.27	35351.70	1218.42	
2019	27949.19	37992.12	10042.92	19.74%
2020	31456.73	41207.67	9750.93	
2021	42613.15	44441.94	1828.79	
2022	38142.10	48044.60	9902.49	
2023	36151.31	51931.44	15780.13	

ETS Model Development

The ets() function[5] selects the optimal ETS (A, Ad, N) model with additive error, damped trend, and no seasonality. Estimated parameters of the model are shown below in Table 3.

Table 3. Estimated parameters of ETS (A, Ad, N)

	ETS (A, Ad, N)
α	0.4033
β	0.4033
φ	0.8
l (Level)	2.5703
b (Initial trend)	1.3478
σ	0.1675
AIC	4.05

Forecasts for the year 2016 to 2023 (Table 4) resulted in MAPE of 8.47% which is less than 10%, indicating model has a strong predictive accuracy.[13]

Table 4. Forecasting Performance of ETS (A, Ad, N) Model for RMG Export

Year	Actual Value	Predicted Value	Error	MAPE
2016	28149.84	29627.78	1477.9390	
2017	30614.76	30990.68	375.9179	
2018	34133.27	32126.00	2007.2695	
2019	27949.19	33064.13	5114.9422	8.47%
2020	31456.73	33834.32	2377.5940	
2021	42613.15	34463.37	8149.7752	
2022	38142.10	34975.03	3167.0742	
2023	36151.31	35389.81	761.4997	

Model Comparison

ETS (A, Ad, N) model outperformed the ARIMA (2, 2, 0) model with lower MAPE (8.47% vs 19.74%) and RMSE (3794.72 vs 8334.12), as shown in Table 5.

Table 5. Model Accuracy Comparison

Model	*MAPE*	*RMSE*
ARIMA	19.74%	8334.12
ETS	8.47%	3794.72

The Diebold-Mariano has been employed to determine whether the difference in forecasting accuracy between these two models is statistically significant. Test confirmed that ETS statistically outperformed ARIMA at a 15% level of significance. (Table 6)

Table 6. Diebold-Mariano Test Table

	Diebold-Mariano Test
DM Statistics	1.6442
Loss function power	2
p-value	0.1441

Forecasting with final Model (ETS)

As ETS model has the lowest measurement errors, this modeling approach has been further used to forecast the future RMG Export from Bangladesh. So, ETS model has been employed to the full dataset. This time, the ets () function selects the ETS (A, Ad, N) as the optimal model with estimated parameters given below in Table 7.

Table 7. Estimated parameters of new ETS (A, Ad, N)

	ETS (A, Ad, N)
α	0.3765
β	0.3765
φ	0.8
l (Level)	2.5931
b (Initial trend)	1.3468
σ	0.163
AIC	10.19

Diagnostic checks confirmed residual stationarity and white noise properties. (Figure 1).

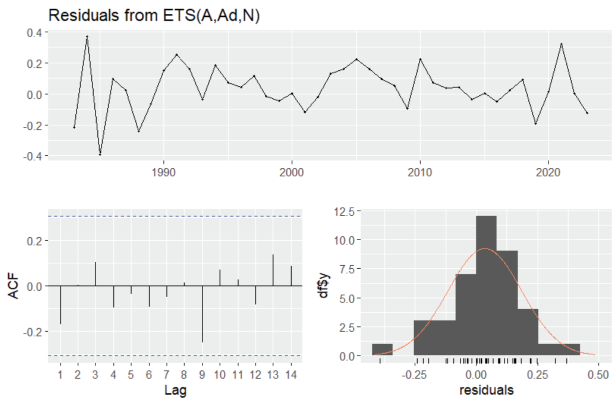

Fig. 1. Diagnostic Check of the ARIMA (2,2,0) Model

The forecasted values for 2024 to 2028 of RMG export has been shown in Table 8.

Table 8. ARIMA Forecasts for RMG Exports (2024 – 2030)

Year	*Forecasted RMG Export (in Million USD)*
2024	39855.12
2025	40487.08
2026	40999.80
2027	41414.75
2028	41749.68

A visual representation of the actual value (test) and predicted value (test) from ETS model along with the future forecast (2024-2030), is shown in figure 2.

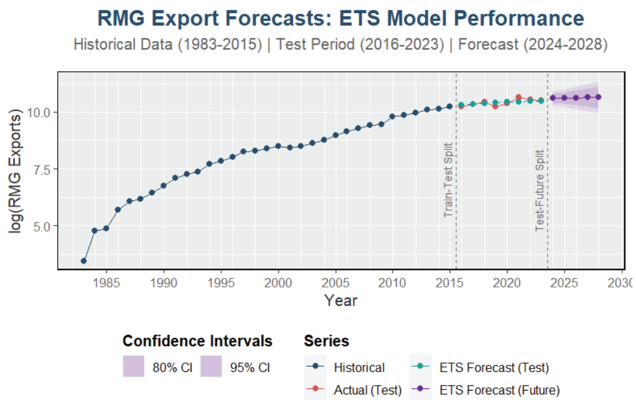

Fig. 2. RMG Export Forecasts: ETS Model Performance

The logarithmic value of RMG exports are presented due to the excessive differences between export in 1983 and 2023. The plot demonstrates the accuracy of the ETS model.

V. Discussion

This study evaluates the forecasting performance of ARIMA and ETS models for Bangladesh's annual RMG exports. The results establish the ETS (A, Ad, N) model as the more effective framework, achieving significantly lower error metrics (MAPE: 8.47% vs. ARIMA's 19.74%; RMSE: 3,794.72 vs. 8,334.12).

The strength of ETS lies in its capacity to dynamically adjust smoothing parameters and model damped trends. This feature enables it to capture non-linear patterns and adopt to the volatility inherent in RMG export data. While ARIMA remains a robust tool for linear trend analysis, its limitation in accommodating non-stationary data reduces its utility for Bangladesh RMG exports.

The forecasted RMG export for the year 2024 to 2028 indicate sustained growth in this sector, reflecting its resilience and economic importance.

VI. Conclusion

This study concludes the ETS (A, Ad, N) model is the superior choice for forecasting Bangladesh's RMG exports, combining accuracy with adaptability to address the sector's volatility. While ARIMA provides foundational insights into linear trends, its inflexibility in modeling non-linear dynamics limits its relevance for the RMG sector's evolving contexts.

The forecasts for the year 2024 to 2030, derived from ETS, provide actionable insights for policymakers to prepare for sustained growth in RMG exports. However, the model's dependence on historical patterns underscores the need for methodologies that accounts for external factors, such as global demand or political shifts. Future work should prioritize hybrid models or machine learning integrations to bridge this gap.

For Bangladesh's economy, where RMG exports drive growth and employment, this analysis reaffirms the importance of aligning forecasting tools with the sector's unique dynamics. ETS's reliability offers a pragmatic foundation for strategic decision-making, ensuring resilience in an increasingly unpredictable global landscape.

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