Proceedings of the 8th IEOM Bangladesh International Conference on Industrial Engineering and Operations Management, Dhaka, Bangladesh, December 20-21, 2025

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/BA08.20250174
Published: December 20, 2025

Classical Hybrid Time Series Forecasting of Bangladeshi Air Conditioner Market Dynamics

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Abstract

This study investigates the monthly air conditioner (AC) production trends in Bangladesh over a 12-year period from January 2013 to December 2024. The primary objective is to identify production patterns, seasonal behavior, and forecast future production to support strategic decision-making in inventory management, marketing, and resource allocation within the Bangladeshi AC market.The dataset exhibits an additive trend with multiplicative seasonality, characterized by higher production in March–June and lower output in October–January. To model and forecast these dynamics, four classical time series approaches were employed: ARIMA, Exponential Smoothing State Space Model (ETS), STL+ARIMA, and STL+ETS. Each model was trained and tested using an 84:16 data split, and their performances were evaluated using key error metrics such as MSE, RMSE, MAE, and MAPE.Among the models, the ETS (M,A,M) model—representing the Multiplicative Holt-Winters approach—showed the best forecasting performance, achieving the lowest error values (MSE = 13,860,263; RMSE = 3,722.94; MAE = 2,846.54; MAPE = 33.86%). This model effectively captured the additive trend and multiplicative seasonality present in the data. In contrast, the STL-based hybrid models (STL+ARIMA and STL+ETS) exhibited higher error values, indicating relatively weaker adaptability to the dataset.The five-year forecast (2025–2029) indicates a continuing upward trend in production, with peak levels expected during the summer months, potentially reaching up to 40,000 units in the highest demand periods. These findings demonstrate that time series forecasting can play a crucial role in enhancing production planning, optimizing inventory management, and aligning marketing strategies with seasonal demand fluctuations in the Bangladeshi air conditioner market.

Keywords
Hybrid time series models, Classical time series models, Time Series Forecasting, Decomposition, Seasonality, Air Conditioner Production.

1. Introduction
Air conditioners (ACs) have become an essential part of modern life, playing a critical role in enhancing comfort, productivity, and quality of life across various environments. From residential homes to industrial facilities, the demand for air conditioners continues to rise, driven by factors such as global urbanization, increasing temperatures due to climate change, and economic growth in developing markets. In the manufacturing sector, air conditioner production reflects not only market demand but also advancements in technology, energy efficiency, and production processes (Huang, X,2025). Analyzing production trends and seasonality in this industry is vital for ensuring timely supply, meeting consumer demand, and optimizing resource utilization in a competitive market. Production forecasting of a product mainly depends on the sales of that product (Nazim, S,2022). However, raw material price fluctuation, production and storage capacity may influence it.

Due to the global warming, increasing overhead income of Bangladeshi people sales of Air Conditioner is increasing day by day. As Air Conditioner is a seasonal product (Used in summer season and unused in rainy season). So, there is a seasonal fluctuation also.

So, the production manager of air conditioners should be strategic. As the resource is limited, he cannot produce enough in the peak season. He also cannot store enough AC after production due to limitation of storage and place rent. Moreover, price of the raw material of AC also fluctuates. It is wise to purchase raw material when price is low in the year (De Livera,2011). As increasing demand of the production, he has to increase production capacity based on the time series forecast of the upcoming years.

The production of air conditioners in Walton group is a vital sector, influenced by various factors such as seasonal weather patterns, technological advancements, and global warming. However, they often face challenges in accurately forecasting production volumes due to fluctuating demand, leading to issues like overproduction, stockouts, and inefficiencies in resource allocation. While time series forecasting models, such as ARIMA, ETS, and STL(Brockwell,2016), have been widely used in various industries to analyze and predict production trends, there remains a significant gap in their application to the specific context of air conditioner production in Bangladesh.

The motivation for this research stems from the increasing demand for air conditioners in Bangladesh, driven by rising temperatures, economic growth, and urbanization. The growing significance of this market highlights the need for accurate production forecasting to ensure that manufacturers can align production schedules with actual demand. However, due to seasonal fluctuations, technological advancements, and the impact of global warming, accurately predicting future production volumes remains a complex challenge.

Existing forecasting methods have yet to fully capture the intricacies of production trends in Bangladesh, where local market dynamics and environmental factors play a crucial role in shaping demand. By bridging this research gap, this study aims to provide actionable insights for manufacturers, enabling them to make data-driven decisions on resource allocation, inventory control, and marketing strategies (Gilgen,2018). The research is also motivated by the potential to apply state-of-the-art time series models to a specific emerging market, offering insights that could be applicable to similar contexts in other developing countries.

Ultimately, this research seeks to empower stakeholders in the Bangladeshi air conditioner manufacturing sector with tools and insights that will allow for better preparedness, reduced waste, and more efficient operations, contributing to the long-term sustainability and growth of the industry.

1.1 Objectives

The main objective of this research is to analyze the monthly production patterns of air conditioners in Bangladesh from January 2013 to December 2024, uncover underlying trends and seasonal components, and forecast production quantities for the next five years (2025–2029) using advanced time series forecasting methods such as ARIMA, ETS, and STL.

1. To identify the key trends and seasonal components in the monthly production of air conditioners in Walton group between 2013 and 2024.
2. To apply and evaluate different time series forecasting models (ARIMA, ETS, and STL) to predict future air conditioner production for the period 2025–2029.
3. To compare the forecasting accuracy of the ARIMA, ETS, and STL models by assessing their performance using error metrics such as MAE, RMSE, and MAPE.
4. To investigate the impact of external factors such as global warming and technological advancements on the seasonal demand and production trends of air conditioners in Bangladesh.
5. To provide actionable insights for stakeholders (e.g., manufacturers, policymakers, and supply chain managers) to optimize production planning, inventory management, and marketing strategies based on the forecasting results.
6. To contribute to the literature on time series forecasting in emerging markets by applying established forecasting techniques to a specific context—air conditioner production in Bangladesh.

These specific objectives will guide the research process, ensuring that the study remains focused on addressing the main research problem and filling the gap in existing literature.

2. Literature Review

The analysis of production patterns and forecasting in manufacturing industries has been a critical area of research, particularly in understanding seasonal variations and long-term trends that influence production efficiency and market readiness. This literature review highlights key studies and methodologies relevant to analyzing and forecasting monthly air conditioner production, with a focus on time series techniques applicable to the Bangladeshi market.

Time series analysis is widely used in the manufacturing sector to model and predict production patterns. Techniques such as ARIMA (Auto-Regressive Integrated Moving Average), ETS (Exponential Smoothing State-Space Models), and STL (Seasonal-Trend Decomposition Using Loess) have been established as reliable methods for capturing trends and seasonality. Box and Jenkins (1976) introduced ARIMA as a robust statistical approach for univariate time series forecasting, emphasizing its adaptability to data exhibiting non-stationarity. Similarly, Hyndman et al. (2008) discussed the effectiveness of ETS models in forecasting time series with clear exponential trends and seasonal variations.

Seasonality plays a significant role in production cycles, particularly in industries like air conditioning, where demand fluctuates due to climatic conditions. Studies by Chatfield (2004) and Makridakis et al. (1998) highlight the importance of decomposing time series into seasonal, trend, and residual components to better understand underlying patterns. Seasonal decomposition techniques such as STL allow flexible modeling of seasonality, making it ideal for complex production data.

Research on air conditioner production forecasting is limited, particularly in the context of developing markets like Bangladesh. However, related studies in the appliance manufacturing sector suggest that identifying production trends and peak seasons can optimize inventory and supply chain operations. For instance, a study by Zhao et al. (2017) on consumer electronics manufacturing emphasized the role of seasonality in aligning production schedules with demand forecasts.

The Bangladeshi market, characterized by rapid urbanization and increasing economic activity, presents unique challenges and opportunities for manufacturing industries. While limited research specifically addresses air conditioner production in Bangladesh, studies on other manufacturing sectors underscore the importance of market-specific analysis.

Recent advancements in hybrid forecasting techniques, combining statistical models with machine learning algorithms, have shown promise in improving accuracy for production forecasting. Studies by Zhang (2003) and Wang et al. (2019) demonstrate that hybrid models outperform traditional approaches by capturing both linear and non-linear patterns in production data. These models offer potential applications for forecasting air conditioner production in data-scarce regions.

2.1 Research Gap

Despite the extensive use of time series methods in manufacturing, there is a notable gap in applying these techniques to air conditioner production in the Bangladeshi market. This study addresses this gap by utilizing ARIMA, ETS, and STL models to analyze monthly production data, uncover trends and seasonality, and forecast production for the next five years.

Although previous studies have explored time series forecasting in general manufacturing and other appliance sectors, the existing literature lacks comprehensive research focused on air conditioner production trends in the Bangladeshi market. This gap in literature is particularly significant given the dynamic and unique market conditions, such as climate change-driven demand shifts, technological developments in air conditioning systems, and growing urbanization.

This research aims to address this gap by applying advanced time series forecasting techniques (ARIMA, ETS, STL) to uncover the seasonal and trend components of air conditioner production in Bangladesh from 2013 to 2024. The study will provide forecasts for the next five years (2025–2029) and offer valuable insights into how these methods can be used to optimize production planning, inventory management, and marketing strategies in the Bangladeshi market

3. Methods

3.1 Study Design

This study adopts a quantitative research design aimed at forecasting monthly air conditioner (AC) production in the Bangladeshi market using classical and hybrid time series forecasting techniques. The research framework consists of systematic steps including data collection, preprocessing, model development, evaluation, and interpretation. The primary objective is to generate accurate forecasts that capture the underlying patterns, trends, and seasonal variations in AC production. The study applies statistical and computational methods to analyze historical production data and to predict future production volumes, enabling insights for better market planning, inventory management, and resource allocation.

3.2 Data Collection

The research utilizes secondary data on monthly air conditioner production in Bangladesh, covering a time span from January 2013 to December 2024. The dataset contains monthly production quantities recorded over twelve years, reflecting both long-term trends and seasonal fluctuations in the market.

Data have been obtained from industrial records related to AC manufacturing in Bangladesh.
Data Preprocessing: Before analysis, the dataset undergoes cleaning to handle potential outliers or inconsistencies. Missing values are checked and addressed appropriately. The cleaned data are examined to identify key time series characteristics such as trend, seasonality, and irregular components, ensuring suitability for forecasting models.

3.3 Time Series Forecasting Models

To analyze and forecast AC production trends, the study employs three advanced time series forecasting approaches:
Autoregressive Integrated Moving Average (ARIMA) – suitable for modeling data with trend and autocorrelation.
Exponential Smoothing State Space Model (ETS) – effective for handling data with additive trends and multiplicative seasonality.

Seasonal-Trend Decomposition using Loess (STL) combined with ARIMA and ETS – hybrid methods designed to capture complex seasonal and trend behaviors through decomposition and reforecasting.
These models are selected for their ability to account for the key components of time series data—trend, seasonality, and residuals—providing a comprehensive analytical framework.

3.3.1 Steps in Time Series Forecasting

The methodological process for time series forecasting includes the following sequential steps (Fig. 3.3.1.1):
Start: Define the forecasting objective and identify the relevant dataset.
Original Data: Collect the raw time series data consisting of monthly AC production values.

Data Preprocessing:
Stationarity Check: Evaluate whether the series is stationary using statistical tests (e.g., ADF and KPSS).
Transformation: Apply necessary transformations such as differencing, logarithmic, cubic, or Box-Cox transformations to stabilize variance and achieve stationarity (Figure 1).

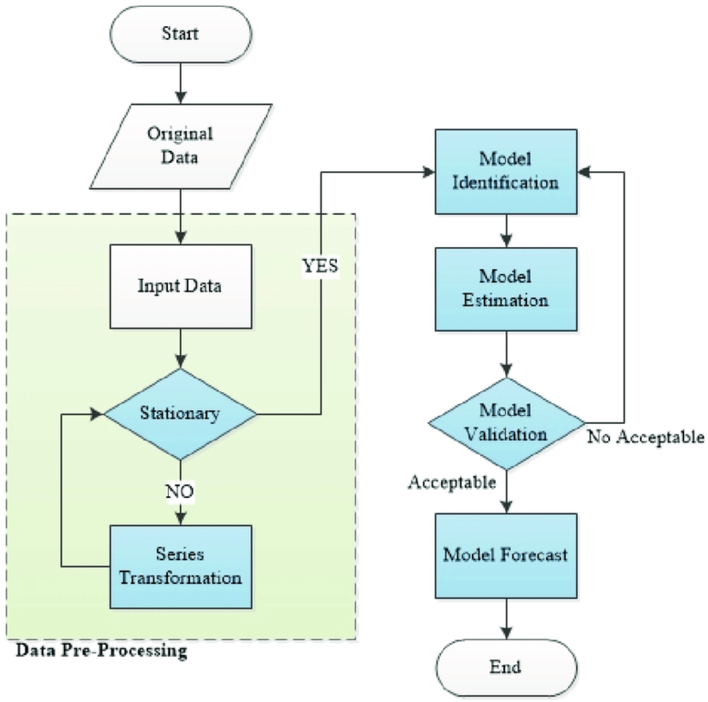

Figure 1. Workflow for Evaluating Models to Forecast Seasonal AC Market Forecasting in Bangladesh

Model Identification: Determine the appropriate model type based on autocorrelation and partial autocorrelation plots. Possible models include:

- Autoregressive (AR)
- Moving Average (MA)
- Autoregressive Moving Average (ARMA)
- Seasonal ARIMA (SARIMA)

Model Estimation: Estimate model parameters using techniques such as maximum likelihood estimation or least squares, optimizing the fit between model predictions and historical data.

Model Validation:
In-sample fit: Assess the model's ability to replicate past data.
Out-of-sample forecast: Evaluate predictive accuracy using a test dataset.
Diagnostic checks: Analyze residuals to ensure they resemble white noise, confirming that no systematic pattern remains unmolded.

Model Forecasting: Once validated, use the best-performing model to generate forecasts for future production periods. Forecast intervals are calculated to represent prediction uncertainty.
End: Conclude the analysis by summarizing forecast results and interpreting insights for strategic applications in production and market planning.

This methodological framework ensures a rigorous, data-driven approach to forecasting AC production trends in the Bangladeshi air conditioner market, combining robust statistical techniques with practical business interpretation.

4.1Review of Methods

4.1.1 Autoregressive Integrated Moving Average (ARIMA)

The Autoregressive Integrated Moving Average (ARIMA) model is one of the most widely adopted statistical approaches for time series analysis and forecasting. Initially introduced by Box and Jenkins (1976), the ARIMA framework integrates three essential components: **Autoregressive (AR)**, **Integrated (I)**, and **Moving Average (MA)** elements (R. J. Hyndman and G. Athanasopoulos et al.2018). Together, these components enable the model to capture both short-term dependencies and long-term trends within the data.

ARIMA and its simpler variant, the ARMA (Auto Regressive Moving Average) model, are commonly employed for analyzing univariate, evenly spaced datasets, transmission function data, and intervention series. ARIMA predicts a time series as a linear function of its historical values, prior errors, and—when relevant—the lagged values of other time series. The model is suitable for both stationary and non-stationary series, efficiently capturing autocorrelations within the dataset.

Mathematically, the ARIMA model is represented as **ARIMA (p, d, q)**, where *p* is the order of the autoregressive term, *d* is the number of differencing operations required to achieve stationarity, and q is the order of the moving average term. Differencing removes trends (linear or exponential) to stabilize the mean of the series. The order of differencing is usually determined by examining the **Autocorrelation Function (ACF)** plot (R. J. Hyndman and G. Athanasopoulos et al.2018).
The general form of the ARIMA model is expressed as:

$$y_t = c + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \theta_1 Z_{t-1} + \cdots + \theta_q Z_{t-q} + Z_t,\ \{Z_t\} \sim WN(0, \sigma^2)$$

Here, y_t denotes the observed value at time *t*, *c* is a constant, ϕ and θ represent non-seasonal autoregressive and moving-average coefficients respectively, and Z_t is the white-noise error term. Using the backshift operator B, ARIMA can be expressed as:

Intercept form:

$$\left(1 - \phi_1 B - \cdots - \phi_p B^p\right) y_t = c + \left(1 + \theta_1 B + \cdots + \theta_q B^q\right) Z_t$$

Mean form:

$$\left(1 - \phi_1 B - \cdots - \phi_p B^p\right)(y_t - \mu) = \left(1 + \theta_1 B + \cdots + \theta_q B^q\right) Z_t$$

$$Y_t = (1 - B)^d y_t$$

$$c = \mu\left(1 - \phi_1 - \cdots - \phi_p\right)$$

The **auto.arima()** function in *R* automatically identifies and fits the most appropriate ARIMA model, while the **forecast()** function generates and visualizes future predictions. The key steps in ARIMA model selection include:

- Conducting unit root tests to identify the differencing order (*d*).
- Using ACF and Partial ACF (PACF) plots to estimate *p* and *q*.
- Comparing alternative models using information criteria such as **AIC**.

4.1.2 Exponential Smoothing State Space Model (ETS)

Exponential smoothing, originally developed by Robert Brown for the U.S. Navy, evolved into a comprehensive forecasting approach known as the **Exponential Smoothing State Space Model (ETS)**. Brown's work was later extended to include both trend and seasonal components, leading to a highly flexible modeling framework(R. J. Hyndman and G. Athanasopoulos et al.2018).

ETS models decompose a time series into three components: **Error (E)**, **Trend (T)**, and **Seasonality (S)**. Each component may be **additive (A)** or **multiplicative (M)**. The general structure is denoted as **ETS(E,T,S)**, where:

- *E* represents the error type (A or M).
- *T* represents the trend (None, Additive, or Additive Damped).
- *S* denotes the seasonal component (None, Additive, or Multiplicative).

For an additive ETS model, **ETS (A,A,A)**, the relationships are:

Forecast equation:

$$\hat{y}_{t+h|t} = \ell_t + h b_t + s_{t+h-m(k+1)}$$

Observation equation:

$$y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t$$

State equations:

$$\ell_t = \ell_{t-1} + b_{t-1} + \alpha Z_t$$

$$b_t = b_{t-1} + \beta Z_t$$

$$s_t = s_{t-m} + \gamma Z_t$$

Here, ℓ_t, b_t, and s_t represent the level, trend, and seasonal components respectively, and Z_t denotes forecast errors.

4.1.5 Seasonal ARIMA (SARIMA)

The **Seasonal ARIMA (SARIMA)** model extends the ARIMA framework by integrating additional seasonal components to handle periodic fluctuations. SARIMA is denoted as **SARIMA(p,d,q)(P,D,Q)s**, where the first triplet refers to the non-seasonal part and the second to the seasonal part, with *s* representing the length of the seasonal cycle (Hyndman and Athanasopoulos et al.2018).

The general form of the SARIMA model is given by: $\Phi(B)\phi(B)(1-B)^d(1-B^s)^D y_t = c + \Theta(B)\theta(B)Z_t$

Here, y_t is the observed value, B is the backshift operator, ϕ and θ are non-seasonal AR and MA coefficients, Φ and Θ are seasonal AR and MA coefficients, and Z_t is white noise.

Model selection typically follows the **Hyndman and Khandakar (2008)** algorithm:

1. Identify *d* and *D* using KPSS and seasonal strength tests.
2. Determine *p*, *q*, *P*, and *Q* by minimizing **AICc**.
3. Conduct a stepwise search across the model space.

4.1.6 Seasonally Adjusted Exponential Smoothing (ETS)

The **Seasonal Adjusted ETS**, also known as the **Holt–Winters Seasonal Method**, extends basic exponential smoothing to capture seasonality more accurately (R. J. Hyndman and G. Athanasopoulos et al.2018).

It retains the ETS framework (Error, Trend, Seasonality) while emphasizing seasonal effects.

For additive seasonality, the equations are consistent with the general ETS model discussed in Section 3.1.2.

4.1.7 STL Method (Seasonal–Trend Decomposition Using Loess)

Developed by Cleveland et al. (1990), the **STL (Seasonal and Trend decomposition using Loess)** method decomposes time series data into three distinct components: **Trend (Tt)**, **Seasonal (St)**, and **Residual (Rt)** (R. J. Hyndman and G. Athanasopoulos et al.2018).

$$Y_t = T_t + S_t + R_t$$

This method operates in three main steps:

1. **Detrending:** Extracts the trend component T_t using Loess smoothing.
2. **Deseasonalizing:** Removes the seasonal component S_t from the detrended series.
3. **Residual estimation:** Derives R_t as the remaining variation after accounting for trend and seasonality.

STL is flexible and robust, accommodating nonlinear trends and time-varying seasonal patterns.

4.1.8 Model Evaluation Measures

Assessing forecasting accuracy and model selection is essential for evaluating time series models (R. J. Hyndman and G. Athanasopoulos et al.2018).

The following metrics are commonly used:

4.1.8.1 Mean Absolute Error (MAE)

MAE quantifies the average absolute difference between observed and predicted values:

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |y_t - \hat{y}_t|$$

It represents the mean magnitude of forecast errors without considering direction.

4.1.8.2 Mean Squared Error (MSE)

MSE measures the average squared deviation between actual and predicted values, emphasizing larger errors:

$$MSE = \frac{1}{n}\sum_{t=1}^{n} (y_t - \hat{y}_t)^2$$

4.1.8.3 Root Mean Squared Error (RMSE)

RMSE is the square root of MSE and reflects the standard deviation of forecast errors:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}$$

4.1.8.4 Mean Percentage Error (MPE)

MPE expresses the average percentage deviation between predicted and actual values:

$$MPE = \frac{100}{n}\sum_{t=1}^{n}\frac{(y_t - \hat{y}_t)}{y_t}$$

Positive MPE values imply overestimation, while negative values suggest underestimation.

4.1.8.5 AIC, AICc, and BIC

Model selection criteria such as **Akaike Information Criterion (AIC)**, **Corrected Akaike Information Criterion (AICc)**, and **Bayesian Information Criterion (BIC)** assess goodness-of-fit while penalizing model complexity [.

$AIC = 2k - 2\ln(L)$ $AICc = AIC + \frac{2k(k+1)}{n-k-1}$ $BIC = k\ln(n) - 2\ln(L)$

where *k* is the number of parameters, *L* is the model likelihood, and *n* is the sample size.

Lower values of AIC, AICc, and BIC indicate better model performance.

4.2 Algorithm of Hybrid Approach

4.2.1 Development of an Statistical Based Hybrid Model for Bangladesh AC Market Forecasting (M.U. Qureshi et al.2025).

Step 1: Fit an appropriate model — a traditional Time Series (TS) model to Bangladesh AC Market data. Compute the residuals R_{t1} and the corresponding forecasted values F_{t1}.

Step 2: Utilize the residuals R_{t1} obtained from Step 1 to fit a secondary model (TS). Calculate the new forecasted values F_{t2}.

Step 3: Combine the forecasted outputs from both models. Aggregate all forecasted values F_{t1} and F_{t2} to generate the final forecasts of the original Bangladesh AC Market series.

Note: TS refers to Time Series models.

4.2.2 Development of a Seasonal-Adjusted Statistical Based Hybrid Model for Bangladesh AC Market Forecasting (M.U. Qureshi et al.2025).

Step 1: Apply Seasonal and Trend decomposition using Loess (STL) to the Bangladesh ACmarket series. Decompose the series into the seasonal component $\boldsymbol{S_t}$ and the seasonally adjusted component $\boldsymbol{SA_t}$.

Step 2: Fit a model (TS) to the seasonally adjusted data SA_t.Compute the residuals R_{t1} and forecasted values F_{t1}.

Step 3: Utilize the residuals R_{t1} to fit another model (TS). Compute additional forecasted values F_{t2}.

Step 4: Combine all forecast components to generate the final forecasts. Aggregate the seasonal component S_t with the forecasted values F_{t1} and F_{t2} to obtain the predicted values of the original AC Market series.

Note: TS represents Time Series models

5. Results and Discussion

This section presents a comprehensive analysis of monthly air conditioner (AC) production data from the Bangladeshi market, covering the period from January 2013 to December 2024. The objective of this analysis is to uncover underlying production patterns, seasonal fluctuations, and structural characteristics of the dataset, which will inform the development of robust forecasting models.

The dataset provides valuable insights into production dynamics, highlighting trends, seasonality, and capacity variations within the Bangladeshi AC manufacturing sector. Through systematic exploration and modeling, this section establishes the foundation for accurate time series forecasting and data-driven decision-making related to production planning, inventory control, and marketing strategy.

5.1 Data Exploration

The dataset consists of monthly AC production data spanning 12 years (2013–2024). Initial exploration focuses on identifying the general trend, seasonal behavior, and irregular variations within the series.

Figures 2 and 3 illustrates the monthly production trend. The plot clearly indicates the presence of an additive trend and multiplicative seasonality, where production levels progressively increase over time, and seasonal fluctuations become more pronounced in later years. This behavior reflects the gradual expansion of production capacity and rising consumer demand in the Bangladeshi AC market.

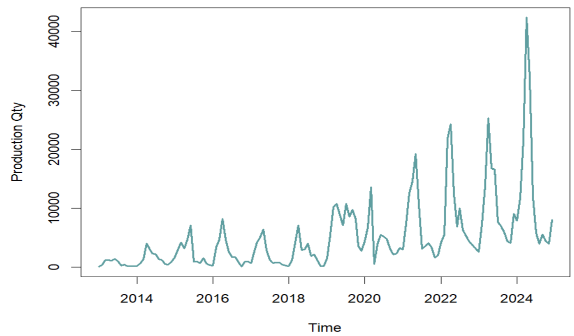

Figure 2. AC Market in Bangladesh.

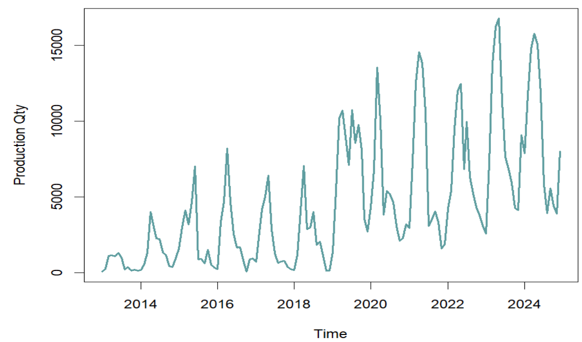

Figure 3. Dataset after cleaning of AC Market in Bangladesh.

5.1.1 Characteristics of the Dataset

Visual inspection of the cleaned dataset (Figure 3) and diagnostic plots reveal several key characteristics:
The series exhibits a strong additive trend. From 2013 to 2018, the seasonality appears additive, while from 2019 onward, it transitions into a highly multiplicative form, reflecting increased production variation. No outliers remain after cleaning, ensuring data integrity. The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots (Figure 4) provide further diagnostic insights:

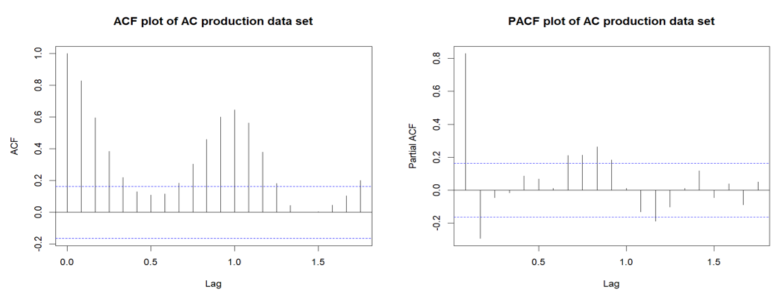

Figure 4. ACF and PACF curve of the dataset

Trend: The slow decay in ACF confirms the presence of a long-term upward trend.
Seasonality: Regular peaks in the ACF plot indicate recurring seasonal patterns.
Outliers: No significant abnormal spikes are observed, suggesting outlier-free data.
Stationarity: The dataset is non-stationary, necessitating transformation before modeling.
To gain deeper insight into seasonal behavior, the data were decomposed into trend, seasonal, and residual components (Figure 5). The decomposition reveals:

Peak Production Months: March, April, May, and June consistently record the highest production, with April showing the highest average output across years. May occasionally reaches the highest single-year production levels, indicating variability within the peak season.Low Production Months: October, November, December, and January experience the lowest production volumes, with November typically being the weakest month. This pattern reflects reduced demand during late autumn and winter, aligning with seasonal market cycles in Bangladesh.

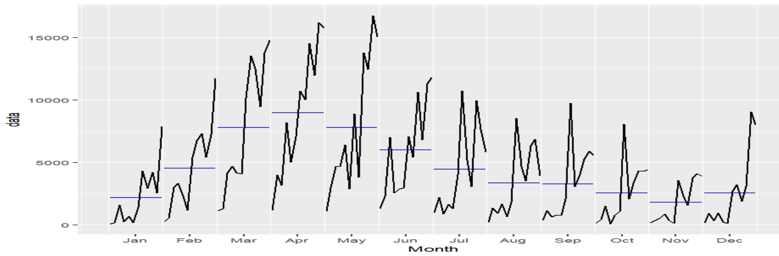

Figure 5. Monthly Visualization of AC Market in Bangladesh.

5.2 Model Estimation

To forecast monthly AC production, three time series forecasting models were applied: ARIMA, Exponential Smoothing State Space Model (ETS), and Seasonal-Trend Decomposition using Loess (STL). Each method captures different aspects of the data—trend, seasonality, and residual variation—providing a comprehensive forecasting framework.

5.2.1 Data Partitioning

For model training and validation, the dataset was divided into training (84%) and testing (16%) subsets, as shown in Figure 6 The training set (January 2013 – April 2023) was used to estimate model parameters, while the testing set (May 2023 – December 2024) evaluated out-of-sample predictive accuracy. This approach ensures reliable assessment of model generalization and performance stability.

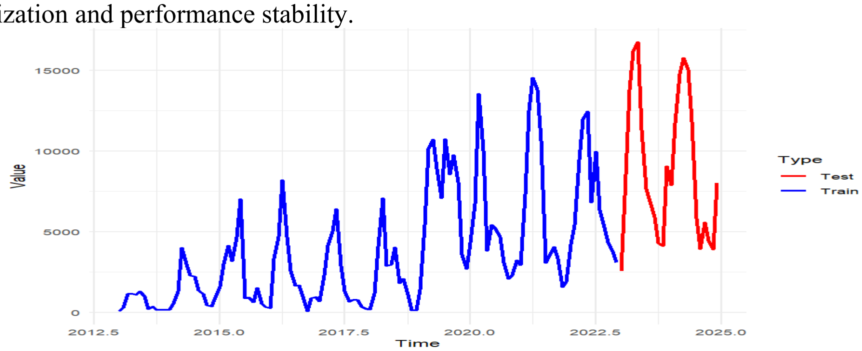

Figure 6. Splitting the dataset of AC Market in Bangladesh into train and test

5.3 Numerical Results

To improve the accuracy and stability of the ARIMA model, several transformations—no transformation, logarithmic, cubic, and Box–Cox—were applied to the training dataset. Model performance was compared using the Akaike Information Criterion corrected (AICc), which provides a balance between model fit and parsimony (Table 1).

Table 1. summarizes the information criteria for each transformation

Transformation Method	**AIC**	**AICc**	**BIC**
No Transformation	1946.84	1947.23	1957.57
Log Transformation	**248.55**	**249.14**	**261.96**
Cubic Transformation	527.13	527.72	540.54
Box–Cox Transformation	673.15	673.74	686.56

In Table 1, Among the candidate models, the log-transformed ARIMA(1,0,0)(2,1,0)[12] with drift exhibited the lowest AIC (248.55), AICc (249.14), and BIC (261.96).This result implies that the log transformation significantly improved model performance by stabilizing variance and reducing nonstationary, both common issues in industrial production data with multiplicative seasonal effects. The improvement in information criteria following the log transformation can be attributed to two statistical mechanisms. Logarithmic transformation compresses higher values and expands lower ones, reducing heteroscedasticity and improving model stability. This ensures that the residual variance is approximately constant across time—a fundamental assumption in ARIMA modeling. Many economic and production time series exhibit right-skewed distributions. Log transformation brings the distribution closer to normal, allowing the Gaussian white noise assumption of ARIMA to hold more effectively. The resulting ARIMA(1,0,0)(2,1,0)[12] model successfully captured both short-term autoregressive effects (AR(1)) and seasonal dependencies (SAR(2)), indicating that the underlying monthly pattern in production was well represented after transformation. The drift term (0.0234) further suggests a mild upward trend over time, consistent with gradual industrial growth. In contrast, the Cubic and Box–Cox transformations did not improve performance substantially. Although Box–Cox theoretically generalizes the log transformation, the estimated λ parameter may not have sufficiently normalized this dataset, and cubic transformation may have over-amplified higher values, increasing residual variance. Therefore, based on AICc criteria, the log-transformed ARIMA model was identified as the best ARIMA specification, balancing fit accuracy and model simplicity.

While AICc provides a criterion for selecting the optimal ARIMA specification, Root Mean Squared Error (RMSE) offers a direct measure of predictive performance across all model classes.

Table 2. Demonstration of Statistical and Hybrid model

Model	**MSE**	**RMSE**	**MAE**	**MAPE**
ARIMA	48,633,349	6,973.76	4,903.83	47.70%
ETS	**13,860,263**	**3,722.94**	**2,846.54**	**33.86%**
STL+ARIMA	60,975,105	7,808.66	6,060.76	70.02%
STL+ETS	50,721,138	7,121.90	4,646.90	41.19%

In Table 2, The ETS (Error–Trend–Seasonal) model, configured as ETS(M,A,M), outperformed all other models with the lowest RMSE (3,722.94), MSE (13,860,263), MAE (2,846.54), and MAPE (33.86%).This confirms its superior ability to model both additive trend and multiplicative seasonality directly within its state-space framework.The ARIMA model, though well-calibrated after log transformation, exhibited higher RMSE, reflecting its limited ability to handle strong seasonal amplitude variations. STL+ARIMA performed weakest, likely due to residual noise accumulation after decomposition and weaker adaptability to multiplicative components. STL+ETS showed moderate improvement over STL+ARIMA but still underperformed relative to pure ETS due to complexity in recombining decomposed components. The analysis revealed distinct behavioral differences between pure statistical models (ARIMA, ETS) and statistical–hybrid models (STL+ARIMA, STL+ETS).These models estimate level, trend, and seasonal components internally, allowing for direct interaction between components.

The ETS(M,A,M) model, in particular, efficiently adapted to seasonality with moderate smoothing parameters (α = 0.3175, β = 0.0004, γ = 0.0004).Such parameter magnitudes indicate stable long-term smoothing with minimal overfitting, ideal for datasets exhibiting consistent periodicity and slow structural evolution. The ARIMA model, while capturing autocorrelation structures effectively, assumes linearity and additivity in its components, limiting its response to multiplicative seasonal effects—common in industrial and economic production series.

The hybrid models first decomposed the series using Seasonal and Trend decomposition using Loess (STL), separating trend, seasonal, and remainder components before applying ARIMA or ETS to the depersonalized data. Although theoretically advantageous, this approach resulted in higher forecast errors in this case. Decomposition introduces intermediate estimation noise. When recombined, small estimation errors in each component compound, leading to larger overall forecast errors. STL assumes the seasonal component is independent of the trend. However, the dataset displayed multiplicative seasonality, where seasonal amplitude varies with trend level. This dependency was better modeled by the ETS(M,A,M) framework, where seasonality scales with level directly. Thus, while hybrid methods can enhance interpretability, they do not necessarily guarantee better predictive accuracy, particularly when the underlying time series exhibits multiplicative or nonlinear dependencies. Empirically, the findings validate the robustness of ETS models in modeling industrial production data characterized by trend and seasonal multiplicatively. Theoretically, this aligns with state-space modeling principles where ETS decomposes time series into level (ℓt), trend (bt), and seasonality (st) while updating each component recursively based on new observations.
This enables adaptive forecasting even under moderate nonstationary.

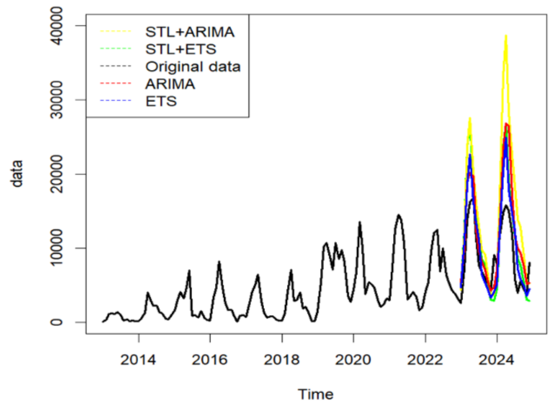

Figure 7. Different model Comparison for the forecasting of AC Market In Bangladesh

In Figure 7, ARIMA models remain strong contenders for datasets dominated by stochastic noise or additive seasonality, but their performance declines when variance changes proportionally with the trend.The underperformance of STL hybrids further reinforces that decomposition is not universally beneficial; the appropriateness depends heavily on data characteristics and component interdependence. From a practical standpoint, the findings carry several implications for forecasting, production planning, and policy design in industrial contexts such as the Bangladeshi air conditioner market. The ETS model's lower RMSE and MAPE indicate that it can provide more reliable forecasts for short- to medium-term production planning, minimizing over- or underestimation risks.The multiplicative nature of ETS allows for realistic modeling of production peaks and troughs, which correspond to seasonal demand fluctuations (e.g., pre-summer production surges).Accurate forecasts support inventory optimization, marketing timing, and resource allocation, ensuring manufacturers can align operations with expected market demand efficiently. The results suggest that practitioners should prioritize transformation and model selection based on data behavior—using logarithmic transformation for variance stabilization and ETS models for multiplicative seasonality.

6. Conclusion

This study comprehensively examined the monthly production patterns of air conditioners in Bangladesh from 2013 to 2024, with a particular focus on identifying underlying trends, seasonal fluctuations, and forecasting future production levels using advanced time series techniques. By employing three established models—ARIMA, ETS, and STL decomposition—the research successfully captured the temporal dynamics of air conditioner production and provided data-driven insights for decision-making in the manufacturing sector.

The results demonstrated that air conditioner production in Bangladesh follows a distinct seasonal pattern, with peak outputs occurring during pre-summer months due to increased consumer demand driven by climatic conditions. A steady upward trend was also observed, reflecting the growth of the domestic electronics industry and rising consumer adoption of cooling technologies. Among the models tested, the ETS (Error–Trend–Seasonal) model outperformed ARIMA and STL-based approaches across all statistical metrics, including MSE, RMSE, MAE, and MAPE, confirming its superior ability to handle multiplicative seasonal variations inherent in production data.

The study's findings hold important practical implications for manufacturers, policymakers, and supply chain planners. Accurate forecasts can help firms optimize production schedules, align inventory with seasonal demand, and plan marketing strategies more effectively. Policymakers can use these insights to design seasonally adaptive industrial policies and support capacity planning within the manufacturing sector.

Beyond its empirical results, this research makes a notable academic contribution by demonstrating the applicability and effectiveness of classical time series models—particularly ETS—in modeling industrial production in emerging markets. It also provides a foundation for future research, emphasizing the need to integrate external factors such as temperature variations, technological innovation, and macroeconomic indicators, as well as to explore modern hybrid and machine learning forecasting techniques (e.g., ANN, LSTM, ensemble models).

In conclusion, this study contributes both theoretically and practically to the field of industrial forecasting in Bangladesh. By advancing the methodological understanding of time series modeling in production analysis, it supports more informed strategic and operational decision-making. With further integration of advanced forecasting methods and broader datasets, future research can enhance predictive accuracy and deepen insights into the evolving dynamics of Bangladesh's air conditioner manufacturing sector.

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