International Journal Of Engineering Research And Development
e- ISSN: 2278-067X, p-ISSN: 2278-800X, www.ijerd.com
Volume 20, Issue 12 (December, 2024), PP 315-326

Assessing product Delivery and Forecasting for fast Moving Consumer Goods (FMCGs)

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Abstract
This study explores the application of the SARIMA model for demand forecasting and inventory management in the FMCG sector, using Majesty Group as a case study. Historical sales data from 2021 to 2023 were analyzed to identify trends, seasonality, and demand fluctuations. The SARIMA model, optimized through hyperparameter tuning, demonstrated its effectiveness in capturing cyclical and seasonal patterns despite challenges posed by Nigeria's economic constraints. Forecasting performance was evaluated using MAE and MAPE metrics, highlighting areas for improvement in products with high variability. Inventory sustainability analysis revealed gaps in replenishment strategies, emphasizing the need for precise adjustments to balance demand, supply, and cost efficiency. This research underscores the importance of integrating advanced forecasting models with strategic inventory practices to enhance supply chain resilience.

Date of Submission: 11-12-2024 Date of Acceptance: 23-12-2024

I. Introduction

The FMCG sector is a vast and dynamic global industry that deals with fast-selling, low-priced products like food, beverages, personal care items, and household essentials. Due to their high turnover, these products drive intense competition, pushing companies to build agile supply chains and optimize inventory systems to meet demand efficiently (Heizer, Render, & Munson, 2023). The industry's hallmarks include mass production, intricate distribution networks, and short product lifespans, all of which pose challenges for demand and inventory management (Nguyen, Le & Nguyen, 2022).

Despite technological advancements improving operations, Majesty Group's struggles need help with inventory management and demand forecasting. Changing consumer preferences, volatile markets, and complex supply chains highlight the need for accurate forecasting and cost-effective inventory practices. Effective inventory management involves balancing stock levels to meet demand while minimizing costs of overstocking or shortages, while demand forecasting informs procurement decisions and prevents financial losses due to errors (Ivanov et al., 2022). To remain competitive, Majesty Group must adopt advanced models to anticipate demand shifts in this fast-evolving industry (Wang, Lu, & Sun, 2022).

II. Literature Review

Demand Forecasting

In the fast-moving consumer goods (FMCG) sector, demand forecasting is critical as it directly impacts inventory control, production planning, and the efficiency of distribution systems. Simpler techniques such as exponential smoothing and moving averages are widely adopted due to their straightforward application. However, these methods often fall short when dealing with demand patterns influenced by seasonal or cyclical variations.

To overcome these shortcomings, advanced models like ARIMA (Auto-Regressive Integrated Moving Average) and its seasonal counterpart, SARIMA, have been developed. SARIMA, in particular, stands out because it effectively captures both trends and seasonal fluctuations in time series data. This makes it a preferred tool for forecasting in contexts where seasonal variations significantly affect demand, ensuring more reliable and precise predictions (Box et al., 2016; Hyndman & Athanasopoulos, 2021; Shumway & Stoffer, 2017).

The SARIMA Model: Overview and Use

The SARIMA (Seasonal Auto-Regressive Integrated Moving Average) model expands the ARIMA framework by including seasonal elements, making it ideal for industries like FMCG, where demand often follows seasonal trends. ARIMA consists of autoregressive (AR), integrated (I), and moving average (MA) components, represented by (p, d, q). SARIMA enhances this by adding seasonal parameters (P, D, Q) and a seasonal period, 'm,' which accounts for recurring demand patterns (Box et al., 2016).

For Majesty Group, adopting SARIMA could greatly enhance demand forecasting, especially for items with apparent seasonal fluctuations. FMCG sales, often driven by seasonal factors, require accurate predictions for efficient inventory management. Research, such as Kumar and Arthanari's (2021), shows that SARIMA outperforms traditional models in forecasting perishable goods with strong seasonality. By modeling these variations, SARIMA enables better production planning, reduces forecast errors, lowers inventory costs, and boosts supply chain efficiency.

Inventory Control in FMCG

Proper inventory control and demand forecasting are essential in the FMCG sector, where consistent product availability and prompt restocking are key to staying competitive. According to Chen et al. (2018), accurate demand forecasting helps minimize overstocking and avoid stockouts, directly improving operational efficiency and customer satisfaction. Models like ARIMA and SARIMA are commonly used to predict demand from historical data, with their accuracy playing a critical role in setting reorder points and calculating safety stock to handle demand variations and supply chain issues.

Choi et al. (2020) highlight that integrating real-time data with forecasting models increases flexibility, enabling FMCG companies to quickly respond to market shifts, reduce risks, and cut inventory costs. Sharma and Patel (2021) note that FMCG firms face challenges such as short product lifespans and unpredictable demand, making precise forecasting crucial. Adopting practices like demand-driven restocking and just-in-time (JIT) systems can save costs and boost service quality. Aligning forecasting with inventory management ensures optimal order sizes, shorter lead times, and better supply chain efficiency, which are critical for maintaining an edge in today's fast-changing market.

Demand-Driven Replenishment

Demand-driven replenishment is a key strategy for improving inventory management, especially in FMCG sectors where demand can be highly unpredictable. Unlike conventional methods that use fixed reorder points, this approach adjusts stock levels based on real-time consumption trends, aligning inventory with actual demand changes. Towill and Disney (2020) note that this dynamic system enhances supply chain responsiveness, minimizing risks of overstocking or stockouts by adjusting quickly to market conditions.

By incorporating demand forecasting tools like SARIMA and machine learning models, businesses can achieve more accurate demand signals, resulting in better order precision and lead time control. Smith and Waller (2019) emphasize that demand-driven replenishment works well with advanced technologies such as automated stock tracking and data analytics, leading to higher efficiency, lower storage costs, and improved customer satisfaction. Its adaptability is particularly valuable for FMCGs, where supply chain flexibility is essential to meeting consumer demand in real time.

Case Studies and Practical Applications

Procter & Gamble (P&G): P&G utilized the SARIMA model to address seasonal demand for personal care products, achieving a 20% reduction in forecast errors and optimizing inventory for peak sales periods like holidays. This minimized stockouts, enhanced customer satisfaction, and improved alignment between production and distribution strategies (Kumar & Patel, 2020).

Nestlé: Nestlé implemented SARIMA to forecast demand for dairy and confectionery products across regions with distinct seasonal trends. By integrating SARIMA with automated inventory systems, the company improved forecast accuracy, reduced overstocking, and achieved a 10% increase in order fulfillment rates (Adeoye & Adebayo, 2021).

III. Methodology

This study employed a mixed-method approach, integrating quantitative and qualitative methods to examine the impact of demand forecasting and inventory control in the FMCG sector. Historical sales and inventory data were digitized and structured for analysis, with demand trends predicted using the SARIMA model, focusing on seasonal variations. Key inventory metrics, including safety stock levels, reorder points, and safety stock coverage, were analyzed alongside performance indicators such as order fill rate, stockout frequency, inventory carrying costs, and the sustainability period of the inventory. This comprehensive methodology enabled a detailed evaluation of factors influencing forecasting accuracy and inventory efficiency.

Data Collection

Sales records from Majesty Group (2021–2023) were manually retrieved and digitized. Relevant details, such as product names, sales volumes, unit prices, and dates, were entered into spreadsheets for analysis. Data validation involved cross-checking monthly figures with original records to ensure reliability. This dataset covered a range of FMCG products, forming a robust foundation for studying demand trends and inventory turnover.

Table 3.1: Qualitative Data

S/N	Qualitative data	Description
1	Lead Time	21- 25 days (Varies on each product)
2	Intended service level	having enough stock to meet the demand. (Resulting in a Z-score of 90%)
3	Method of Inventory	Based on intuition and Seasonal expected sales

The SARIMA Model

The SARIMA model for Majesty FMCG involved preprocessing historical sales data into a continuous time series, identifying trends and seasonality through EDA, and using the ADF test to check stationarity. Non-stationary data was differenced to achieve stationarity, and ACF/PACF plots guided parameter selection. The model was built with seasonal and non-seasonal parameters, and hyperparameter tuning minimized errors.

Residual analysis confirmed no significant autocorrelation, validating the model's accuracy. MAE and MAPE tests assessed performance, and out-of-sample testing refined the model for improved accuracy and reliability.

Inventory Control Using Demand-Driven Replenishment

Demand-driven replenishment focused on key inventory metrics, including safety stock, reorder points, and days of inventory on hand. Historical sales data were analyzed to identify demand patterns, which informed safety stock calculations based on demand and lead time variability. Reorder points were determined by combining average lead-time demand with safety stock, ensuring timely replenishment to avoid stockouts and minimize overstocking.

Days of inventory on hand were evaluated to measure inventory efficiency relative to sales trends. A comparative analysis of reorder points, lead-time sales, and safety stock coverage provided a robust inventory performance and responsiveness assessment. Additionally, inventory sustainability was assessed to determine how well existing stock could meet forecasted demand. This framework optimized inventory levels, improved service reliability, and aligned replenishment strategies with real-time customer demand.

The process began by collecting three years of historical sales data (2021-2023). This dataset was the foundation for identifying demand trends and variability, which is critical to determining safety stock and reorder points. The data analysis included:

Calculating Average Demand: Monthly average demand for each product, offering insights into typical sales volumes.

Calculate Average Daily Demand (ADD) = $\frac{total\ demand\ over\ a\ period}{Number\ of\ Days\ in\ that\ Period}$…………..4

Using 4 months (104 days) period sales data below is the average daily demand.

Table 3.2:Average Daily Demand Calculation table

Product	Total product sold (104 days)	Average Daily Demand (ADD)
Good Morning Oats	507	4.88
Anty Bella Oats	411	3.95
Kelloggs Cornflakes	254	2.44
Funsnacks Cornflakes	352	3.38
Dano Milk	1514	14.56
Supercow Milk	941	9.05

Identifying Demand Variability: Standard deviation in demand was assessed to capture fluctuations in monthly sales, reflecting demand volatility. (Process shown in Appendix C)

Table 3.3: Standard Deviation for the Six Product

Product	Standard deviation(month)
Good Morning Oats	21.07

Anty Bella Oats	21.51
Kelloggs Cornflakes	15.34
Funsnacks Cornflakes	14.58
Dano Milk	85.80
Supercow Milk	64.95

Calculating Safety Stock

Safety stock is crucial to maintaining product availability during unexpected surges in demand or delays in replenishment. To calculate safety stock, the following formula was applied:

Calculate Safety Stock using the following formula:

$\text{Safety Stock} = Z \times \sigma d \times \sqrt{\text{Lead Time}}$ …………………………………………… 5

- Z: Z-score corresponding to your desired service level.
- σd: Standard deviation of demand during lead time.
- Lead Time: Number of days for supplier delivery.

Convert Monthly Standard Deviation to Weekly Standard Deviation: the standard deviation (σd) is calculated from monthly demand data, using Python but the lead time is in days, a conversion was made on the standard deviation to match the lead time unit.

Convert Monthly to Days: Since there are approximately 29.66 days in a month (356 days in a year / 12 months), you can convert the standard deviation from monthly to weekly by dividing by 29.66

$\sigma\text{days} = \frac{\sigma\text{monthly}}{29.66}$…………………………………….………………….. 6

Table 3.4: Standard Deviation Conversion Table

Product	Standard deviation(month)	Standard deviation (daily)
Good Morning Oats	21.07	0.710
Anty Bella Oats	21.51	0.725
Kelloggs Cornflakes	15.34	0.517
Funsnacks Cornflakes	14.58	0.492
Dano Milk	85.80	2.893
Supercow Milk	64.95	2.190

Determine Lead Time: Measure the time it takes for inventory to be replenished once an order is placed.

- Safety Stock: Maintain a buffer to protect against demand surges or delays in replenishment.
- Choosing a Z-score of 90%, which is equivalent to 1.28. The safety stock calculation:
- $\text{Safety Stock} = 1.28 \times \sigma\text{daily(product)} \times \sqrt{\text{lead time (days)}}$……………………….7

Table 3.5: Safety Stock Calculation Table

Product	Standard deviation (daily)	Lead Time (days)	Safety Score
Good Morning Oats	0.71	20	4.06
Anty Bella Oats	0.73	22	4.35
Kelloggs Cornflakes	0.52	23	3.17
Funsnacks Cornflakes	0.49	20	2.82
Dano Milk	2.89	21	16.97
Supercow Milk	2.19	25	14.02

Safety stock for each product was calculated using demand variability and lead time, ensuring a tailored buffer to manage sales fluctuations. This approach minimized stockouts and overstocking by aligning safety stock levels with each product's demand patterns

3.4.5 Establishing the Reorder Point

The reorder point represents the inventory level at which a replenishment order should be placed to avoid stockouts. It integrates both lead time demand and safety stock, ensuring timely replenishment. The reorder point was calculated using the formula:

$\text{ROP} = (\text{Average Daily Demand} \times \text{Lead Time}) + \text{Safety Stock}$……………………. 8

Converting Average Daily Demand into weeks =

Average Daily Demand x 6 days (excluding Sundays) ………………………………….. 9

- **Average Daily Demand**: Derived from historical monthly sales data, providing a day-to-day perspective on typical demand.
- **Lead Time**: The duration required for inventory replenishment, which varies depending on supplier and logistics factors.

Table 3.6: Reorder Point Calculation Table

Product	Average Daily Demand	Lead time (days)	Safety Stock	Reorder Point
Good Morning Oats	4.88	20	4.06	106.44
Anty Bella Oats	3.95	22	4.35	90.21
Kellogys Cornflakes	2.44	23	3.17	57.56
Funsnacks Cornflakes	3.38	20	2.82	73.85
Dano Milk	14.56	21	16.97	338.13
Supercow Milk	9.05	25	14.02	220.47

Evaluating the Sustainability Period of Majesty Group's Inventory Against Forecasted Demand

To evaluate inventory sustainability within a demand-driven inventory system, it is essential to determine the duration for which the current inventory can satisfy forecasted demand. This assessment requires a comparison of available stock levels against projected usage over time. The following key parameters are involved:

- **Available Inventory (AI):** The current quantity of stock on hand.
- **Forecasted Demand (FD):** The anticipated demand per time unit (e.g., daily or weekly).
- **Replenishment Lead Time (LT):** The time required to replenish inventory after placing an order.
- **Safety Stock (SS):** Additional inventory held as a buffer to address uncertainties in demand or supply.

The analysis focuses on three products; Dano Milk, Super Cow Milk, and Funsnacks Cornflakes selected for their consistent performance in forecasting accuracy, as demonstrated by stable Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) values.Using Forecasted Demand for December

Table 3.7: Sustainability Period Calculation Table

S/N	Product	Available Inventory	Forecasted Demand	Replenishment Lead Time	Safety Stock (days)
1	Super Cow Milk	300	358	25	6.36
2	Dano Milk	350	537	21	5.23
3	Funsnacks Cornflakes	80	41	20	3.82

$\text{Sustainability period (Days) (without safety stock)} = \frac{Avaliable\ Inventory}{Forecasted\ Demand\ (daily)}$…………12

$Sustainabilty\ period\ (days)(with\ safety\ stock) = \frac{Avaliable\ inventory - Safety\ stock}{Forecasted\ Demand(daily)}$ ……13

Converting the Forecasted demand from months to days (divided by 30 days)

S/N	Product	Available Inventory	Forecasted Demand	Replenishment Lead Time	Safety Stock (days)
1	Super Cow Milk	300	11.93	25	6.36
2	Dano Milk	350	17.9	21	5.23
3	Funsnacks Cornflakes	80	1.37	20	3.82

Solving;

$$\text{SuperCow Milk (SP with SS)} \quad = \frac{300 - 6.36}{11.93} = 24.14\ days$$

$$Dano\ Milk\ (SP\ with\ SS) = \frac{350 - 5.23}{17.9} = 19\ days$$

$$Funsnacks\ Cornflakes\ (SP\ with\ SS) = \frac{80 - 3.83}{1.39} = 55\ days$$

Sustainability Check:

$$\begin{cases} \text{Sustainable, if Sustainability Period} \geq \text{Lead Time (LT)} \\ \text{Unsustainable, if Sustainability Period} < \text{Lead Time (LT)} \end{cases}$$

3. **Discussion on Analysis of Forecast Plot of Products**

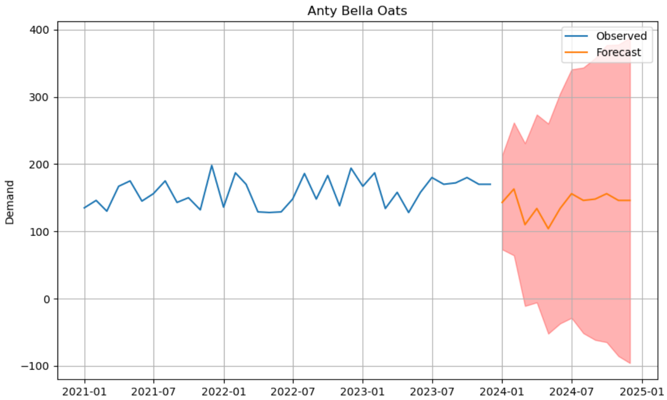

Figure 4.1: Anty Bella Oat Forecast Plot

Table 4.1: Anty Bella Oat Prediction

Anty Bella Oat			
Month	Prediction	Lower Prediction	Upper Prediction
1/2024	143	73	213
2/2024	163	64	262
3/2024	110	11	231
4/2024	134	6	274
5/2024	104	52	260
6/2024	134	37	305
7/2024	156	29	341
8/2024	146	51	343
9/2024	148	61	357
10/2024	156	65	377
11/2024	146	86	378
12/2024	146	96	388

Demand Analysis for Anty Bella Oats

From January 2021 to December 2023, demand for Anty Bella Oats displayed a cyclical pattern, with peaks and troughs influenced by seasonal trends and marketing efforts. Similar behaviors were observed in staples like Good Morning Oats and Dano Milk, reflecting heightened demand during specific periods. The forecast for January 2023 to December 2024 shows a continued pattern of regular fluctuations, indicating stable consumer interest. The confidence interval around the estimates highlights potential variability, emphasizing the importance of strategic planning to address demand uncertainties.

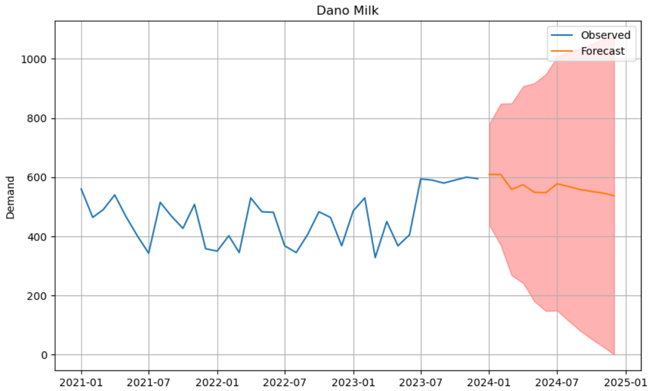

Figure 4.2: Dano Milk Demand Plot

Table 4.2: Dano Milk Prediction

Dano Milk			
Month	Prediction	Lower Prediction	Upper Prediction
1/2024	609	438	780
2/2024	609	369	849
3/2024	559	268	850
4/2024	574	242	907
5/2024	549	180	918
6/2024	548	147	948
7/2024	578	149	1006
8/2024	568	114	1023
9/2024	558	81	1036
10/2024	552	53	1051
11/2024	546	27	1065
12/2024	537	0	1075

From January 2021 to December 2023, the demand for Dano Milk has shown significant fluctuation, ranging from slightly below 400 to just over 600 units. This variability aligns with the cyclical and seasonal trends seen in other staple products like Anty Bella Oats and Good Morning Oats. Demand peaks likely reflect increased consumer interest during holidays, promotional campaigns, and the everyday use of milk in products like pastries, underscoring milk’s role as a staple. Beginning in January 2023, the forecasted demand extends to December 2024, represented by the red line, with the surrounding shaded area indicating the confidence interval and forecast uncertainty. The model suggests a potential downward trend, possibly due to factors like market saturation, shifts in consumer preferences, economic constraints, or rising competition.

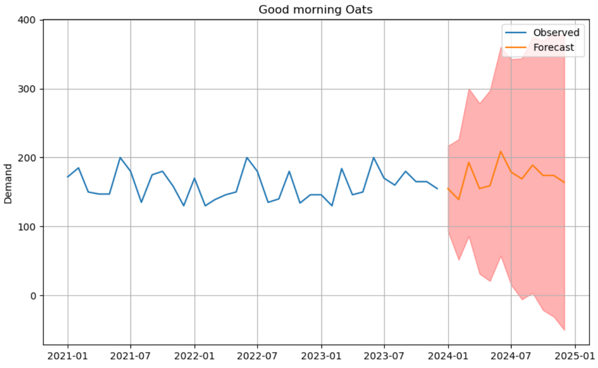

Figure 4.3: Good Morning Oats Forecast Plot

Table 4.3: Good Morning Oat prediction

Good Morning Oat			
Month	Prediction	Lower Prediction	Upper Prediction
1/2024	155	93	217
2/2024	139	52	226
3/2024	193	86	300
4/2024	155	31	279
5/2024	159	21	297
6/2024	209	58	360
7/2024	179	15	343
8/2024	169	6	344
9/2024	189	4	374
10/2024	174	22	370
11/2024	174	31	379
12/2024	164	50	378

Forecasted Demand for Good Morning Oats

From January 2024 to December 2025, the forecasted demand for Good Morning Oats builds on historical data (January 2021 to December 2023), which fluctuated between 100 and 200 units. These variations reflect a cyclical demand pattern driven by seasonal trends, promotions, and its role as a staple product, with spikes often linked to holidays or marketing efforts.

The forecasted red line indicates a continuation of this pattern, with regular peaks and troughs suggesting stable demand drivers. The shaded confidence interval highlights prediction uncertainty, aiding risk management by preparing for potential demand fluctuations and ensuring readiness during high-variability periods.

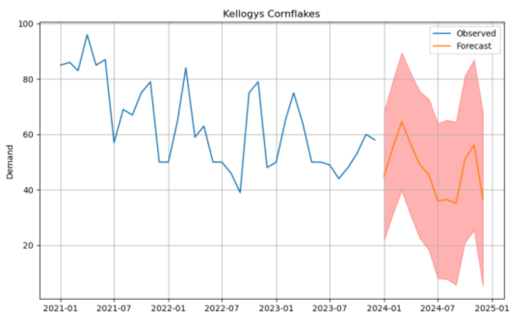

Figure 4.4: Kellogy'sCornflaks Forecast Plot

Table 4.4: Kellogy's Cornflakes Prediction

Kellogy's Cornflakes			
Month	Prediction	Lower Prediction	Upper Prediction
1/2024	45	22	68
2/2024	56	32	80
3/2024	65	40	89
4/2024	56	31	82
5/2024	49	23	76
6/2024	45	18	73
7/2024	36	8	64
8/2024	36	8	65
9/2024	35	6	64
10/2024	51	21	81
11/2024	56	25	87
12/2024	37	5	68

From January 2021 to September 2021, the observed demand for Kellogg's Cornflakes fluctuates significantly, ranging from 20 to 100 units. This variability highlights the cyclical nature of consumer demand, influenced by factors such as seasonal trends, marketing campaigns, and the everyday use of cornflakes as a staple breakfast item. For instance, peaks in demand may correspond to back-to-school seasons or holiday periods when consumers are more likely to purchase larger quantities of cornflakes. The observed data provides a historical baseline that helps in understanding past consumption patterns and identifying periods of high and low demand.

Starting from September 2021, the forecasted demand extends to January 2025. The forecasted line, shown in orange, indicates a projected trend in demand. The shaded area around the forecast line represents the confidence interval, reflecting the uncertainty in the predictions. This interval is crucial for risk management, as it provides a range within which the actual demand is likely to fall. The forecast suggests that the demand will continue to follow a similar cyclical pattern, with regular peaks and troughs, indicating that the factors influencing demand are expected to persist.

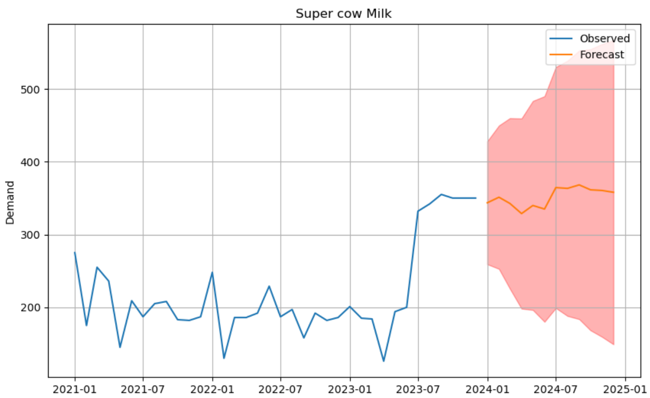

Figure 4.5: Super Cow Milk

Table 4.5: Super Cow Prediction

Super Cow Milk			
Month	Prediction	Lower Prediction	Upper Prediction
1/2024	344	259	428

2/2024	351	253	450
3/2024	343	226	460
4/2024	329	198	459
5/2024	340	196	483
6/2024	335	180	490
7/2024	364	199	530
8/2024	363	188	539
9/2024	368	184	553
10/2024	361	168	554
11/2024	360	159	562
12/2024	358	149	567

From January 2021 to December 2023, the observed demand for Super Cow Milk fluctuates significantly, ranging from 200 to below 400 units. This variability highlights the cyclical nature of consumer demand, influenced by factors such as seasonal trends, marketing campaigns, and the everyday use of milk as a staple product. For instance, peaks in demand may correspond to holiday seasons or promotional periods when consumers are more likely to purchase larger quantities of milk. The observed data provides a historical baseline that helps in understanding past consumption patterns and identifying periods of high and low demand.

Starting from January 2023, the forecasted demand extends to December 2024. The forecasted line, shown in orange, indicates a projected trend in demand. The shaded area around the forecast line represents the confidence interval, reflecting the uncertainty in the predictions. This interval is crucial for risk management, as it provides a range within which the actual demand is likely to fall. The forecast suggests that the demand will continue to follow a similar cyclical pattern, with regular peaks and troughs, indicating that the factors influencing demand are expected to persist.

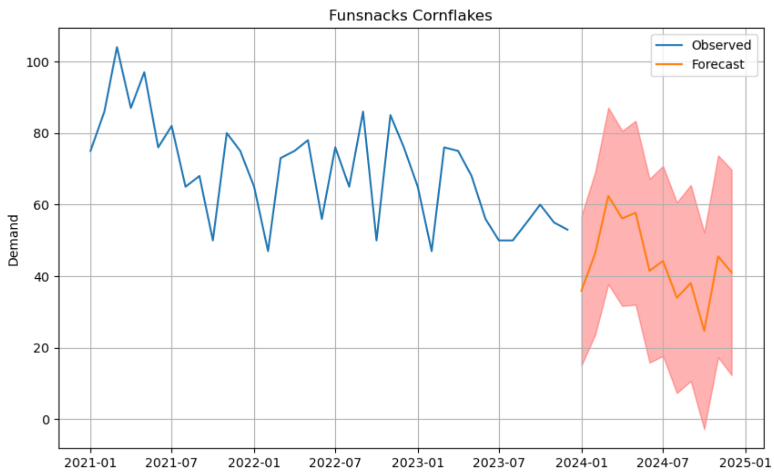

Figure 4.6:Funsnacks Cornflakes Forecast Plot

Table 4.6:Funsnacks Cornflakes Prediction

Fun snacks Cornflakes			
Month	Prediction	Lower Prediction	Upper Prediction
1/2024	36	15	57
2/2024	46	24	69
3/2024	62	38	87
4/2024	56	32	81

5/2024	58	32	83
6/2024	42	16	67
7/2024	44	18	71
8/2024	34	7	61
9/2024	38	11	65
10/2024	25	-3	52
11/2024	46	17	74
12/2024	41	12	70

Demand Analysis for Funsnacks Cornflakes

From January 2021 to December 2023, demand for Funsnacks Cornflakes fluctuated between 20 and 100 units, reflecting cyclical patterns driven by seasonal trends, marketing, and its role as a staple breakfast item. Peaks often coincide with back-to-school and holiday periods. This historical data provides valuable insights into high and low-demand periods.

The forecast from January 2023 to December 2024 continues this cyclical trend, with regular peaks and troughs. The confidence interval around the estimates highlights uncertainty, offering a range for potential demand and aiding in risk management. Persistent demand drivers suggest the trend will remain stable.

Discussion on the MAE and MAPE Table

Table 4.7 MAE and MAPE Values

Product	MAE	MAPE
Good Morning Oats	48.99	20.21
Anty Bella Oats	58	30
Kellogys Cornflakes	40.45	44.29
Funsnacks Cornflakes	27.22	35.072
Dano Milk	25.13	30.78
Super Cow Milk	23.36	24.21

1. **Good Morning Oats:** The model shows moderate accuracy with an MAE of 48.99 and MAPE of 20.21%. Stable demand supports the forecast, and emphasizing its affordability and health benefits in marketing could sustain interest, especially in tough economic times.
2. **Anty Bella Oats:** An MAE of 58 and MAPE of 30% reflect lower accuracy, influenced by seasonal and marketing-driven demand variability. As an affordable staple, strategic marketing on nutrition and cost-effectiveness could mitigate forecasting challenges.
3. **Kellogy's Cornflakes:** The highest MAPE of 44.29% and MAE of 40.45 indicate significant forecasting errors, driven by cyclical demand during back-to-school and holiday seasons and competition from cheaper brands. Inflation and reduced purchasing power further complicate predictions.
4. **Funsnacks Cornflakes:** An MAE of 27.22 and MAPE of 35.07% indicate moderate accuracy with notable percentage deviations. Seasonal demand fluctuations and economic constraints pose challenges, but well-timed promotions could help sustain consumer interest.
5. **Dano Milk:** The model demonstrates stable accuracy despite fluctuations with an MAE of 25.13 and MAPE of 30.78%. Economic pressures may drive shifts toward cheaper alternatives, aligning with a forecasted demand decline.
6. **Super Cow Milk:** The most accurate forecast with an MAE of 23.36 and MAPE of 24.21%. Steady demand is likely due to brand loyalty and perceived quality, supporting the reliability of the forecast.

Economic factors like inflation, fluctuating oil prices, and currency devaluation influence consumer spending and shape demand patterns. Essential and affordable products like oats and milk exhibit mixed demand stability. In contrast, higher MAPE values in products like Kellogy's and Funsnacks Cornflakes highlight areas where SARIMA struggles with variability, likely due to external economic pressures and seasonal spikes

Discussion: MAE/MAPE and Nigeria's Economic Context

Nigeria's economic challenges—inflation, fluctuating oil prices, and currency devaluation—affect consumer purchasing power, shaping demand and forecasting accuracy (MAE and MAPE) for various products.

- **Anty Bella Oats:** Moderate forecasting accuracy with noticeable percentage error reflects cyclical demand influenced by seasonal trends and marketing. As an affordable staple, it remains appealing to budget-conscious consumers if positioned as a cost-effective, nutritious option.
- **Dano Milk:** Demand fluctuations and a downward trend, coupled with moderate MAPE, suggest economic pressures are pushing consumers toward cheaper alternatives or reducing milk consumption, impacting forecast reliability.
- **Good Morning Oats:** Stable demand with low MAPE aligns with its affordable, healthy image. Marketing highlighting these qualities could maintain consistent demand in an economically constrained environment.
- **Kellogy's Cornflakes:** High MAPE reveals significant forecast errors, likely due to seasonal spikes (e.g., back-to-school, holidays) and competition from cheaper local brands, exacerbated by economic pressures.
- **Super Cow Milk:** The lowest MAE and MAPE demonstrate stable demand, likely due to brand loyalty and perceived quality. Despite financial strain, consumers consider it essential to ensure resilience.
- **Funsnacks Cornflakes:** Moderate forecasting errors reflect demand peaks driven by seasonal trends and marketing campaigns. Economic challenges may push consumers to cheaper options, but strategic promotions could sustain demand.

4Sustainability Period Discussion

Table 4.8: Sustainability Period Table

S/N	Product	Replenishment Lead Time	S. Period (days)
1	Super Cow Milk	25	24.14
2	Dano Milk	21	19
3	Funsnacks Cornflakes	20	55

Inventory Sustainability Assessment

The sustainability check determines whether the current inventory can meet forecasted demand during the replenishment lead time by comparing the sustainability period to the lead time. Inventory is sustainable if the sustainability period equals or exceeds the lead time, ensuring sufficient stock to prevent stockouts.
Analysis reveals unsustainability for **Super Cow Milk** and **Dano Milk**, with sustainability periods of 24.14 and 19 days, respectively, falling short of lead times (25 and 21 days). This signals potential stockout risks. Conversely, **Funsnacks Cornflakes** is sustainable, with a 55-day sustainability period exceeding its 20-day lead time, which indicates overstocking and higher holding costs. These findings underscore the importance of precise inventory adjustments to align supply, demand, and cost efficiency.

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