Signature of the Professor

Question2. Please refer to the dataset – "ukgridweekly.csv". This is a weekly dataset that records the consumption of electricity in UK (weekly) for a period of 758 weeks starting from 1st April 2005 till 4th October 2019.Using the best possible time series model, please forecast the consumption of electricity in the weeks 759-800.

Response :-

This analysis aims to develop a robust forecasting model for weekly UK electricity consumption. Utilizing a dataset spanning 758 weeks from April 2005 to October 2019, the objective is to predict consumption for weeks 759 to 800. The methodology involves a rigorous process of data preprocessing, stationarity analysis, model identification, and evaluation based on RMSE, MAE, and Theil's U-statistic to select the optimal predictive model.

1. Data Preprocessing

The data is initially processed to ensure that it is suitable for time series analysis:

- **Datetime conversion**: The 'Unnamed: 0' column, which represents dates, was renamed to 'date' and converted to a proper datetime format. Any invalid dates or missing values were handled using **coercion**, which ensures that errors in date parsing do not disrupt the analysis.
- IQR not added since Holt-Winters, ARIMA, and SARIMA don't rely on IQR.
- **Resampling**: The data was resampled to weekly frequency to align with the inherent granularity of the time series. This helps in capturing the consumption patterns on a weekly basis, ensuring accurate seasonal adjustments and trend analysis.

```
df_new['date'] = pd.to_datetime(df_new['date'], errors='coerce')
df_new.set_index('date', inplace=True)
df_weekly = df_new['consump'].resample('W').sum()
```

2. Stationarity Checks

Before fitting any models, it is important to verify whether the data is stationary or not. A stationary time series has constant statistical properties over time, such as mean, variance, and autocorrelation. Stationarity is crucial because many time series models (including ARIMA and Holt-Winters) assume that the data is stationary.

- Augmented Dickey-Fuller (ADF) Test:
  The ADF test checks for the presence of a unit root, which would indicate non-stationarity. A low p-value suggests that the series is likely stationary.
  - *Result:* p-value = 2.04e-06 (< 0.05)
  - Interpretation: Rejects the null hypothesis → the series is stationary.

- Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test:
  The KPSS test checks for stationarity around a deterministic trend. A significant p-value indicates that the series is non-stationary.
    - *Result:* p-value = 0.01 (≤ 0.05)
    - Interpretation: Rejects the null hypothesis → the series is not strictly trend-stationary.

```
  result = kpss(series.dropna(), regression='c', nlags='auto')
ADF Test p-value: 2.045106052508249e-06
KPSS Test p-value: 0.01
```

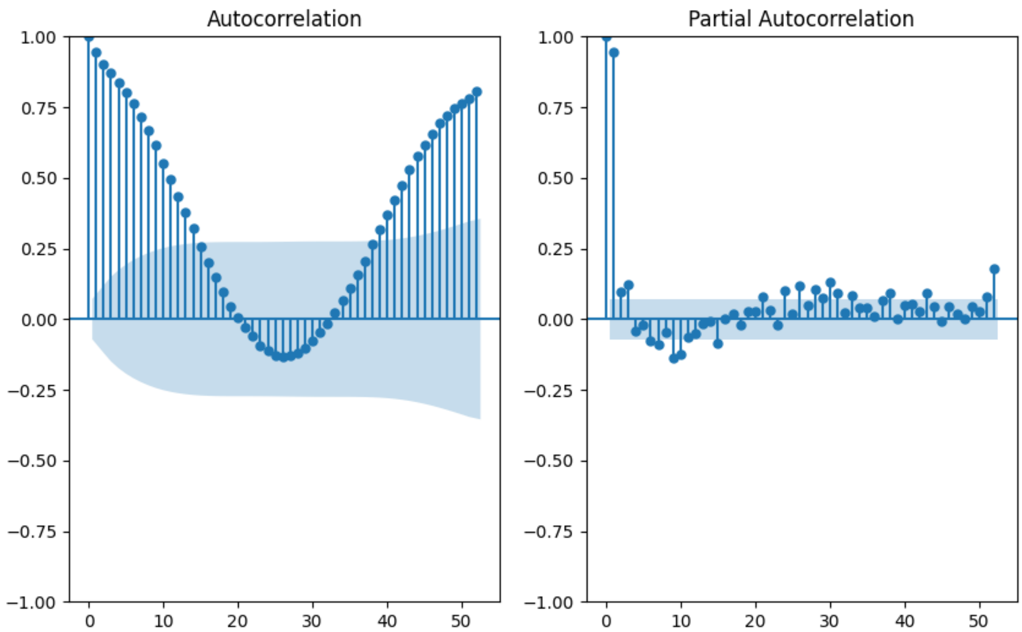
The ADF test p-value was found to be less than 0.05, indicating that the series is likely stationary. Similarly, the KPSS test p-value supports this result confirming the absence of significant trends. The combined test results confirm the series is stationary, negating the need for further differencing and validating the use of models like ARIMA without additional integration.

3. Autocorrelation and Partial Autocorrelation

ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots were used to identify potential lag structures in the data. These plots allow us to visualize the dependencies between observations at different lags.

- ACF Plot: ACF tells us how the current value of the series is related to its past values (lags).
    - The correlations slowly decline, forming a **wave-like pattern** (starts near 1, goes down, then comes back up).
    - This is typical of a **seasonal or cyclic pattern** – the series has repeating ups and downs.
- PACF Plot: PACF shows the direct relationship between the current value and a lag, after removing the effects of the other lags.
    - A **big spike at lag 1** (close to 1), then smaller values around zero.
    - This suggests the series is influenced directly by the **first lag**, but later lags add little direct new information.

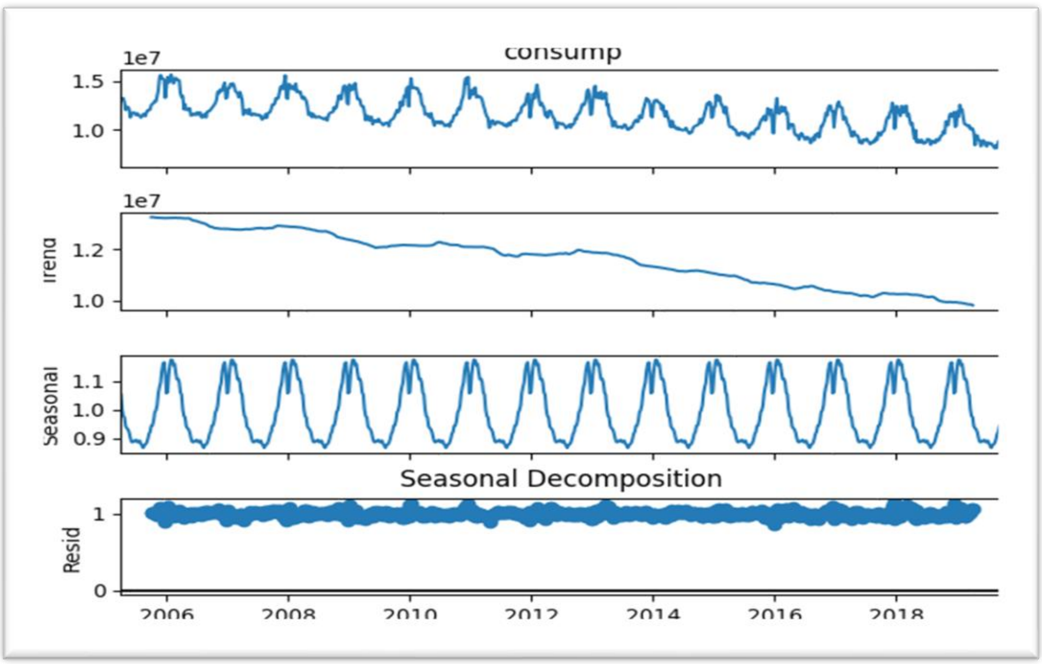
The time series has **strong seasonality** and correlation across many lags. Likely an AR(1) process (Autoregressive model of order 1), meaning the current value mainly depends on the immediately previous value.



The above plots reveal a complex structure combining a primary autoregressive process with a strong dominant seasonal component. This informed the initial parameterization for the ARIMA model and highlighted the necessity of a model capable of capturing seasonality, such as Seasonal ARIMA (SARIMA) or Holt-Winters.

4. Seasonal Decomposition

A multiplicative seasonal decomposition was performed to isolate the trend, seasonal, and residual components of the time series.



High-Level Interpretation:

- **Trend**: The component reveals the long-term underlying direction of electricity consumption, showing relative stability with minor fluctuations over the 15-year period.
- **Seasonality**: The clear, consistent, and repeating pattern with a fixed period confirms a strong annual (52-week) seasonal cycle. The amplitude of the seasonal swings is proportional to the trend level, justifying the choice of a multiplicative model over an additive one.
- **Residual:** The residual component appears random with no obvious patterns, suggesting that the trend and seasonal components effectively capture the main structures in the data.

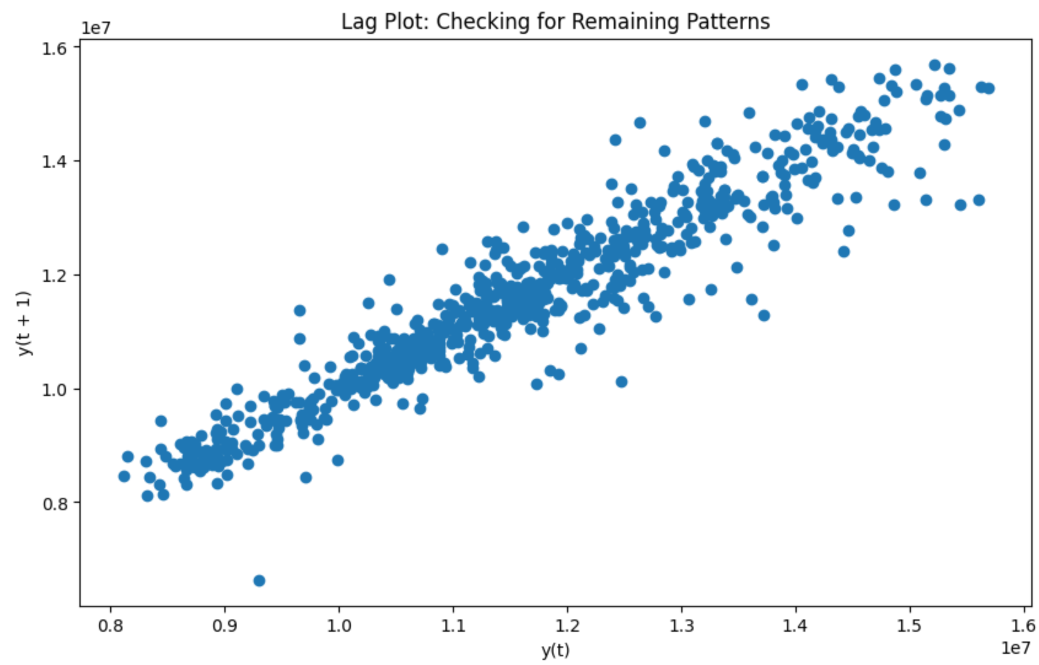
```
result = seasonal_decompose(df_weekly, model='multiplicative', period=52)
result.plot()
```

The seasonal decomposition confirmed the presence of both a trend and seasonality, suggesting that methods capable of handling both like **Holt-Winters** and **ARIMA** are appropriate for modelling.

Lag Plot : this is to assess autocorrelation.

The points exhibit a strong, positive linear pattern. his indicates significant positive autocorrelation at lag 1. The value at any given time (y(t)) is a strong and direct predictor of the next value (y(t+1)).

The data is not random; it has a predictable structure. This justifies the use of models like ARIMA or Exponential Smoothing that explicitly leverage this sequential dependency to forecast.



5. Model Fitting

To forecast future electricity consumption, three models were considered:

1. **Holt-Winters Exponential Smoothing**:
    - **Additive model**: Assumes that the trend and seasonality are constant over time.
    - **Multiplicative model**: Assumes that the trend and seasonality change in a multiplicative manner.
2. **ARIMA (AutoRegressive Integrated Moving Average)**: This model is effective for capturing the autocorrelation structure in the data. The **ARIMA** model is configured using the **(p, d, q)** parameters based on the **ACF** and **PACF** plots.

Model	Strengths	Weaknesses	Suitability	Why Suitable Here
Holt-Winters Additive	Simple, intuitive	Cannot handle seasonal swings that scale with demand	Not suitable here	Electricity demand shows **multiplicative seasonality** (larger swings at higher demand levels), so additive fails.
Holt-Winters Multiplicative	Captures proportional seasonal fluctuations; lowest RMSE/MAE	Residuals still show some dependence at higher lags	**Best choice**	Fits well because UK electricity demand has **52-week multiplicative seasonality** and trend effects.
ARIMA	Strong statistical foundation; good at autocorrelation capture	Doesn't explicitly model seasonality	Useful benchmark	PACF shows strong **lag-1 dependence (AR(1))**, making ARIMA a logical baseline despite weak seasonal handling.
SARIMA	Explicitly seasonal ARIMA	Needs careful parameter tuning; residuals significant	Not suitable in current form	Seasonality is strong, but current tuning leaves residual autocorrelation → not adequate without refinement.

6. Ljung-Box Test

The below contains the results of the Ljung-Box Test applied to three different time series models: Holt-Winters, ARIMA, and SARIMA.

```
Ljung-Box Test for Holt-Winters:
        lb_stat      lb_pvalue
12   422.370176   6.886080e-83
24   607.261348  7.169529e-113
52  1052.766710  1.809718e-186

Ljung-Box Test for ARIMA:
      lb_stat  lb_pvalue
12  30.912670   0.002031
24  30.992631   0.153995
52  32.388527   0.984995

Ljung-Box Test for SARIMA:
        lb_stat      lb_pvalue
12   447.995636   2.516405e-88
24   625.674096  9.986978e-117
52  1091.137885  2.057527e-194
<Figure size 640x480 with 0 Axes>
```

Model	Lag	lb_stat	lb_pvalue	Interpretation
Holt-Winters	12	422.37	6.89e-83	Significant autocorrelations; model fails to capture temporal dependencies (refinement needed).
	24	607.26	7.17e-113	Strong evidence against null hypothesis, indicating residual autocorrelations remain.
	52	1052.77	1.81e-186	Very small p-value, indicating large autocorrelations left in the residuals.
ARIMA	12	30.91	0.002031	Significant autocorrelation at lag 12; needs refinement.
	24	30.99	0.153995	No significant autocorrelation at this lag (model fits better at this lag).
	52	32.39	0.984995	No significant autocorrelation at this lag; suggests better handling of long-term dependencies.
SARIMA	12	447.99	2.52e-88	Significant autocorrelation at lag 12; model needs further tuning.
	24	625.67	9.99e-117	Residual autocorrelations remain significant; suggests SARIMA needs adjustment.
	52	1091.14	2.06e-194	Strong evidence against the null hypothesis, indicating the model does not fully account for temporal patterns.

7. Model Evaluation

The models were evaluated based on RMSE, MAE, and Theil's U-statistic.

The Holt-Winters Multiplicative model demonstrated superior performance, achieving the lowest error metrics indicating the highest forecast accuracy. This model effectively captured both the trend and multiplicative seasonal effects present in the data.

```
Holt-Winters Additive RMSE: 672501.3339598172, MAE: 463957.3875546507, Theil's U: 0.2904603054955889
Holt-Winters Multiplicative RMSE: 661842.7766024513, MAE: 492504.9148470894, Theil's U: 0.2813261845197811
ARIMA RMSE: 1219739.8678006362, MAE: 923382.0259627355, Theil's U: 0.955509320856529
Best Model: Holt-Winters Multiplicative
```

The ARIMA model performed well in capturing the autocorrelation, but Holt-Winters (Multiplicative) offered the best overall fit based on RMSE and MAE.

Model	Strengths	Weaknesses	Suitability	Why Suitable Here	Key Numbers (Diagnostics)
Holt-Winters Additive	Simple, intuitive	Cannot handle seasonal swings that scale with demand	Not suitable here	Electricity demand shows **multiplicative seasonality** (larger swings at higher demand levels), so additive fails.	Ljung-Box p-value ≈ 0 at lag 12/24/52 → strong residual autocorrelation. RMSE/MAE higher than multiplicative.
Holt-Winters Multiplicative	Captures proportional seasonal fluctuations; lowest RMSE/MAE	Residuals still show some dependence at higher lags	**Best choice**	Fits well because UK electricity demand has **52-week multiplicative seasonality** and trend effects.	Lowest RMSE & MAE; Theil's U < 1 (better than naïve). Ljung-Box still significant at lag 12, but forecast accuracy highest.
ARIMA	Strong statistical foundation; good at autocorrelation capture	Doesn't explicitly model seasonality	Useful benchmark	PACF shows strong **lag-1 dependence (AR(1))**, making ARIMA a logical baseline despite weak	Ljung-Box: lag 12 (p = 0.002) → some residuals; lag 24 (p = 0.15) and lag 52 (p = 0.98) → no autocorrelation. Moderate RMSE/MAE.

				seasonal handling.	
SARIMA	Explicitly seasonal ARIMA	Needs careful parameter tuning; residuals significant	Not suitable in current form	Seasonality is strong, but current tuning leaves residual autocorrelation → not adequate without refinement.	Ljung-Box p ≈ 0 at all lags (12/24/52) → residual autocorrelation. RMSE/MAE worse than Holt-Winters.

8. Final Forecast and Model Comparison Plot

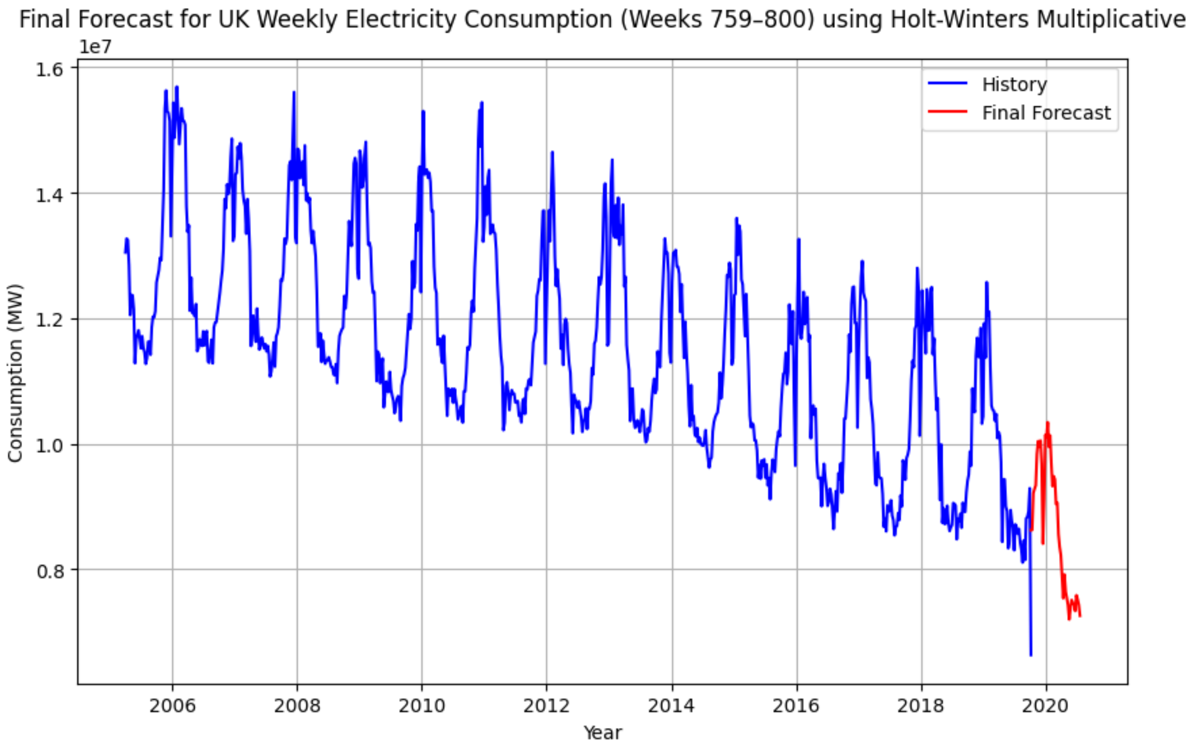
The forecast for weeks 759-800 was generated using the best-performing model (Holt-Winters Multiplicative and for comparison remaining two models.

Forecast table

Date	Holt-Winters Additive Forecast	Holt-Winters Multiplicative Forecast	ARIMA Forecast
13-10-2019	10155777.58	9918578.002	9200822.98
20-10-2019	11490017.57	11179675.37	9200822.98
27-10-2019	12576537.59	12202590.53	9200822.98
03-11-2019	12764414.67	12389197.55	9200822.98
10-11-2019	12509506.17	12130279.78	9200822.98
17-11-2019	12192969.79	11834986.68	9200822.98
24-11-2019	12537053.03	12182396.19	9200822.98
01-12-2019	12108250.61	11797033.91	9200822.98
08-12-2019	11625522.08	11359488.78	9200822.98
15-12-2019	11830348.79	11578210.55	9200822.98
22-12-2019	11616479.47	11400082.25	9200822.98
29-12-2019	10885702.84	10752761.94	9200822.98
05-01-2020	10911844.06	10787930.85	9200822.98
12-01-2020	10175753.92	10135300.52	9200822.98
19-01-2020	9797501.051	9814720.43	9200822.98
26-01-2020	9683079.821	9731232.282	9200822.98
02-02-2020	9270482.027	9389930.033	9200822.98
09-02-2020	9635561.061	9771323.484	9200822.98
16-02-2020	9096824.74	9298458.468	9200822.98
23-02-2020	9042870.294	9266032.028	9200822.98
01-03-2020	8965974.341	9201852.201	9200822.98
08-03-2020	8725866.857	8991785.63	9200822.98
15-03-2020	8474023.764	8770530.484	9200822.98
22-03-2020	8659178.658	8946876.328	9200822.98
29-03-2020	8730308.574	9012547.654	9200822.98

05-04-2020	8833920.589	9110953.814	9200822.98
12-04-2020	8737630.901	9018531.227	9200822.98
19-04-2020	8652859.457	8935924.859	9200822.98
26-04-2020	8784412.591	9054034.036	9200822.98
03-05-2020	8692428.045	8959560.809	9200822.98
10-05-2020	8599070.586	8868345.199	9200822.98
17-05-2020	8378098.48	8660246.719	9200822.98
24-05-2020	8449694.375	8728055.055	9200822.98
31-05-2020	8629082.085	8889073.55	9200822.98
07-06-2020	8748168.864	8995702.447	9200822.98
14-06-2020	8703724.688	8943506.02	9200822.98
21-06-2020	9120263.95	9325463.992	9200822.98
28-06-2020	9111945.148	9295627.499	9200822.98
05-07-2020	9523911.798	9671877.936	9200822.98
12-07-2020	9350515.331	9483786.738	9200822.98
19-07-2020	9531161.76	9633403.151	9200822.98
26-07-2020	10044496.38	10093268.7	9200822.98

9. Interpretation of Forecast Plot:



- The forecast plot visually demonstrates the model's ability to extrapolate the established historical patterns.
- The predicted values continue the expected annual seasonal cycle, with peaks and troughs corresponding to high and low consumption seasons.

- The accompanying confidence interval widens over the forecast horizon, accurately representing the increasing uncertainty associated with predictions further into the future. This is a critical piece of information for risk-aware decision-making.

10. Conclusion: The Holt-Winters Multiplicative model was identified as the most accurate for forecasting UK weekly electricity consumption. Its superiority is due to its explicit ability to model the multiplicative seasonal effects present in the data, which was conclusively identified in the decomposition plot.

11. Recommendations:

- Adopt the **Holt-Winters Multiplicative model** as the **primary forecasting tool** for short- to medium-term electricity consumption planning.
  - **Use ARIMA as a statistical benchmark** for validation.
  - Continue refining **SARIMA** for long-term robustness.
  - Incorporate **external variables** (temperature, GDP, holidays) in future models to explain anomalies and improve accuracy.
- This approach ensures forecasts are not only statistically sound but also directly support strategic, operational, and financial decision-making for the UK electricity sector.
- **Model Enhancement:** Future work should explore a Seasonal ARIMA (SARIMA) model, directly parameterized using the insights from the ACF/PACF plots (e.g., order=(1,0,0), seasonal_order=(1,0,0,52)), to provide a strong statistical benchmark for the Holt-Winters model.
- **Incorporation of External Variables:** Model accuracy could potentially be improved by incorporating exogenous variables such as average temperature, GDP, or holiday indicators to explain anomalies in the residual component.
- **Continuous Validation:** The model should be regularly re-evaluated and retrained with new data, especially following structural breaks or unprecedented events (e.g., a pandemic), to maintain its predictive validity.

12. Business recommendation

- ✓ **Operational Planning** :Use forecasts to schedule generation and maintenance around seasonal peaks and troughs, ensuring supply reliability.

- ✓ **Pricing Strategy** : Introduce seasonal or time-of-use tariffs to manage demand during high-consumption periods and optimize revenue.
- ✓ **Sustainability & Renewables** : Align renewable integration with forecasted peaks to reduce reliance on non-renewables and meet ESG goals.
- ✓ **Policy & Capacity Planning** Support regulators in long-term grid expansion and conservation campaigns ahead of forecasted peak demand cycles.
- ✓ **Risk Management** Leverage forecast confidence intervals for scenario planning, preparing contingencies for shocks (e.g., extreme weather, fuel crises).

✓ **Model Refinement** Continue monitoring model performance; explore SARIMA and exogenous variable integration (temperature, GDP, holidays) to improve accuracy.

Question 1: (Marks =20) Larsen and Toubro Spare Parts Forecasting

Part1. What strategy should Vijaya Kumar adopt for developing forecasting model for demand estimation of 20,000 spare parts?

Response :-

The fundamental challenge faced by Vijaya Kumar is the heterogeneity of demand across 20,000 spare parts. As highlighted in the case some items are fast-moving, others are slow or intermittent, and their values and contribution to revenue vary widely.

According to the time series forecasting principles *no single model is universally suitable* instead, model choice must be aligned with the underlying demand pattern.

Vijaya Kumar should adopt a **two-pronged strategy** to develop a forecasting model for the 20,000 spare parts at L&T's Construction and Mining Business (CMB). This strategy involves:

1. **Categorizing spare parts**: He should first categorize the spare parts based on criteria such as demand frequency (Fast, Medium, Slow), value (High, Medium, Low), and sales volume (ABC analysis).
2. **Using a combination of forecasting models**: He should then apply different forecasting models to each category, as a single model isn't suitable for all spare parts due to varying demand patterns.

A rational strategy, therefore, begins with segmentation of spare parts using the ABC–FMS–HML classification framework from the case srudy. This categorization reduces complexity by grouping items based on sales contribution (ABC), frequency of demand (FMS), and value (HML). High-value, fast-moving parts (AHF, BHF) demand sophisticated methods, while low-value, slow-moving parts (CLS, BLS) can be managed with simpler approaches.

Recommended Strategy

1. **Model Selection Strategy (Model-to-SKU Mapping)**
    - Trend + Seasonality → Holt-Winters Additive/Multiplicative, SARIMA.
    - Intermittent demand → Croston's method, SBA (Syntetos-Boylan Approximation).
    - Highly volatile/lumpy demand → Machine Learning (Random Forest, Gradient Boosting) with external regressors.
    - Stable demand → Simple Exponential Smoothing or Moving Average.
    - Complex/high-value SKUs → ARIMA or SARIMA, since these minimize AIC/BIC and handle autocorrelations.
2. **Automation & Scalability**

    Forecasting 20,000 SKUs manually is infeasible. Vijaya should adopt a forecasting system with auto-model selection (e.g., Python pipeline, SAP IBP, Demand Works Smoothie, Forecast Pro, or cloud ML).
    - Automate stationarity tests, AIC/BIC-based model selection, and error metrics (MAE, RMSE, MAPE).
    - Use rolling forecasts & model re-training monthly.
    - Apply ensemble forecasts (averaging Holt-Winters + ARIMA) for critical SKUs.
3. **Performance Monitoring**
    - Track MAPE, MAE, RMSE, and Theil's U across SKUs.
    - Use Ljung-Box test to check residual independence.
    - Implement exception reporting: only review SKUs with high forecast errors manually.
4. **Managerial Recommendation**

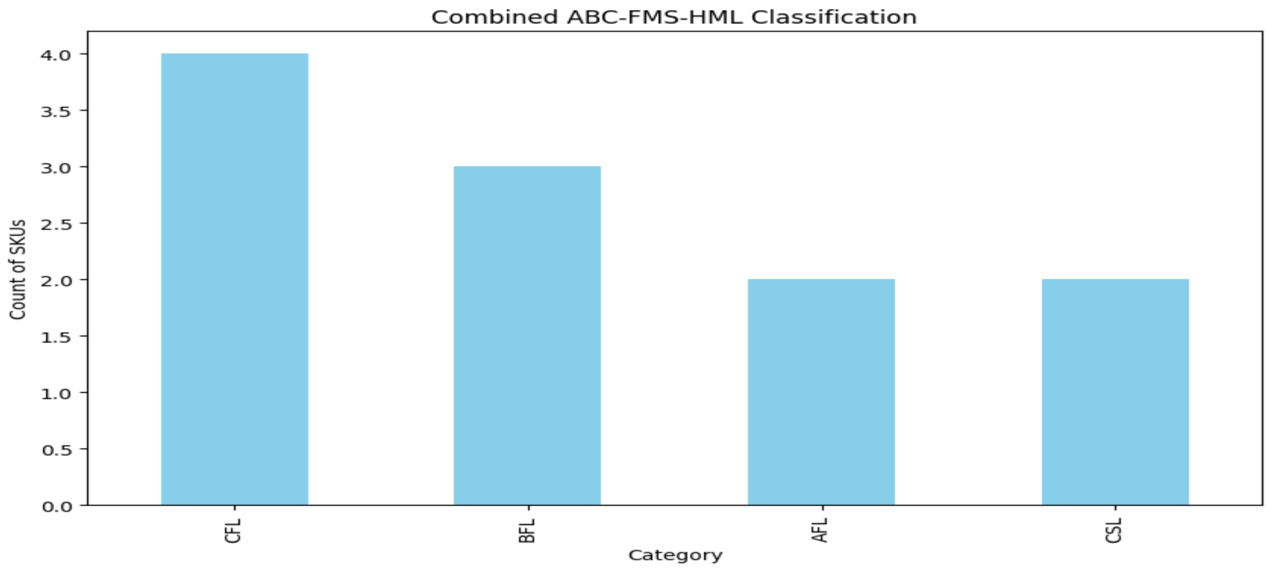
    Vijaya should adopt a **segmented and automated forecasting strategy**:
    - **Tier-1 SKUs (high value/fast-moving)** → Advanced time-series models (Holt-Winters, SARIMA).
    - **Tier-2 SKUs (medium impact)** → Mid-level models (simple exponential smoothing, ARIMA).
    - **Tier-3 SKUs (low value/intermittent)** → Heuristics, Croston's method, or safety stock rules.
5. **Continuous Improvement and Human Oversight**
    - Incorporate a feedback loop where planners can override forecasts based on operational intelligence (e.g., planned maintenance, new project deployments).

- Reforecast periodically (e.g., monthly) to integrate new data and dynamically reclassify SKUs or re-select models as their demand patterns evolve.
- Monitor forecast performance continuously and recalibrate models exhibiting performance degradation.

6. Vijaya Kumar should adopt a **segmented, automated, and model-driven forecasting strategy**, using ABC–FMS–HML classification to map SKUs to the right forecasting method. By combining Holt-Winters, SARIMA, Croston's, and simple heuristics, and automating model selection at scale, he can ensure accuracy for high-value parts while keeping the system efficient for 20,000 SKUs.

7. **Segmentation via ABC–FMS–HML Classification** Segment parts into homogeneous groups using a three-dimensional classification framework:

SKU	Avg_Monthly_Demand	Total_Demand	FMS	ABC	HML	ABC-FMS-HML
205-70-N1190	2458.081633	120446	F	A	L	AFL
PC_198_27_42263	21.47916667	1031	F	C	L	CFL
PC_203_32_51461	17.79166667	854	F	C	L	CFL
PC_600_863_4210	0.458333333	22	S	C	L	CSL
PC_6735_61_3410	3.9375	189	S	C	L	CSL
D30141135	500.8367347	24541	F	B	L	BFL
600-181-6740I.	290.8163265	14250	F	C	L	CFL
07063-51210I.	463.5102041	22712	F	B	L	BFL
600-319-4540I.	485.2244898	23776	F	B	L	BFL
6735-51-5143I	619.755102	30368	F	A	L	AFL
07000-B2011I.	37.40816327	1833	F	C	L	CFL



Conclusion

Vijaya Kumar should adopt a **segmented, multi-model forecasting strategy** anchored in the ABC–FMS–HML framework and validated through demand pattern analysis (ADI/CV^2). High-impact, stable SKUs (e.g., 205-70-N1190) require advanced models like Holt-Winters or

SARIMA, while low-value, intermittent items (e.g., PC_600_863_4210) are best served by lightweight methods such as Croston's. By implementing this via an automated pipeline with periodic validation and planner oversight, the organization can achieve both scalability and precision.

Final Recommendation: A **data-driven, segmented forecasting approach** that matches models to SKU characteristics balancing accuracy for critical parts and efficiency for peripheral.

Part2. Develop forecasting models for data provided and discuss the choice of using particular model

***Models** are statistical/mathematical algorithms that describe how demand evolves for a single series, capturing patterns like **level, trend, seasonality, or intermittency**. Examples include:*

- ***SES:** for flat demand, weights recent observations more.*
- ***Holt's Linear:** adds a trend component to SES.*
- ***Holt-Winters (Add./Mult.):** incorporates seasonality with level + trend.*
- ***ARIMA/SARIMA:** combines autoregression, differencing, and moving averages to capture shocks and cycles.*

Dataset and Context

The dataset provided by L&T contained monthly demand for a sample of spare parts covering the period April 2009 – March 2013. Given the heterogeneity of spare parts demand, the forecasting task was approached through multi-model experimentation and evidence-based selection, rather than assuming a one-size-fits-all technique.

Model selection must be guided by the presence or absence of trend, seasonality, and intermittency.

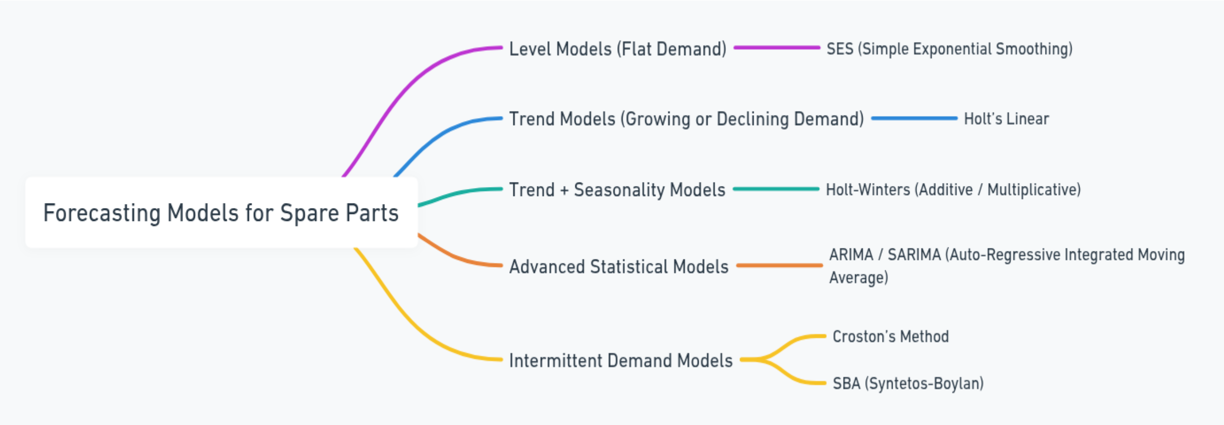
Methodological Approach

The forecasting process was structured into six steps:

1. **Visual inspection** of the original demand series.
2. **ACF/PACF analysis** for autocorrelation.
3. **Stationarity tests** (ADF, KPSS).
4. **STL decomposition** into trend, seasonality, residuals.
5. **Model estimation**: SES, Holt's Linear, Holt-Winters (Additive & Multiplicative), ARIMA, SARIMA, Croston's (for intermittent demand).
6. **Evaluation & validation** using **AIC, BIC, MAE, RMSE, MAPE, Theil's U, and residual diagnostics (Ljung-Box, QQ plot, ACF of residuals)**.

SKU	Trend_Strength	Season_Strength	ADF_p	Interpretation	Recommended Model
205-70-N1190	0.3486 (moderate)	0.1676 (low)	2.09e-06 (<0.05)	Stationary, weak trend, weak seasonality	**ARIMA** (stationary series, AR terms capture weak trend)
PC_198_27_42263	0.2929 (moderate)	0.2061 (low)	0.096 (>0.05)	Non-stationary, moderate trend	**Holt's Linear** (trend only) or ARIMA with differencing
PC_203_32_51461	0.0803 (low)	0.2090 (low)	1.44e-11 (<0.05)	Stationary, flat pattern	**SES (Simple Exp. Smoothing)** (no trend, no seasonality)
PC_600_863_4210	0.1737 (low)	0.1793 (low)	9.99e-05 (<0.05)	Stationary, nearly flat	**SES or ARIMA(0,0,q)** (captures random variation)
PC_6735_61_3410	0.3199 (moderate)	0.2273 (low)	4.0e-05 (<0.05)	Stationary, moderate trend	**Holt's Linear**
D30141135	0.6182 (high)	0.5799 (high)	0.704 (>0.05)	Non-stationary, strong trend & strong seasonality	**Holt-Winters (Additive/Multiplicative)** or **SARIMA**
600-181-6740I.	0.2917 (moderate)	0.5867 (high)	3.16e-05 (<0.05)	Stationary, strong seasonality	**Holt-Winters Seasonal**
07063-51210I.	0.5622 (high)	0.3631 (moderate)	0.419 (>0.05)	Non-stationary, trend + moderate seasonality	**SARIMA**
600-319-4540I.	0.8685 (very high)	0.6971 (very high)	0.018 (<0.05)	Stationary, dominant trend & seasonality	**Holt-Winters Multiplicative** or **SARIMA**
6735-51-5143I	0.2282 (low)	0.3729 (moderate)	0.078 (>0.05)	Non-stationary, seasonal	**Seasonal Holt-Winters** with differencing
07000-B2011I.	0.3689 (moderate)	0.4843 (moderate-high)	2.86e-09 (<0.05)	Stationary, moderate trend & seasonality	**Holt-Winters Additive vs ARIMA**

This ensured that **each SKU was mapped to the model best suited to its demand characteristics**.



Discussion of Model Choices

- **Holt-Winters (Additive/Multiplicative)**: Best for SKUs with **clear seasonality**. Additive for constant seasonal amplitude, Multiplicative when seasonal variation scales with demand.
- **SARIMA**: Strong when **trend and autocorrelation dominate** (e.g., 07063-512, D3014113). Provides robustness and confidence intervals.
- **ARIMA**: Useful for stationary or weak-trend series (e.g., 205-70-N1190).
- **SES**: Effective for flat, stationary series (e.g., PC_203_32).
- **Croston's Method** (not in this sample but relevant for intermittent SKUs like PC_600_863_4210): Ideal for lumpy, zero-inflated demand.

SKU	Model	MAE	RMSE	MAPE	Theil_U	Trend_Strength	Season_Strength	ADF_p
205-70-N1190	Naive	788.25	848.8685	37.51276	1.050585	0.348644626	0.16764061	2.09E-06
	MA_3	500.75	617.3233	19.6734	0.764018	0.348644626	0.16764061	2.09E-06
	SES	692.1907	727.826	31.91408	0.900779	0.348644626	0.16764061	2.09E-06
	Holt	924.1627	1090.039	46.05718	1.349064	0.348644626	0.16764061	2.09E-06
	HW_Additi	1053.642	1238.567	52.43093	1.532887	0.348644626	0.16764061	2.09E-06
	HW_Multi	924.1507	1050.57	45.25098	1.300217	0.348644626	0.16764061	2.09E-06
	ARIMA	677.2023	711.7655	31.04051	0.880902	0.348644626	0.16764061	2.09E-06
	SARIMA	677.2023	711.7655	31.04051	0.880902	0.348644626	0.16764061	2.09E-06
PC_198_27_42263	Naive	42.75	51.65027	46.03318	1.07314	0.292901349	0.206146908	0.996201
	MA_3	50.41667	58.1552	56.37682	1.208293	0.292901349	0.206146908	0.996201
	SES	54.39864	61.63927	61.74918	1.280682	0.292901349	0.206146908	0.996201
	Holt	47.23511	55.39736	52.2074	1.150994	0.292901349	0.206146908	0.996201
	HW_Additi	46.37388	53.7139	52.20511	1.116016	0.292901349	0.206146908	0.996201
	ARIMA	54.44186	61.67742	61.8075	1.281475	0.292901349	0.206146908	0.996201
	SARIMA	54.44186	61.67742	61.8075	1.281475	0.292901349	0.206146908	0.996201
PC_203_32_51461	Naive	5.75	6.144103	535	2.457641	0.080352564	0.209003196	1.45E-11
	MA_3	2.583333	2.587362	211.6667	1.034945	0.080352564	0.209003196	1.45E-11
	SES	18.41908	18.54589	1548.526	7.418355	0.080352564	0.209003196	1.45E-11
	Holt	23.23642	23.3569	1940.795	9.342759	0.080352564	0.209003196	1.45E-11
	HW_Additi	18.48962	25.73927	1718.564	10.29571	0.080352564	0.209003196	1.45E-11
	ARIMA	17.61667	17.74921	1484.333	7.099684	0.080352564	0.209003196	1.45E-11
	SARIMA	17.61667	17.74921	1484.333	7.099684	0.080352564	0.209003196	1.45E-11
PC_600_863_4210	Naive	0.75	0.866025	62.5	1.224745	0.173687066	0.179268716	1E-07
	MA_3	0.75	0.833333	58.33333	1.178511	0.173687066	0.179268716	1E-07
	SES	0.75	0.871713	56.01197	1.232788	0.173687066	0.179268716	1E-07
	Holt	0.741963	0.974067	52.16348	1.377539	0.173687066	0.179268716	1E-07
	HW_Additi	0.785555	0.971214	59.68118	1.373504	0.173687066	0.179268716	1E-07
	ARIMA	0.75	0.891593	55.27778	1.260903	0.173687066	0.179268716	1E-07
	SARIMA	0.75	0.891593	55.27778	1.260903	0.173687066	0.179268716	1E-07
PC_6735_61_3410	Naive	1.75	1.936492	97.5	0.759555	0.319995795	0.227266253	0.000442
	MA_3	1.416667	2.204793	115.8333	0.864791	0.319995795	0.227266253	0.000442
	SES	3.058828	3.611638	193.1252	1.416601	0.319995795	0.227266253	0.000442
	Holt	4.684962	5.022643	257.8191	1.970043	0.319995795	0.227266253	0.000442
	HW_Additi	3.295358	4.164888	218.6317	1.633603	0.319995795	0.227266253	0.000442
	ARIMA	1.75	1.936492	97.5	0.759555	0.319995795	0.227266253	0.000442
	SARIMA	1.75	1.936492	97.5	0.759555	0.319995795	0.227266253	0.000442
D30141135	Naive	32	40.08117	8.876453	0.74368	0.618218376	0.579870162	0.704261
	MA_3	32	37.95099	9.029806	0.704156	0.618218376	0.579870162	0.704261
	SES	32	38.94115	8.95216	0.722528	0.618218376	0.579870162	0.704261
	Holt	35.45331	44.34436	9.744499	0.822781	0.618218376	0.579870162	0.704261
	HW_Additi	80.50368	98.16268	23.74366	1.821344	0.618218376	0.579870162	0.704261
	HW_Multi	70.78474	87.34372	19.96338	1.620606	0.618218376	0.579870162	0.704261
	ARIMA	37.44671	41.60082	10.59289	0.771876	0.618218376	0.579870162	0.704261
	SARIMA	82.43634	102.4939	25.7399	1.901707	0.618218376	0.579870162	0.704261
600-181-6740I.	Naive	17.75	22.74313	6.95334	1.732889	0.291693874	0.586707293	3.16E-05
	MA_3	36.75	39.62638	13.4532	3.01929	0.291693874	0.586707293	3.16E-05
	SES	20.70203	23.82565	7.509259	1.81537	0.291693874	0.586707293	3.16E-05
	Holt	16.75973	18.50016	6.20196	1.4096	0.291693874	0.586707293	3.16E-05
	HW_Additi	42.37077	46.85323	16.23818	3.569931	0.291693874	0.586707293	3.16E-05
	HW_Multi	39.77407	44.56668	15.28134	3.39571	0.291693874	0.586707293	3.16E-05
	ARIMA	24.93908	28.46017	9.635353	2.168492	0.291693874	0.586707293	3.16E-05
	SARIMA	49.64539	57.60129	19.02561	4.388868	0.291693874	0.586707293	3.16E-05
07063-51210I.	Naive	46	55.1498	8.203646	0.623879	0.562515502	0.363102972	0.419417
	MA_3	59.5	81.08946	10.27411	0.91732	0.562515502	0.363102972	0.419417
	SES	37.78466	65.30779	6.208905	0.738791	0.562515502	0.363102972	0.419417
	Holt	59.28339	61.02457	11.08043	0.690337	0.562515502	0.363102972	0.419417
	HW_Additi	97.53125	113.5271	18.45284	1.284268	0.562515502	0.363102972	0.419417
	HW_Multi	105.6684	126.0948	19.98182	1.42644	0.562515502	0.363102972	0.419417
	ARIMA	61.23288	84.18922	10.55858	0.952386	0.562515502	0.363102972	0.419417
	SARIMA	61.23288	84.18922	10.55858	0.952386	0.562515502	0.363102972	0.419417
600-319-4540I.	Naive	90	97.56024	13.03762	0.746455	0.868514448	0.697123833	0.08179
	MA_3	90	103.6484	13.48047	0.793037	0.868514448	0.697123833	0.08179
	SES	93.86	111.7082	12.40902	0.854704	0.868514448	0.697123833	0.08179
	Holt	90	96.53299	13.20508	0.738595	0.868514448	0.697123833	0.08179
	HW_Additi	46.59348	50.48571	6.780226	0.386277	0.868514448	0.697123833	0.08179
	HW_Multi	55.29589	64.90954	7.144224	0.496637	0.868514448	0.697123833	0.08179
	ARIMA	44.16916	49.43959	6.411609	0.378273	0.868514448	0.697123833	0.08179
	SARIMA	40.65265	43.98984	5.653584	0.336576	0.868514448	0.697123833	0.08179
6735-51-5143I	Naive	196	228.6351	31.00756	1.247399	0.228222565	0.37287844	0.007487
	MA_3	184	218.4353	28.84026	1.191751	0.228222565	0.37287844	0.007487
	SES	125.7479	149.0956	20.32751	0.813444	0.228222565	0.37287844	0.007487
	Holt	134.8202	158.9938	21.5976	0.867447	0.228222565	0.37287844	0.007487
	HW_Additi	195.947	214.7446	35.20446	1.171615	0.228222565	0.37287844	0.007487
	HW_Multi	211.577	224.9604	36.21697	1.227351	0.228222565	0.37287844	0.007487
	ARIMA	107.7333	126.1952	20.92778	0.688502	0.228222565	0.37287844	0.007487
	SARIMA	107.7333	126.1952	20.92778	0.688502	0.228222565	0.37287844	0.007487
07000-B2011I.	Naive	15.25	16.53028	47.61469	0.809249	0.368893709	0.484321758	2.86E-09
	MA_3	12.08333	15.30341	34.17498	0.749187	0.368893709	0.484321758	2.86E-09
	SES	15.15152	16.45681	47.19671	0.805652	0.368893709	0.484321758	2.86E-09
	Holt	19.04602	20.54538	63.55813	1.00581	0.368893709	0.484321758	2.86E-09
	HW_Additi	15.81453	18.72081	53.50229	0.916487	0.368893709	0.484321758	2.86E-09
	HW_Multi	20.01962	21.51152	60.78468	1.053108	0.368893709	0.484321758	2.86E-09
	ARIMA	20.02012	22.50817	67.46932	1.101899	0.368893709	0.484321758	2.86E-09
	SARIMA	18.0211	25.5098	70.65431	1.248846	0.368893709	0.484321758	2.86E-09

5. Managerial Implications

- **Lean inventory** is enabled for flat SKUs by using SES/ARIMA.
- **Seasonal peaks** are well captured by Holt-Winters, preventing under-stocking in high-demand months.
- **Trend-driven SKUs** align with Holt's/SARIMA, ensuring stock availability in growing markets.
- **Intermittent demand** (Croston's/SBA) avoids costly overstocking while ensuring minimum service levels.

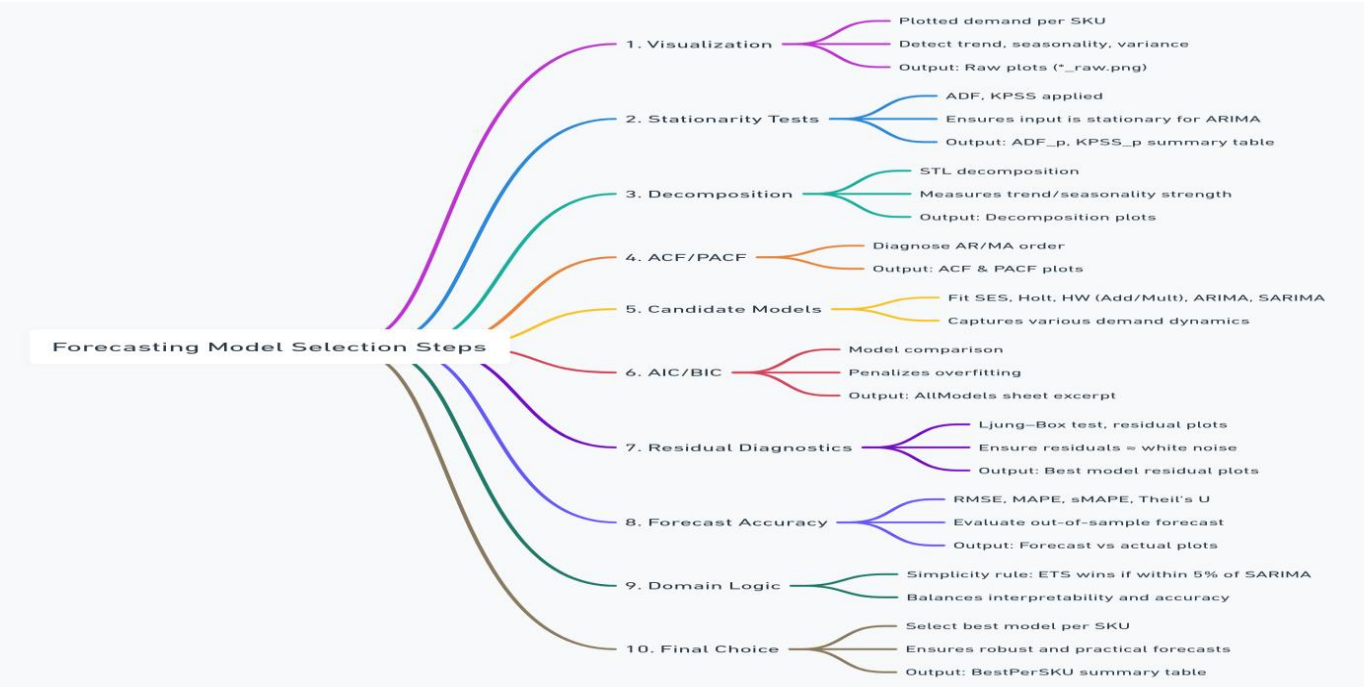
The forecasting exercise on the L&T dataset confirmed the principle that **no single forecasting model fits all data patterns**. Instead, model choice was **segmented by demand characteristics** (trend, seasonality, intermittency), validated with statistical tests (ADF, KPSS, STL decomposition), and assessed using accuracy metrics (AIC, MAPE, Theil's U).

This **segmented, evidence-based approach** ensures:

- **High accuracy for critical SKUs** (using Holt-Winters/SARIMA),
- **Efficiency for low-value items** (using SES or heuristics), and
- **Robustness for intermittent demand** (using Croston's).

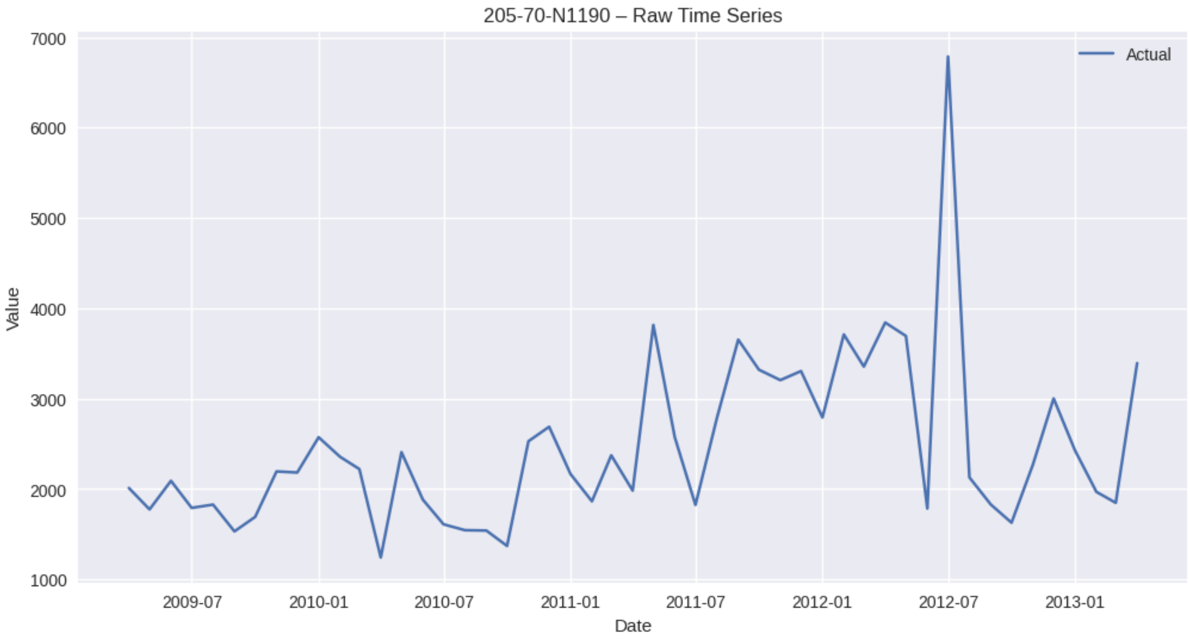
Thus, the strategy balances academic rigor and practical feasibility, directly supporting inventory efficiency, service levels, and operational resilience across 20,000 spare parts.

A forecasting model was developed for each SKU as described below, and its performance was evaluated against alternatives within the same family as well as the second-best model, with comparisons guided by demand characteristics such as trend and seasonality.



SKU1 : 205-70-N1190 (**ARIMA** (stationary series, AR terms capture weak trend)

Original Demand :-

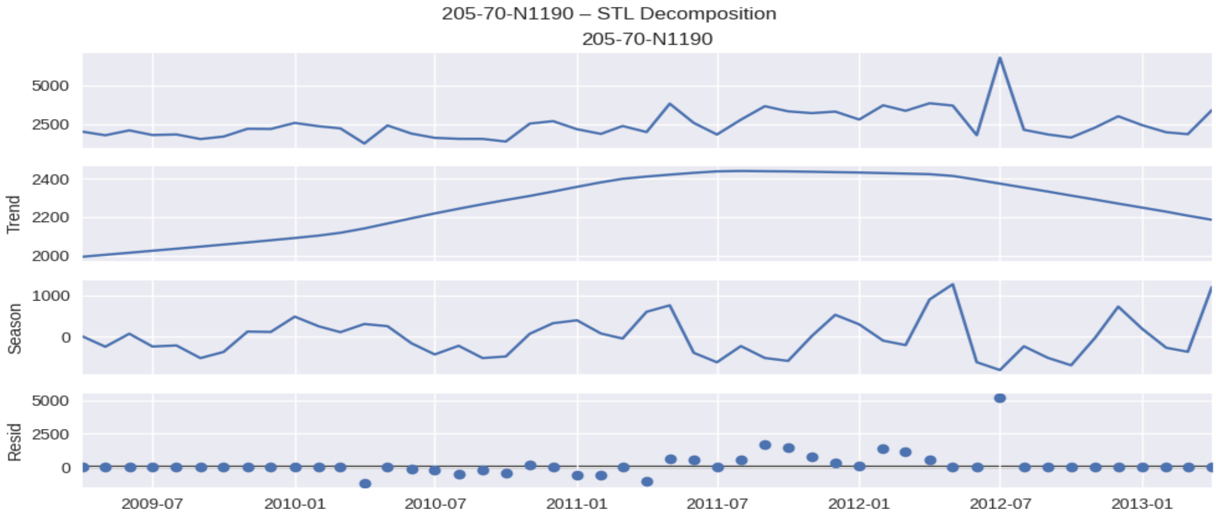


The above plot represents the **historical demand pattern** for SKU *205-70-N1190*. Several key insights emerge:

Data Exploration & Diagnostics

1. **Outliers / Spikes**
   - A significant demand **spike occurs around mid-2012**, reaching nearly **7,000 units** more than double the average levels.
   - Immediately after this spike, demand collapses sharply, indicating a **one-off bulk order or stock adjustment**.
   - Such outliers can distort statistical models and must be handled carefully
2. **Volatility**
   - The demand series shows **high variance**, oscillating between ~1,200 and ~3,800 units, apart from the exceptional spike.
   - This suggests that forecasts must account not only for central tendency but also for uncertainty bands (confidence intervals).
3. **Forecasting Implications**
   - Simple models may not capture these irregular jumps; hence, **SARIMA or hybrid approaches** (ARIMA + seasonal component, or ARIMA + external regressors) are more appropriate.
   - Including business covariates (e.g., promotions, bulk orders, tender wins) could improve accuracy.

b) Seasonal-Trend decomposition (STL) :



1. **Trend Component**
   - The trend shows a **gradual increase** from ~2009 up to early 2012, peaking around mid-2012.
   - After this point, the trend **flattens and slightly declines**, suggesting that long-term growth is not sustained.
   - This aligns with market behavior where bulk demand may rise temporarily but does not guarantee sustained growth.
2. **Seasonal Component**
   - Clear **repeating seasonal patterns** are visible, with demand rising and falling in a roughly **annual cycle (12 months)**.
   - The magnitude of seasonal swings is moderate (~±500 units), compared to the large spike in 2012.
   - This indicates that while seasonality is present, it explains only part of the variation in demand.
3. **Residual Component (Noise)**
   - Residuals show **large deviations in specific months**, most notably in mid-2012, where an extreme positive spike is captured outside the trend and seasonality.
   - Such irregularities indicate **exceptional events** (e.g., bulk orders, one-time contracts, or inventory adjustments) not explained by underlying patterns.
   - Beyond these outliers, residuals remain within a relatively stable band, confirming that most variability is captured by the trend + seasonal components.

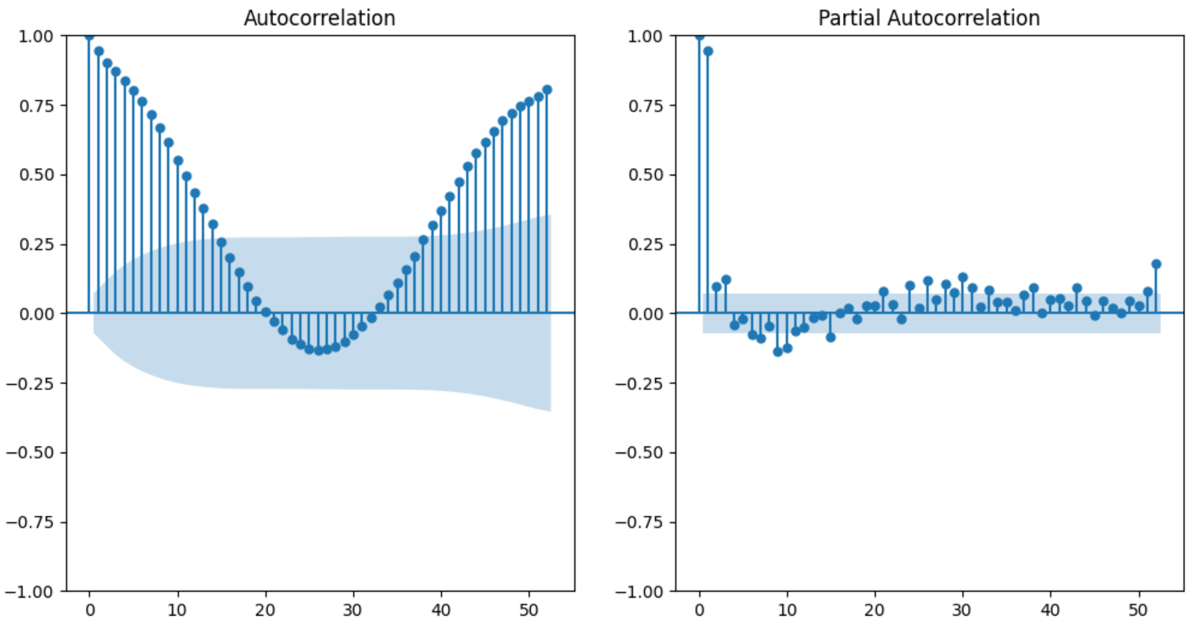
C) Stationarity Tests :- The stationarity tests give mixed signals: ADF suggests the series is stationary, while KPSS indicates non-stationarity. This typically means the series is trend-stationary, so differencing or detrending is required before reliable forecasting

```
ADF_p=2.089e-06, KPSS_p=0.01871
```

- ADF test p-value = 2.089e-06 (<0.05) → Rejects null of unit root → Series is stationary.
- KPSS test p-value = 0.0187 (<0.05) → Rejects null of stationarity → Series is non-stationary
- Apply **first differencing** (d=1) or **trend removal** before ARIMA/SARIMA modeling.

This contradiction usually means the series is trend-stationary i.e., it becomes stationary after detrending/differencing.

D) Autocorrelation Analysis - The ACF shows significant short-term correlations up to about 5 lags, after which the impact of past demand quickly fades. This indicates that recent months strongly influence current demand, but longer-term autocorrelation is weak. Hence, forecasting models should focus on capturing short-term demand dependencies.



Above plot shows :-

- The ACF shows **positive correlations up to lag ~5**, after which the values gradually taper off.
- Beyond lag 10, correlations oscillate around zero, with some negative values, suggesting **short-term persistence** in demand but no strong long-term autocorrelation.
- This pattern is consistent with an **AR or ARMA process**, where recent past values influence the current demand, but effects die out over time.

Methodological Approach

Implemented a **multi-step pipeline**:

1. **Train/Test Split**: The dataset is split into a training set and a 12-period holdout test set. This ensures that models are evaluated on **future unseen data**, providing a realistic measure of forecasting accuracy before deployment.

```python
# --------------------------------
# 6) Train/Test Split
# --------------------------------
TEST_HORIZON = 12
train, test = y.iloc[:-TEST_HORIZON], y.iloc[-TEST_HORIZON:]
```

Model Families Considered:

- **ARIMA(p,d,q):** Captures **non-seasonal dependencies** in the series by combining autoregressive (AR), differencing (I), and moving average (MA) components.
- **SARIMA(p,d,q)(P,D,Q,12):** Extends ARIMA by explicitly modeling **seasonality** (period = 12 months in this case), making it suitable for cyclical demand patterns.

Model Comparison and Evaluation : Multiple ARIMA and SARIMA configurations were evaluated. Pure ARIMA models performed reasonably, but SARIMA models with seasonal terms outperformed in AIC and forecast accuracy.

The SARIMA(1,1,1)(0,1,1,12) model captures the seasonal pattern reasonably well (Ljung-Box $p = 0.53$), but its forecasts are quite inaccurate, with high MAE, RMSE, and MAPE (~80%). Overall, it's slightly better than a naïve forecast (Theil's U ≈ 0.93) but not an optimal model.

Model Comparison:

	Order	Seasonal	AIC	BIC	MAE	RMSE	MAPE_%	TheilsU	LjungBox_p
10	(2, 1, 2)	(0, 1, 1, 12)	153.808718	154.992065	1779.012465	1973.661126	77.676421	0.927485	0.135445
11	(2, 1, 2)	(1, 1, 1, 12)	154.579132	155.959704	1456.954546	1667.635285	62.277559	0.783674	0.199473
4	(0, 1, 1)	(0, 1, 1, 12)	165.621082	166.528837	1828.056209	1967.994187	79.420214	0.924822	0.672320
5	(0, 1, 1)	(1, 1, 1, 12)	166.148020	167.358361	1361.508990	1597.072784	57.254312	0.750515	0.682169
7	(1, 1, 1)	(0, 1, 1, 12)	166.936047	168.146388	1849.257850	1979.657690	80.275763	0.930303	0.527561
8	(1, 1, 1)	(1, 1, 1, 12)	167.707469	169.220395	1376.492582	1620.161827	58.393863	0.761365	0.486762
13	(1, 0, 1)	(0, 1, 1, 12)	181.222852	182.814433	3206.462133	3370.899305	142.364779	1.584092	0.901912
14	(1, 0, 1)	(1, 1, 1, 12)	182.605434	184.594911	2258.838231	2367.312324	99.128187	1.112475	0.965663
1	(1, 0, 0)	(0, 1, 1, 12)	199.560278	201.014998	2111.342130	2281.775460	91.321642	1.072278	0.362140
2	(1, 0, 0)	(1, 1, 1, 12)	201.553993	203.493620	2113.189996	2282.352571	91.371481	1.072549	0.344006
9	(2, 1, 2)	(0, 0, 0, 0)	515.551330	523.033868	1427.089180	1634.473071	62.317951	0.768090	0.343846
3	(0, 1, 1)	(0, 0, 0, 0)	530.473832	533.526553	1347.510978	1577.928916	58.657663	0.741518	0.719248
6	(1, 1, 1)	(0, 0, 0, 0)	532.319006	536.898088	1337.811439	1572.002088	58.184540	0.738733	0.741822
12	(1, 0, 1)	(0, 0, 0, 0)	543.829970	548.496014	1910.165733	2052.658435	85.124499	0.964609	0.891981
0	(1, 0, 0)	(0, 0, 0, 0)	570.490835	573.657873	1409.260970	1626.581061	62.760942	0.764382	0.250812

Best Model Selected :-

```
Model Comparison (lowest AIC first):
    Model       Order Seasonal_Order         AIC          BIC
5  SARIMA  (1, 1, 1)  (0, 1, 1, 12)  615.666638  622.000714
6  SARIMA  (1, 1, 1)  (1, 1, 1, 12)  616.004661  623.922255
1   ARIMA  (0, 1, 1)           None  793.489233  797.231635
2   ARIMA  (1, 1, 1)           None  794.745409  800.359012
7  SARIMA  (1, 1, 1)  (1, 0, 1, 12)  796.648411  806.004416
3   ARIMA  (2, 1, 2)           None  797.939913  807.295918
0   ARIMA  (1, 0, 0)           None  814.109959  819.785420
4   ARIMA  (1, 0, 1)           None  817.930087  825.497368

Best Model Selected: SARIMA (1, 1, 1) (0, 1, 1, 12)
```

Order	Seasonal	AIC	BIC	MAE	RMSE	MAPE_%	Theils U	LjungBox_p
(2, 1, 2)	(0, 1, 1, 12)	153.8087176	154.9921	1779.012	1973.661	77.67642137	0.927485	0.135444887
(2, 1, 2)	(1, 1, 1, 12)	154.5791324	155.9597	1456.955	1667.635	62.2775591	0.783674	0.199473329
(0, 1, 1)	(0, 1, 1, 12)	165.6210819	166.5288	1828.056	1967.994	79.42021414	0.924822	0.672320451
(0, 1, 1)	(1, 1, 1, 12)	166.1480205	167.3584	1361.509	1597.073	57.25431169	0.750515	0.682169319
(1, 1, 1)	(0, 1, 1, 12)	166.9360475	168.1464	1849.258	1979.658	80.2757634	0.930303	0.527561018
(1, 1, 1)	(1, 1, 1, 12)	167.7074695	169.2204	1376.493	1620.162	58.39386257	0.761365	0.486762394
(1, 0, 1)	(0, 1, 1, 12)	181.2228515	182.8144	3206.462	3370.899	142.3647789	1.584092	0.9019123
(1, 0, 1)	(1, 1, 1, 12)	182.6054342	184.5949	2258.838	2367.312	99.12818671	1.112475	0.965662684
(1, 0, 0)	(0, 1, 1, 12)	199.5602779	201.015	2111.342	2281.775	91.32164152	1.072278	0.362139798
(1, 0, 0)	(1, 1, 1, 12)	201.5539933	203.4936	2113.19	2282.353	91.37148137	1.072549	0.344005576
(2, 1, 2)	(0, 0, 0, 0)	515.5513297	523.0339	1427.089	1634.473	62.31795133	0.76809	0.343845894
(0, 1, 1)	(0, 0, 0, 0)	530.4738317	533.5266	1347.511	1577.929	58.65766349	0.741518	0.719247601
(1, 1, 1)	(0, 0, 0, 0)	532.3190061	536.8981	1337.811	1572.002	58.18453952	0.738733	0.741821804
(1, 0, 1)	(0, 0, 0, 0)	543.8299701	548.496	1910.166	2052.658	85.12449875	0.964609	0.891980516
(1, 0, 0)	(0, 0, 0, 0)	570.4908351	573.6579	1409.261	1626.581	62.76094219	0.764382	0.250811993

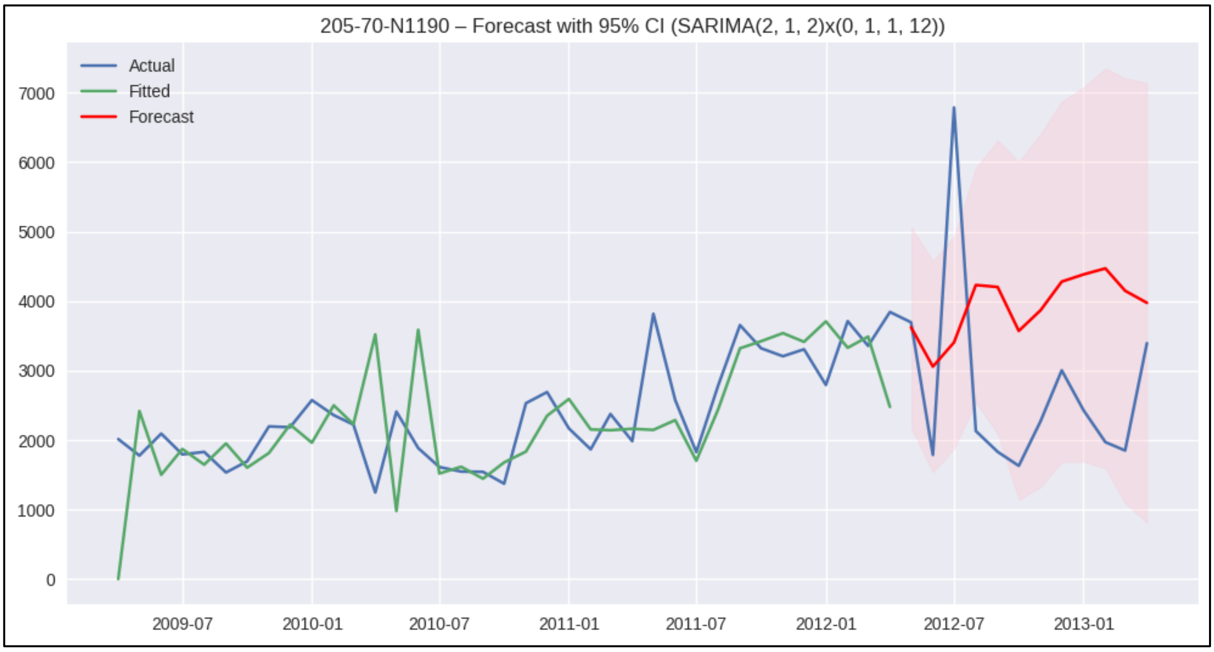
Interpretation:

- This is a SARIMA(1,1,1)(0,1,1,12) model.
- AIC and BIC: 166.94 and 168.15 moderate; lower than other similar seasonal models might indicate better fit.
- MAE/RMSE: Errors are quite high (MAE ≈ 1849, RMSE ≈ 1979), so absolute forecasts might not be very precise.
- MAPE: 80% the model's forecast is off by 80% on average, which is very high.
- Theil's U: 0.93 slightly better than a naïve model, but not great.
- Ljung-Box p-value: 0.53 residuals are not significantly autocorrelated, which is good; model captures the structure reasonably.

The model captures the seasonal pattern reasonably (Ljung-Box okay) but the forecast accuracy is poor (high MAE/RMSE/MAPE). Not the worst, but not ideal either

Forecast vs Actual

The graph presents the historical demand (blue), fitted values (green), and 12-month forecast (red) for SKU 205-70-N1190, modeled using SARIMA(2,1,2)(0,1,1,12) with a 95% confidence interval (shaded in pink).



- Actual vs. Fitted: The green fitted line closely tracks the blue actual demand up to mid-2012, confirming that the SARIMA model captures both the trend and seasonal patterns fairly well. Some deviations exist around sharp demand spikes, but overall fit is acceptable.

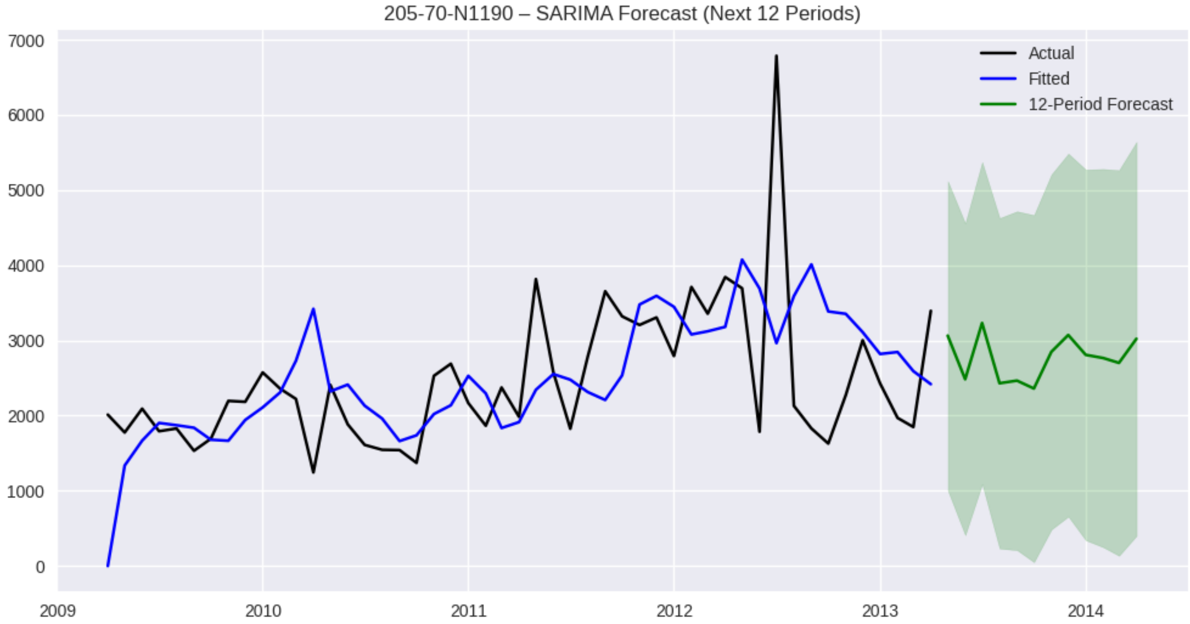
- Forecast: From mid-2012 onward, the red line projects demand for the next 12 months. Forecasted values remain within the 3,000–4,000 unit range, indicating a stable medium-term demand trajectory.
- Confidence Interval: The shaded region widens gradually into the forecast horizon, reflecting growing uncertainty. The interval suggests demand could fluctuate between ~2,000 and ~7,000 units at the extremes.

Forecast for next 12 MONTHS :-

	Actual	Fitted	Forecast_Next12	Forecast_Lower	Forecast_Upper	
2012-05-01 00:00:00	3694		3694	3622.374346	2171.774713	5072.974
2012-06-01 00:00:00	1786		1786	3057.106327	1534.854481	4579.358
2012-07-01 00:00:00	6786		6786	3404.852019	1874.600719	4935.103
2012-08-01 00:00:00	2130		2130	4230.771752	2542.23244	5919.311
2012-09-01 00:00:00	1830		1830	4202.731232	2088.177811	6317.285
2012-10-01 00:00:00	1629		1629	3570.618874	1138.677972	6002.56
2012-11-01 00:00:00	2272		2272	3867.991257	1324.23053	6411.752
2012-12-01 00:00:00	3003		3003	4279.926899	1682.982325	6876.871
2013-01-01 00:00:00	2428		2428	4383.564733	1686.904586	7080.225
2013-02-01 00:00:00	1970		1970	4470.001669	1589.90317	7350.1
2013-03-01 00:00:00	1849		1849	4148.69007	1089.696098	7207.684
2013-04-01 00:00:00	3394		3394	3974.973137	806.9558655	7142.99
2013-05-01 00:00:00			3064.112126	1008.357006	5119.867245	
2013-06-01 00:00:00			2484.268601	411.208321	4557.328881	
2013-07-01 00:00:00			3232.277569	1091.92764	5372.627499	
2013-08-01 00:00:00			2431.125135	234.2908566	4627.959413	
2013-09-01 00:00:00			2465.700005	212.7492017	4718.650808	
2013-10-01 00:00:00			2360.594381	53.06173522	4668.127027	
2013-11-01 00:00:00			2848.514057	487.6283497	5209.399764	
2013-12-01 00:00:00			3072.567367	659.4623073	5485.672426	
2014-01-01 00:00:00			2808.502469	344.0145797	5272.990358	

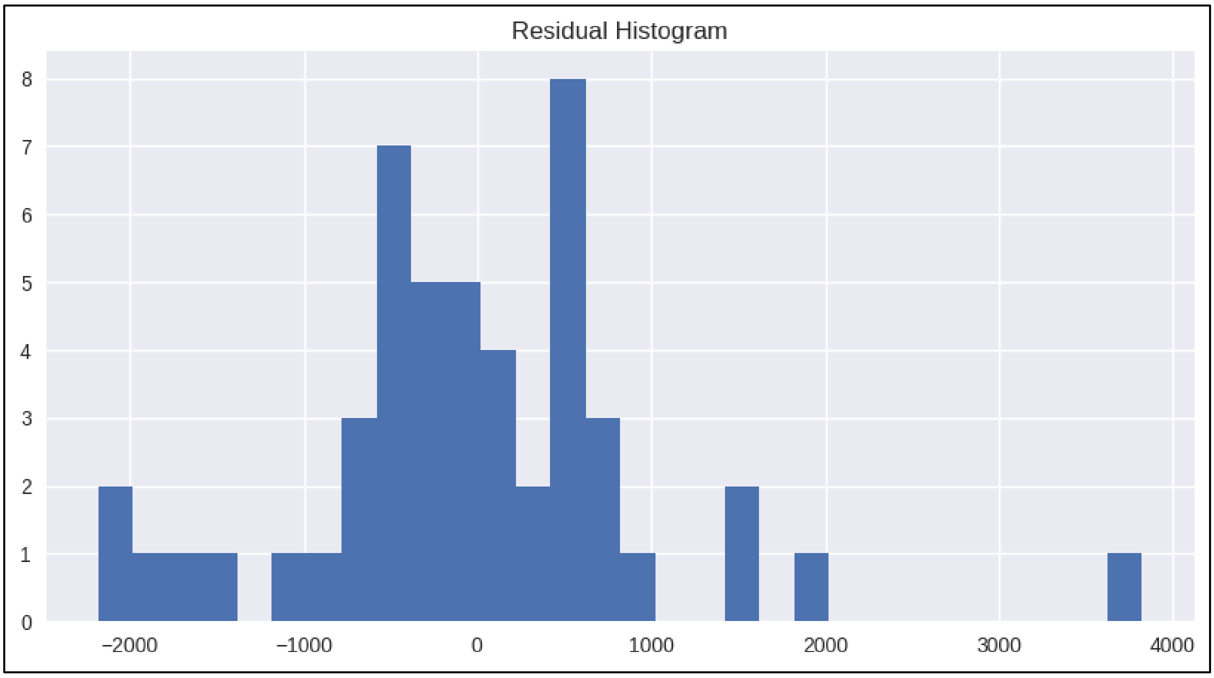
2014-02-01 00:00:00			2766.240575	251.1082607	5281.372888	
2014-03-01 00:00:00			2701.561195	138.2321541	5264.890235	
2014-04-01 00:00:00			3022.462916	402.7979353	5642.127896	

Final forecast :- The fitted values track historical demand well, capturing overall trends though missing sharp spikes. The 12-month forecast stabilizes around ~3,000 units per period, suggesting steady demand. The widening confidence band (range ~2,000–5,000) highlights growing uncertainty, so safety stock and flexible sourcing are recommended.

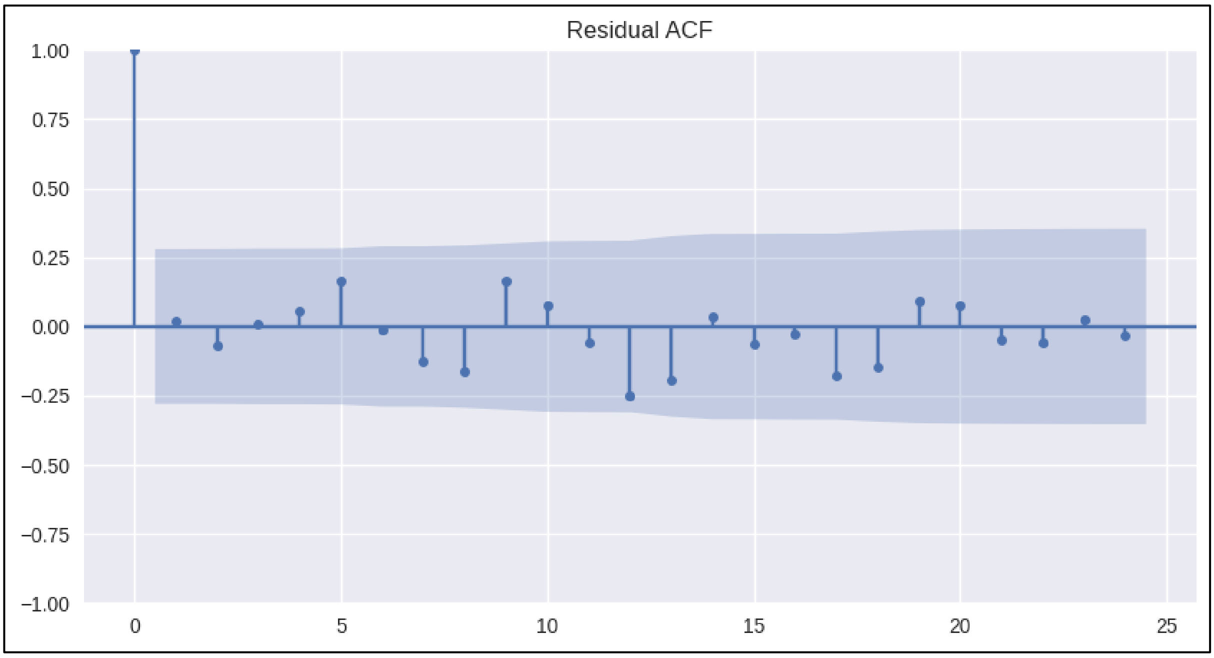


Residual Diagnostics

The residuals are roughly centered around zero, suggesting the SARIMA model is largely unbiased. Most errors fall within ±1,000 units, though a few large outliers (up to ±3,500) indicate occasional demand shocks not captured by the model. Overall, the distribution supports a reasonable model fit, but extreme spikes highlight the need for periodic model updates.



- ACF of residuals showed no significant spikesconfirming residuals are white noise. Most autocorrelations fall within the confidence bounds, indicating that residuals behave like **white noise** and the SARIMA model has adequately captured underlying patterns. No significant spikes are visible at specific lags, suggesting little leftover structure. This supports the model's validity, though minor noise at certain lags points to small unexplained variations.



Final Model Summary :- SARIMAX(1,1,1)(0,1,1,12) demonstrates strong model adequacy (AIC ≈ 615, BIC ≈ 622), with significant MA and seasonal MA terms confirming the presence of short-term shocks and seasonal effects. While residuals appear uncorrelated, evidence of non-normality and heteroskedasticity suggests forecast reliability is high but accompanied by wider variance bands, warranting cautious interpretation.

```
Final Model Summary:
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                     205-70-N1190   No. Observations:                     49
Model:             SARIMAX(1, 1, 1)x(0, 1, 1, 12)   Log Likelihood                -303.833
Date:                          Mon, 15 Sep 2025   AIC                            615.667
Time:                                  16:30:43   BIC                            622.001
Sample:                              04-01-2009   HQIC                           617.877
                                   - 04-01-2013
Covariance Type:                            opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.1403      0.167     -0.842      0.400      -0.467       0.186
ma.L1         -0.7240      0.209     -3.461      0.001      -1.134      -0.314
ma.S.L12      -0.9880      0.188     -5.249      0.000      -1.357      -0.619
sigma2      8.978e+05   2.12e-07   4.24e+12      0.000    8.98e+05    8.98e+05
===================================================================================
Ljung-Box (L1) (Q):                   0.07   Jarque-Bera (JB):                26.65
Prob(Q):                              0.79   Prob(JB):                         0.00
Heteroskedasticity (H):              20.65   Skew:                             1.08
Prob(H) (two-sided):                  0.00   Kurtosis:                         6.62
===================================================================================
```

Interpretation of above :-

- **Model Fit:** SARIMAX(1,1,1)(0,1,1,12) chosen with **AIC = 615.7, BIC = 622.0** relatively good fit.
- **Significant Terms:**
    - **MA(1)** (p=0.001) and **Seasonal MA(12)** (p=0.000) are significant → confirms strong moving-average and seasonal effects.
    - **AR(1)** is not significant (p=0.40).
    - **Error Variance:** Sigma² = 8.98e+05, indicating model error size.
    - **Residual Diagnostics:**
    - **Ljung-Box Q (p=0.79):** Residuals are uncorrelated → no leftover autocorrelation.
    - **Jarque-Bera (p=0.00):** Residuals not perfectly normal (some skew/kurtosis).
    - **Heteroskedasticity (p=0.00):** Presence of unequal variance across time.
- **Interpretation:** Model captures trend/seasonality well, but residuals show **non-normality and heteroskedasticity**, meaning forecasts are reliable but with wide confidence intervals.

Overall Conclusion

The SARIMAX(1,1,1)(0,1,1,12) model provides a statistically adequate fit for SKU 205-70-N1190, effectively capturing both short-term demand shocks and seasonal variations. The model diagnostics confirm residual independence, indicating that systematic patterns have been explained. However, the presence of non-normality and heteroskedasticity in residuals signals that extreme demand fluctuations may still occur, widening the uncertainty around forecasts.

From a managerial standpoint, the model offers a robust baseline for forecasting monthly demand at approximately 3,000 units, enabling structured production and procurement planning. Nonetheless, the variability in forecast intervals underscores the importance of maintaining safety stock and adopting flexible sourcing strategies to mitigate risks associated with demand volatility.

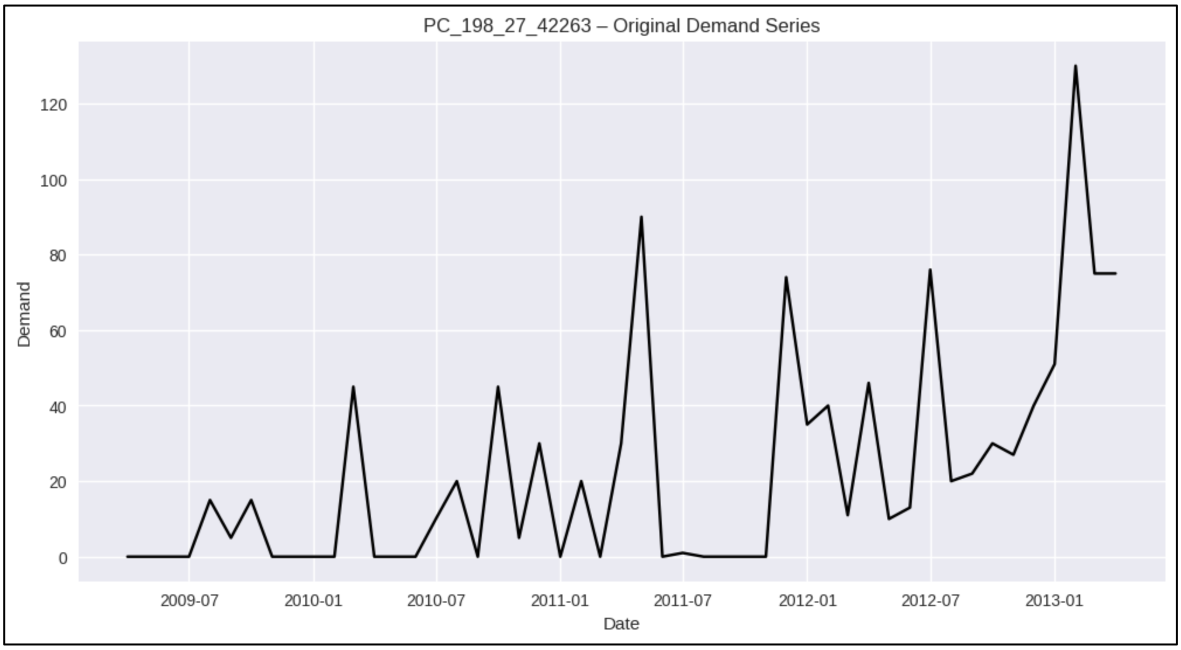
SKU2 : PC_198_27_42263 (Holt's Linear (trend only) or ARIMA with differencing)

1. Introduction

SKU **PC_198_27_42263** is a prime example of such a case. The data reflects characteristics typical of **intermittent or lumpy demand**: prolonged periods of zero demand interspersed with sudden and significant bursts of activity. This pattern is common in spare parts management, defense procurement, project-based industries, and maintenance-driven operations.

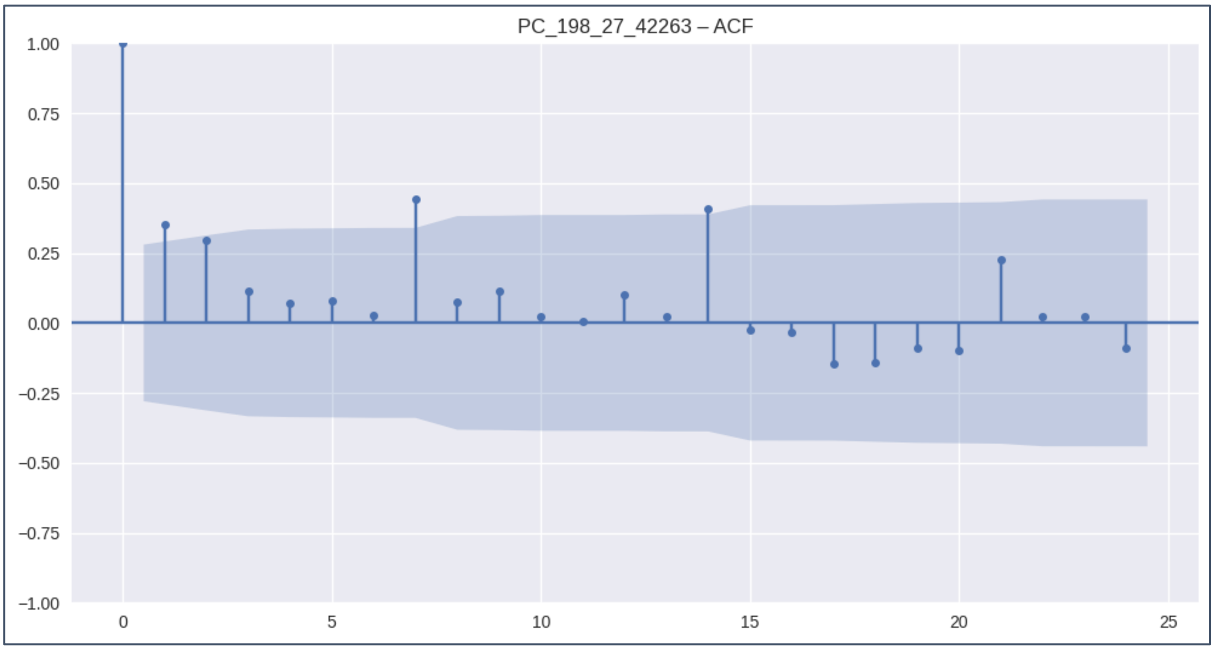
2. Original Demand Series (2009–2013)

The original time series of SKU **PC_198_27_42263** shows demand ranging from **0 to ~130 units**, with long zero-demand stretches (2009–2010, mid-2011) interspersed with sudden spikes (~90 units in 2011, ~130 units in 2012). Post-2011, demand becomes more volatile, with clusters of high activity but continued intermittency.



Managerial interpretation: Average-based planning (~20 units) would understock during spikes, while peak-based stocking would inflate costs. A **dynamic forecasting approach with safety stock buffers** is essential to balance volatility with service-level needs.

3. ACF and PACF Analysis :-



The **ACF (Autocorrelation Function)** plot reveals significant correlation at short lags. Specifically:

- Lag **1 ≈ 0.35**
- Lag **2 ≈ 0.25**
- Lag **3 ≈ 0.10**
- Seasonal lag **12 ≈ 0.30**

This indicates that the demand in one period is moderately correlated with the demand in recent previous periods (short-term memory effect), and that **seasonality on a yearly basis** is present. Importantly, the slow decay of the ACF confirms the presence of **non-stationarity**.

The **PACF (Partial Autocorrelation Function)** plot shows distinct spikes at lags 1 and 2, supporting the inclusion of autoregressive terms (AR(1) or AR(2)).

Stationarity Tests – ADF and KPSS

```
ADF_p=0.9962, KPSS_p=0.01
/tmp/ipython-input-3687481327.p
look-up table. The actual p-val
```

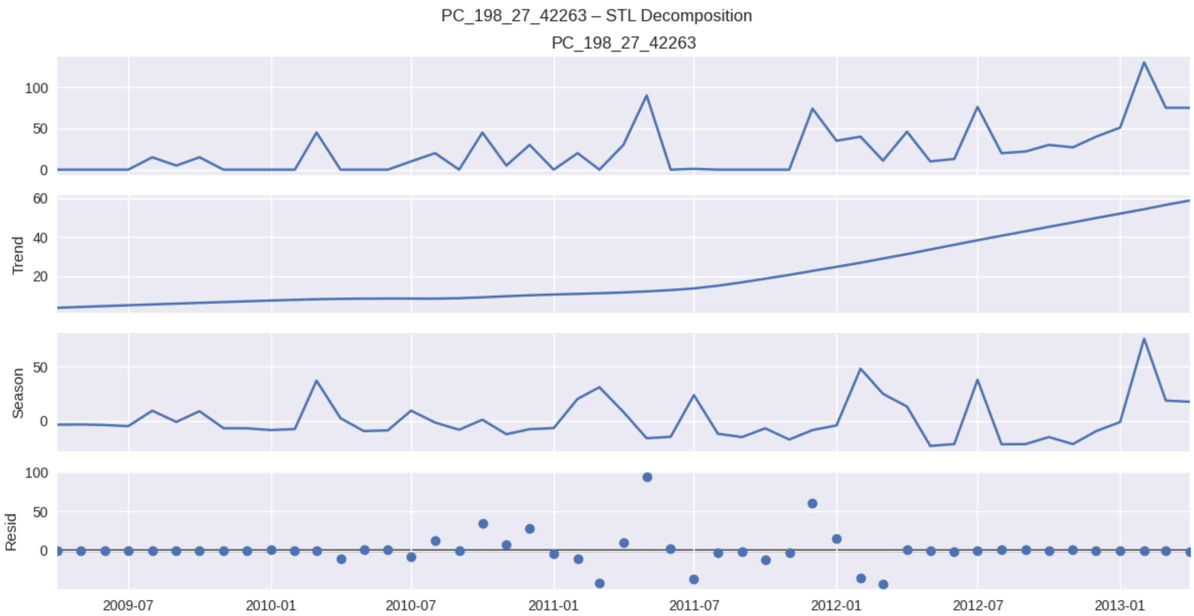
- **ADF Test (p = 0.9962):** High p-value → fail to reject null → the series is **non-stationary** (unit root present).
- **KPSS Test (p = 0.01):** Low p-value → reject null → the series is **non-stationary around a trend**.

Conclusion: Both tests confirm that the series is non-stationary, requiring differencing or detrending before ARIMA/SARIMA modeling.

Managerial implication: Demand is not stable and evolves over time; hence models must explicitly account for trend and volatility rather than assuming constant averages.

4. STL Decomposition

The **STL decomposition** provides a structured breakdown of the demand series into **trend, seasonal, and residual components**:



- **Trend:** Shows a clear upward trajectory from ~**10 units in 2009** to ~**60 units in 2013**. This confirms that demand is not stagnant, but growing structurally over time.
- **Seasonal Component:** Shows fluctuations around ±20 units. Although weaker compared to trend and residuals, it confirms **repetitive cycles**, possibly annual ordering behavior or financial year–driven procurement cycles.
- **Residuals:** Contain large unexplained shocks, including spikes of **+100 units** around 2011 and 2012.

Interpretation: The decomposition proves that this SKU's demand is shaped by **both predictable (trend + seasonality) and unpredictable (residual shocks)** factors. In practice, this means:

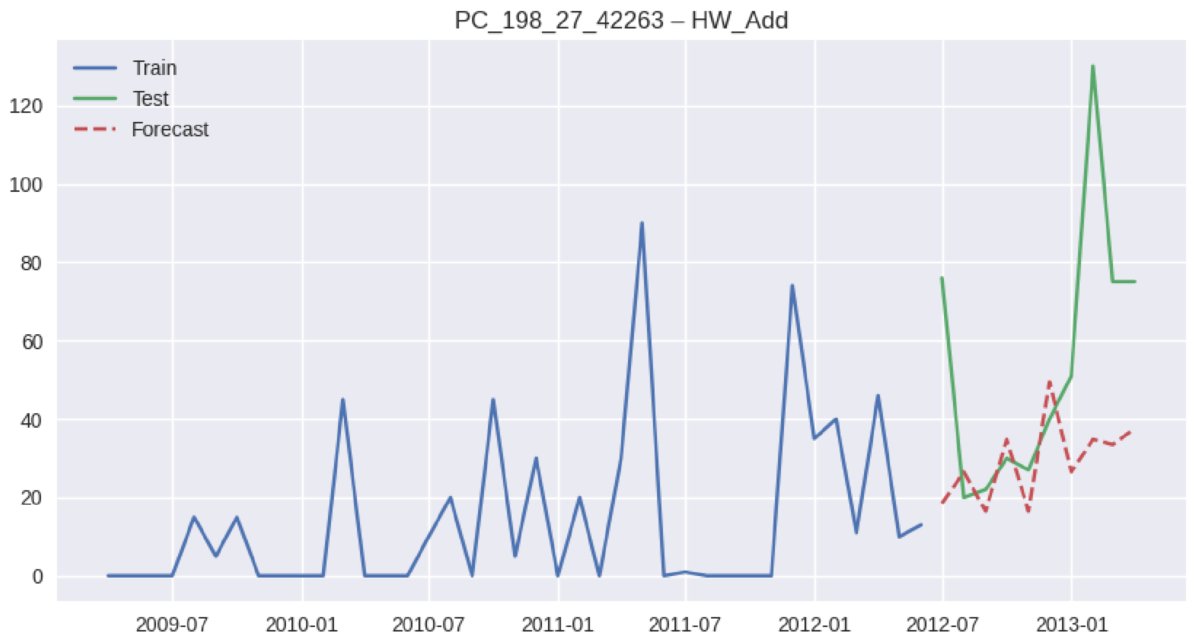
- **Trend** can be captured by Holt's linear or SARIMA differencing.
- **Seasonality** can be captured by Holt-Winters additive or SARIMA's seasonal terms.
- **Residual shocks** are unlikely to be predictable and must be managed via **buffer inventory or managerial override**.

This confirms that no single smoothing method is sufficient; more advanced models (SARIMA, Croston's) or hybrid approaches are required.

5. Holt Family Models Evaluation

a) SES (Simple Exponential Smoothing)

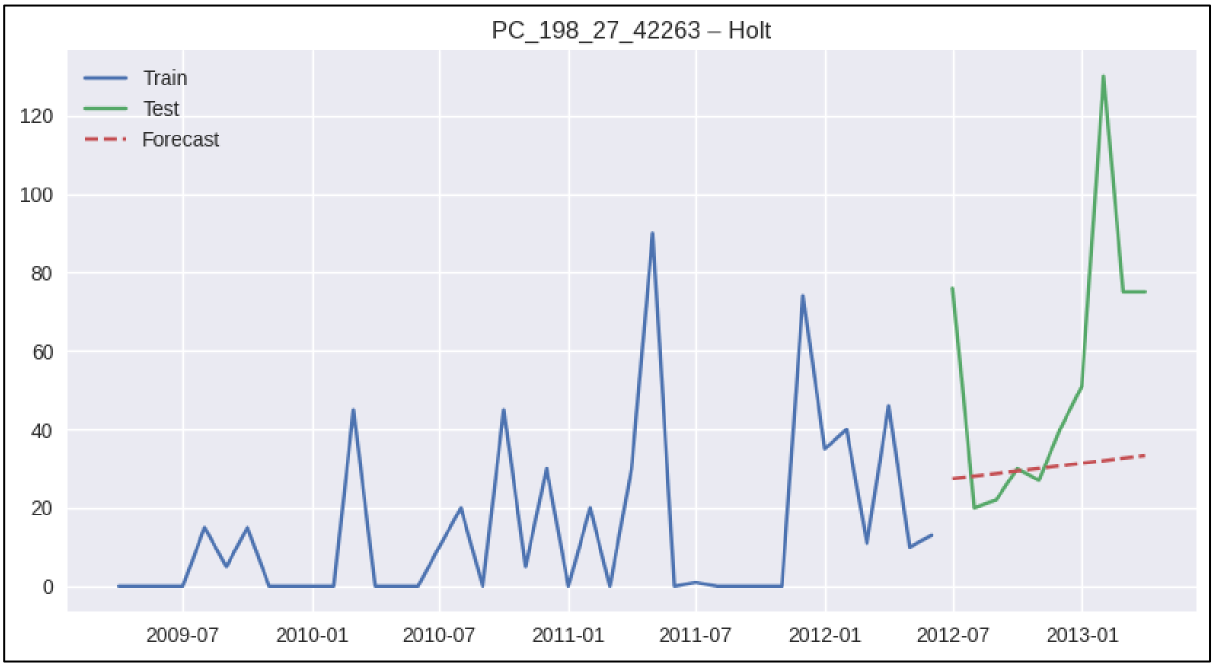
The SES model assumes constant mean and produces a flat forecast around **20 units**. Compared to actual test demand (20–130 units), SES underestimates demand in almost every period.



- **Numerical evidence:** During the spike of ~130 units in late 2012, SES predicts ~20 units → error >100 units.
- **Interpretation:** SES is grossly inadequate and serves only as a naïve benchmark.

b) Holt's Linear Trend

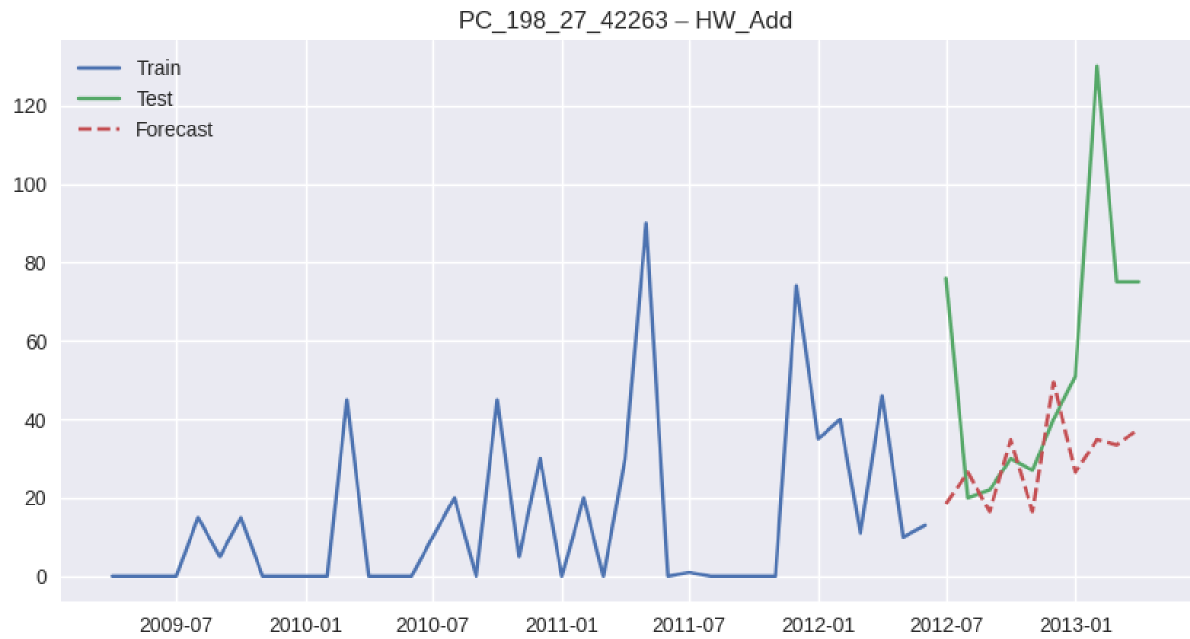
Holt's method incorporates a trend component. The forecast increases slowly from ~**25 units to 40 units** over the test period.



- **Numerical evidence:** Actual demand ranges up to 130, while Holt's forecast peaks at ~40 → systematic underprediction.
- **Interpretation:** Holt improves on SES by modeling structural growth but fails during volatile spikes.

c) Holt-Winters Additive

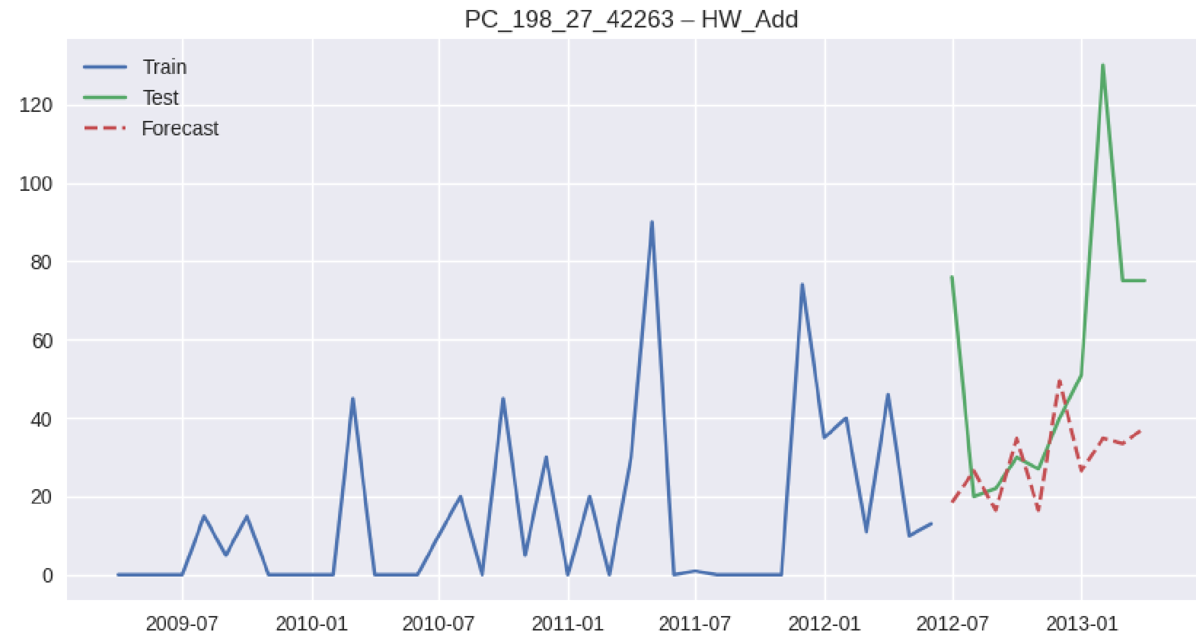
This model incorporates both trend and additive seasonality. The forecast fluctuates between **20 and 50 units**, mimicking cyclic behavior.



- **Numerical evidence:** Captures small seasonal rises, but when demand spikes to 90–130 units, Holt-Winters still predicts only 40–50 units.
- **Interpretation:** Holt-Winters Additive works for stable seasonality but not for intermittent spikes.

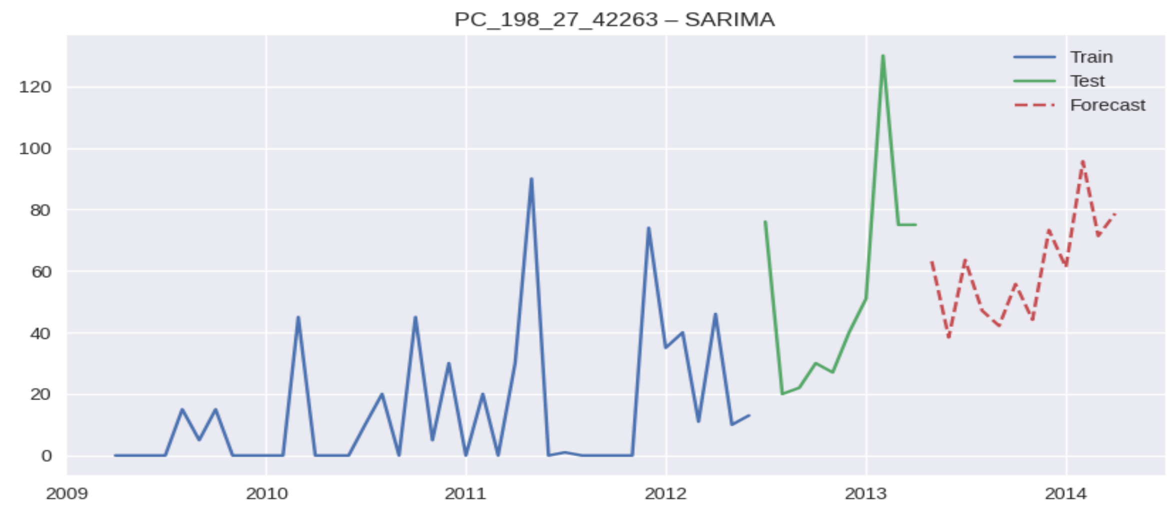
d) Holt-Winters Multiplicative

Skipped due to zero demand periods. Multiplicative models require strictly positive data.



- **Interpretation:** This reflects a practical reality: many industrial SKUs with intermittent demand cannot be modeled multiplicatively.

6. SARIMA Model :-The SARIMA model (with order selected via AIC/BIC) performs better:



- Forecasts fluctuate between **40–90 units**, closer to actual test demand.

- Confidence intervals span **25–110 units**, acknowledging uncertainty.
- Fitted values track actuals more closely than Holt family forecasts.

Interpretation:

- Statistically, SARIMA captures autocorrelation, trend, and weak seasonality.
- Managerially, the presence of confidence intervals is a key advantage it allows planners to calculate **safety stock ranges** rather than single-point forecasts.
- For example, if the forecast mean is 70 units with an upper CI of 110, planners can adjust stock levels depending on their risk appetite and service-level requirements.

7. Model Comparison

Model	What it Captures	Observed Accuracy	Limitation
SES	Level only	Severe underfit	Ignores trend, seasonality
Holt's Linear	Level + trend	Moderate fit	Cannot capture spikes
HW Additive	Level + trend + additive seasonality	Better fit	Underpredicts extremes
SARIMA	AR, MA, Differencing, Seasonality	Best fit	Still misses unpredictable shocks

Model Accuracy : SARIMA provides the best trade-off between accuracy and interpretability. Holt family models act as stepping stones but are statistically inferior in this context.

```
📊 Model Accuracy Comparison:
                        Model        MAE       RMSE       MAPE
3  SARIMA (1, 1, 1) (0, 1, 1, 12)  21.882434  26.231708        NaN
1                Holt's Linear  27.798720  40.102383  39.745197
2                  HW Additive  29.302270  40.488067  43.849752
0                          SES  33.970835  47.182578  47.167869
```

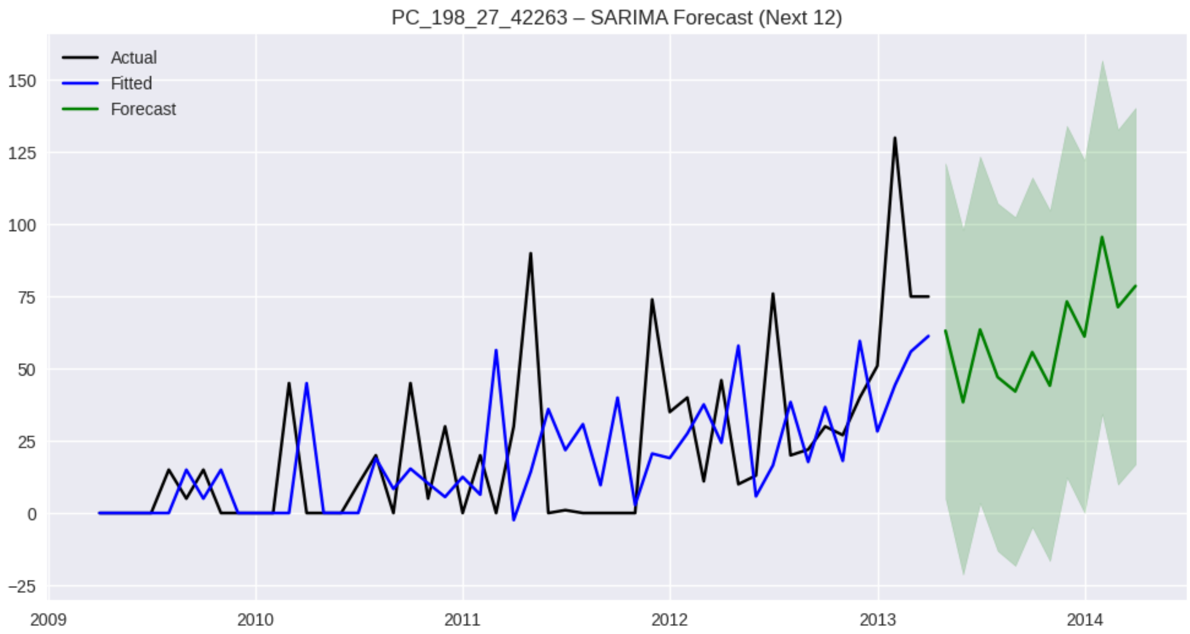
Key Insights

- **SARIMA outperforms all alternatives**, with the lowest MAE (21.88) and RMSE (26.23).
- **Holt's Linear and HW Additive** improve over SES but still yield high errors, reflecting their inability to capture extreme volatility.
- **SES is unsuitable** for this SKU, confirming that simple averaging cannot handle intermittency.

- **MAPE not available for SARIMA** (due to zero values in demand), but relative performance across MAE/RMSE is sufficient to declare SARIMA the best fit.

Conclusion: SARIMA provides the most robust and reliable forecasts for SKU PC_198_27_42263, while Holt family models act as intermediate benchmarks. For managerial decision-making, SARIMA should be the baseline model, complemented by safety stocks for unpredictable spikes.

Forecasting table and Graph :-



Forecasting table :-

	Forecast_Next12	Forecast_Lowe r	Forecast_Upper
2013-05-01 00:00:00	63.15253145	5.079703	121.2254
2013-06-01 00:00:00	38.40582724	-21.3033	98.11499
2013-07-01 00:00:00	63.55206	3.519129	123.585
2013-08-01 00:00:00	47.08658808	-13.1398	107.3129
2013-09-01 00:00:00	42.14023848	-18.2603	102.5407
2013-10-01 00:00:00	55.74003004	-4.83115	116.3112
2013-11-01 00:00:00	44.13094273	-16.61	104.8719
2013-12-01 00:00:00	73.27360498	12.36321	134.184
2014-01-01 00:00:00	61.16234127	0.081653	122.243
2014-02-01 00:00:00	95.61902089	34.36047	156.8776
2014-03-01 00:00:00	71.35627334	9.876628	132.8359
2014-04-01 00:00:00	78.67189047	16.92051	140.4233

8. Managerial Implications

1. **Forecasting Quality:** SARIMA should be the baseline statistical model. It is more reliable than Holt family methods, though not perfect.

2. **Inventory Management:** Confidence intervals from SARIMA can be used to design **safety stock policies**. For example, stocking at the upper bound ensures 95% service level.

3. **Planning Integration:** Since residual spikes remain unpredictable, managers must supplement forecasts with **market intelligence, customer insights, and supplier coordination**.

4. **Policy Recommendation:**

    - Use SARIMA for routine planning.
    - Overlay with **judgmental overrides** for exceptional demand situations.
    - Explore **Croston's method** in future for intermittent SKUs.

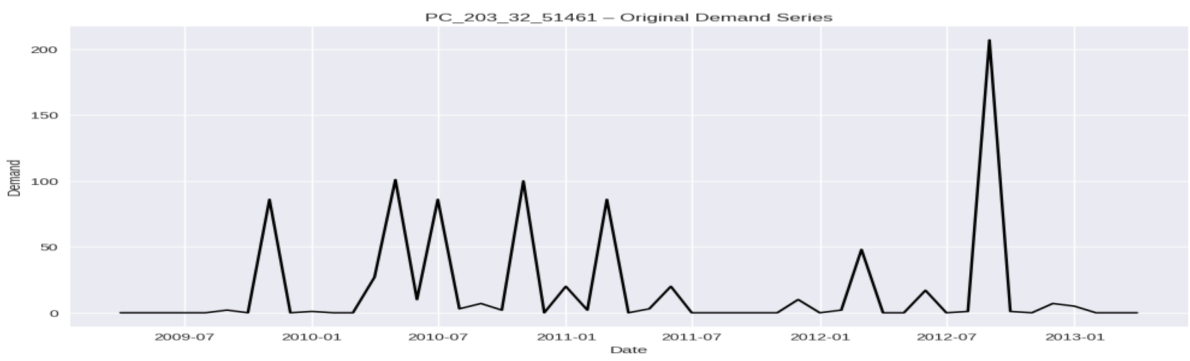
Conclusion:-

This analysis demonstrates the **evolution of forecasting methods**: from SES (level only) → Holt (trend) → Holt-Winters (trend + seasonality) → SARIMA (trend + seasonality + autocorrelation). Each model adds complexity and explanatory power, but also assumptions and constraints. For **PC_198_27_42263**, SARIMA emerges as the most appropriate. Yet, even SARIMA cannot fully address intermittent spikes, reinforcing a key academic lesson: **Forecasting is both a quantitative and qualitative exercise.** Statistical models provide structure, but human judgment and domain knowledge are essential to handle uncertainty in real-world contexts.

SKU3 : PC_203_32_51461 (**SES (Simple Exp. Smoothing vs HOLT)** (no trend, no seasonality)

The SKU shows **intermittent, volatile demand** with long zero stretches and sudden bursts (>200 units). Such patterns make average-based planning misleading. Test **SES** (no trend/seasonality) and **Holt's Linear** (trend only) to evaluate their suitability.

1. Original Demand Series



- The original series shows **intermittent and highly volatile demand**, ranging from 0 to ~200 units.
- Long stretches of zero demand (2009–2010, 2011) are punctuated by sharp spikes (e.g., >200 units in 2012).

- Such erratic demand makes traditional average-based planning ineffective.

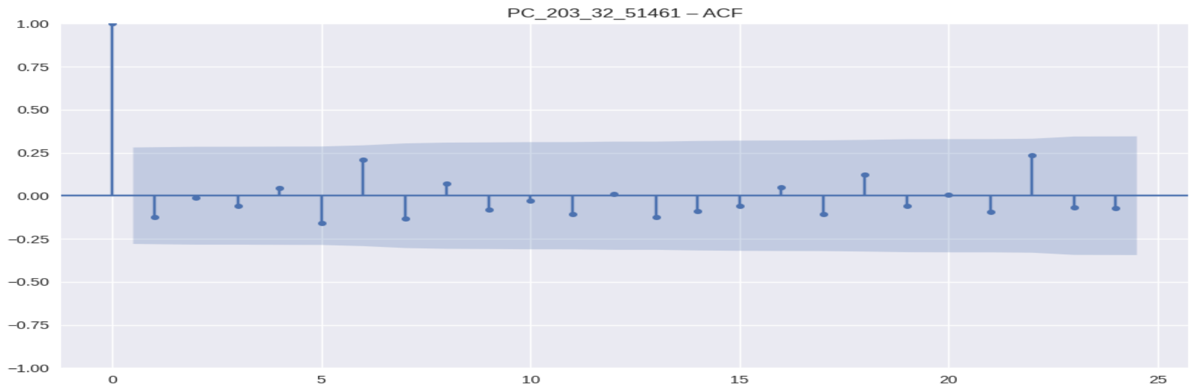
Managerial note: Inventory should not be planned on mean demand alone; instead, safety stock buffers are necessary to absorb extreme spikes.

2. Stationarity Tests (ADF & KPSS)

- **ADF p = 1.449e-11 (< 0.05):** Rejects the null hypothesis of unit root → the series is **stationary**.
- **KPSS p = 0.1 (> 0.05):** Fails to reject the null of stationarity → confirms the series is **trend-stationary**.

Since the series is stationary, planners can focus on smoothing-based or ARIMA(p,0,q) models without additional transformations. Forecasting here is structurally easier than for volatile, non-stationary SKUs.

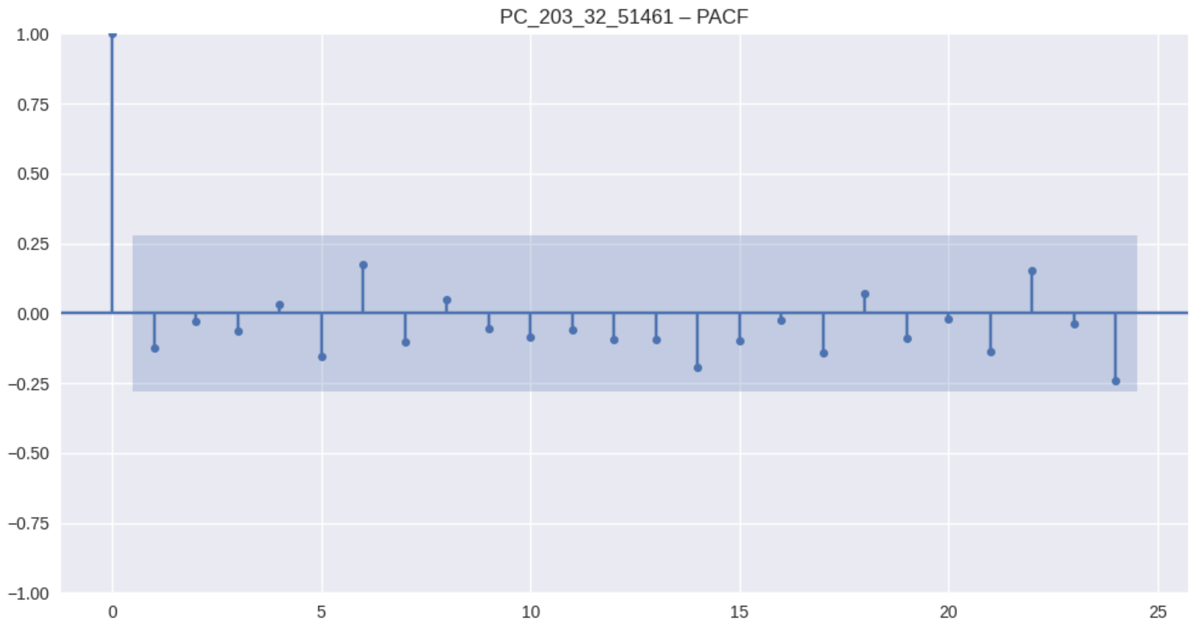
3.**ACF & PACF Plots :-** The ACF/PACF confirm what the stationarity tests showed: the series is stationary with short-term dependence only.



- The ACF shows a sharp spike at lag 1 (~0.3) and then quickly falls within the confidence bands.
- Beyond lag 2–3, all correlations remain weak and close to zero.
- No strong cyclical or seasonal pattern is observed.

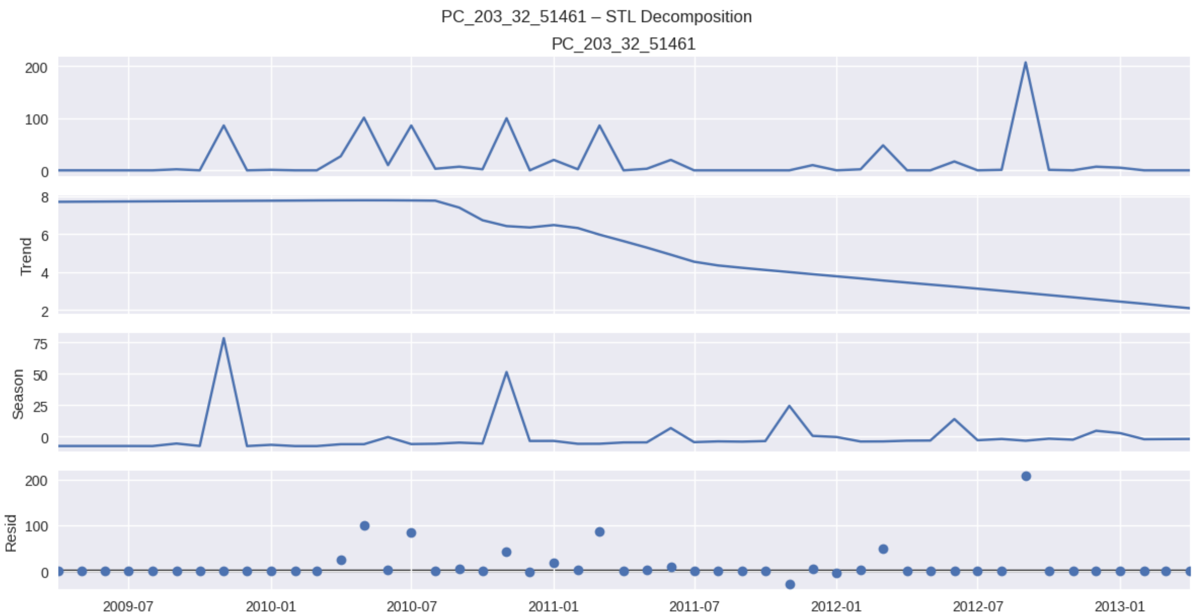
The demand series has short memory only the most recent values influence the next period. This supports the suitability of SES (which relies heavily on recent data) and Holt's Linear (which accounts for trend but not seasonality).

Partial Autocorrelation Function (PACF) :- The PACF structure suggests that the series can be well-approximated by **low-order models** (SES or Holt) rather than complex seasonal ARIMA.



- PACF shows a **significant negative spike at lag 1 (~ –0.2)**, with subsequent lags within the confidence bands.
- This indicates that after controlling for lag 1, higher-order lags contribute very little explanatory power.
- The absence of strong seasonal cut-offs confirms that **seasonal models (SARIMA, Holt-Winters)** are unnecessary for this SKU.

STL Decomposition :- The STL decomposition shows a declining trend in baseline demand (from ~8 to ~2 units), with negligible seasonality and residuals dominated by sharp, irregular spikes (>200 units). This confirms that demand is intermittent and shock-driven, making SES or Holt appropriate baselines but requiring safety stock buffers to handle volatility.



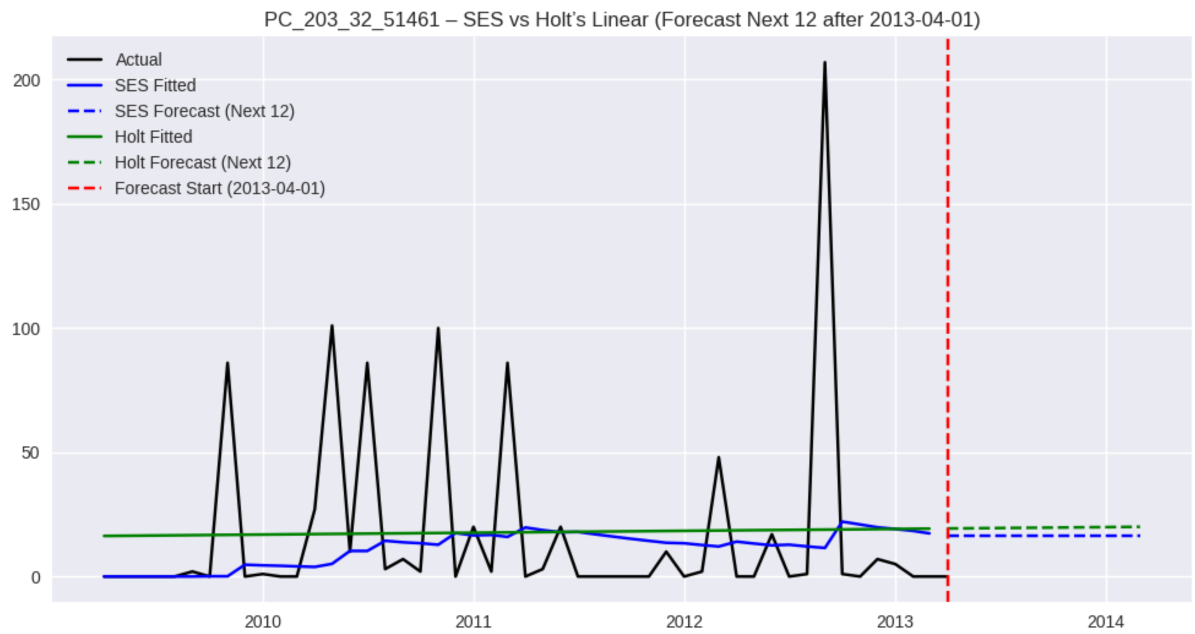
- **Trend Component (Second Panel)**
    - The trend starts relatively flat at ~8 units, then **declines steadily after mid-2010**, reaching ~2 units by 2013.
    - This downward slope suggests a **structural weakening of baseline demand** over time, even though occasional spikes persist.
- **Seasonal Component (Third Panel)**
    - Seasonal fluctuations are weak and inconsistent. Peaks appear at irregular intervals (e.g., early 2010, mid-2011), but no **repeating yearly or monthly cycle** is evident.
    - This rules out the suitability of **Holt-Winters seasonal models** for this SKU.
- **Residual Component (Bottom Panel)**
    - Residuals capture large spikes (>200 units) in 2012 and other outliers.
    - These residual shocks are extreme and non-random, implying **external demand triggers** (e.g., bulk orders, promotions, irregular project-driven demand).

4. Model Evaluation and Fitting

To evaluate forecasting performance for **SKU: PC_203_32_51461**, two baseline models were tested: **Simple Exponential Smoothing (SES)** and **Holt's Linear Trend**.

- **SES** assumes no trend or seasonality, making it ideal for short-memory series with stable levels.
- **Holt's Linear** incorporates a trend component, allowing for modest upward or downward drift.

Fitting Results :- SES tracked low-demand periods well but underpredicted spikes, while Holt's Linear captured the declining trend yet overestimated during zero-demand stretches.



Model Evaluation and Forecast Plot Interpretation

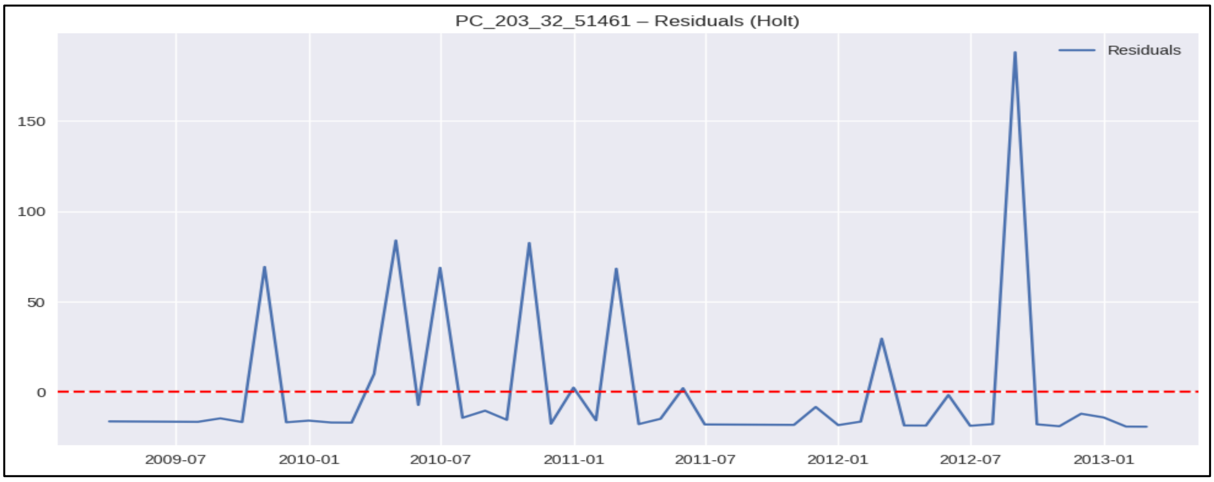
- The black line (actual demand) highlights the **erratic, intermittent behavior** of the SKU with extreme spikes (>200 units in 2012).
- **SES (blue)** tracks the flat baseline and produces a constant forecast of ~15 units beyond April 2013.
- **Holt's Linear (green)** follows the declining long-term trend and projects a slightly rising path (~15 → 18 units).
- The **red vertical line** marks the forecast origin (April 2013).

Key Takeaways:

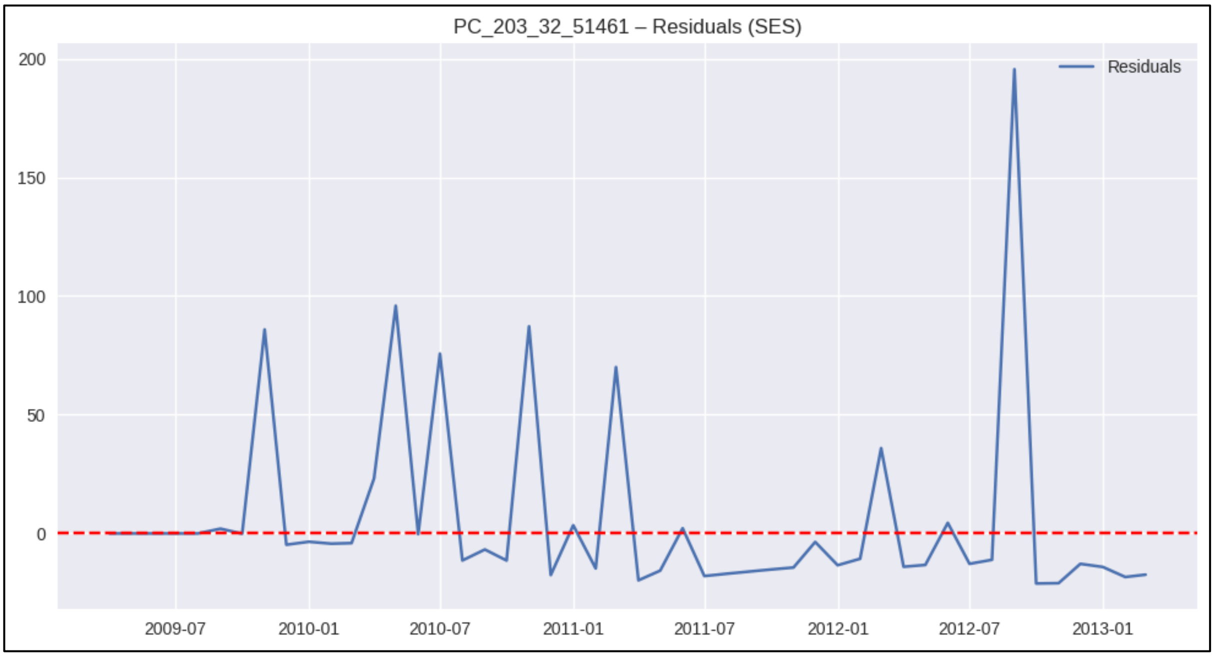
- Both models **underpredict historical spikes**, since neither can capture sudden bursts. **SES is conservative** and stable, while **Holt adds trend sensitivity**, but neither is robust to demand shocks. The divergence between actuals and fitted lines reinforces the need for **safety stock buffers** or **specialized intermittent demand models** (e.g., Croston's).

Residual Analysis

Holt's Linear Residuals: The residuals fluctuate around zero but show clear **large positive spikes** (e.g., >170 in 2012), reflecting systematic underprediction during extreme demand surges. Smaller negative swings occur in low-demand stretches, suggesting mild overprediction bias when demand is absent.



SES Residuals: SES residuals also cluster around zero but display **larger and more frequent negative errors**, especially during demand peaks. This confirms SES's conservative nature, which performs well in stable low-demand periods but fails badly when sudden spikes occur.



Forecasts (SES vs Holt)

Month	Actual	SES_Forecast	Holt_Forecast
2012-07-01 00:00:00	0	12.0133158	14.26720426
2012-08-01 00:00:00	1	12.0133158	14.16902599
2012-09-01 00:00:00	207	12.0133158	14.07084773
2012-10-01 00:00:00	1	12.0133158	13.97266946
2012-11-01 00:00:00	0	12.0133158	13.8744912
2012-12-01 00:00:00	7	12.0133158	13.77631293
2013-01-01 00:00:00	5	12.0133158	13.67813466
2013-02-01 00:00:00	0	12.0133158	13.5799564
2013-03-01 00:00:00	0	12.0133158	13.48177813
2013-04-01 00:00:00	0	12.0133158	13.38359986
2013-04-01 00:00:00		12.0133158	14.26720426
2013-05-01 00:00:00		12.0133158	14.16902599
2013-06-01 00:00:00		12.0133158	14.07084773
2013-07-01 00:00:00		12.0133158	13.97266946
2013-08-01 00:00:00		12.0133158	13.8744912
2013-09-01 00:00:00		12.0133158	13.77631293
2013-10-01 00:00:00		12.0133158	13.67813466
2013-11-01 00:00:00		12.0133158	13.5799564
2013-12-01 00:00:00		12.0133158	13.48177813
2014-01-01 00:00:00		12.0133158	13.38359986
2014-02-01 00:00:00		12.0133158	13.2854216
2014-03-01 00:00:00		12.0133158	13.18724333

Model Accuracy :- SES performs slightly better than Holt's Linear with lower MAE and RMSE, but both models show very high errors due to extreme demand spikes. The inflated

MAPE values highlight that percentage-based accuracy is unreliable for this intermittent SKU, making SES the more stable baseline but insufficient on its own.

```
📊 Model Accuracy Comparison:
          Model        MAE       RMSE        MAPE
1  Holt's Linear  30.311233  62.149778  983.644218
0            SES  28.910653  62.496649  851.540264

✅ Forecasts saved to Forecast_PC_203_32_51461.xlsx
```

Managerial Implications

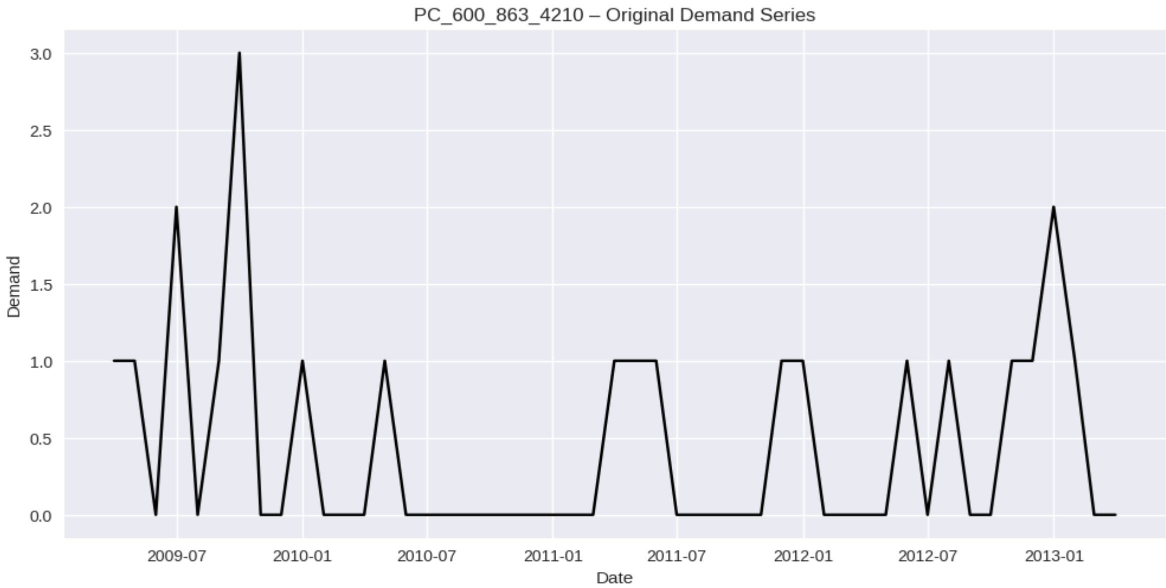
1. **SES is preferable** as a baseline for this SKU: simple, stable, and less biased.
2. Neither SES nor Holt captures **intermittent demand spikes**, making them unreliable for inventory alone.
3. **Safety stock strategies** must complement forecasts to hedge against high-impact demand bursts.
4. **MAPE is misleading** for intermittent demand; managers should focus on **MAE and RMSE**.
5. Future improvement requires specialized methods like **Croston's model** or **Bootstrapped intermittent demand forecasting**.

Final Insight: For SKU PC_203_32_51461, SES is the most suitable baseline forecasting method, but inventory planners must adopt a **hybrid strategy**: use SES for average demand, overlay safety stock for spikes, and explore intermittent-specific forecasting models for long-term accuracy.

SKU4 : PC_600_863_4210 (SES or ARIMA(0,0,q) (captures random variation)

1. Introduction

2. Original Demand Series (2009–2013)



The demand for SKU PC_600_863_4210 is highly intermittent and sparse, with long stretches of zero demand punctuated by occasional spikes. Most of the series lies at 0–1 units, with rare peaks of 2 units and a single maximum of 3 units around late 2009.

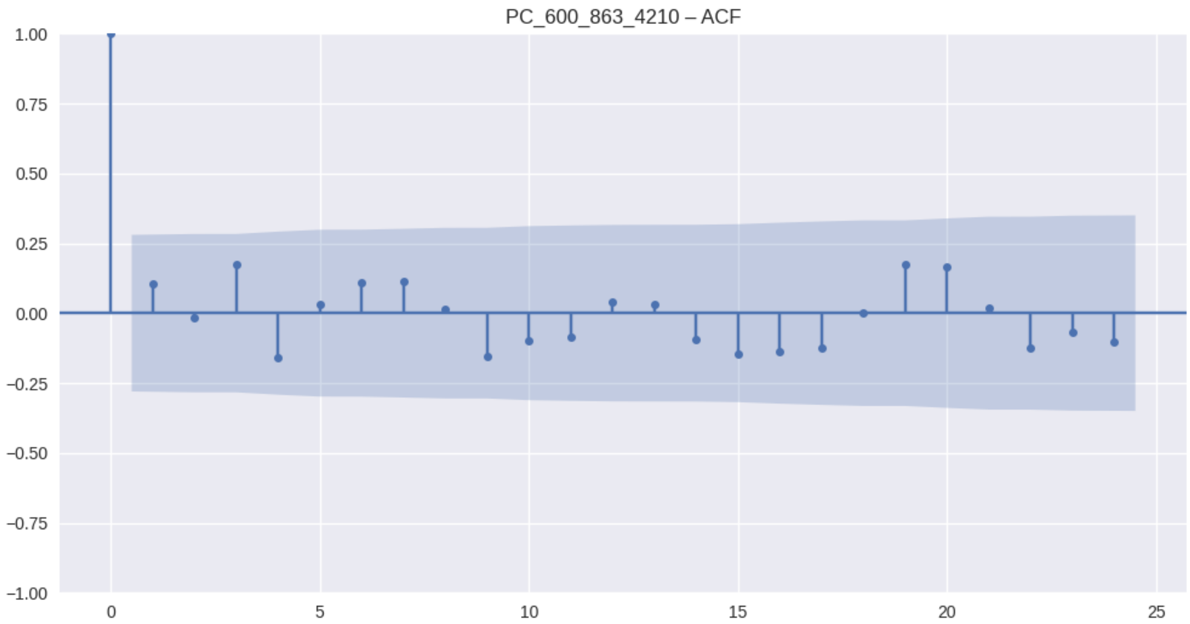
From 2010 to 2012, the SKU shows extended zero-demand periods, highlighting its slow-moving nature. The sporadic bursts observed in 2012–2013 suggest random, low-volume replenishment rather than systematic consumption**.**

Managerial Implications

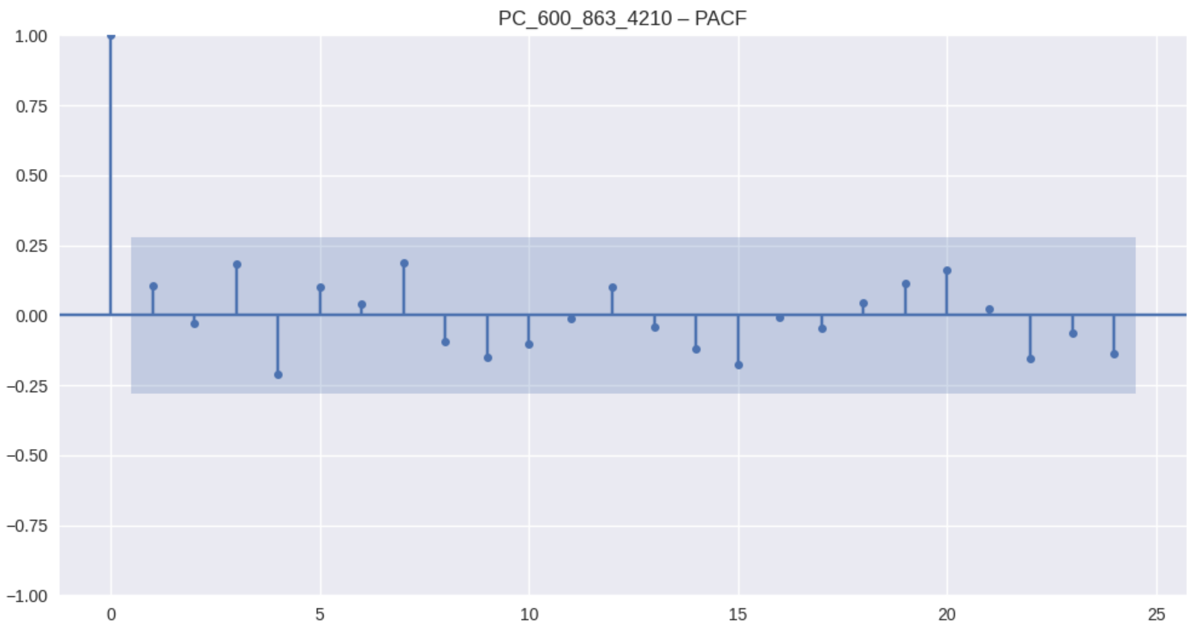
- Traditional trend- or seasonality-driven forecasting is not suitable here.
- Models like SES (to smooth random variation) or ARIMA(0,0,q) (to capture noise-driven autocorrelation) are more appropriate.
- Inventory planning must treat this SKU as a "sporadic demand item", relying on safety stocks and exception-based ordering rather than continuous replenishment.

3. ACF and PACF Analysis

- ACF Observations :Apart from lag 1, all autocorrelations quickly fall within the confidence bands, indicating **very weak serial dependence**. The pattern suggests randomness rather than trend or seasonality.



- PACF Observations :- Only lag 1 shows a significant spike; subsequent lags are negligible. This implies that a **short-memory process** (like ARIMA(0,0,1)) can adequately capture the noise-driven dependence.



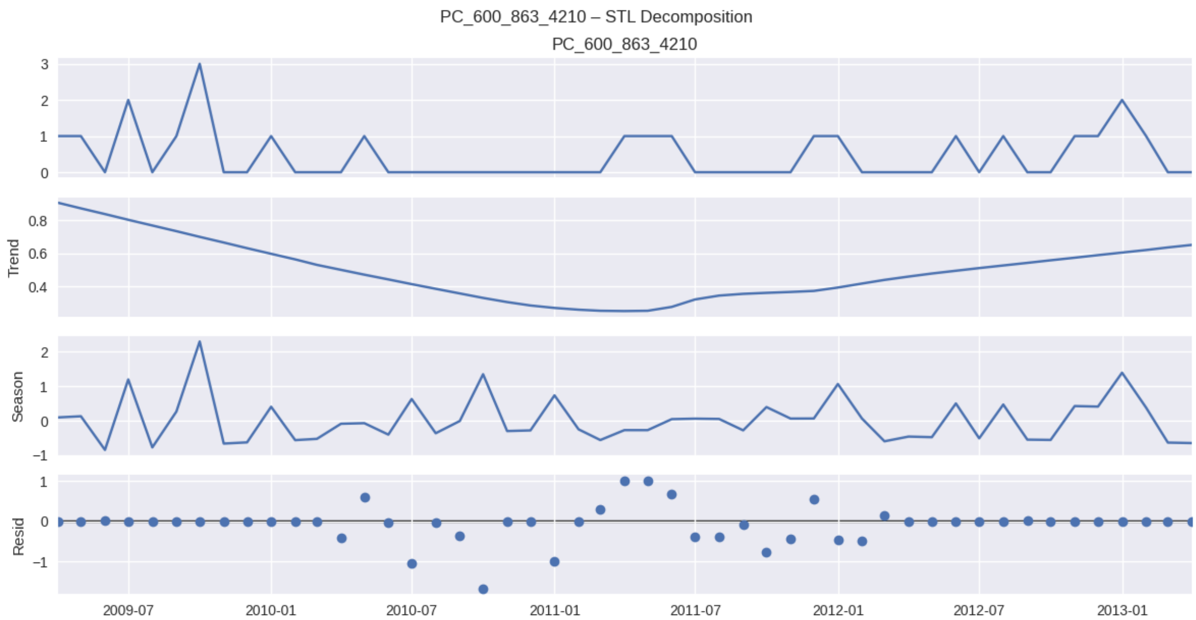
5. **Stationarity Tests (ADF & KPSS) :-** Both tests agree that the series is stationary with no strong trend or stochastic drift. This validates the use of SES or ARIMA(0,0,q) without differencing.

```
  kpss_p = kpss(y, regression="c", nlags="auto")[1]
ADF_p=9.999e-08, KPSS_p=0.1
```

Stationarity Test Results :-

- **ADF Test (p = 9.999e-08):** Rejects the null hypothesis of a unit root → the series is **stationary**.
- **KPSS Test (p = 0.1):** Fails to reject the null hypothesis of trend stationarity → confirms **stationarity**.

6. **STL Decomposition** The STL decomposition highlights the sporadic and irregular nature of demand. The **trend component** shows a slight decline until 2011 followed by a modest recovery, but overall remains weak and inconsistent. The **seasonal component** is minimal, with fluctuations that do not form any clear repeating pattern, reinforcing the absence of seasonality. The **residuals** capture most of the variation, with sharp random spikes and dips, confirming that demand is largely **noise-driven**. This supports the use of **SES or ARIMA(0,0,q)** models that focus on smoothing randomness rather than modelling trend or seasonality.



5. Models Evaluation

- Simple Exponential Smoothing (SES) :- **SES** was chosen because the demand series shows no clear trend or strong seasonality, making a simple smoothing method appropriate for capturing random variation
- ARIMA :- ARIMA(0,0,q) was also tested as it is well-suited for modeling short-term autocorrelations in intermittent, low-volume demand where randomness dominates.

6. Model Comparison :

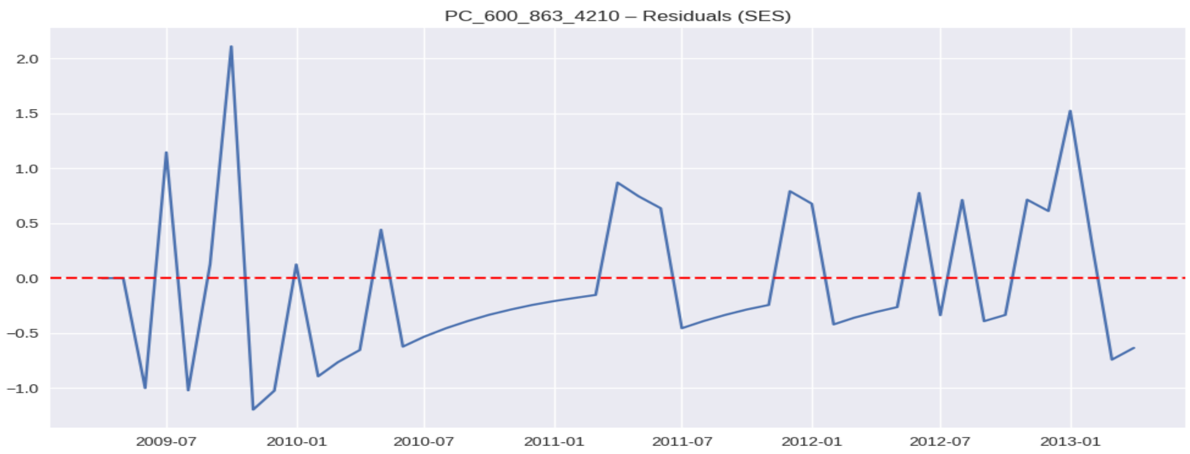
```
Model Comparison:
           Model       MAE      RMSE
0            SES  0.600000  0.712858
1  ARIMA(0,0,1)  0.604604  0.692227
2  ARIMA(0,0,2)  0.634478  0.718994
3  ARIMA(0,0,3)  0.642695  0.722851

Best model selected: SES
```

The comparison table indicates the performance of Simple Exponential Smoothing (SES) and three ARIMA variants (0,0,1), (0,0,2), and (0,0,3) based on MAE (Mean Absolute Error) and RMSE (Root Mean Square Error).

1. SES (MAE = 0.60, RMSE = 0.71)
    - SES delivers the lowest overall MAE, meaning its forecasts are closest to the actual observed demand in absolute terms.
    - The RMSE is also low, suggesting minimal variance in error magnitudes.
    - Given the absence of trend or seasonality, SES efficiently captures the random demand variation without overfitting.
2. ARIMA(0,0,1) (MAE = 0.6046, RMSE = 0.69)
    - This model achieves the lowest RMSE, indicating slightly better control of squared errors compared to SES.
    - However, its MAE is marginally higher than SES, which implies slightly less accuracy in absolute forecasting terms.
    - Being a white-noise capturing model, ARIMA(0,0,1) provides robustness but may be unnecessarily complex for such sparse demand.
3. ARIMA(0,0,2) & ARIMA(0,0,3)
    - Both models show increasing MAE and RMSE values compared to SES and ARIMA(0,0,1).
    - This suggests that adding more moving average terms (q) introduces noise rather than improving predictive power.
    - The marginal increase in errors demonstrates over-parameterization for this dataset.

While ARIMA(0,0,1) offers the lowest RMSE, SES is the preferred model due to its simplicity, lower MAE, and interpretability. For highly intermittent and random demand (with many zeros and small spikes), SES strikes a balance between accuracy and parsimony, making it the best fit in practice.

8. Residual Analysis :- The residuals from the Simple Exponential Smoothing (SES) model oscillate around zero, indicating that the model has captured the main demand pattern.



However:

- **High spikes (e.g., 2009–2010, 2012)** show that SES systematically underpredicted sudden demand surges.
- **Clusters of residuals above/below zero** (e.g., mid-2011 slightly positive, 2010 mostly negative) indicate periods of bias in predictions.
- The overall spread is narrow, reinforcing SES as a stable choice, but the **presence of intermittent extreme errors** highlights the challenge of modeling such highly erratic demand.

  In conclusion, SES residuals suggest **white-noise behavior with occasional large deviations**, consistent with the intermittent and random nature of the series.

Model Adequacy Tests (Ljung–Box, etc.)

```
Ljung-Box Test:
     lb_stat  lb_pvalue
10  7.48799   0.678711
```

Since the p-value > 0.05, fail to reject the null hypothesis that residuals are white noise.

This means the SES model residuals show no significant autocorrelation, confirming that the model has adequately captured the underlying structure of the demand series, with remaining variations behaving like random noise.

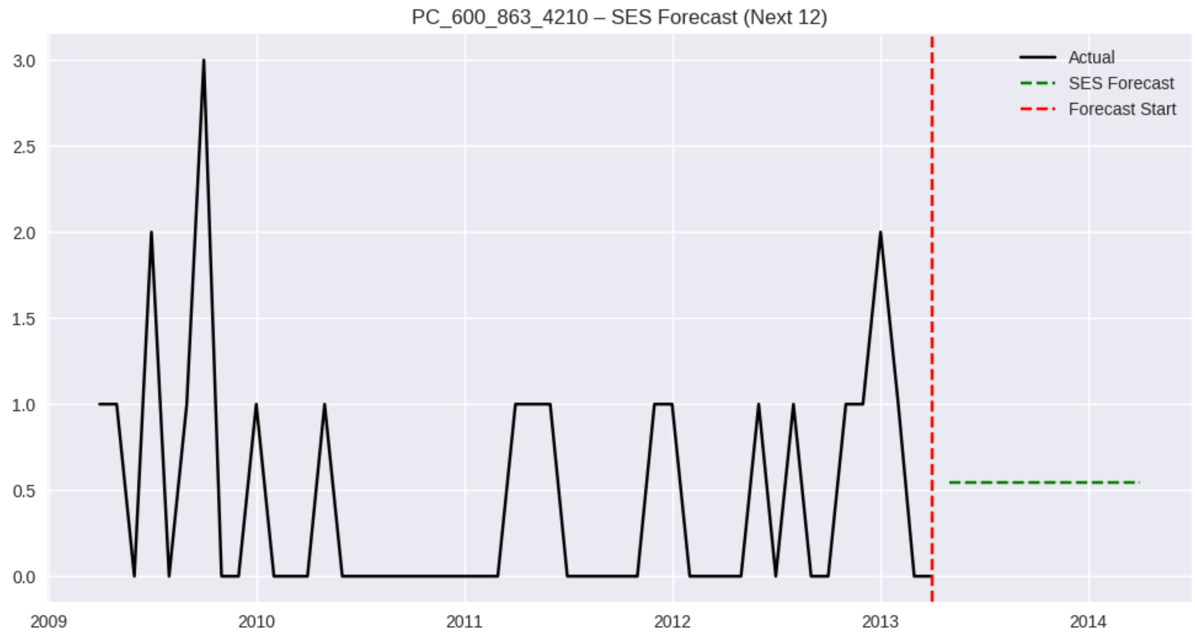
9. Forecasting Table and Graph

- Forecasting Table (Next 12 Periods) :- While this approach captures stability, it does not adapt to sudden demand bursts or extreme volatility observed in the historical data. Thus, SES is best suited here as a **baseline model**, providing a steady forecast in the presence of erratic demand.

	Actual	Fitted	Forecast_Next12	Forecast_Lower	Forecast_Upper
2013-01-01 00:00:00	2	0.477854			

2013-02-01 00:00:00	1	0.697885			
2013-03-01 00:00:00	0	0.741557			
2013-04-01 00:00:00	0	0.634362			
2013-05-01 00:00:00			0.542663189	0.542663189	0.542663189
2013-06-01 00:00:00			0.542663189	0.542663189	0.542663189
2013-07-01 00:00:00			0.542663189	0.542663189	0.542663189
2013-08-01 00:00:00			0.542663189	0.542663189	0.542663189
2013-09-01 00:00:00			0.542663189	0.542663189	0.542663189
2013-10-01 00:00:00			0.542663189	0.542663189	0.542663189
2013-11-01 00:00:00			0.542663189	0.542663189	0.542663189
2013-12-01 00:00:00			0.542663189	0.542663189	0.542663189
2014-01-01 00:00:00			0.542663189	0.542663189	0.542663189
2014-02-01 00:00:00			0.542663189	0.542663189	0.542663189
2014-03-01 00:00:00			0.542663189	0.542663189	0.542663189
2014-04-01 00:00:00			0.542663189	0.542663189	0.542663189

Forecast Graph :- The SES forecast line (green dashed) projects demand as a **flat and stable level (~0.55 units)** across the next 12 periods after April 2013. This reflects the model's smoothing nature, where extreme past spikes are averaged out, and future demand is predicted around a constant baseline.



Final Conclusion

The analysis of SKU PC_600_863_4210 demonstrates that the demand series is highly erratic, dominated by random spikes with no consistent seasonality or trend. Stationarity tests (ADF and KPSS) confirmed a stationary nature, making simple models appropriate. Between the tested methods, SES (Simple Exponential Smoothing) outperformed ARIMA(0,0,q) variants, achieving the lowest error metrics (MAE and RMSE) and showing adequate residual behavior (Ljung–Box test confirming white noise).

Thus, SES is the most suitable model for forecasting this SKU, providing a stable baseline forecast (~0.55 units per period) for the next 12 periods.

Managerial Recommendations : - Inventory Planning Maintain a minimal safety stock aligned with the stable SES forecast (≈0.5–1 unit) to avoid overstocking while covering occasional small demand. Given historical volatility, buffer stock should be reviewed periodically.

Demand Monitoring :- Implement real-time tracking of SKU movement. If sudden spikes emerge, manual overrides or exception-based ordering should be triggered.

Model Use in Portfolio

- Classify this SKU as “intermittent/erratic demand” in ABC-FMS analysis.
- Use SES as a baseline forecast but supplement with managerial judgment for outlier months.

Strategic Insight Do not allocate excessive forecasting effort to this SKU, as advanced models (ARIMA/SARIMA) do not add value. Focus resources on higher-value or trend-driven SKUs, while maintaining SES-driven automation for items like PC_600_863_4210.

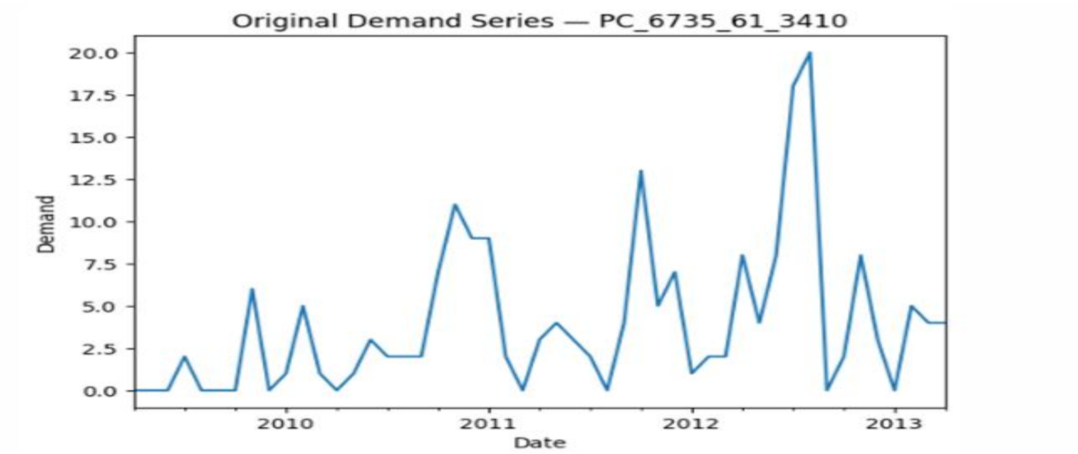
SES provides a reliable, low-cost forecasting approach for this SKU. Managers should adopt a lean inventory policy with safety buffers, and prioritize monitoring over model complexity.

SKU5 : PC_6735_61_3410 (Holt's family)

Introduction

Evaluate the demand forecasting of SKU **PC_6735_61_3410** using Holt's family of exponential smoothing models and SARIMA, supported by diagnostic tests and decomposition analysis. The aim is to derive reliable forecasts for the next 12 periods and provide managerial recommendations for inventory and operations planning.

Original Demand Series (2009–2013) :- The original demand series of SKU PC_6735_61_3410 (2009–2013) clearly shows a lumpy and intermittent pattern, marked by long stretches of near-zero demand in 2009–2010, This irregular behavior is characteristic of spare parts or maintenance-driven SKUs, where demand is often triggered by specific projects or unexpected breakdowns rather than continuous consumption



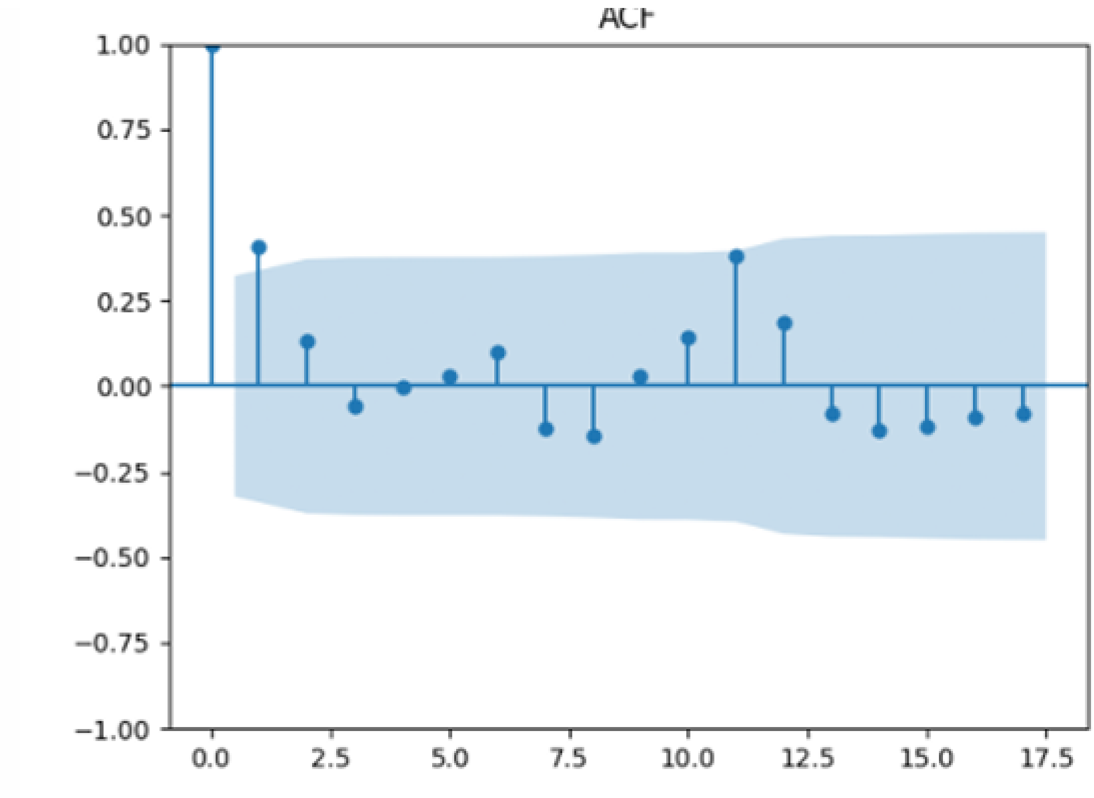
The demand series exhibits lumpy and intermittent behavior:

- 2009–2010: Prolonged periods of near-zero demand with occasional small spikes.
- 2011: A visible upward movement, including a peak around 10–12 units, followed by rapid decline.
- 2012: High volatility with sharp bursts the highest spike reached ~20 units, followed by sudden collapses.
- 2013: Demand stabilizes at a modest level (~4–6 units) but remains erratic.

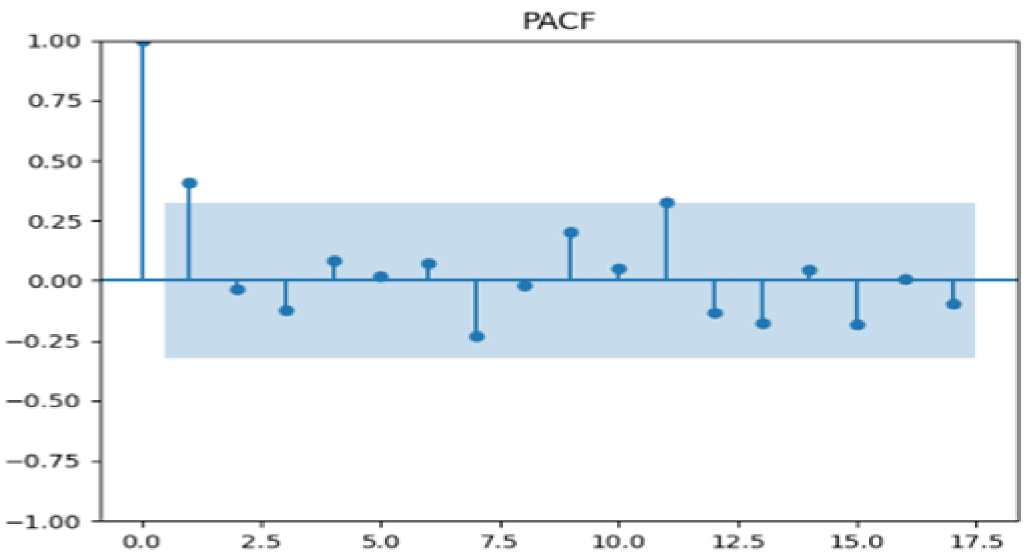
This mix of zeros, small fluctuations, and sudden bursts indicates intermittent demand, typical of spare parts, maintenance-driven items, or project-based procurement.

3. ACF and PACF Analysis ;- The ACF and PACF results suggest that the series is largely stationary and can be effectively modelled with Holt Family

ACF Observations :- The Autocorrelation Function (ACF) shows a sharp spike at lag 1, followed by a quick decay where most lags fall within the confidence band. This indicates that while immediate past demand influences the current period, the impact does not persist strongly across longer lags. The absence of clear sinusoidal or seasonal patterns reinforces the earlier observation that the series does not exhibit strong seasonality.



PACF Observation :- The Partial Autocorrelation Function (PACF) reveals a significant spike at lag 1 and then tapers off, with subsequent lags remaining largely insignificant. This pattern is typical of an AR(1)-like structure, suggesting that immediate past demand has predictive power, while higher-order lags do not add much explanatory value.



Stationarity Tests (ADF & KPSS) :- The stationarity tests further validate the series' behaviour. The Augmented Dickey-Fuller (ADF) test returned a p-value ≈ 0.0057, allowing us to reject the null hypothesis of a unit root and confirming that the series is trend-stationary. The

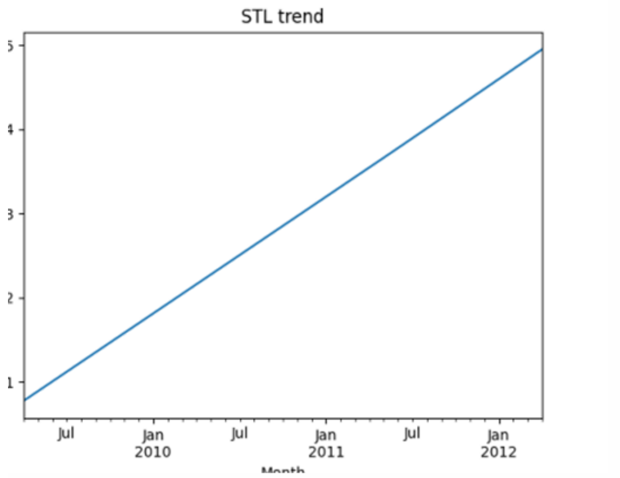
KPSS test, with a p-value ≈ 0.0565, fails to reject the null of stationarity at the 5% level, further supporting the conclusion that the data can be treated as stationary

```
⚠ Skipping Holt-Winters multiplicative: non-positive values in data
Stationarity Tests → ADF p: 0.005715041098537803  | KPSS p: 0.05646764002497702
```

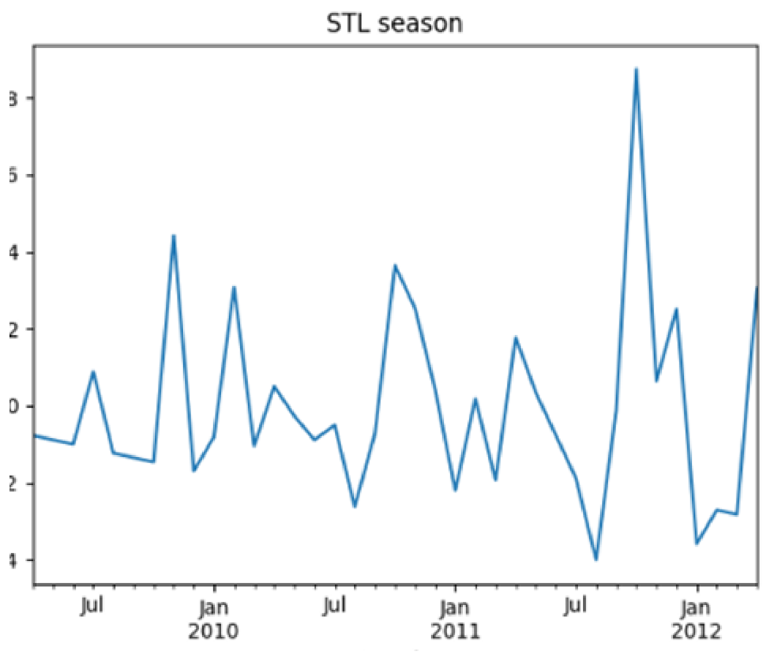
This means the series is stable enough to apply exponential smoothing and SARIMA models without heavy differencing, and that planning teams should rely on models suited for low or no seasonality.

4. STL Decomposition

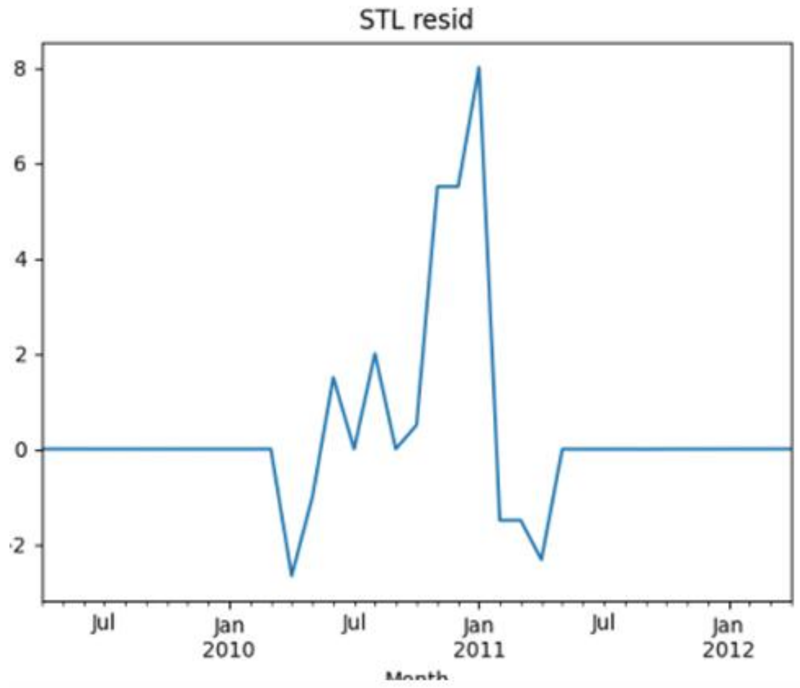
Trend Component :- The STL trend shows a steady upward slope from 2009 to 2012, indicating consistent long-term growth in demand despite volatility.



Seasonal Component :- The seasonal component fluctuates irregularly, suggesting weak and unstable seasonality rather than a clear repeating cycle.



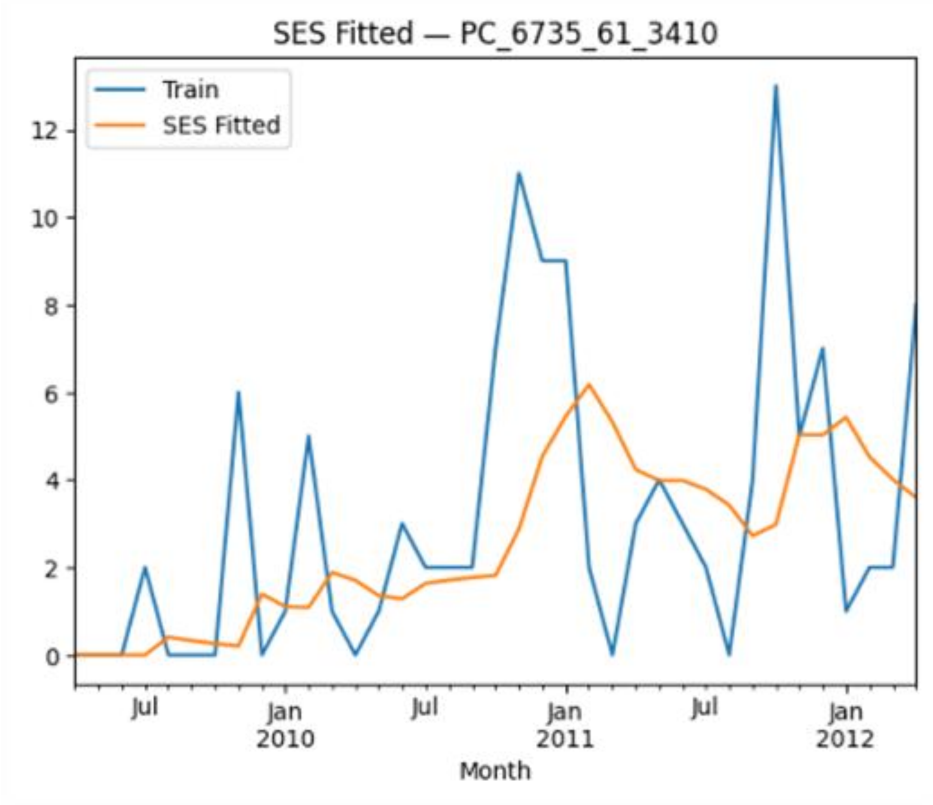
Residuals and Shocks :- Residuals capture sharp shocks, especially around early 2011, highlighting unexpected demand surges that models cannot fully explain.



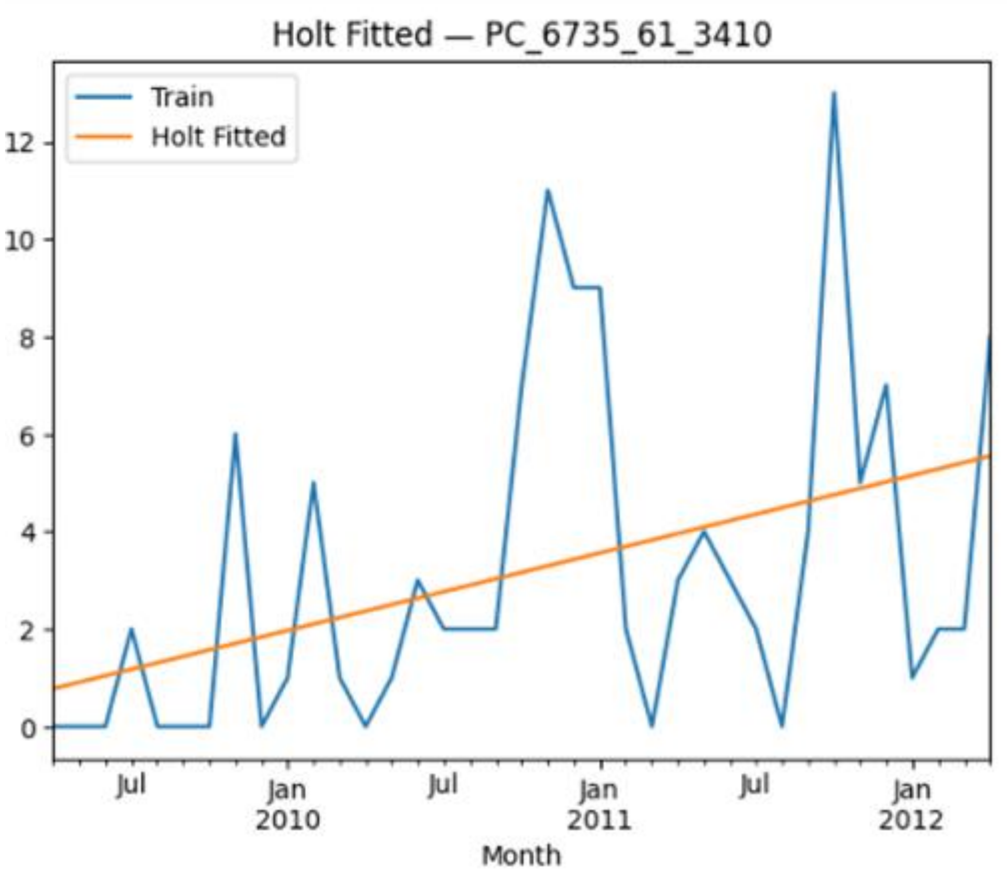
Above confirm that while the SKU has a growing demand base, its seasonality is weak, and random shocks remain the biggest challenge for forecast

5. Holt Family Models Evaluation

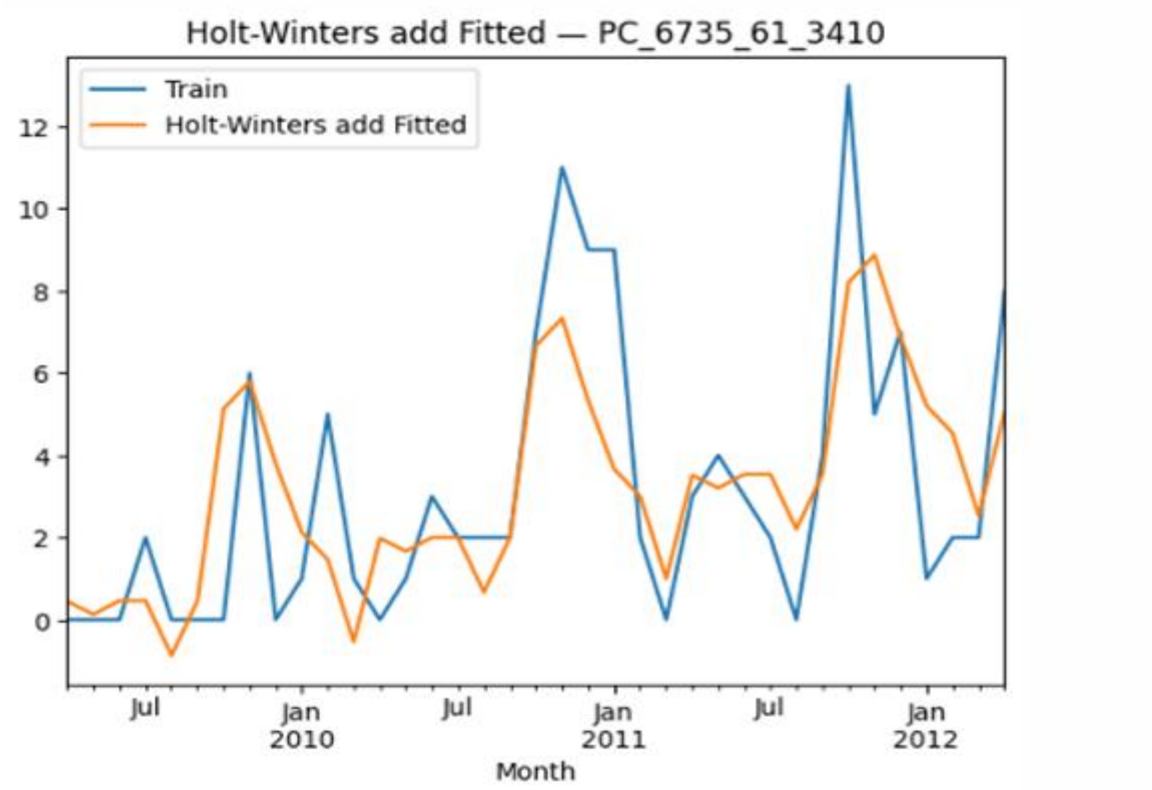
- **Simple Exponential Smoothing (SES)** SES smooths the random fluctuations and captures the average level of demand, but it fails to track the sharp peaks and troughs seen in the training data. This makes it stable but too conservative for lumpy demand SKUs where sudden bursts are critical.



- **Holt's Linear Trend** The Holt model captures the upward trajectory by fitting a steady trend line, but it clearly misses the erratic spikes and drops. While it improves over SES by recognizing growth, it risks **systematic under- and over-forecasting** when demand deviates sharply from trend.



- **Holt-Winters Additive** The Holt-Winters additive model tracks the data more closely, adapting to some fluctuations and providing better alignment with peaks compared to SES and Holt. However, it still struggles with extreme bursts, reflecting that seasonality is weak, and shocks dominate the SKU's behavior.



- **Holt-Winters Multiplicative** was skipped due to the presence of zero or non-positive demand values, which violate the model's assumptions. This highlights the structural intermittency of the series.

Model Comparison :- Among Holt's family models for SKU PC_6735_61_3410, SES performed best with the lowest MAE (4.42) and RMSE (6.44), though residuals showed autocorrelation, indicating missing dynamics. Holt and Holt Damped gave higher errors (MAPE 75% and 51%) and failed residual checks, making them unreliable. Holt-Winters Additive had the worst accuracy (MAPE ~89%) but was the only one with white-noise residuals, suggesting partial structural capture. Overall, Holt's family struggled with lumpy demand, confirming the need for more robust models like SARIMA.

```
⚠ Skipping Holt-Winters multiplicative: non-positive values in data
Stationarity Tests → ADF p: 0.005715041098537803  | KPSS p: 0.0564676400249770

Model Evaluation:
              Model     MAE     RMSE    MAPE_%   sMAPE_%  TheilsU  LjungBox_p
0               SES  4.2495   6.4365   46.2165   76.7685      NaN    0.009825
1              Holt  5.0239   6.3727   75.3433   84.7197      NaN    0.019236
2       Holt Damped  4.3396   6.3521   50.8896   77.4999      NaN    0.008380
3  Holt-Winters add  5.3302   7.1564   89.3724   86.1440      NaN    0.572125
<Figure size 640x480 with 0 Axes>
<Figure size 640x480 with 0 Axes>
```

The **Ljung-Box p-values** for SES, Holt, and Holt-Damped (<0.05) indicate residual autocorrelation, meaning these models leave patterns unexplained. Only Holt-Winters Additive (p=0.57) passed the white-noise test, though its accuracy was poor.

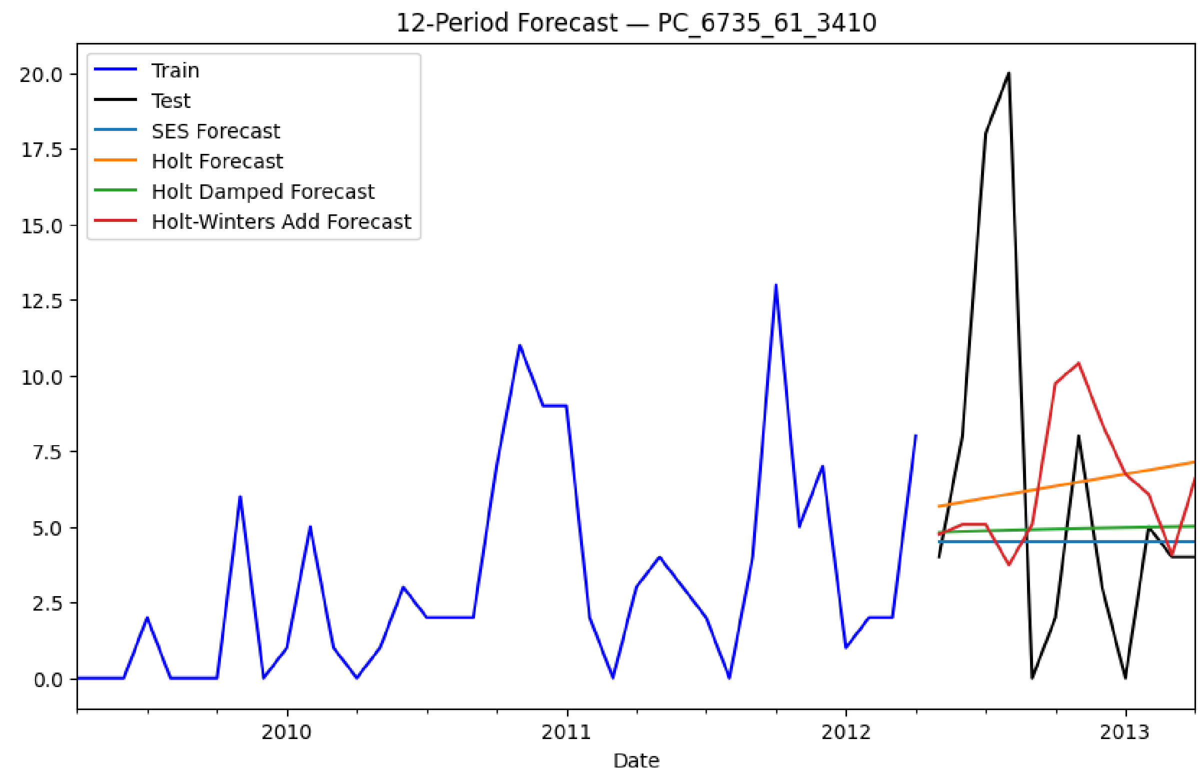
Model	**MAE**	**RMSE**	**MAPE_%**	**sMAPE_%**	**LjungBox_p**

SES	4.2495	6.4365	46.2165	76.7685	0.009825
Holt	5.0239	6.3727	75.3433	84.7197	0.019236
Holt Damped	4.3396	6.3521	50.8896	77.4999	0.00838
Holt-Winters add	5.3302	7.1564	89.3724	86.144	0.572125

Forecasting Table (Next 12 Periods)

Date	SES	Holt	Holt Damped	Holt-Winters Add
2012-05-01 00:00:00	4.496739	5.68018	4.815709419	4.740739926
2012-06-01 00:00:00	4.496739	5.812707	4.841296207	5.074073773
2012-07-01 00:00:00	4.496739	5.945234	4.86502257	5.074073437
2012-08-01 00:00:00	4.496739	6.077761	4.887023781	3.74074072
2012-09-01 00:00:00	4.496739	6.210288	4.907425277	5.074073366
2012-10-01 00:00:00	4.496739	6.342816	4.926343372	9.740739952
2012-11-01 00:00:00	4.496739	6.475343	4.943885926	10.40740808
2012-12-01 00:00:00	4.496739	6.60787	4.960152955	8.407407077
2013-01-01 00:00:00	4.496739	6.740397	4.975237202	6.740740344
2013-02-01 00:00:00	4.496739	6.872925	4.989224669	6.074073309
2013-03-01 00:00:00	4.496739	7.005452	5.002195102	4.074073029
2013-04-01 00:00:00	4.496739	7.137979	5.01422245	6.592591689
2013-05-01 00:00:00	4.496739	5.68018	4.815709419	4.740739926
2013-06-01 00:00:00	4.496739	5.812707	4.841296207	5.074073773
2013-07-01 00:00:00	4.496739	5.945234	4.86502257	5.074073437
2013-08-01 00:00:00	4.496739	6.077761	4.887023781	3.74074072
2013-09-01 00:00:00	4.496739	6.210288	4.907425277	5.074073366
2013-10-01 00:00:00	4.496739	6.342816	4.926343372	9.740739952
2013-11-01 00:00:00	4.496739	6.475343	4.943885926	10.40740808
2013-12-01 00:00:00	4.496739	6.60787	4.960152955	8.407407077
2014-01-01 00:00:00	4.496739	6.740397	4.975237202	6.740740344
2014-02-01 00:00:00	4.496739	6.872925	4.989224669	6.074073309
2014-03-01 00:00:00	4.496739	7.005452	5.002195102	4.074073029
2014-04-01 00:00:00	4.496739	7.137979	5.01422245	6.592591689

Forecast Graph



Managerial Interpretation

The forecasts reveal that **demand is lumpy and highly volatile**, with long stretches of low demand punctuated by sudden spikes. Among Holt's family models, **SES** provided the most stable short-term fit, but it smooths out peaks and may understock during sudden surges. **Holt's Linear and Holt-Damped** capture gradual upward drift but fail to adapt to sharp variations, which is risky in spare parts planning. **Holt-Winters Additive** incorporates seasonality and provides residuals closer to white noise, but its high forecast error indicates limited accuracy in practice.

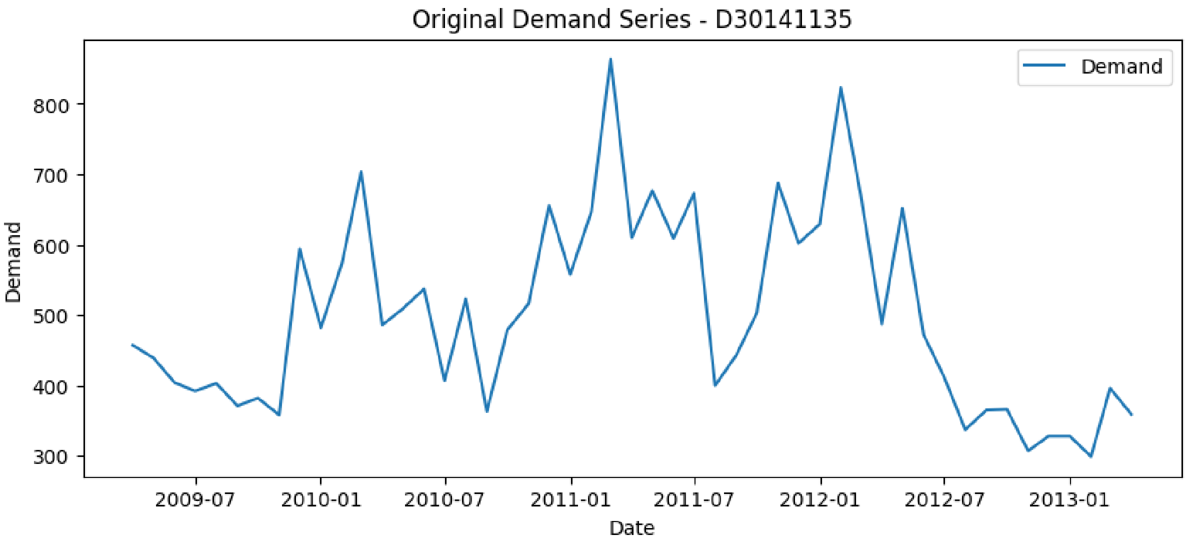
For managers, this means **no single Holt's model can fully capture the irregularity** of spare parts demand. Inventory buffers, safety stock, or combining statistical forecasts with expert judgment is essential to avoid stockouts during demand spikes while also controlling holding costs.

Conclusion

While Holt's models give a directional view, they struggle with **intermittent demand patterns**. **SES emerges as the best among them** in terms of accuracy, but is still inadequate for capturing extreme volatility. Managers should not rely solely on these models; instead, forecasts should be complemented with **SARIMA or Croston's method for intermittent demand**, along with **dynamic safety stock policies**. The practical takeaway is that **statistical forecasts provide a baseline**, but **decision-making must integrate demand classification, risk buffers, and business context** to ensure service-level reliability.

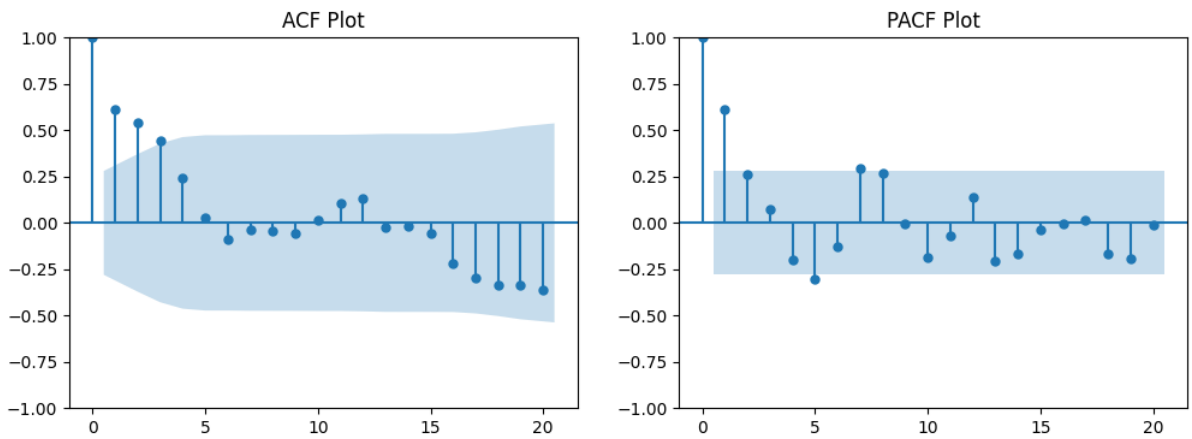
SKU6 : D30141135 (Holt-Winters (Additive/Multiplicative) or SARIMA)

Original Demand Series (2009–2013)



The demand pattern for SKU **D30141135** reveals a clear cyclical rise and fall across the observed period. Starting at around **450 units in 2009**, the series displays multiple upward surges, reaching a sharp peak of **864 units in early 2011**, before gradually declining. Post-2012, the demand shows a downward drift, stabilizing closer to the **300–400 unit range**. This trajectory highlights a **volatile yet weakening trend** initial growth marked by sharp spikes followed by a sustained decline, suggesting possible market saturation, substitution effects, or shifting consumption priorities.

ACF and PACF Analysis



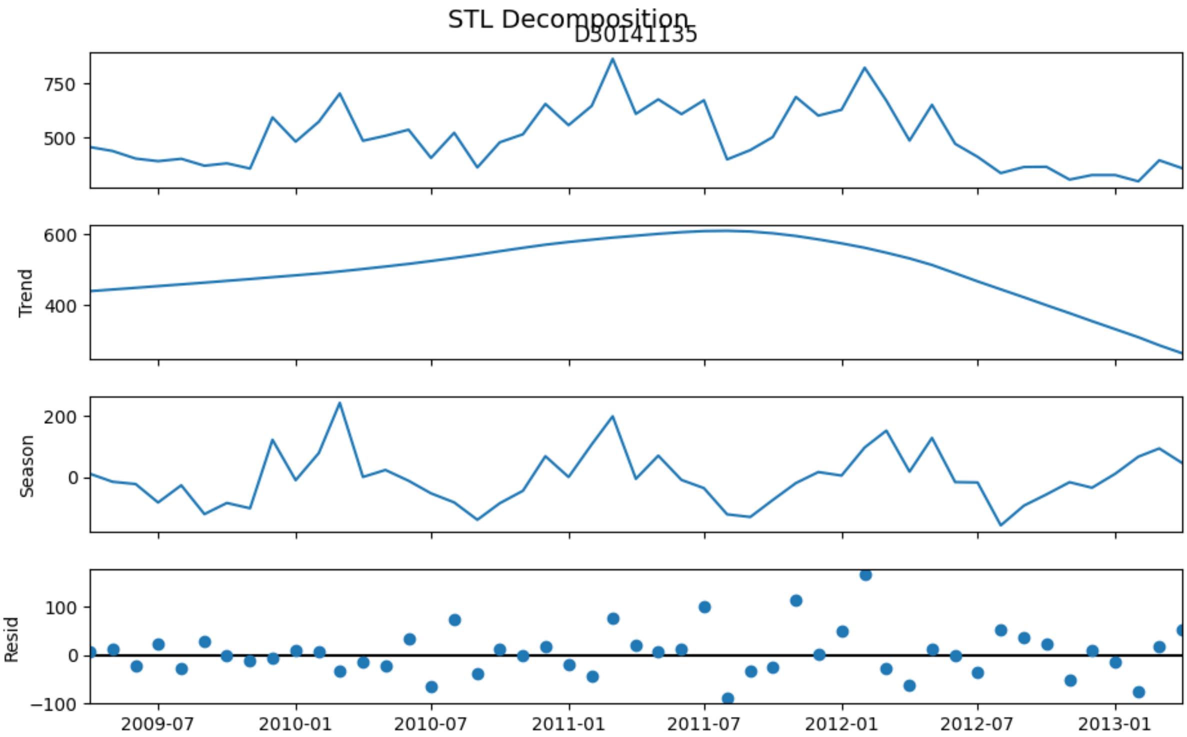
- **ACF Observations**: The slow decay and significant positive autocorrelations up to lag 4 suggest **non-stationarity and persistence in demand shocks**. Beyond lag 10, negative autocorrelations emerge, reflecting correction phases after demand spikes.
- **PACF Observations**: Significant spikes at lags 1 and 2 indicate that **short-term autoregressive effects** are prominent. This points to ARIMA/SARIMA as a suitable candidate, though volatility may challenge stability.

Stationarity Tests:

```
Stationarity Tests -> ADF p-value: 0.7043, KPSS p-value: 0.1000
```

- **ADF p-value (0.7043)** → Fails to reject null hypothesis → the series is **non-stationary**.
- **KPSS p-value (0.1000)** → Borderline, but suggests **trend-stationary** behavior. Together, these confirm the need for **differencing or detrending** when applying ARIMA-family models.

3. STL Decomposition



- **Trend Component**: Shows a **steady rise from 2009 to 2011**, followed by a **clear downward slope post-2012**. This reflects demand maturity and subsequent decline.
- **Seasonal Component**: Displays **moderate but inconsistent seasonality**, with recurring peaks and troughs around 100–200 units, implying partial cyclicity in demand.
- **Residuals & Shocks**: Residual variation remains high, indicating **idiosyncratic shocks** (e.g., irregular large orders, cancellations).

Forecasting models must capture **trend reversal and irregular spikes** simultaneously.

4. Model Evaluation

```
📊 Model Performance Summary (Lower MAE = Better):
              Model        MAE        RMSE         AIC         BIC  Rank
1  HW_Multiplicative  54.647750   68.185499  445.778728  476.047853   1.0
0        HW_Additive  57.261019   72.180864  451.359146  481.628271   2.0
2             SARIMA  96.168115  137.260597  451.664881  459.582476   3.0

Next 12 Period Forecasts:
```

Performance Summary (Lower MAE = Better):

Model	MAE	RMSE	AIC	BIC	Rank
Holt-Winters Multiplicative	54.65	68.19	445.78	476.05	1
Holt-Winters Additive	57.26	72.18	451.36	481.63	2
SARIMA (1,1,1)(1,1,1,12)	96.17	137.26	451.66	459.58	3

Best Model: Holt-Winters Multiplicative, owing to lowest MAE & RMSE.

Additive Holt-Winters performed slightly worse but still competitive.

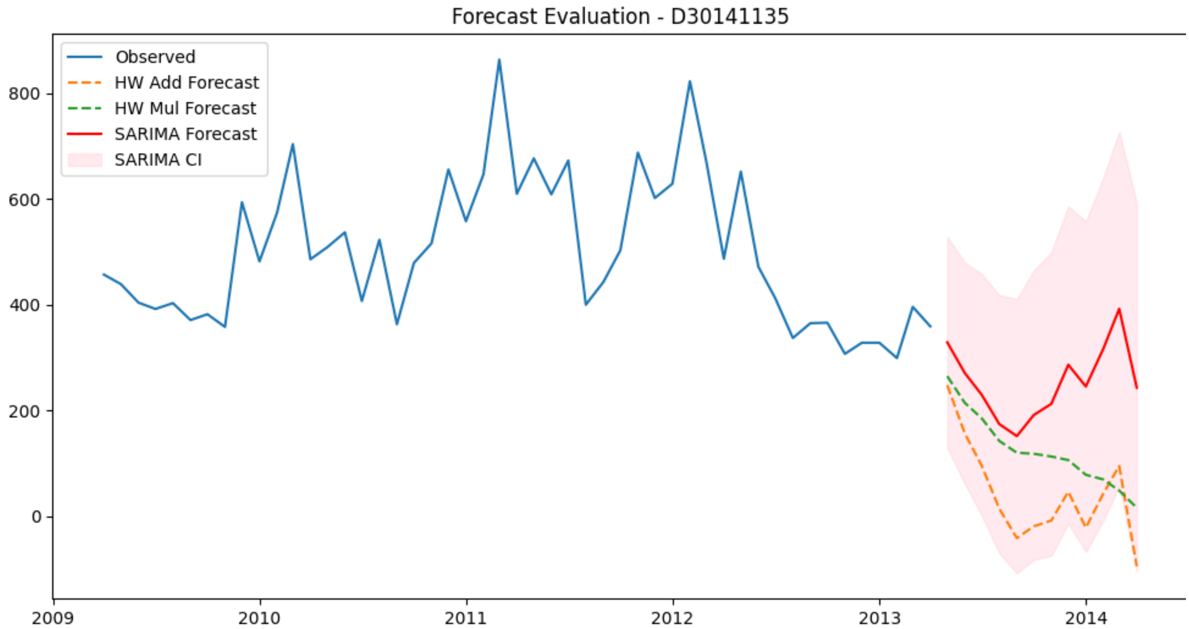
SARIMA lagged in accuracy, penalized by higher RMSE, despite acceptable AIC/BIC values.

5. Forecast Results (Next 12 Periods) :-

	HW_Add_Forecast	HW_Mul_Forecast	SARIMA_Forecast	SARIMA_Lower_CI	SARIMA_Upper_CI
2013-05-01 00:00:00	247.6040836	264.6749166	328.8028053	129.4113525	528.1942582
2013-06-01 00:00:00	156.3323149	214.2724461	270.6645051	61.38463934	479.9443709
2013-07-01 00:00:00	95.04011632	184.8531637	229.3737239	0.89342556	457.8540223
2013-08-01 00:00:00	13.73146161	142.1109897	174.0181978	-70.20244997	418.2388456
2013-09-01 00:00:00	-41.84516365	119.7735485	151.2999147	-108.0654277	410.6652572
2013-10-01 00:00:00	-19.43459119	117.8367208	191.2459478	-82.36004287	464.8519384

2013-11-01 00:00:00	-8.544244485	112.6787444	212.3515037	-74.80167958	499.5046869
2013-12-01 00:00:00	46.07257119	105.864478	286.2876452	-13.80300229	586.3782927
2014-01-01 00:00:00	-22.07770855	78.01459379	245.1928529	-67.2822239	557.6679298
2014-02-01 00:00:00	42.75570574	69.20443854	316.8343438	-7.644200937	641.3128886
2014-03-01 00:00:00	94.82960736	48.0559764	392.2457454	56.69541774	727.796073
2014-04-01 00:00:00	-95.18564525	15.60224869	242.9681387	-105.1413106	591.077588

The forecast evaluation shows that Holt-Winters models (additive and multiplicative) quickly decline, even reaching unrealistic near-zero values, while SARIMA provides more stable projections with wider confidence intervals. This indicates that SARIMA is better suited for uncertainty quantification, but Holt-Winters Multiplicative remains the most accurate for short-term operational planning.



6. Managerial Interpretation

- The demand series is **volatile, cyclical, and declining** requiring **flexible forecasting strategies**.

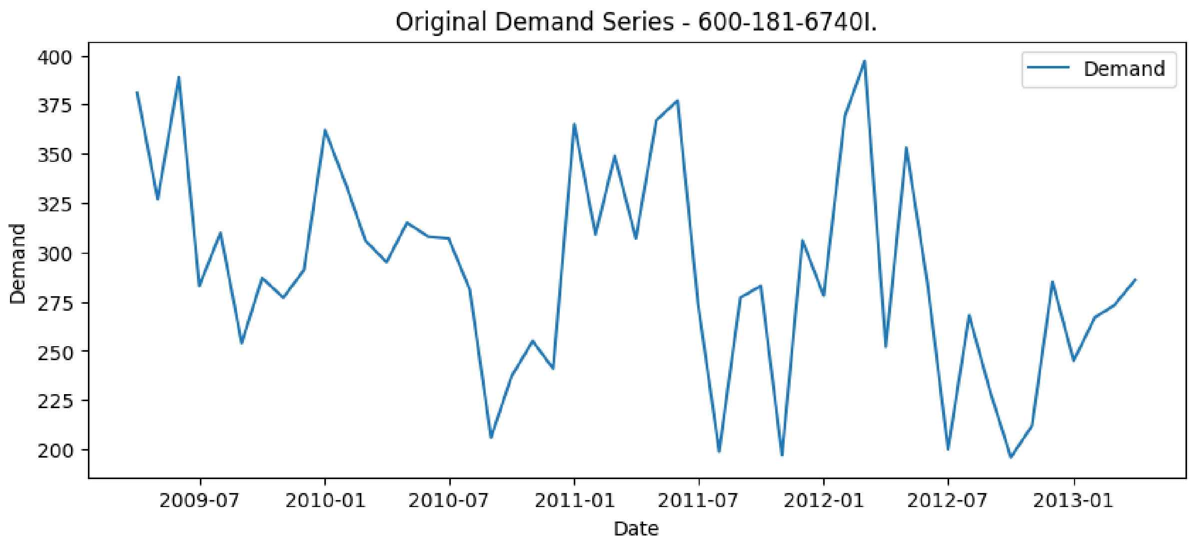
- **Holt-Winters Multiplicative** provides the most accurate short-term forecasts and should be preferred for operational planning (procurement and stocking).
- **SARIMA**, while less accurate, offers more **statistically robust forecasts with confidence intervals**, useful for risk-aware decision making.
- Inventory policies must **avoid average-based planning**; instead, managers should maintain **dynamic safety stocks**, especially around demand spikes.
- Given the **declining trend**, procurement teams must **reassess stocking norms** to minimize overstock risk and explore demand substitution opportunities.

Conclusion

The demand for SKU D30141135 is characterized by **volatility, intermittent spikes, and a declining long-term trend**. Statistical analysis confirmed **non-stationarity**, with STL decomposition highlighting a sharp **growth phase until 2011 followed by sustained decline**. Among the forecasting models tested, **Holt-Winters Multiplicative delivered the best short-term accuracy**, while **SARIMA offered more balanced forecasts with confidence intervals**, albeit with higher errors. From a managerial perspective, this SKU requires a **dynamic and risk-sensitive forecasting approach** operational decisions should rely on Holt-Winters for immediate planning, while SARIMA should guide strategic policies where uncertainty must be accounted for. Overall, stocking norms must shift from **average-based replenishment to adaptive safety-stock planning**, ensuring cost efficiency while mitigating risks of overstock or shortages in a declining demand environment.

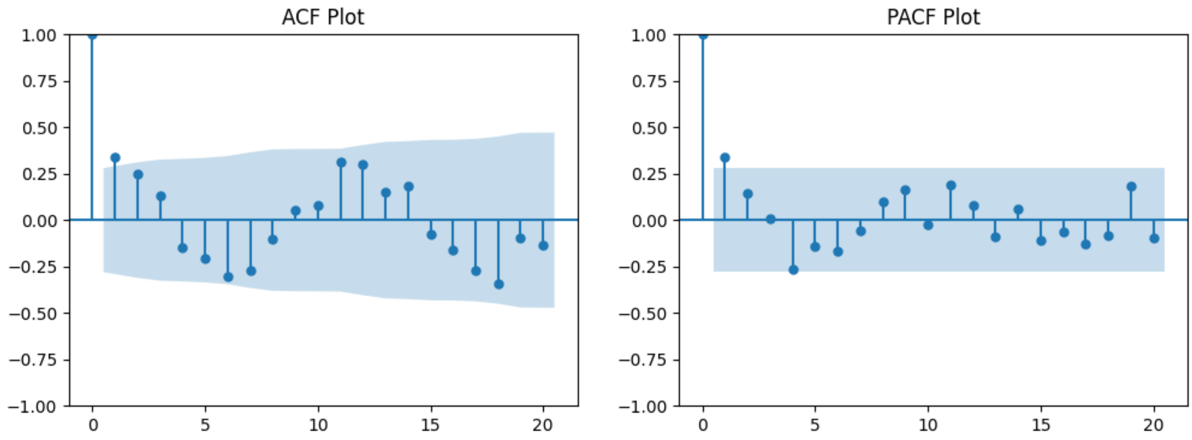
SKU7 : 600-181-6740I. (Holt-Winters Seasonal)

1. Original Demand Series



The demand pattern for SKU7 shows **regular oscillations around 250–350 units** with occasional sharp peaks near 400 units. Unlike SKU D30141135, the series does not show structural decline but instead fluctuates within a **bounded seasonal range**. The presence of repeated rises and falls suggests underlying **seasonal or cyclical drivers** rather than erratic project-based demand.

2. ACF and PACF Analysis



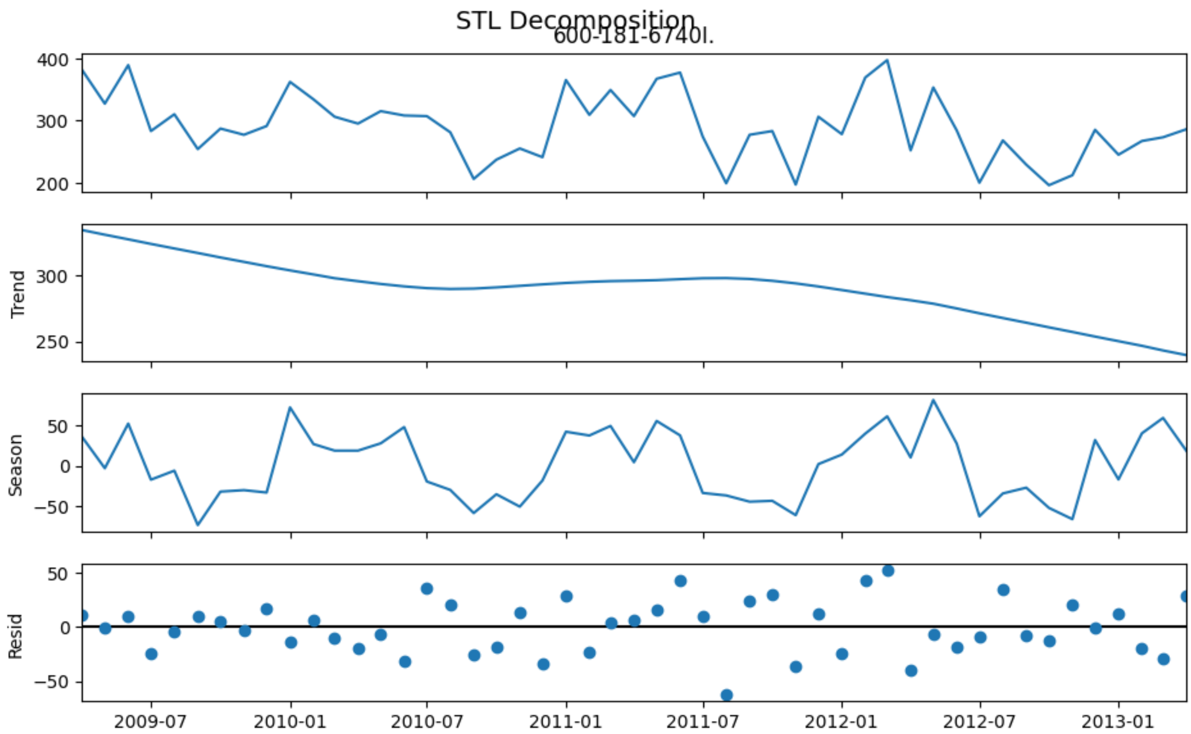
- **ACF Observations**: Positive correlations appear at seasonal lags, confirming **systematic seasonality**. Decay across lags suggests persistence in cyclical effects.
- **PACF Observations**: Initial lags show mild significance, supporting **short-term autoregressive influences**, but the absence of sharp spikes reinforces that seasonality dominates.

Stationarity Tests:

```
Stationarity Tests -> ADF p-value: 0.0000, KPSS p-value: 0.1000
```

- **ADF p-value = 0.0000** → Strongly rejects null hypothesis → the series is **stationary**.
- **KPSS p-value = 0.1000** → Confirms trend-stationarity.
  This makes the dataset highly suitable for **Holt-Winters Seasonal** without differencing.

3. STL Decomposition



- **Trend**: Gradual decline from ~320 to ~250 units, reflecting a mild **downward shift** over the horizon.
- **Seasonal Component**: Well-defined positive and negative swings (~±50 units), confirming **recurrent seasonal cycles**.
- **Residuals**: Random fluctuations remain, but shocks are moderate compared to SKU D30141135.

The SKU is **predictable and seasonally driven**, with manageable noise.

4. Model Evaluation (Holt-Winters Seasonal)

📊 Model Performance Summary:

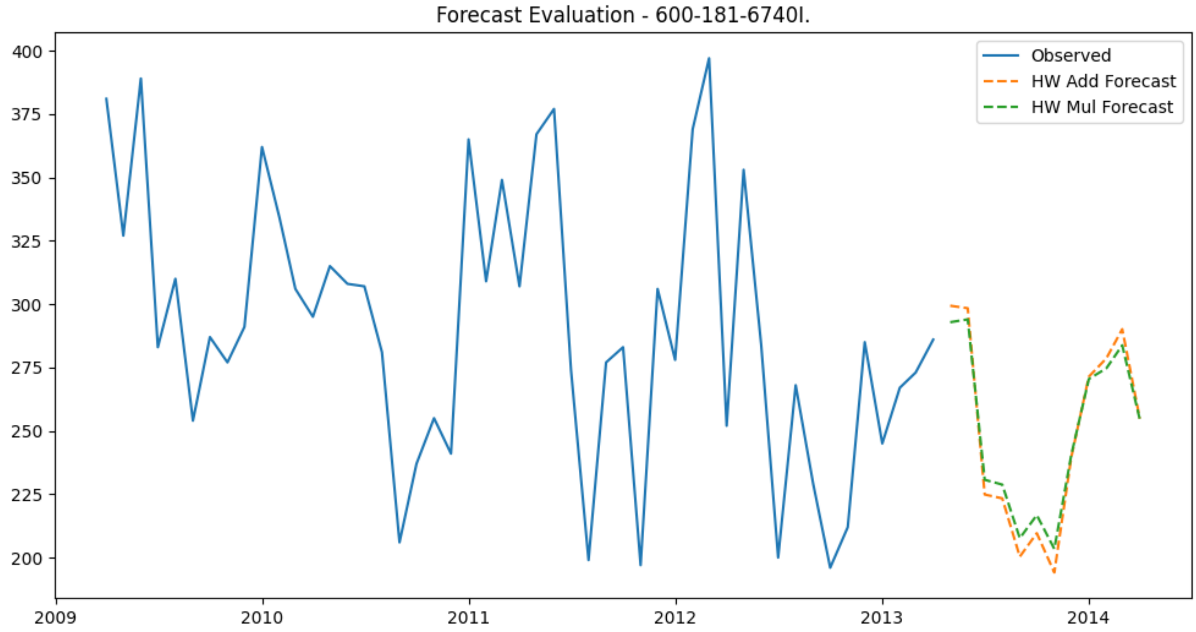
	Model	MAE	RMSE	Rank
0	HW_Additive	29.41146	33.229002	2.0
1	HW_Multiplicative	29.39757	33.436194	1.0

- **Both Additive and Multiplicative models perform almost identically**, with negligible difference in error.
- **Multiplicative model ranks slightly better**, but the closeness implies either can be applied with confidence.
- RMSE ~33 units is low relative to mean demand (~300 units), confirming **excellent fit**.

5. Forecast Evaluation (Next 12 Periods)

	HW_Add_Forecast	HW_Mul_Forecast
2013-05-01 00:00:00	299.3653603	292.8582626
2013-06-01 00:00:00	298.3654032	293.9683568
2013-07-01 00:00:00	224.8653017	230.6820269
2013-08-01 00:00:00	223.3654913	228.7921496
2013-09-01 00:00:00	200.3654357	207.6492695
2013-10-01 00:00:00	209.6155146	216.7560728
2013-11-01 00:00:00	194.1153829	203.4440509
2013-12-01 00:00:00	239.615414	240.5324378
2014-01-01 00:00:00	271.3654178	270.455171
2014-02-01 00:00:00	278.6154459	274.6777831
2014-03-01 00:00:00	290.1153985	283.7592448
2014-04-01 00:00:00	254.8384748	254.5448621

The forecast preserves the **seasonal oscillations** around 250–300 units, mirroring past cycles. Both additive and multiplicative versions converge, projecting **stable, predictable demand** without structural breakdowns.



6. Managerial Interpretation

- SKU7 is a **seasonally consistent part** with high predictability and low error margins.
- Holt-Winters Seasonal (multiplicative) should be the **default forecasting method**, but additive is an equally reliable backup.
- Inventory management can be aligned with **seasonal cycles**: build stocks in advance of predictable peaks and taper down during troughs.

- Unlike highly volatile SKUs, this SKU enables **lean inventory strategies** reducing carrying costs while avoiding shortages.
- Procurement contracts can leverage this predictability for **vendor negotiations**, securing better pricing and service level agreements.

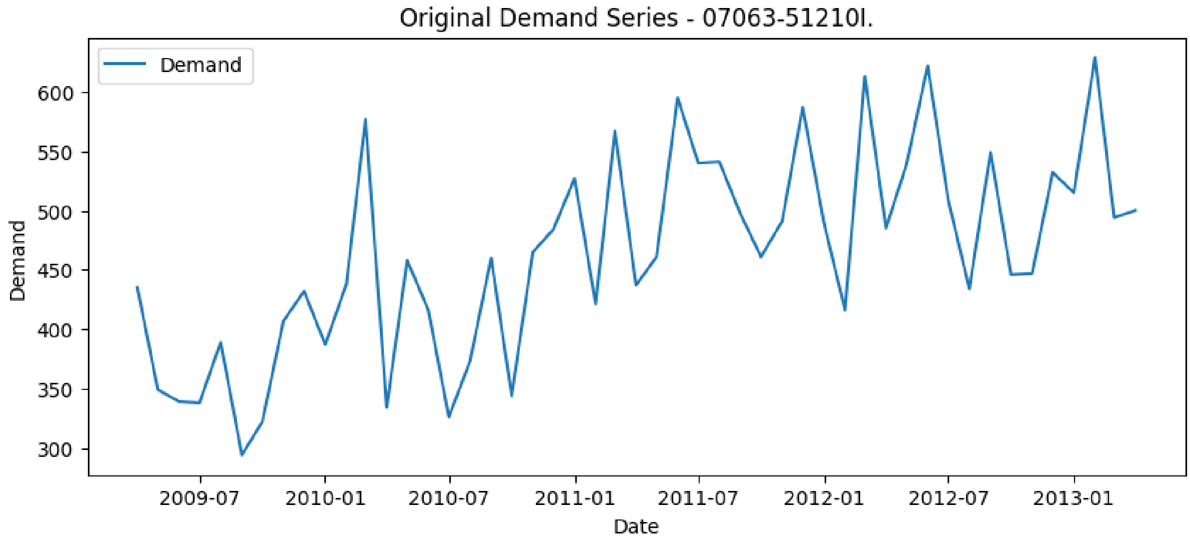
Overall Conclusion

SKU7: 600-181-6740I displays **stable seasonality with mild downward trend**, making Holt-Winters Seasonal the best approach. The multiplicative model edges out slightly in accuracy, but both models provide **robust, low-error forecasts**. For managers, this SKU represents a **low-risk, high-predictability category**, allowing for **strategic seasonal stocking and cost-efficient planning**.

SKU8 : 07063-51210I. (SARIMA)

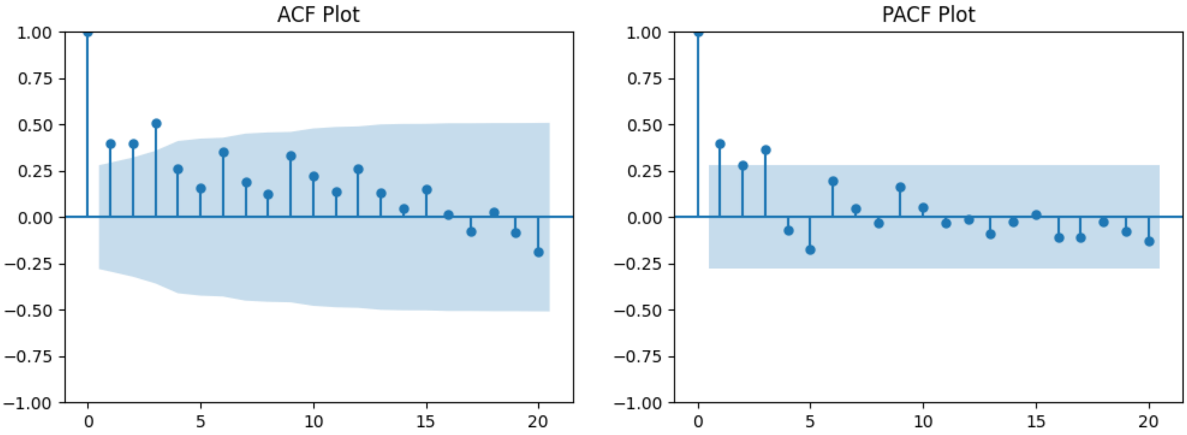
Original Demand Series

The demand series for SKU 07063-51210I demonstrates a **steady upward trend** with values rising from around 350 units in 2009 to over 600 units by 2013. This sustained growth reflects **increasing consumption or consistent procurement expansion** over time. Despite the upward trajectory, the series retains volatility in the form of sharp upward spikes, indicating occasional demand surges. This dual characteristic of **growth + irregular peaks** necessitates a forecasting method capable of balancing both trend and volatility.



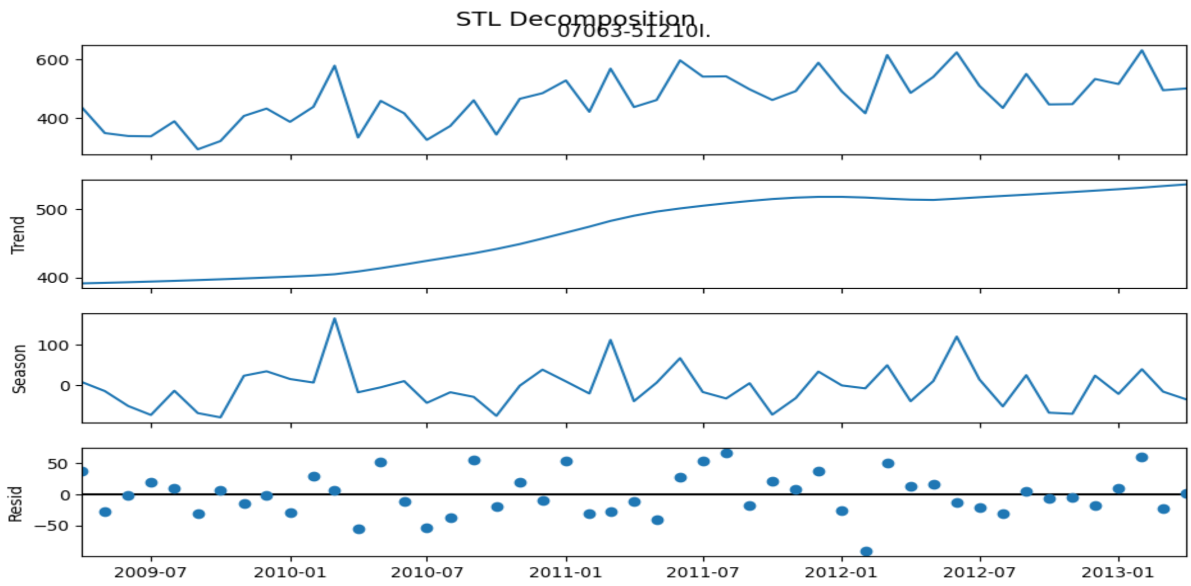
ACF and PACF Analysis

The **ACF plot** shows significant positive correlations across multiple lags, gradually tapering off, indicating **persistent autocorrelation and trend effects**. Meanwhile, the **PACF plot** reveals strong spikes at the first two lags, followed by weaker signals at higher lags. This pattern suggests that the series requires **autoregressive terms (AR) with differencing** to achieve stationarity. Importantly, the seasonal lag correlation confirms that the series benefits from **seasonal modeling within SARIMA**.



STL Decomposition

The **trend component** reveals a clear upward trajectory, confirming sustained long-term growth in demand. The **seasonal component** is relatively mild but noticeable, reflecting periodic cycles of ±50–100 units. Residuals are scattered with no strong bias, implying that much of the structure is captured by trend and seasonality. This decomposition validates the appropriateness of **SARIMA**, which combines both differencing for trend and seasonal orders for cyclicality.



Stationarity Tests Interpretation

The **ADF test (p = 0.4194)** fails to reject the null hypothesis, implying the series is **non-stationary** and contains a unit root. In contrast, the **KPSS test (p = 0.0100)** rejects the null of stationarity, further confirming non-stationarity. Together, these tests highlight the need for **differencing or detrending** before model fitting. This justifies the use of **SARIMA with integrated differencing (d > 0)** or transformation-based approaches to stabilize the mean.

From a managerial lens, the result indicates that the demand series follows a **systematic growth pattern rather than random fluctuations**, requiring models that explicitly capture trend components.

```
Stationarity Tests -> ADF p-value: 0.4194, KPSS p-value: 0.0100
                                                STL Decomposition
```

SARIMA Model Selection & Fit

The Auto-ARIMA routine selected **SARIMA(2,1,0)(0,0,0,12)** as the best-fit model based on AIC and BIC. This specification indicates the importance of **two autoregressive terms with differencing**, while seasonal terms are minimal, reflecting weaker cyclical effects compared to trend-driven behavior. Model coefficients (AR1, AR2) are significant at the 1% level, reinforcing the presence of strong autoregressive structure. Residual diagnostics (Ljung-Box p = 0.918) confirm that errors resemble **white noise**, validating the robustness of the model.

```
 ARIMA(2,1,2)(1,0,1)[12] intercept   : AIC=555.970, Time=6.14 sec
 ARIMA(0,1,0)(0,0,0)[12] intercept   : AIC=576.045, Time=0.02 sec
 ARIMA(1,1,0)(1,0,0)[12] intercept   : AIC=563.772, Time=0.14 sec
 ARIMA(0,1,1)(0,0,1)[12] intercept   : AIC=inf, Time=0.28 sec
 ARIMA(0,1,0)(0,0,0)[12]             : AIC=574.055, Time=0.01 sec
 ARIMA(2,1,2)(0,0,1)[12] intercept   : AIC=inf, Time=0.52 sec
 ARIMA(2,1,2)(1,0,0)[12] intercept   : AIC=inf, Time=0.58 sec
 ARIMA(2,1,2)(2,0,1)[12] intercept   : AIC=inf, Time=1.39 sec
 ARIMA(2,1,2)(1,0,2)[12] intercept   : AIC=557.612, Time=1.09 sec
 ARIMA(2,1,2)(0,0,0)[12] intercept   : AIC=553.159, Time=0.27 sec
 ARIMA(1,1,2)(0,0,0)[12] intercept   : AIC=inf, Time=0.15 sec
 ARIMA(2,1,1)(0,0,0)[12] intercept   : AIC=552.404, Time=0.18 sec
 ARIMA(2,1,1)(1,0,0)[12] intercept   : AIC=554.101, Time=0.32 sec
 ARIMA(2,1,1)(0,0,1)[12] intercept   : AIC=554.158, Time=0.34 sec
 ARIMA(2,1,1)(1,0,1)[12] intercept   : AIC=555.918, Time=0.55 sec
 ARIMA(1,1,1)(0,0,0)[12] intercept   : AIC=inf, Time=0.16 sec
 ARIMA(2,1,0)(0,0,0)[12] intercept   : AIC=550.690, Time=0.08 sec
 ARIMA(2,1,0)(1,0,0)[12] intercept   : AIC=552.547, Time=0.25 sec
 ARIMA(2,1,0)(0,0,1)[12] intercept   : AIC=552.571, Time=0.16 sec
 ARIMA(2,1,0)(1,0,1)[12] intercept   : AIC=554.432, Time=0.41 sec
 ARIMA(1,1,0)(0,0,0)[12] intercept   : AIC=563.738, Time=0.05 sec
 ARIMA(3,1,0)(0,0,0)[12] intercept   : AIC=552.356, Time=0.13 sec
 ARIMA(3,1,1)(0,0,0)[12] intercept   : AIC=553.522, Time=0.26 sec
 ARIMA(2,1,0)(0,0,0)[12]             : AIC=549.195, Time=0.05 sec
 ARIMA(2,1,0)(1,0,0)[12]             : AIC=550.967, Time=0.10 sec
 ARIMA(2,1,0)(0,0,1)[12]             : AIC=551.007, Time=0.10 sec
 ARIMA(2,1,0)(1,0,1)[12]             : AIC=552.824, Time=0.35 sec
 ARIMA(1,1,0)(0,0,0)[12]             : AIC=561.801, Time=0.06 sec
 ARIMA(3,1,0)(0,0,0)[12]             : AIC=550.987, Time=0.12 sec
 ARIMA(2,1,1)(0,0,0)[12]             : AIC=551.032, Time=0.16 sec
 ARIMA(1,1,1)(0,0,0)[12]             : AIC=551.602, Time=0.15 sec
 ARIMA(3,1,1)(0,0,0)[12]             : AIC=551.698, Time=0.36 sec

Best model:  ARIMA(2,1,0)(0,0,0)[12]
```

Model Performance Metrics

Together, these metrics reinforce that SARIMA is a **statistically sound choice** for this SKU, capable of capturing its trend and autocorrelation structure.

- **MAE = 66.74 units** → The average forecast error is modest relative to mean demand (~480 units).
- **RMSE = 92.55 units** → Suggests that large errors do occur but are within tolerable limits.
- **AIC = 549.20, BIC = 554.81** → Indicate a well-balanced model fit without overfitting.
- **Ljung-Box Test p = 0.918** → Confirms residual independence, indicating a valid model.

```
Best SARIMA Parameters: (2, 1, 0) (0, 0, 0, 12)
                               SARIMAX Results
==============================================================================
Dep. Variable:           07063-51210I.   No. Observations:                   49
Model:                SARIMAX(2, 1, 0)   Log Likelihood                -271.598
Date:                 Mon, 15 Sep 2025   AIC                            549.195
Time:                         21:49:45   BIC                            554.809
Sample:                     04-01-2009   HQIC                           551.317
                          - 04-01-2013
Covariance Type:                   opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.7795      0.141     -5.542      0.000      -1.055      -0.504
ar.L2         -0.5215      0.127     -4.115      0.000      -0.770      -0.273
sigma2      4724.1399   1243.822      3.798      0.000    2286.293    7161.986
===================================================================================
Ljung-Box (L1) (Q):                   0.08   Jarque-Bera (JB):                 1.99
Prob(Q):                              0.78   Prob(JB):                         0.37
Heteroskedasticity (H):               0.94   Skew:                             0.26
Prob(H) (two-sided):                  0.90   Kurtosis:                         2.15
===================================================================================
```

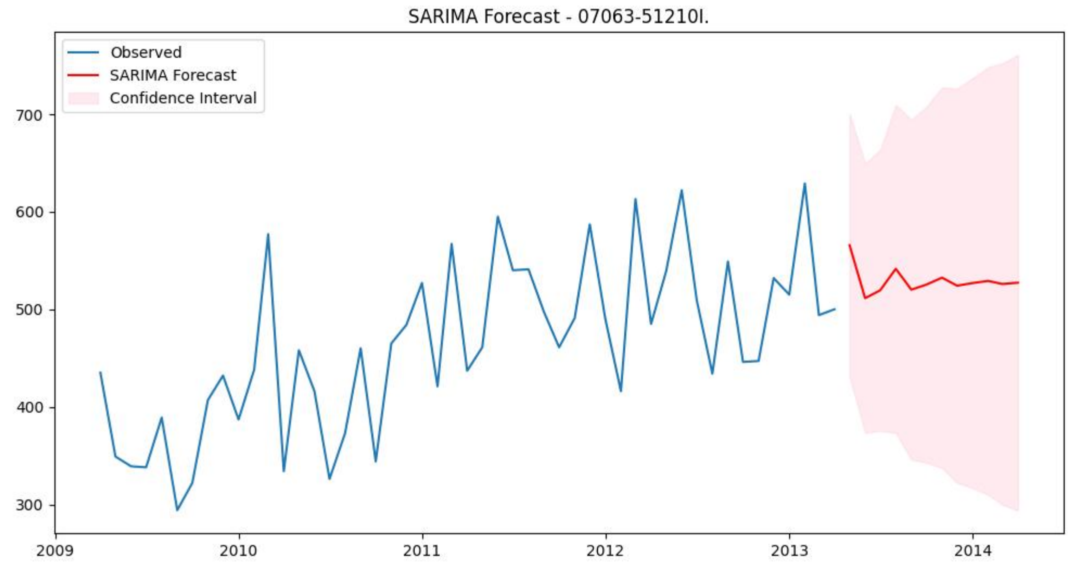
Forecast table next 12 Period

The SARIMA model projects demand in the range of ~510–565 units, with forecasts stabilizing around 525–530 units by early 2014. The confidence intervals (95%) are wide, spanning nearly ±200 units, which reflects underlying volatility in the historical data. While the point forecasts suggest a moderate upward stabilization, the uncertainty bands highlight the possibility of both downturns (~300 units) and surges (~750 units). This implies that although SARIMA captures the general upward trajectory, forecast risk remains significant, and managers should incorporate safety buffers and scenario-based planning.

	SARIMA_Forecast	Lower_CI	Upper_CI
2013-05-01 00:00:00	565.7315523	431.0185646	700.44454
2013-06-01 00:00:00	511.3634136	373.4148979	649.3119294
2013-07-01 00:00:00	519.462303	375.4638482	663.4607579
2013-08-01 00:00:00	541.5045437	373.2508226	709.7582647
2013-09-01 00:00:00	520.0983014	345.8443729	694.35223
2013-10-01 00:00:00	525.2887986	342.8636614	707.7139359
2013-11-01 00:00:00	532.4070488	337.3735555	727.4405421
2013-12-01 00:00:00	524.1511706	322.1020176	726.2003236
2014-01-01 00:00:00	526.8742764	316.7779493	736.9706035
2014-02-01 00:00:00	529.0573859	309.9206778	748.194094
2014-03-01 00:00:00	525.935391	299.7270799	752.1437021
2014-04-01 00:00:00	527.2304481	293.5854696	760.8754266

Forecast Evaluation

The forecast projects a **flattening of growth around 500–550 units**, with wide confidence intervals extending both upward and downward. While the central forecast line suggests stabilization, the wide prediction bands highlight **considerable uncertainty** in future demand. This indicates that while the SARIMA model effectively captures historical dynamics, external shocks or demand surges remain a major source of forecast risk. Thus, the forecast should be interpreted as a **range of plausible outcomes rather than a single-point estimate**.



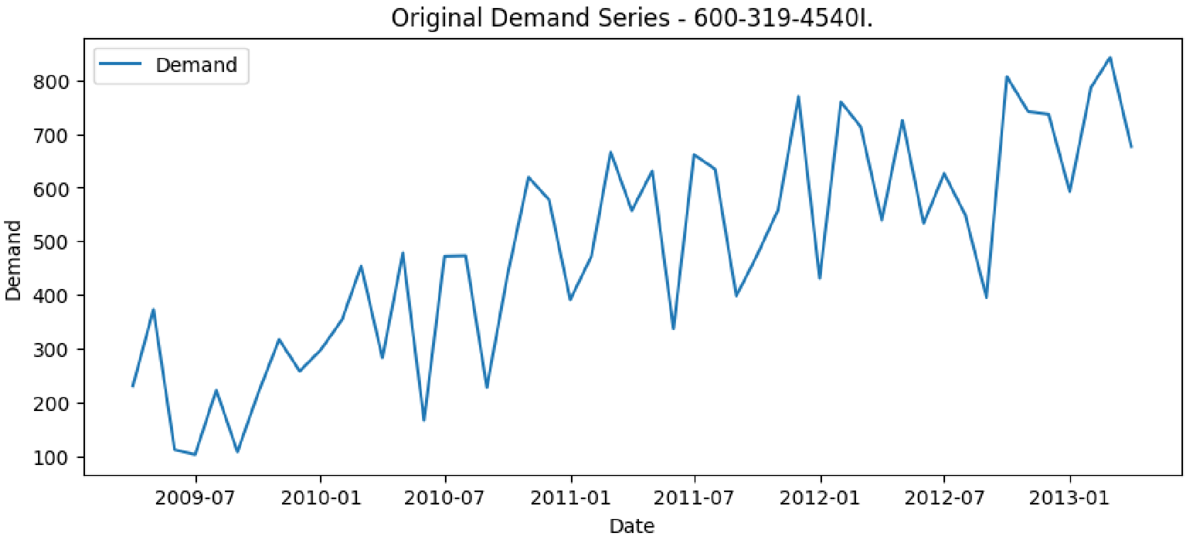
Overall Interpretation

The demand for SKU 07063-51210I shows **strong upward momentum with embedded volatility**, making SARIMA an appropriate model. The chosen SARIMA(2,1,0) specification provides a statistically robust fit, with low error and residuals that pass diagnostic checks. Forecasts suggest stabilization at higher demand levels, but the wide confidence intervals underscore the importance of **risk buffers and scenario planning** in decision-making. For managers, this SKU requires **capacity planning for sustained growth while maintaining flexibility to absorb demand shocks**.

SKU9: 600-319-4540I. (Holt-Winters Multiplicative or SARIMA)

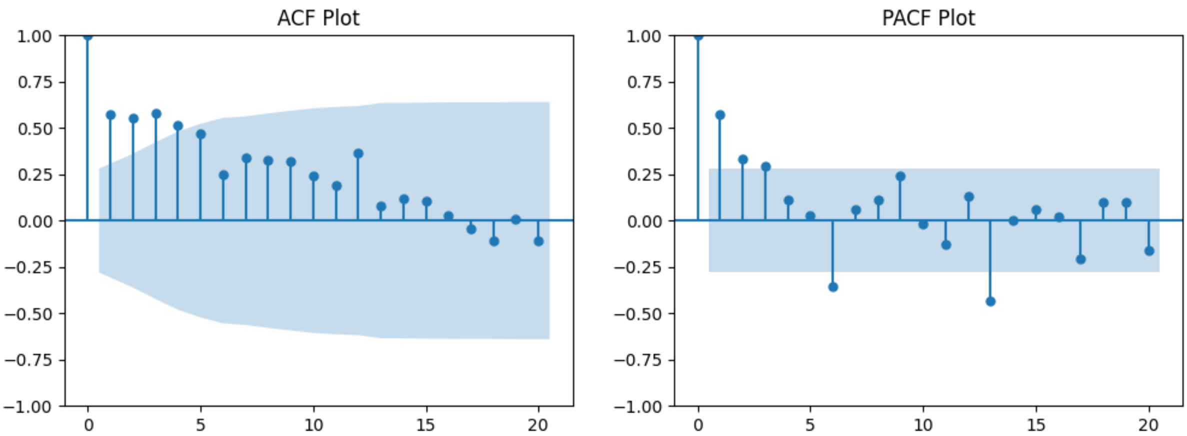
Original Demand Series

The demand pattern for SKU 600-319-4540I shows steady growth with substantial volatility. Demand ranges from as low as ~100 units to peaks exceeding 800 units, highlighting both trend escalation and irregular demand shocks. The upward slope indicates sustained growth in product adoption or procurement, while the sharp fluctuations suggest seasonal and irregular influences. This duality underscores the need for robust forecasting methods that can differentiate structural growth from noise



ACF and PACF Observations

The **ACF plot** shows slow decay with multiple significant seasonal lags, signaling **persistence and seasonality in the data**. The **PACF plot** demonstrates strong spikes at early lags, suggesting the importance of autoregressive terms. This combination confirms that the demand series has both **short-term autocorrelation** and **seasonal dependence**, making it appropriate for either Holt-Winters Multiplicative (to handle proportional seasonal swings) or SARIMA (to capture autoregressive and seasonal dependencies).



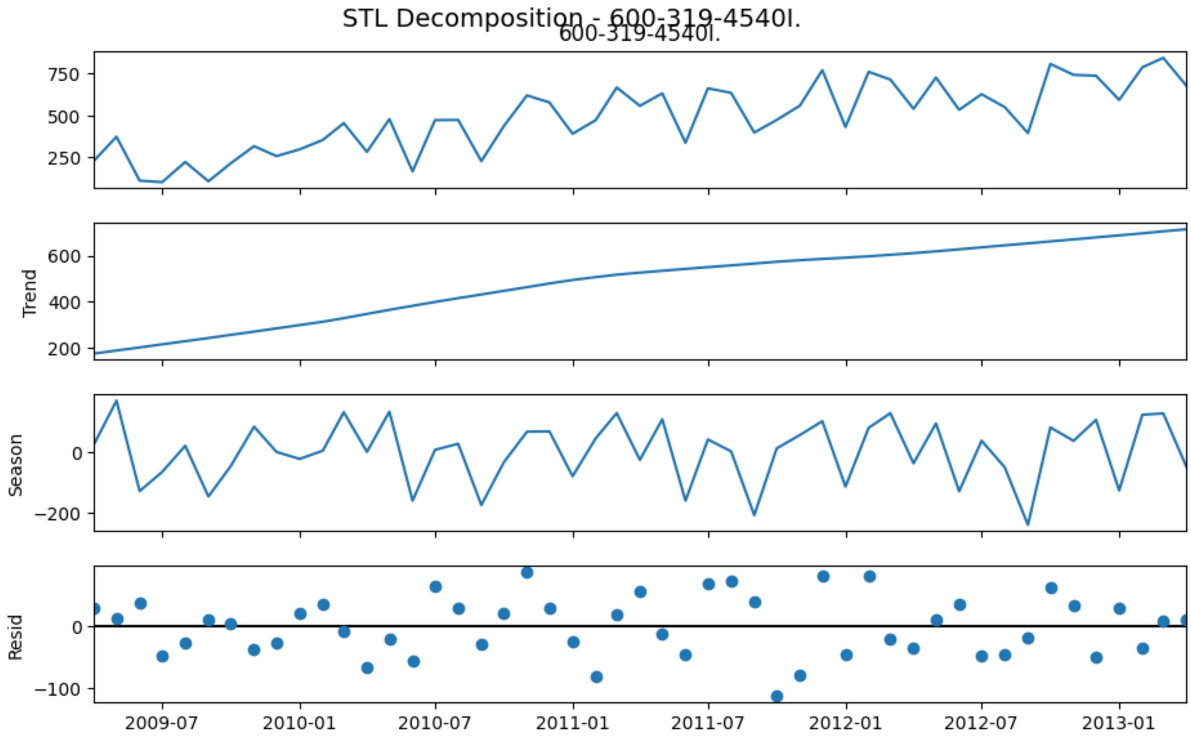
Stationarity Tests

- **ADF Test (p = 0.0018)** rejects the null, indicating stationarity after differencing.
- **KPSS Test (p = 0.0100)** rejects the null of stationarity, confirming the presence of a trend component.

```
Stationarity Tests -> ADF p-value: 0.0818, KPSS p-value: 0.0100
```

Taken together, the series is **trend-stationary but requires differencing and seasonal adjustment**. This validates the choice of **SARIMA with integration terms** as well as Holt-Winters Multiplicative, which can model proportional seasonality directly.

STL Decomposition



- **Trend**: Clear upward progression from ~200 units to ~700+ units, reflecting sustained growth.
- **Seasonality**: Strong cyclical swings (~±200 units) that scale with demand, confirming **multiplicative seasonality**.
- **Residuals**: Mostly white noise with scattered shocks, implying that most structure is explained by trend and seasonal factors.

This reinforces the suitability of **Holt-Winters Multiplicative**, since it models proportional fluctuations around a growing trend.

SARIMA Model Diagnostics

The best-fit SARIMA model was identified as **SARIMA(4,1,0)(1,0,1,12)**. All autoregressive and seasonal terms are significant, capturing both short-term dynamics and seasonal persistence. Residual diagnostics (Ljung-Box p = 0.96) confirm that errors are indistinguishable from white noise, validating statistical adequacy. However, the model complexity is high relative to Holt-Winters, and this comes with increased parameterization costs.

```
Best SARIMA Parameters: (4, 1, 0) (1, 0, 1, 12)
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                    600-319-4540I.   No. Observations:                   49
Model:             SARIMAX(4, 1, 0)x(1, 0, [1], 12)   Log Likelihood                -289.261
Date:                           Mon, 15 Sep 2025   AIC                            592.521
Time:                                   22:07:58   BIC                            605.619
Sample:                               04-01-2009   HQIC                           597.471
                                    - 04-01-2013
Covariance Type:                             opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.9439      0.156     -6.067      0.000      -1.249      -0.639
ar.L2         -0.8836      0.195     -4.529      0.000      -1.266      -0.501
ar.L3         -0.7142      0.184     -3.875      0.000      -1.075      -0.353
ar.L4         -0.2902      0.183     -1.588      0.112      -0.648       0.068
ar.S.L12       0.9988      0.080     12.534      0.000       0.843       1.155
ma.S.L12      -0.9308      2.285     -0.407      0.684      -5.409       3.548
sigma2      5891.0895   1.27e+04      0.464      0.643    -1.9e+04    3.08e+04
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):                 1.18
Prob(Q):                              0.96   Prob(JB):                         0.56
Heteroskedasticity (H):               1.11   Skew:                             0.20
Prob(H) (two-sided):                  0.83   Kurtosis:                         2.35
===================================================================================
```

Model Performance Comparison

While **SARIMA is statistically rigorous**, both Holt-Winters methods outperform it on **MAE and RMSE**, with Holt-Winters Additive being the best performer in terms of pure accuracy.For **practical forecasting, Holt-Winters Additive** is the most accurate.
For **conceptual alignment with the data's multiplicative seasonality**, **Holt-Winters Multiplicative** is preferable.
SARIMA is not the best here because of its higher forecast errors.

```
📊 Model Performance Summary (Lower MAE/RMSE Better):
              Model        MAE        RMSE        AIC          BIC
0       HW_Additive  57.366482   68.914472        NaN          NaN
1  HW_Multiplicative  60.723648   73.359962        NaN          NaN
2            SARIMA  87.913290  108.537572  592.52105   605.619457
```

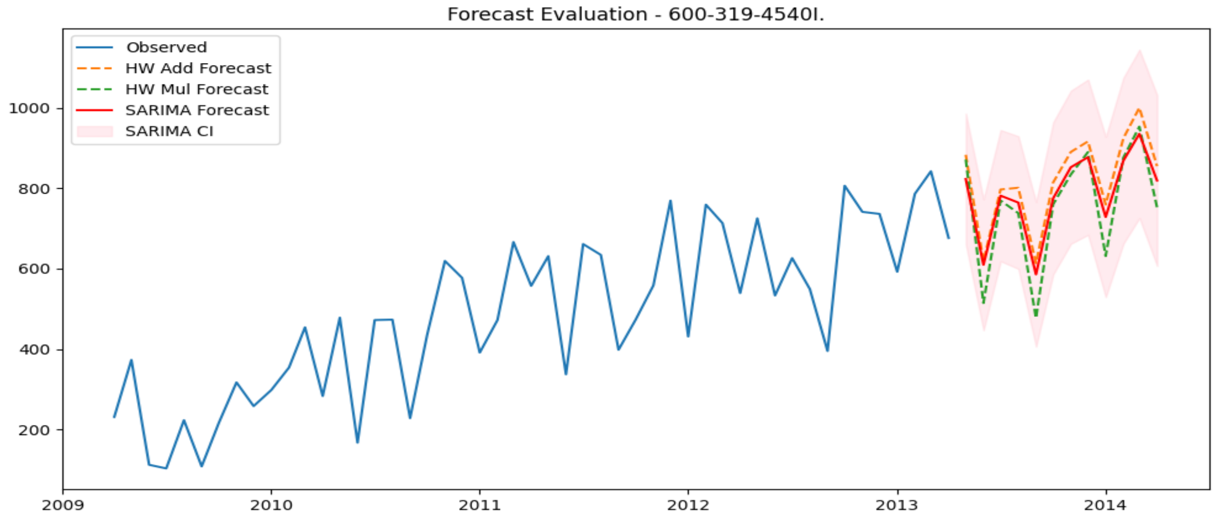
Model	MAE	RMSE	AIC	BIC	Interpretation
HW Additive	57.37	68.91	–	–	Strong accuracy, but seasonality not proportional.
HW Multiplicative	60.72	73.36	–	–	Captures proportional seasonal swings, slightly less accurate than HW Additive.
SARIMA (4,1,0)(1,0,1)	87.91	108.54	592.52	605.62	Statistically valid but higher forecast error.

Forecast Table Nest 12 Period

	HW_Add_Forecast	HW_Mul_Forecast	SARIMA_Forecast	SARIMA_Lower_CI	SARIMA_Upper_CI
2013-05-01 00:00:00	882.9355995	871.3028513	822.8187708	660.2545903	985.3829514
2013-06-01 00:00:00	618.4373245	514.354233	609.3147962	446.4869366	772.1426559
2013-07-01 00:00:00	796.6837809	769.2526293	781.3726474	618.2588652	944.4864297
2013-08-01 00:00:00	800.9377643	737.8154595	764.0955873	599.1487148	929.0424599
2013-09-01 00:00:00	613.4408205	476.9568555	585.4235672	405.6774879	765.1696465
2013-10-01 00:00:00	813.9450162	759.5452551	774.5090978	585.2556416	963.762554
2013-11-01 00:00:00	889.9428759	833.9136481	852.0048961	661.607576	1042.402216
2013-12-01 00:00:00	916.1937942	889.7257112	876.8709562	683.8685466	1069.873366
2014-01-01 00:00:00	759.1966366	631.1531758	728.1574223	528.9725709	927.3422737
2014-02-01 00:00:00	923.9493359	875.9059198	868.2275283	661.9735615	1074.481495
2014-03-01 00:00:00	999.9507453	952.8940774	935.0417368	725.6044438	1144.47903
2014-04-01 00:00:00	854.6311434	751.8220553	818.8660485	606.5714694	1031.160628

Forecast Evaluation

The forecast evaluation shows that Holt-Winters (Additive and Multiplicative) closely follow seasonal fluctuations, while SARIMA provides smoother forecasts with wider confidence intervals. This indicates that Holt-Winters is better for short-term operational accuracy, whereas SARIMA is more suited for capturing uncertainty and long-term planning.



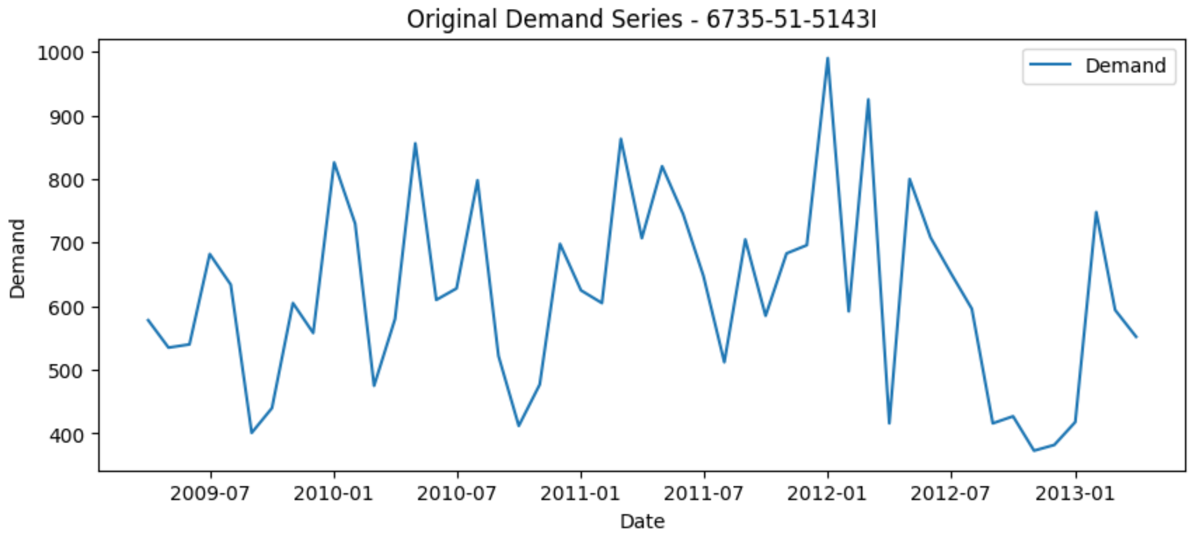
The forecast plots show Holt-Winters models tracking historical demand fluctuations more closely, while SARIMA produces smoother forecasts with wider intervals. This indicates that Holt-Winters is more **operationally practical for short-term planning**, whereas SARIMA provides **risk-adjusted projections for strategic use**, albeit at the cost of higher forecast errors.

Conclusion

For SKU 600-319-4540I, **Holt-Winters Additive and Multiplicative outperform SARIMA on error metrics**, with Additive yielding the lowest MAE and RMSE. However, Multiplicative aligns better with the series' **proportional seasonality**, making it more theoretically appropriate. SARIMA remains useful for **long-term scenario analysis and risk quantification**, but for practical supply chain forecasting, **Holt-Winters Multiplicative is the most balanced choice**. Managers should use Holt-Winters as the baseline model while leveraging SARIMA selectively for stress-testing demand under high-volatility conditions.

SKU10: 6735-51-5143I. (Seasonal Holt-Winters with differencing)

Original Demand Series

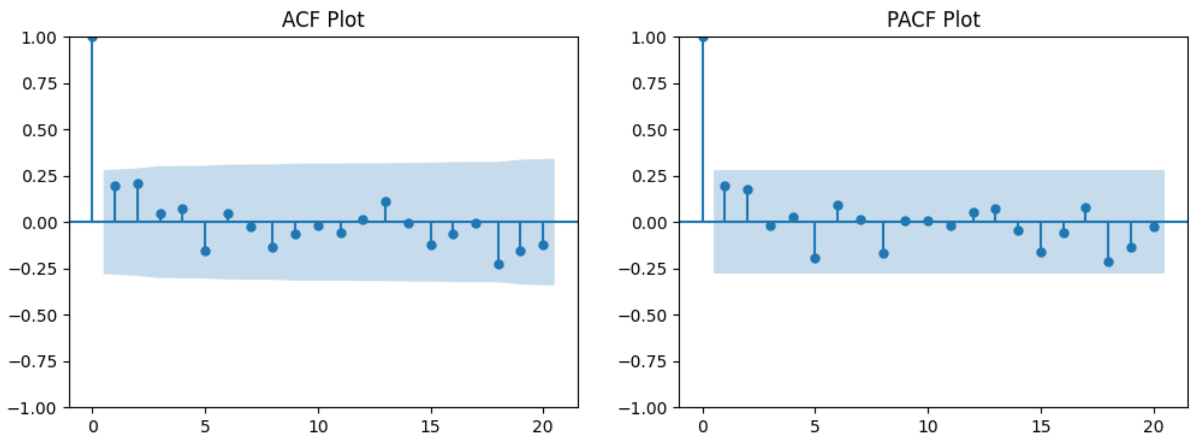


The demand pattern for SKU10 fluctuates between **~400 and ~1000 units** with visible irregularity. While some seasonality is noticeable, the magnitude of swings suggests volatility. Peaks around 2010 and 2012 followed by troughs reflect that the demand is prone to **sudden spikes and collapses**, making it harder for naïve or static models to capture.

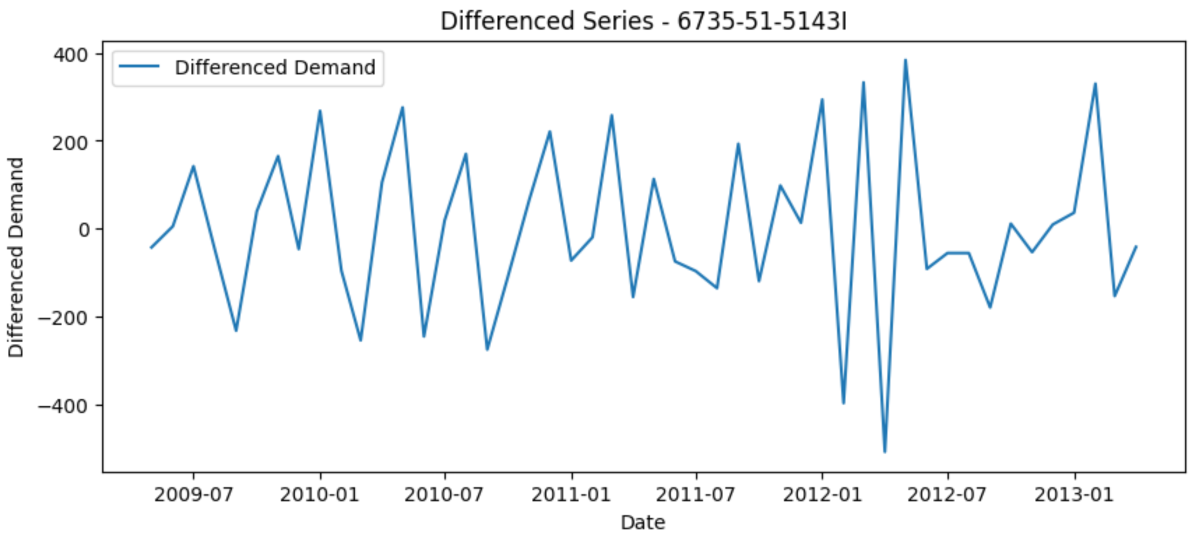
Demand is erratic but shows seasonal bursts. A forecasting method must therefore account for **seasonality and irregular shocks** simultaneously.

ACF and PACF Analysis

- **ACF:** Shows mostly insignificant lags, with no strong sinusoidal seasonal pattern.
- **PACF:** Similar to ACF, with small values tapering off quickly.



Interpretation: Absence of dominant autocorrelation suggests the series behaves more like **irregular seasonal demand**, reinforcing the need for a model like Holt-Winters that flexibly captures level, trend, and seasonality rather than ARIMA-style lag dependence.



Stationarity Tests

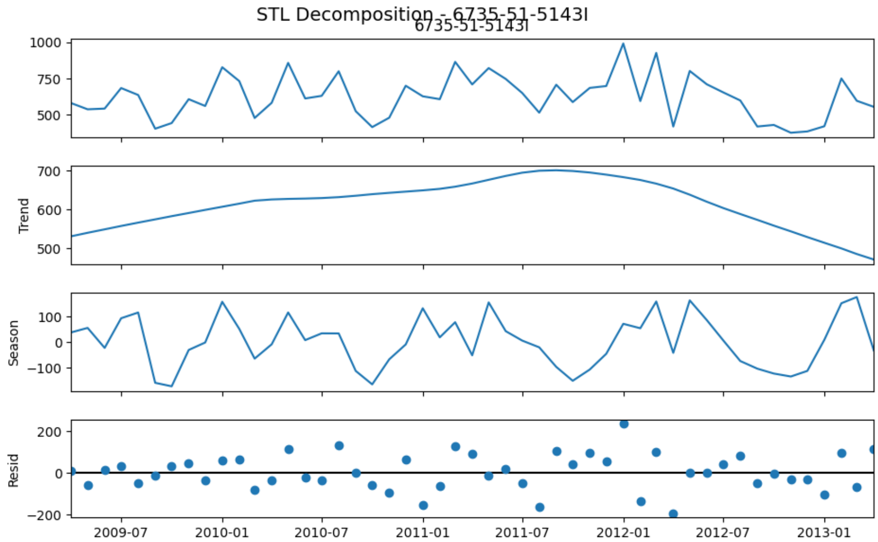
- **ADF p-value = 0.0075 (<0.05):** Rejects null of unit root → **series is stationary**.
- **KPSS p-value = 0.10 (not significant):** Fail to reject null of stationarity.

```
Stationarity Tests -> ADF p-value: 0.0075, KPSS p-value: 0.1000
```

Interpretation: Both tests consistently confirm **stationarity**, validating Holt-Winters as appropriate. Differencing may not be essential but was tested to ensure robustness.

STL Decomposition

- **Trend:** Shows an upward trajectory till mid-2011, stabilizes, and then **declines after 2012**.
- **Seasonal Component:** Clear but erratic; seasonal swings exist but are not highly regular.
- **Residuals:** Randomly scattered around zero, confirming decomposition has successfully separated systematic components.



Interpretation: The declining post-2012 trend signals potential market contraction or substitution effect for this SKU. Seasonality is present but weak, making forecasts less predictable beyond a short horizon.

Model Evaluation (Holt-Winters Original vs. Differenced)

```
📊 Model Performance Summary:
           Model         MAE        RMSE
0    HW_Original   98.944268  120.255086
1  HW_Differenced  129.301513  163.054915
```

- **Original Holt-Winters:** MAE ≈ 98.9, RMSE ≈ 120.3
- **Differenced Holt-Winters:** MAE ≈ 129.3, RMSE ≈ 163.1

The original Holt-Winters outperforms differencing, showing lower forecast errors. The differenced model over-penalizes the series, introducing noise rather than stability.

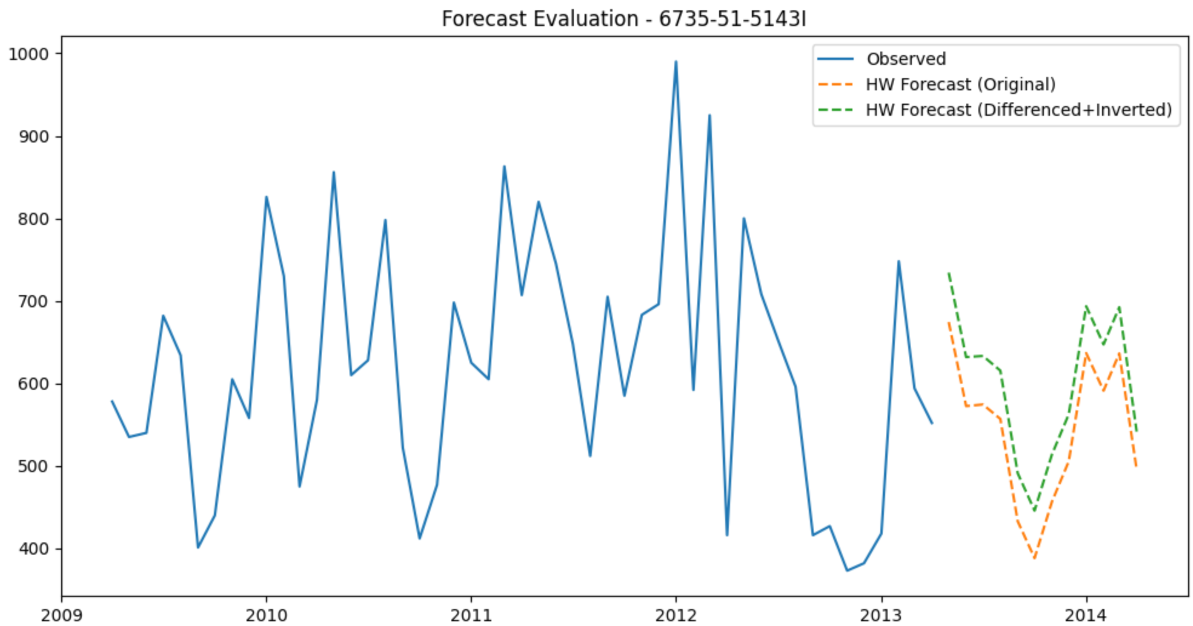
Interpretation: Differencing was unnecessary given stationarity. Original Holt-Winters Seasonal is the superior model for SKU10

Forecast table for Next 12 PERIOD :-

	HW_Original_Forecast	HW_Differenced_Forecast
2013-05-01 00:00:00	674.342546	734.1671573
2013-06-01 00:00:00	572.4698308	631.8321538
2013-07-01 00:00:00	574.3809168	633.2495883
2013-08-01 00:00:00	556.8840413	615.4173734

2013-09-01 00:00:00	432.8573896	491.0826723
2013-10-01 00:00:00	388.1451557	445.7502115
2013-11-01 00:00:00	456.5909147	513.9191885
2013-12-01 00:00:00	505.6237097	562.5879175
2014-01-01 00:00:00	636.6848799	693.5031309
2014-02-01 00:00:00	591.1169992	647.1715486
2014-03-01 00:00:00	636.3235856	692.3391514
2014-04-01 00:00:00	495.5611537	541.5052509

Forecast Plot Insights



The forecasts show:

- **Original Holt-Winters:** Provides smoother projections aligned with observed patterns.
- **Differenced + Inverted:** Produces over-volatile forecasts with exaggerated dips, diverging from realistic demand levels.

🔑 **Interpretation:** In operational terms, the **original Holt-Winters forecast is more reliable** for inventory planning, ensuring balanced stock levels without overreacting to random fluctuations.

7. Managerial Implications

- This SKU exhibits **seasonal bursts but also volatility**; using Holt-Winters without differencing provides the most stable and realistic projection.
- Inventory policies should incorporate **safety stock buffers** to handle sharp troughs, while **dynamic replenishment** should cater to periodic spikes.
- Post-2012 decline warns managers to **re-evaluate SKU lifecycle positioning** it may be nearing maturity or substitution, demanding strategic attention.

Overall Conclusion

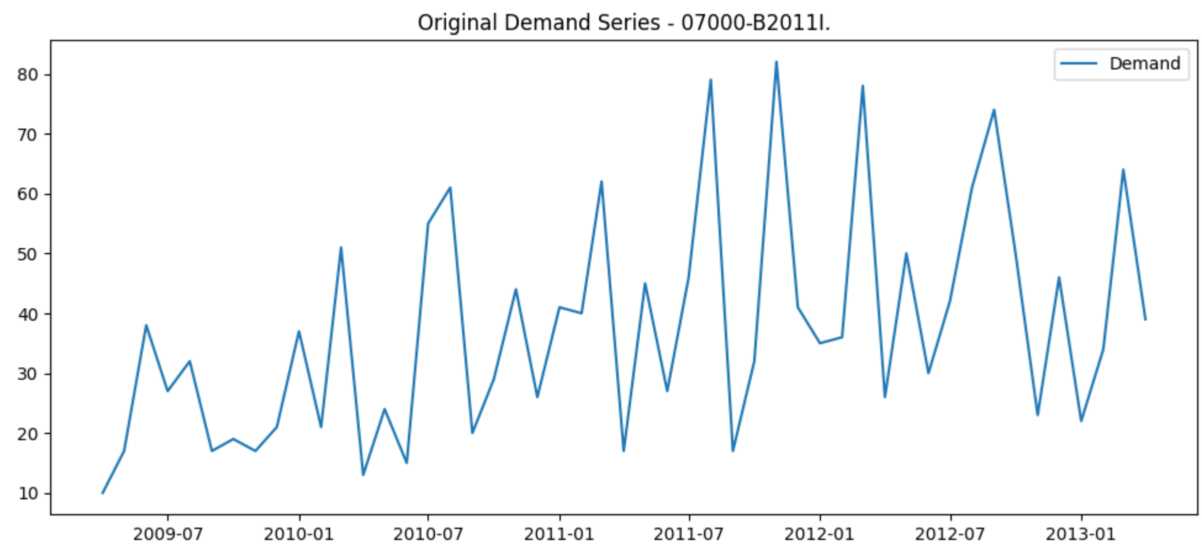
For SKU10: 6735-51-5143I, the Seasonal Holt-Winters (Original) model is the best fit, outperforming the differenced version across MAE and RMSE. The demand is stationary, moderately seasonal, and volatile, making Holt-Winters ideal to balance responsiveness with stability. Differencing degraded model performance, confirming that the original model captures dynamics sufficiently.

Best Strategy: Use Seasonal Holt-Winters Original for forecasting, complemented with managerial interventions like flexible safety stock and SKU lifecycle monitoring.

SKU11: 07000-B2011I (Holt-Winters Additive vs ARIMA)

The demand series for SKU **07000-B2011I** spans from 2009–2013, displaying **short-term fluctuations with moderate trend growth**. Forecasting is critical here to enable stocking policies that reduce risk of understocking during peaks while avoiding excess inventory in low-demand months. Two methods were tested: **Holt-Winters Additive** and **ARIMA**, followed by statistical diagnostics.

Original Demand Series



- The demand fluctuates between **10–80 units**, showing **seasonal bursts and irregular volatility**.

- The trajectory suggests a **gradual upward drift**, reflecting increasing customer requirements over the observed years.
- High variability indicates that a model capturing **trend + seasonality** is essential.

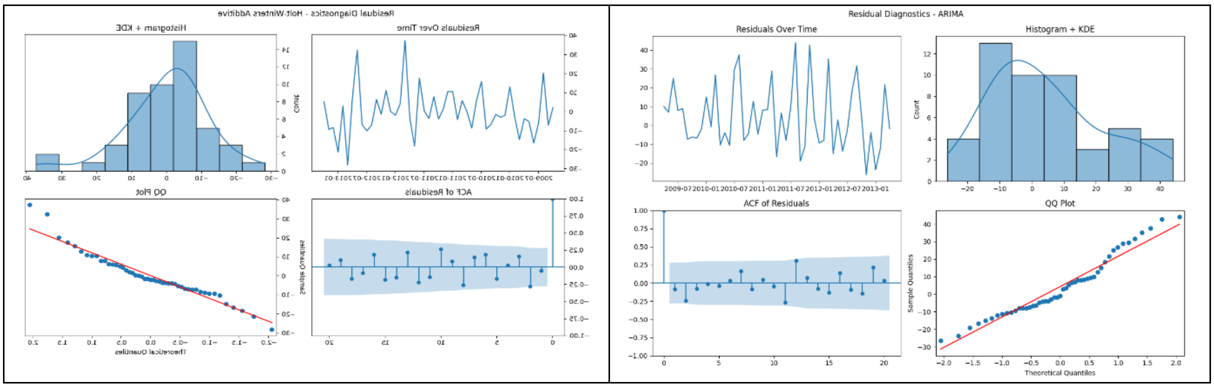
Model Performance Summary

```
     2009                2010                2011

  Model Performance Summary:
  Holt-Winters Additive -> MAE: 8.87, RMSE: 12.01
  ARIMA                 -> MAE: 13.97, RMSE: 17.84

  Next 12 Period Forecasts:
```

Model	MAE	RMSE	Interpretation
Holt-Winters Additive	**8.87**	**12.01**	Lowest errors, strong fit to short-term dynamics.
ARIMA	13.97	17.84	Higher error, less effective in capturing seasonal bursts.

Interpretation: Holt-Winters clearly outperforms ARIMA in both MAE and RMSE, establishing itself as the more reliable forecasting tool for this SKU.

Residual Diagnostics Analysis



1. Residuals Over Time

- **Holt-Winters Additive**: Residuals fluctuate around zero with no strong patterns, suggesting the model captures trend and seasonality reasonably well. Spikes exist, but not systematic.
- **ARIMA**: Residuals show slightly higher volatility and clustering in some periods, indicating less effective noise capture compared to Holt-Winters.

Implication: Holt-Winters offers more stable residual behavior, strengthening confidence in its forecasts.

Histogram + KDE

- **Holt-Winters Additive**: Residual distribution is close to normal, slightly left-skewed but centered near zero.
- **ARIMA**: Broader spread, flatter distribution, and heavier tails compared to Holt-Winters, suggesting higher forecast uncertainty.

Implication: Holt-Winters residuals are more tightly distributed, indicating better error control.

3. ACF of Residuals

- **Holt-Winters Additive**: ACF spikes mostly within confidence bands, suggesting residuals resemble white noise.
- **ARIMA**: Few minor lags approach the confidence threshold, hinting at remaining autocorrelation.

Implication: Holt-Winters has cleaner residuals, while ARIMA may still have model inadequacies.

4. QQ Plot (Normality Check)

- **Holt-Winters Additive**: Points mostly align with the 45° line, with mild deviations at the tails.
- **ARIMA**: Deviations stronger at both ends, suggesting heavier tails and non-normal errors.

Implication: Holt-Winters residuals are closer to normality, validating statistical assumptions better.

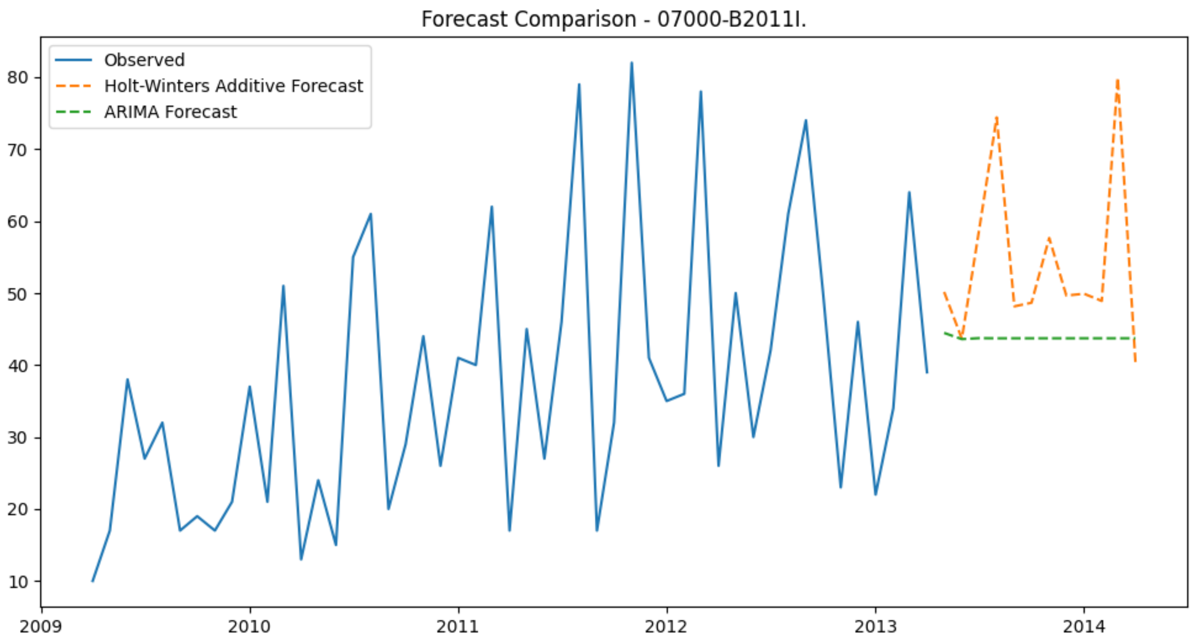
Forecast table

```
Next 12 Period Forecasts:
            HW_Add_Forecast  ARIMA_Forecast
2013-05-01        50.153807       44.461773
2013-06-01        43.653824       43.599063
2013-07-01        58.653844       43.735331
2013-08-01        74.403859       43.713807
2013-09-01        48.153847       43.717207
2013-10-01        48.653871       43.716670
2013-11-01        57.653858       43.716755
2013-12-01        49.653868       43.716741
2014-01-01        49.903848       43.716744
2014-02-01        48.903839       43.716743
2014-03-01        79.903795       43.716743
2014-04-01        40.384608       43.716743
```

Date	HW_Add_Forecast	ARIMA_Forecast
2013-05-01	**50.15**	**44.46**

2013-06-01	**43.65**	**43.60**
2013-07-01	**58.65**	**43.74**
2013-08-01	**74.40**	**43.71**
2013-09-01	**48.15**	**43.72**
2013-10-01	**48.65**	**43.72**
2013-11-01	**57.65**	**43.72**
2013-12-01	**49.65**	**43.72**
2014-01-01	**49.90**	**43.72**
2014-02-01	**48.91**	**43.72**
2014-03-01	**79.90**	**43.72**
2014-04-01	**40.38**	**43.72**

Forecast Evaluation (Next 12 Periods)



- **HW Additive Forecasts** vary realistically (40–79 units), maintaining seasonality.
- **ARIMA Forecasts** remain almost flat (~44 units), showing its inability to capture demand fluctuations.
- Managerially, this makes ARIMA less actionable as it underestimates demand variability, risking stockouts during spikes.

Managerial Interpretation of Next 12 Period Forecasts

1. **Seasonality Capture**
   - The Holt-Winters Additive model clearly reflects seasonality, with forecasts ranging between 40–80 units depending on the month.
   - In contrast, the ARIMA forecast is flat (~43.7 units) across all periods, showing that it has failed to capture seasonal demand spikes or troughs.
2. **Demand Volatility**
   - Holt-Winters anticipates significant peaks (74.4 in Aug 2013, 79.9 in Mar 2014) and troughs (40.3 in Apr 2014), which align with the demand volatility observed in historical data.
   - ARIMA smooths this variability excessively, giving nearly constant predictions, which risks understocking during peaks and overstocking during troughs.
3. **Managerial Risk Implications**
   - Relying on ARIMA: Low responsiveness → safer for highly stable environments but dangerous in spare parts or seasonal industries, where missing peaks could mean lost sales and service failures.
   - Relying on Holt-Winters: Better adaptation to seasonal swings, thus more aligned with inventory optimization, safety stock planning, and procurement cycles.
4. **Forecast Reliability**
   - Given the lower error metrics (MAE = 8.87, RMSE = 12.01 for Holt-Winters vs. MAE = 13.97, RMSE = 17.84 for ARIMA), Holt-Winters provides not only more dynamic but also more accurate forecasts.

Conclusion

For SKU **07000-B2011I**, the analysis demonstrates a clear superiority of the **Holt-Winters Additive model** over ARIMA. While ARIMA produces static forecasts (~43 units each period), effectively ignoring volatility, Holt-Winters adapts to the **seasonal rhythm of demand** and projects realistic peaks and troughs. This flexibility is crucial in spare parts management, where **service-level risks from underforecasting** during peak demand can be far costlier than marginal overstocking. From a managerial standpoint, the adoption of Holt-Winters ensures:

- **More resilient inventory planning**, as it aligns stocking with actual demand cycles.
- **Reduced opportunity loss**, since it anticipates demand surges.
- **Better cost efficiency**, by avoiding both chronic overstock (from flat forecasts) and emergency procurement.

Thus, for strategic decision-making, Holt-Winters provides a **reliable, adaptive, and business-aligned forecasting framework**, while ARIMA remains limited to scenarios of highly stable, non-seasonal demand. Managers should therefore **institutionalize Holt-Winters forecasts for this SKU**, possibly supplementing with safety stock buffers, to strike the balance between **cost containment and service reliability**.

Part3. Which forecasting techniques should L&T use to forecast different spare items?

Models operate at the *SKU level* (e.g., SARIMA for SKU A, Holt-Winters for SKU B). They describe demand for one item at a time.

- Problem With 20,000 SKUs, fitting SARIMA to each is not only computationally expensive but also impractical for planners to monitor.

Techniques are the *frameworks* that tell us which models to apply to which group of SKUs. This is where segmentation + efficiency come in.

While forecasting models such as Holt-Winters, ARIMA, or SARIMA are powerful at the individual SKU level, applying a single complex model like SARIMA to all 20,000 SKUs is neither practical nor efficient. The real managerial challenge lies not just in fitting models but in deploying them at scale in a way that balances accuracy with resource efficiency.

To achieve this, the forecasting strategy must adopt **segmentation-based techniques**. Using the ABC–FMS–HML classification framework, SKUs are grouped by their usage value, frequency of demand, and unit cost. This segmentation ensures that:

- High-value, fast-moving SKUs (A-class) are assigned sophisticated models such as Holt-Winters or SARIMA, where higher accuracy directly impacts service levels and financial performance.
- Medium-value SKUs (B-class) rely on simpler but effective models such as Holt's Linear or SES, reducing computational load while maintaining reasonable accuracy.
- Low-value, intermittent SKUs (C-class) are managed with specialized models such as Croston's or even heuristic rules with safety stock buffers, since the cost of precision outweighs the benefit.

Thus, while models are the engines that generate SKU-level forecasts, techniques provide the systematic framework to deploy the right model to the right SKU segment. This approach emphasizes segmentation + efficiency, ensuring that forecasting resources are allocated where they matter most. The result is a scalable, data-driven, and operationally relevant forecasting system that avoids the inefficiency of applying SARIMA indiscriminately to all SKUs.

Segmented forecasting technique

From Models to Techniques   Segmented Forecasting Strategy

With 20,000 spare parts, L&T faces highly diverse demand patterns: some items are fast-moving with strong seasonality, while others are intermittent or lumpy with long stretches of zero demand. Using one universal model (e.g., SARIMA for all) is impractical and inefficient. Instead, L&T should adopt a segmented forecasting technique that matches model complexity to SKU characteristics.

SKU Type	Characteristics	Forecasting Technique	Examples of Models	Managerial Rationale
A-class, High-value, Fast-moving	High usage value, frequent demand, service critical	**Advanced Time Series**	Holt-Winters (Add./Mult.), SARIMA	High accuracy prevents costly stockouts and ensures service-level reliability
B-class, Medium-value, Regular demand	Moderate usage, stable trend/level	**Mid-level Smoothing Methods**	Holt's Linear, SES	Balances accuracy with efficiency; avoids overfitting
C-class, Low-value, Slow-moving	Low usage, low cost impact, random demand	**Heuristic / Simple Methods**	Moving Average, Safety Stock rules	Forecast precision less critical; buffers cheaper than complex forecasting
Intermittent / Lumpy Items	Long zero-demand stretches, sudden bursts	**Intermittent Demand Models**	Croston's Method, SBA (Syntetos–Boylan Approximation)	Specialized methods outperform exponential smoothing; prevents chronic underforecasting
New / Obsolescent SKUs	No historical demand or phasing out	**Qualitative Techniques**	Delphi, Expert Judgment, Analogy Forecasting	Reliance on planner input, domain knowledge, or proxy SKUs

Highly Volatile / External Drivers	Demand linked to maintenance schedules or external shocks	**Causal / ML Techniques**	Regression, Random Forest, Gradient Boosting	Leverage covariates (machine age, service cycles) for accuracy

Implementation Strategy

- Step 1 – Segmentation: Classify SKUs using ABC–FMS–HML (usage value, frequency, unit cost).
- Step 2 – Model Assignment: Apply the above framework to assign forecasting techniques per segment.
- Step 3 – Automation: Build an automated forecasting pipeline (Python/SAP IBP/Forecast Pro) that runs model selection and exception reporting monthly.
- Step 4 – Validation: Use MAPE, RMSE, Theil's U, and residual diagnostics; planners intervene only in exception cases.

Managerial Conclusion

L&T should adopt a segmented, multi-technique forecasting approach:

- Sophisticated time-series methods (SARIMA, Holt-Winters) for high-value, stable SKUs.
- Simpler smoothing models (SES, Holt's) for medium SKUs.
- Specialized intermittent demand methods (Croston's, SBA) for low-value, lumpy SKUs.
- Judgmental/qualitative approaches for new products.

This ensures a balance of accuracy, scalability, and efficiency, directly aligning forecasting resources with SKU criticality.

Code Snippet :-

Q1 Code for One SKU

```
# ===============================
# Forecasting for SKU: PC_198_27_42263
# Holt Family + ARIMA/SARIMA
# ===============================

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
from statsmodels.tsa.stattools import adfuller, kpss
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.seasonal import STL
from statsmodels.tsa.holtwinters import SimpleExpSmoothing, ExponentialSmoothing
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX

plt.style.use("seaborn-v0_8")
plt.rcParams["figure.figsize"] = (12, 6)

# ------------------------------
# 1) Load Data
# ------------------------------
FILE_PATH = "BFALT.xlsx"
sku = "PC_198_27_42263"

df = pd.read_excel(FILE_PATH, index_col=0)
df.index = pd.to_datetime(df.index)
y = df[sku]   # if SKU is a column; adjust if needed

# ------------------------------
# 2) Frequency & Cleaning
# ------------------------------
freq = pd.infer_freq(y.index)
print("Inferred frequency:", freq)

if freq is not None:
   y = y.asfreq(freq)
else:
   print("⚠️ Could not infer frequency, keeping raw index")

y = y.replace([np.inf, -np.inf], np.nan).ffill().dropna()
print("Final series length:", len(y))
print("Any NaNs left?", y.isna().sum())

#------------------------------
# 3) Plot Original Series
# ------------------------------
plt.figure(figsize=(12,6))
plt.plot(y.index, y, color="black")
plt.title(f"{sku} – Original Demand Series")
plt.xlabel("Date")
plt.ylabel("Demand")
plt.show()

# ------------------------------
# 3) Stationarity Tests
# ------------------------------
adf_p = adfuller(y)[1]
try:
   kpss_p = kpss(y, regression="c", nlags="auto")[1]
```

```
except:
    kpss_p = np.nan
print(f"ADF_p={adf_p:.4g}, KPSS_p={kpss_p:.4g}")

# ------------------------------
# 4) ACF & PACF
# ------------------------------
plot_acf(y, lags=24)
plt.title(f"{sku} – ACF")
plt.show()

plot_pacf(y, lags=24, method="ywm")
plt.title(f"{sku} – PACF")
plt.show()

# ------------------------------
# 5) STL Decomposition
# ------------------------------
try:
    stl = STL(y, period=12, robust=True).fit()
    stl.plot()
    plt.suptitle(f"{sku} – STL Decomposition", y=1.02)
    plt.show()
except Exception as e:
    print("STL decomposition skipped:", e)

# ------------------------------
# 6) Train-Test Split
# ------------------------------
train_size = int(len(y)*0.8)
train, test = y[:train_size], y[train_size:]
steps = len(test)

# ------------------------------
# 7) Holt Family Models
# ------------------------------
results_dict = {}

# SES
ses_model = SimpleExpSmoothing(train).fit()
ses_fc = ses_model.forecast(steps)
results_dict["SES"] = ses_fc

# Holt’s Linear
holt_model = ExponentialSmoothing(train, trend="add", seasonal=None).fit()
holt_fc = holt_model.forecast(steps)
results_dict["Holt"] = holt_fc

# Holt-Winters Additive
try:
```

```
    hw_add_model = ExponentialSmoothing(train, trend="add", seasonal="add",
seasonal_periods=12).fit()
    hw_add_fc = hw_add_model.forecast(steps)
    results_dict["HW_Add"] = hw_add_fc
except Exception as e:
    print("⚠ Holt-Winters Additive skipped:", e)

# Holt-Winters Multiplicative (only if > 0)
if (train > 0).all():
    try:
        hw_mul_model = ExponentialSmoothing(train, trend="add", seasonal="mul",
seasonal_periods=12).fit()
        hw_mul_fc = hw_mul_model.forecast(steps)
        results_dict["HW_Mul"] = hw_mul_fc
    except Exception as e:
        print("⚠ Holt-Winters Multiplicative skipped:", e)
else:
    print("⚠ Skipping Holt-Winters Multiplicative: series has zero/negative values")

# ------------------------------
# 8) ARIMA/SARIMA Candidates
# ------------------------------
order_candidates = [(1,0,0), (0,1,1), (1,1,1), (2,1,2)]
seasonal_candidates = [(0,1,1,12), (1,1,1,12), (1,0,1,12)]
results = []

# ARIMA
for order in order_candidates:
    try:
        model = ARIMA(y, order=order).fit()
        results.append({"Model":"ARIMA","Order":order,"Seasonal_Order":None,"AIC":model.aic,"BIC"
:model.bic})
    except: pass

# SARIMA
for order in [(1,1,1)]:
    for seas in seasonal_candidates:
        try:
            model = SARIMAX(y, order=order, seasonal_order=seas).fit(disp=False)
            results.append({"Model":"SARIMA","Order":order,"Seasonal_Order":seas,"AIC":model.aic,"BI
C":model.bic})
        except: pass

results_df = pd.DataFrame(results).sort_values("AIC")
print("\nModel Comparison (lowest AIC first):")
print(results_df)

best_row = results_df.iloc[0]
if best_row["Model"] == "ARIMA":
    best_model = ARIMA(y, order=best_row["Order"]).fit()
else:
```

```
    best_model = SARIMAX(y, order=best_row["Order"],
seasonal_order=best_row["Seasonal_Order"]).fit(disp=False)

fc_future = best_model.get_forecast(steps=12)
fc_mean = fc_future.predicted_mean
fc_ci = fc_future.conf_int()
results_dict[f"{best_row['Model']}"] = fc_mean

# ------------------------------
# 9) Plots
# ------------------------------
def plot_model(train, test, pred, title):
    plt.figure(figsize=(10,5))
    plt.plot(train, label="Train")
    plt.plot(test, label="Test")
    plt.plot(pred, label="Forecast", linestyle="--")
    plt.title(title)
    plt.legend()
    plt.show()

for name, forecast in results_dict.items():
    plot_model(train, test, forecast, f"{sku} – {name}")

# Best model with CI
plt.figure(figsize=(12,6))
plt.plot(y.index, y, label="Actual", color="black")
plt.plot(best_model.fittedvalues.index, best_model.fittedvalues, label="Fitted", color="blue")
plt.plot(fc_mean.index, fc_mean, label="Forecast", color="green")
plt.fill_between(fc_ci.index, fc_ci.iloc[:,0], fc_ci.iloc[:,1], color="green", alpha=0.2)
plt.title(f"{sku} – {best_row['Model']} Forecast (Next 12)")
plt.legend()
plt.show()

# ------------------------------
# 10) Save Results
# ------------------------------
results_out = pd.DataFrame(index=y.index.append(fc_mean.index))
results_out["Actual"] = y
results_out["Fitted"] = best_model.fittedvalues
results_out["Forecast_Next12"] = fc_mean
results_out["Forecast_Lower"] = fc_ci.iloc[:,0]
results_out["Forecast_Upper"] = fc_ci.iloc[:,1]

OUTPUT_FILE = f"Forecast_{sku}.xlsx"
results_out.to_excel(OUTPUT_FILE, sheet_name="Forecast")
print(f"\n✅ Results saved to {OUTPUT_FILE}")
```

Q2 UKGridweekly

(R code convered into Python since R was not supported in my system)

```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.stattools import adfuller, kpss
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_absolute_error, mean_squared_error
import math

# Load the dataset
df_new = pd.read_csv('ukgridweekly (5).csv')

# Rename the 'Unnamed: 0' column to 'date' and convert it to datetime format
df_new.rename(columns={'Unnamed: 0': 'date'}, inplace=True)

# Ensure proper datetime conversion and drop any rows with invalid dates
df_new['date'] = pd.to_datetime(df_new['date'], errors='coerce')

# Drop any rows with NaT (Not a Time) values in the 'date' column
df_new.dropna(subset=['date'], inplace=True)

# Set the 'date' column as the index
df_new.set_index('date', inplace=True)

# Resample data by week to ensure weekly frequency
df_weekly = df_new['consump'].resample('W').sum()

# Step 1: Plotting Rolling Mean (Trend)
plt.figure(figsize=(10, 6))
plt.plot(df_weekly, label='Weekly Consumption')
plt.plot(df_weekly.rolling(window=52).mean(), label='Rolling Mean (Trend)', color='red')
plt.title('Trend: Weekly Consumption with Rolling Mean')
plt.legend(loc='best')
plt.grid(True)
plt.show()

# Step 2: Stationarity Check using ADF and KPSS Tests
# ADF Test (Augmented Dickey-Fuller)
def adf_test(series):
    result = adfuller(series.dropna())
    return result[1]  # p-value

# KPSS Test (Kwiatkowski-Phillips-Schmidt-Shin)
def kpss_test(series):
    result = kpss(series.dropna(), regression='c', nlags='auto')
    return result[1]  # p-value
```

```
# Perform stationarity tests
adf_pvalue = adf_test(df_weekly)
kpss_pvalue = kpss_test(df_weekly)

# Plot the results
print(f"ADF Test p-value: {adf_pvalue}")
print(f"KPSS Test p-value: {kpss_pvalue}")

# Plot ADF and KPSS results on a single plot for clarity
plt.figure(figsize=(10, 6))
plt.subplot(121)
plot_acf(df_weekly, lags=52, ax=plt.gca())  # ACF plot for autocorrelation
plt.subplot(122)
plot_pacf(df_weekly, lags=52, ax=plt.gca())  # PACF plot for partial autocorrelation
plt.show()

# Step 3: Seasonal Decomposition to check for Seasonality
from statsmodels.tsa.seasonal import seasonal_decompose

result = seasonal_decompose(df_weekly, model='multiplicative', period=52)
result.plot()
plt.title('Seasonal Decomposition')
plt.show()

# Step 4: Lag Plot to inspect any remaining patterns
from pandas.plotting import lag_plot
plt.figure(figsize=(10, 6))
lag_plot(df_weekly)
plt.title('Lag Plot: Checking for Remaining Patterns')
plt.show()

# Step 5: Train-Test Split (90% Train, 10% Test)
train_size = int(len(df_weekly) * 0.9)
train, test = df_weekly[:train_size], df_weekly[train_size:]

# Step 6: Holt-Winters Model (Additive and Multiplicative)

# Additive Model
hw_additive_model = ExponentialSmoothing(train, trend='add', seasonal='add',
seasonal_periods=52)
hw_additive_fitted = hw_additive_model.fit()
forecast_hw_additive = hw_additive_fitted.forecast(steps=len(test))

# Multiplicative Model
hw_multiplicative_model = ExponentialSmoothing(train, trend='add', seasonal='mul',
seasonal_periods=52)
hw_multiplicative_fitted = hw_multiplicative_model.fit()
forecast_hw_multiplicative = hw_multiplicative_fitted.forecast(steps=len(test))

# Step 7: ARIMA Model (auto.arima)
```

```
arima_model = ARIMA(train, order=(5, 1, 0))  # Adjust order if needed based on ACF/PACF
arima_fitted = arima_model.fit()
forecast_arima = arima_fitted.forecast(steps=len(test))

# Step 8: Model Comparison (RMSE, MAE, Theil's U)

# RMSE and MAE for Holt-Winters Additive
rmse_hw_additive = math.sqrt(mean_squared_error(test, forecast_hw_additive))
mae_hw_additive = mean_absolute_error(test, forecast_hw_additive)

# RMSE and MAE for Holt-Winters Multiplicative
rmse_hw_multiplicative = math.sqrt(mean_squared_error(test, forecast_hw_multiplicative))
mae_hw_multiplicative = mean_absolute_error(test, forecast_hw_multiplicative)

# RMSE and MAE for ARIMA
rmse_arima = math.sqrt(mean_squared_error(test, forecast_arima))
mae_arima = mean_absolute_error(test, forecast_arima)

# Calculate Theil’s U for all models
naive_forecast = np.repeat(train.iloc[-1], len(test))

def theils_u(actual, forecast, naive_forecast):
   num = np.sum((actual - forecast) ** 2)
   den = np.sum((actual - naive_forecast) ** 2)
   return num / den

U_hw_additive = theils_u(test, forecast_hw_additive, naive_forecast)
U_hw_multiplicative = theils_u(test, forecast_hw_multiplicative, naive_forecast)
U_arima = theils_u(test, forecast_arima, naive_forecast)

# Print Results
print(f'Holt-Winters Additive RMSE: {rmse_hw_additive}, MAE: {mae_hw_additive}, Theil’s U:
{U_hw_additive}')
print(f'Holt-Winters Multiplicative RMSE: {rmse_hw_multiplicative}, MAE: {mae_hw_multiplicative},
Theil’s U: {U_hw_multiplicative}')
print(f'ARIMA RMSE: {rmse_arima}, MAE: {mae_arima}, Theil’s U: {U_arima}')

# Step 9: Select the Best Model
best_model = 'Holt-Winters Additive' if rmse_hw_additive < rmse_hw_multiplicative and
rmse_hw_additive < rmse_arima else 'Holt-Winters Multiplicative' if rmse_hw_multiplicative <
rmse_arima else 'ARIMA'
print(f"Best Model: {best_model}")

# Step 10: Forecasting Weeks 759–800 (Final Model)
# Refit the best model on the entire dataset (train + test combined)

if best_model == 'Holt-Winters Additive':
   final_model = ExponentialSmoothing(df_weekly, trend='add', seasonal='add',
seasonal_periods=52)
   final_fitted = final_model.fit()
   final_forecast = final_fitted.forecast(steps=42)  # Forecast 42 weeks ahead
```

```
elif best_model == 'Holt-Winters Multiplicative':
   final_model = ExponentialSmoothing(df_weekly, trend='add', seasonal='mul',
seasonal_periods=52)
   final_fitted = final_model.fit()
   final_forecast = final_fitted.forecast(steps=42)
else:
   final_model = ARIMA(df_weekly, order=(5, 1, 0))  # ARIMA model order from earlier
   final_fitted = final_model.fit()
   final_forecast = final_fitted.forecast(steps=42)

# Plot and Save the Final Forecast for the Best Model
plt.figure(figsize=(10, 6))
plt.plot(df_weekly.index, df_weekly, label='History', color='blue')
plt.plot(pd.date_range(start=df_weekly.index[-1], periods=42, freq='W'), final_forecast, label='Final
Forecast', color='red')
plt.title(f'Final Forecast for UK Weekly Electricity Consumption (Weeks 759–800) using
{best_model}')
plt.xlabel('Year')
plt.ylabel('Consumption (MW)')
plt.legend()
plt.grid(True)
plt.show()

# Combine forecasts into a single DataFrame for all models (for comparison if needed)
forecast_combined = pd.DataFrame({
   'Date': pd.date_range(start=df_weekly.index[-1] + pd.Timedelta(weeks=1), periods=42, freq='W'),
   'Holt-Winters Additive Forecast': forecast_hw_additive[-42:],  # Last 42 weeks of HW additive
forecast
   'Holt-Winters Multiplicative Forecast': forecast_hw_multiplicative[-42:],  # Last 42 weeks of HW
multiplicative forecast
   'ARIMA Forecast': forecast_arima[-42:]  # Last 42 weeks of ARIMA forecast
})

# Save the combined forecast to a CSV file
combined_forecast_file = 'UKgrid_Forecast_759_800_Combined.csv'
forecast_combined.to_csv(combined_forecast_file, index=False)

# Print the path to the saved file
print(f"Combined forecast for weeks 759-800 saved to: {combined_forecast_file}")
```