14th Annual International Conference on Industrial Engineering and Operations Management
Dubai, United Arab Emirates (UAE), February 12-14, 2024
Publisher: IEOM Society International, USA DOI: 10.46254/AN14.20240272
Published: February 12, 2024

Integrated Time Series Analysis for Long Term Demand Planning and Capacity Expansion

Ibrahim M.G. Khayat, Mohammed F. Hariri, Mohammed H. Baggazi, Yousef J. Bassyoni and Ammar Y. Alqahtani
Department of Industrial Engineering, Faculty of Engineering, King Abdulaziz University, P.O. Box 80204, Jeddah 21589, Saudi Arabia

Abstract

Within the dynamic landscape of the fast-moving consumer goods (FMCG) industry, a food company encountered challenges associated with fluctuating demand forecasting, resulting in inefficiencies in determining production volumes for various product formats. The paper outlined a comprehensive methodology applied to tackle these challenges, it incorporated the use of exponential smoothing (specifically Holt-Winters' additive with dampening) and autoregressive integrated moving average (ARIMA) models, alongside a combination method to enhance forecast reliability. Forecasting models were evaluated through residual diagnostics and performance metrics such as root mean squared error (RMSE) and mean absolute percentage error (MAPE). The report delved into prediction intervals and scenario-based forecasting, and it provided a holistic perspective on managing forecast uncertainty. To sustain enhanced forecasting, tracking signals were employed to detect persistent bias. In production planning, this paper assessed line utilization based on forecasted data. Results indicate that the combination of ARIMA yielded the best performance with a MAPE of 3.75%. Additionally, over three years, line utilization averaged 94% in normal states, emphasizing the effectiveness of the forecasting methods in production planning. Furthermore, the paper recommends the ongoing use of the ARIMA combination method and emphasizes the incorporation of tracking signals for model validation to enhance accuracy and reliability. Looking ahead, the paper suggests considering an expansion in the five-year plan, aligning production capabilities with forecasted demand to further optimize operational efficiency in the FMCG industry. The proposed model sets the stage for sustained efficiency and strategic growth in the ever-evolving FMCG landscape.

Keywords
Time series analysis, Demand forecasting, Forecast combination, Capacity expansion and Line utilization.

1. Introduction
With a focus on a food company, this article explores the necessity of improved forecasting for FMCG (fast-moving consumer goods) after Covid-19. The study is important because precise forecasting has a significant impact on production planning, which is a tactical requirement for businesses navigating volatile markets. The difficulties the food firm is facing highlight the critical need for an advanced forecasting model, especially in light of demand variations and uncertainty. The articles' goals are to greatly increase prediction accuracy, from choosing the best forecasting model to comparing historical and predicted data. A strategic advantage may be gained in the FMCG market, which is marked by ongoing demand volatility, by efficient forecast and planning. The research's conclusions can completely transform the way the industry plans and allocates resources by providing a comprehensive answer to the problems caused by erratic market dynamics. In addition, the study tackles the pragmatic obstacles encountered by the company, which is observing a surge in chip sales despite contending with manufacturing limitations and recurrent shortages. It is warranted to shift toward an automated R programming language forecasting solution due to the shortcomings of the existing human Excel-based method. The research solves the problems with manual

calculations, data management, and advanced analytics capabilities, which are crucial for enhancing the company's forecasting process's accuracy, efficiency, and scalability. The value of this research ultimately rests in equipping the company with the knowledge and instruments required to determine if a capacity expansion is necessary to satisfy the needs of a constantly shifting and growing consumer landscape.

1.1 Objectives

1. Determine the forecasting model with the least RMSE.
2. Develop a monitoring process for forecasting models.
3. Assess the capacity over the next three years and the need for expansion.

2. Literature Review

In this literature review, an overview of the main topic of this paper is discussed, as well as the relative references. This paper mainly discusses forecasting and the different relative methods and the resulting line utilization of capacity against forecasted demand analysis to assess the need for expansion over the next three years.

Forecasting plays a pivotal role in predicting the future of any event. It may vary from day-to-day activities, such as the weather, to long-term investments of enormous funds on giga projects. The difficulty of forecasting may vary according to four main factors, which are the current understanding of the factors that contribute to the forecast, the size of the data available, the similarity of the future to the past, the dependency of other factors on the forecast (Hyndman and Athanasopoulos 2021). forecasting situations differentiate based on time horizon; this is commonly divided into three main sections: short-range, which is less than three months; medium range, which is up to three years; long-range would be three years or more it is common that the bigger the time horizons, the less accurate your forecast becomes (Armstrong 2001).

Time series data is a collection of observations measured sequentially over time. This section is divided into two crucial tools in the time series analysis. The first tool is time plots, the most straightforward visualization tool for time series data. They visualize data points against time to find trends, seasonal patterns, and abnormalities (Cleveland 1993). Time plots' primary objective is to visually represent data progress across time, making them a critical starting point for time series analysis (Unwin 2015). The second tool is Seasonal and Trend Loess decomposition (STL) According to Cleveland et al. (1990), Decomposition is a robust and widely utilized time series analysis method that provides a structured approach for analyzing the underlying components of time series data, which filters time series data into three elements: trend, seasonality, and remainder. Seasonal components capture recurring patterns or cycles, while the trend component represents long-term changes or trends. The remainder captures irregularities, noise, or residuals.

The following section discusses the different relative forecasting methods. Four essential methods are covered. The first method is The Holt-Winters additive with dampening method, which is an advanced variant of the Holt-Winters exponential smoothing method introduced by Holt-Winters in the 1950s, which is used to anticipate time series data with trends and seasonality. It adds a dampening parameter to the basic Holt-Winters model. This option would decrease the trend line to a flat line, allowing the model to adjust to changes in the data more gradually (Gardner 2006). The second method is ARIMA, which is an effective forecasting technique. It was created in the 1970s and has been shown to be reliable and adaptable for quickly fluctuating forecasts (Brockwell and Davis 2016). ARIMA is made up of three parts: autoregressive (AR) for modeling the linear connection between a variable and its lagged values, integrated (I) for differencing the data to make it stationary, and moving average (MA) for capturing the short-term variability (Hyndman and Khandakar 2008). The third method is the combination of forecast models, which is a concept that indicates by combining multiple forecasts by taking the average of models that are opposite in characteristics from each other, one can obtain a better-fit forecast for the dataset than what a single forecasting model can achieve through years of research on different industries (Bates and Granger 1969). According to Clemen (1989), With the combination of five or more forecasting methods, one can increase the accuracy of the forecast by 3 to 24% under ideal conditions. Lastly, according to Önkal et al. (2013), scenario-based forecasting results from today's volatile market, and in a competition demanding more than ever, an adaptable tool that could look at a problem from different standpoints is needed. Scenario-based forecasting equips organizations with tools capable of assessing the impact of various factors on their future operations. By evaluating multiple scenarios, firms can better prepare for uncertainty while mitigating associated risks.

The following equations are used:

a. Holt-Winters additive with dampening

$$D(t) = \phi * (Y(t) - L(t) - S(t-m)) + (1 - \phi) * D(t-m)$$

b. Seasonal autoregressive integrated moving average (SARIMA)

$$SARIMA(p, d, q)(P, D, Q)s$$

Where,

"D(t)" represents the dampening component at time period t.
"ϕ" (phi) is the smoothing parameter for the dampening component.
'Y(t)" represents the actual value at time period t.
"L(t)" denotes the level component at time period t.
"S(t-m)" represents the seasonal component at the corresponding season in the previous year.
"D(t-m)" represents the dampening component at the corresponding season in the previous year.
"p" is the autoregressive order.
"d" is the degree of differencing.
"q" is the moving average order.
"P" is the seasonal autoregressive order.
"D" is the seasonal differencing degree.
"Q" is the seasonal moving average order.
"s" is the length of the season.

The next section covers forecasting accuracy, the model predicting reliability, and monitoring tools, which are essential to ensuring a successful forecast. First, forecasting accuracy is measured by how well a model's predictions match the observed values. Several statistical metrics, such as mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and others, are often employed for this purpose (Armstrong 1985). The choice of error metric depends on the forecasting activity's unique context and the data's nature (Hyndman and Koehler 2006). Second, autocorrelation (correlogram) in time series analysis measures the degree of linear dependence between lagged values of a time series. The concept is essential for recognizing and measuring the correlation in data, which is required to ensure the model predicting reliability. Third, According to Heizer et al. (2016), The concept of a tracking signal has been established as a key performance indicator. A tracking signal assesses the quality of forecasts over time. Positive or negative tracking signals indicate that forecasts consistently overestimate or underestimate actual values, which is visualized using a control chart that shows whether this forecasting model is still valid or not.

The following equations are used:

c. Forecast error

$$e_{T+h} = y_{T+h} - \hat{y}_{T+h|T'}$$

d. Root mean squared error

$$RMSE = \sqrt{mean(e_t^{2})}$$

e. Mean absolute percentage error

$$MAPE = mean\left(\left|\frac{100e_t}{y_t}\right|\right)$$

f. Correlogram

$$r_k = \frac{\sum_{t=k+1}^{T}(y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^{T}(y_t - \bar{y})^2}$$

g. Tracking signal

$$TS = \frac{CFE}{MAD}$$

Where,

"T" represents the current time.
"h" is a specified time horizon or forecast horizon.
"T'" represents the information set available up to time T'.
"e_t" is the errors at time t, representing the differences between the predicted and observed values.
"y_{t+h}" is a specified time horizon or forecast horizon T + h.
"$\hat{y}_{(T+h|T')}$" is the predicted (or estimated) value at time T + h given information up to time T'.
"y_t" is the value of the time series at time t.

"k" is the lag, representing the number of time periods between the observations.
"r_k" is the autocorrelation coefficient at lag k.
"$\bar{y}$" is the mean of the time series values.
"CFE" is employed to signify the cumulative forecast error.
"MAD" serves as the representation of the mean absolute deviation.

Utilization refers to the degree or extent to which something is used or employed effectively. In various contexts, utilization can refer to efficiently deploying resources, such as equipment and workforce, to achieve optimal results. Investigations of aligning line utilization with forecasted demand help in projecting expansion needs and optimizing resources (Goldratt and Cox 1984).

Utilization equation:

$$\boldsymbol{U = \frac{Rn}{On}}$$

Where,
"U" is designated as the variable representing line utilization.
"Rn" is employed to signify the forecasted production output for the nth month.
"On" serves as the representation of the actual production output per nth month.

In this rich literature review, various topics were covered, which revolved around forecasting to solve demand planning. It includes forecasting basic concepts to plots and complex methods of predictive models, how forecasting results can be evaluated using different metrics, and monitoring the whole process. Moving to the idea behind utilization and efficient deployment of resources and how it can contribute to the expansion decision.

3. Methods

The forecasting methodology begins with cleansing of historical data. Then, exploratory data analysis is initiated to recognize patterns and trends, guaranteeing a full understanding of the data landscape. The choice of forecasting models balances quantitative accuracy with qualitative insights and is closely linked to business requirements. By applying measures like RMSE and MAPE, these models are put through an exhaustive training and assessment process that eventually identifies the most accurate model for prediction development. By including tracking signals, iterative refinement, and stakeholder feedback, the technique fosters an approach that is both flexible and responsive while embracing continuous improvement. Continuous observation reinforces the methodology's adaptability even further. This all-encompassing framework combines qualitative with quantitative precision to produce an extensive forecasting technique. Specifically, scenario-based forecasting makes forecasts more flexible to accommodate a wider range of future conditions. The forecasting workflow diagram shown in Figure 1 consists of seven steps:

1. Data Preparation (Tidy): Import historical chip sales data into R using the tsibble package, handling missing numbers and outliers. Divide the dataset into training and test sets for model evaluation.
2. Plot The Data (Visualize): Plot time series data and produce seasonal graphs with gg_season() to analyze patterns, trends, and seasonality. Use the seasonal and trend decomposition Loess (STL) technique for data decomposition.
3. Define A Model (Specify): Comprehend data via visualization and describe forecasting models such as Exponential Smoothing (Holt-Winters' additive with dampening), and ARIMA. Consider unit root testing and differentiating for non-stationary time series.
4. Train The Model (Estimate): Train models in R using the model() function to fine-tune coefficients and parameters for accurate predictions and investigate model combinations for increased accuracy.
5. Check Model Performance (Evaluate): Use residual diagnostics, uncorrelated residuals, zero mean residuals, histogram plots, and metrics like RMSE and MAPE to select the most accurate model.
6. Produce Forecasts (Forecast): Forecast chip sales using trained models and the forecast() function. To accommodate for uncertainty, include scenario-based forecasting, creating scenarios based on prediction intervals.
7. Continuous Improvement (Monitor): Plot new data onto a tracking signal chart and investigate the need to change the model when it's out of control.

Lastly, the approach extends to capacity assessment, as shown in Figure 1, comprising a full study of the manufacturing process. This comprises calculating overall production, thoroughly analyzing line usage, and calculating the yearly growth rate. This broader approach enables a thorough evaluation of capacity-related issues, allowing for a comprehensive knowledge of production efficiency, growth dynamics, and overall operating capacities.

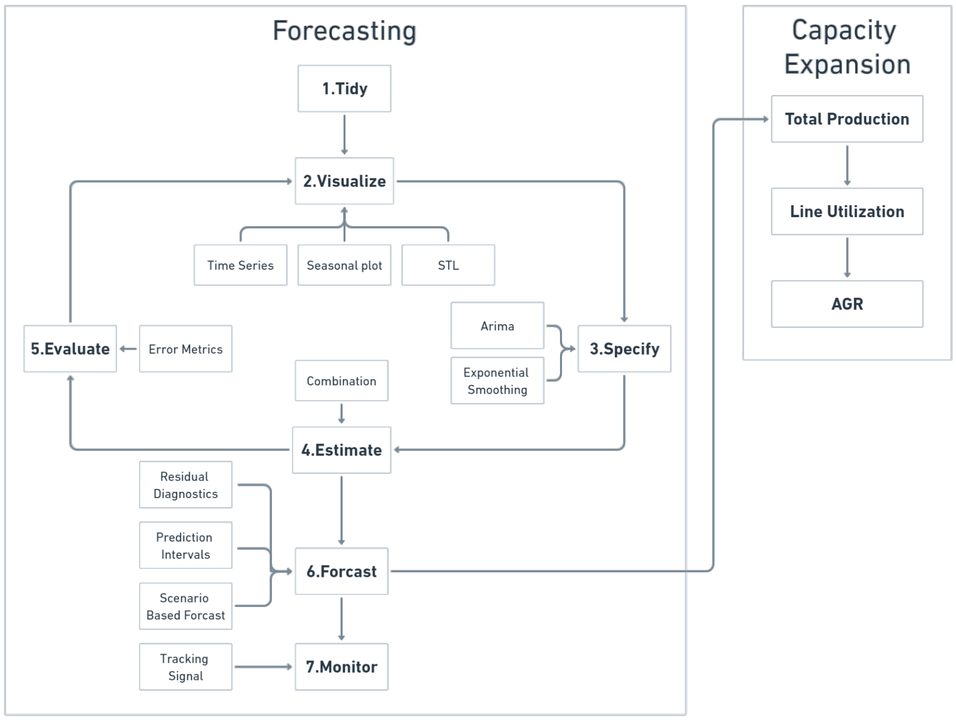

Figure 1. Workflow diagram

4. Data Collection

The data was collected from two departments, supply chain and production planning. The head of the supply chain provided sales data for the past four years as shown in Table 1. The data pertains to the packs of chips' product line, and it represents aggregated sales figures for all colors and formats. Additionally, it is important to note that each pack of chips contains 24 bags. This data set included essential information on demand patterns and fluctuations, facilitating a deep analysis of demand forecasting challenges.

Table 1. Chips sales over four years in number of packs sold

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
2019	1296	1112	1129	979	752	676	748	998	1299	1727	1992	1999	14708
2020	1700	1518	1508	1208	1157	915	1284	1494	1773	2135	2201	2195	19088
2021	1662	1305	1389	1164	908	1116	1471	1527	1771	1952	2005	2144	18413
2022	1837	1655	1692	1387	1351	1521	1694	1667	2034	2255	2342	2502	21938

Complementing this contribution, the head of production planning furnished Table 2 and Table 3, which are essential data on the production side of the operation. Specifically, information was provided on the number of packs produced per hour for each product format and color, and this was detailed for three distinct formats. Additionally, data was supplied for five different color types, allowing for the creation of various product combinations, totaling five unique products within each format.

Table 2. Percentage distribution of colors across different formats

Color	Format 1	Format 2	Format 3
C1	30%	24.07%	25%
C2	39%	22.45%	35%
C3	16%	21.73%	35%
C4	16%	21.73%	20%
C5	11%	15.61%	16%

Table 3. Percentage distribution of formats with corresponding output in packs per hour

Measurement	Format 1	Format 2	Format 3
Format Mix	43%	13%	44%
Packs/Hour	7	6	8

Additional data, encompassing information related to working days, maintenance days, holidays, and other significant occurrences, was acquired. This dataset added a crucial temporal dimension to the analysis, enabling the project to consider the impact of these events on line utilization, as seen in Table 4.

Table 4. Monthly breakdown of production days with total hours and output

Month	# of Days	Fridays & Holidays (Days)	Maintenance Days	Other Off Days	Total Working Days	Production Time (Hours/Month)	Output (Packs/Month)
Jan	31	8	4	-	19	456	3337
Feb	28	8	5	0.1	15	358	2617
Mar	31	8	5	0.0	18	432	3161
Apr	30	10	5	0.1	15	358	2617
May	31	13	5	0.0	13	312	2283
Jun	30	8	5	0.1	17	406	2968
Jul	31	14	5	0.0	12	288	2107
Aug	31	8	5	0.1	18	430	3143
Sep	30	10	5	0.0	15	360	2634
Oct	31	8	5	0.1	18	430	3143
Nov	30	8	4	0.0	18	432	3161
Dec	31	9	5	0.1	17	406	2968
Total	365	112	58	1	194	4666	34138

With this dataset in hand, the subsequent steps of data analysis and forecasting could be undertaken, aiming to address the challenges of demand fluctuation and enhance the accuracy of forecasts.

5. Results and Discussion

5.1 Data Preparation (Tidy)

The data was transformed into a tsibble object in R to make time series analysis easier. The data was then split into two separate sets: the test data and the training data. The training dataset known as "Chips_train" which is used for training the models, comprised 80% of the original data spanning three years of historical chip sales data, from January 2019 to February 2022. The test dataset, called "Chips_Test" comprised 20% of the data from March 2022 to December 2022, which, for validation purposes, represented the next year.

5.2 Plot the Data (Visualize)

Figure 2's STL decomposition separates observations into components related to trend, seasonality, and remainder. Positive market dynamics are suggested by the trend graph, which shows an overall increase in sales from 2019 to 2022. The season_year component shows a yearly pattern that is repeated. Unexpected events or outliers that are not captured by trend or seasonality are represented by the remaining component.

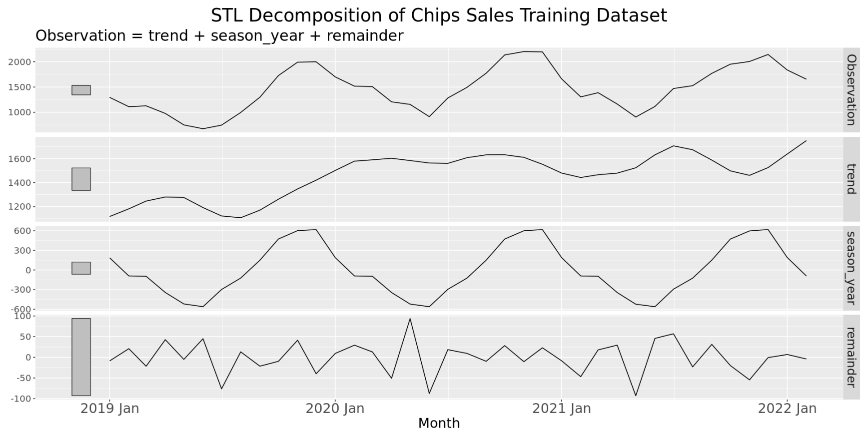

Figure 2. STL decomposition of chips monthly sales

Figure 3 demonstrates how a periodic pattern is consistently displayed by each year. A reasonable number of sales at the beginning of the year provides a basis for analyzing post-holiday customer behavior. The year 2022 is noteworthy because it represents a major divergence from earlier years. Early in 2022, sales were much higher than in the same months the previous year. This might indicate a change in consumer behavior.

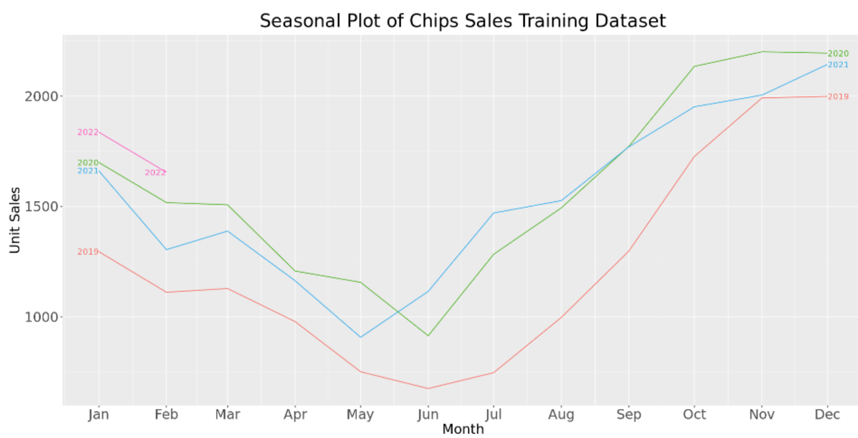

Figure 3. Seasonal plot of chips monthly sales

5.3 Define a Model (Specify) and Train the Model (Estimate)

5.3.1 Holt-Winters' Exponential Smoothing and ARIMA

Since the seasonal variations are constant throughout the time series, Holt-winters' additive dampening model was used as shown in Figure 4. The estimated smoothing parameters are α, β, γ, ϕ and the values are 0.9941133, 0.0001002238, 0.0001004395 and 0.9799788 respectively. Additionally, an ARIMA model was made by automatically generating it with the R language using the code auto = ARIMA(Observation, stepwise = FALSE, approx = FALSE). The parameters are ARIMA(0,1,0)(1,1,0). The model is shown in Figure 4.

5.3.2 Combination of Models

Table 5 shows the model used for the combination. The models were generated through the best guess approach method and using the MAPE as an indicator. Figure 5 shows how each model looks like before combining them. Figure 5 shows the combination of the six models.

Table 5. Models used for the combination

Model	(p,d,q)	(P,D,Q)
CARIMA1	(0,1,3)	(1,0,0)
CARIMA2	(0,1,2)	(1,0,0)
CARIMA3	(0,1,0)	(1,1,0)
CARIMA4	(1,1,3)	(1,1,0)
CARIMA5	(0,1,1)	(1,1,0)
CARIMA6	(0,1,1)	(0,1,0)

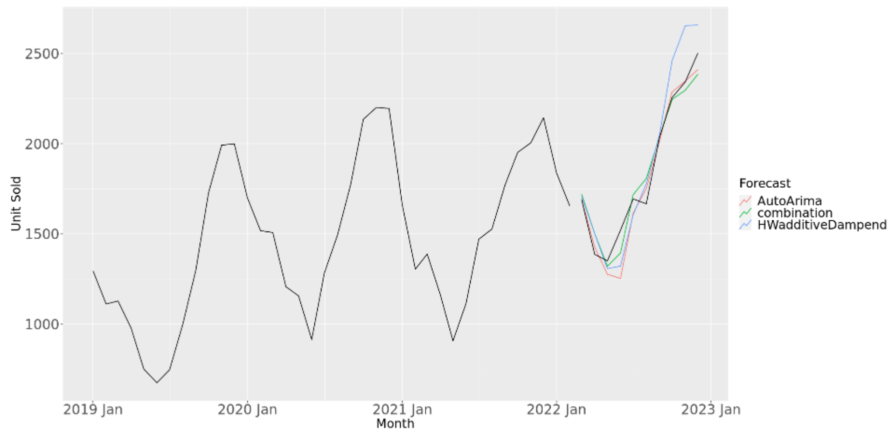

Figure 4. Forecasting models for monthly chips sales

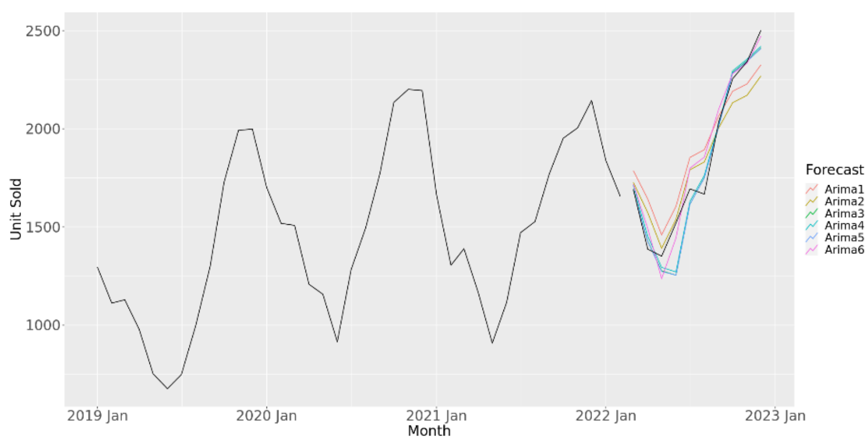

Figure 5. ARIMA models before the combination

5.4 Check Model Performance (Evaluate)

Table 6 shows the errors for the forecasting models in ascending order of the RMSE. The most accurate standalone method was the combination.

Table 6. Comparison of errors

Model	RMSE	MAPE
Combination	81.93	3.75%
Auto ARIMA	100.71	4.20%
Holt-Winters' Additive Dampened	123.73	5.55%

5.5 Produce Forecasts (Forecast)

The chip sales forecast is shown in Figure 6, along with a combined prediction for the next three years, ending in January 2026. Two confidence intervals, 80%, and 95%, provide a range in which actual future sales are likely to fall with their corresponding probability.

5.5.1 Scenario-Based Forecasting

The central forecast is the bold line that shows the most likely course. As the median prediction, this line provides a realistic picture of predicted sales without straying too close to the extreme. Based on the core forecast, an estimated increase of 24.91% is predicted by the end of 2025. The worst-case scenario (lower 80% confidence interval) is represented by the border that delineates the bottom of the lighter-tinted zone. If the lower limit is followed from the same starting point in 2022 and an endpoint in 2025, an approximate decline of 35.47% is forecasted for this scenario. best-case scenario (upper 80% confidence interval), on the other hand, the top edge of the faintly tinted area represents the ideal situation. This forecast suggests an extremely optimistic forecast, an increase of almost 65.18% from 2022 to 2025.

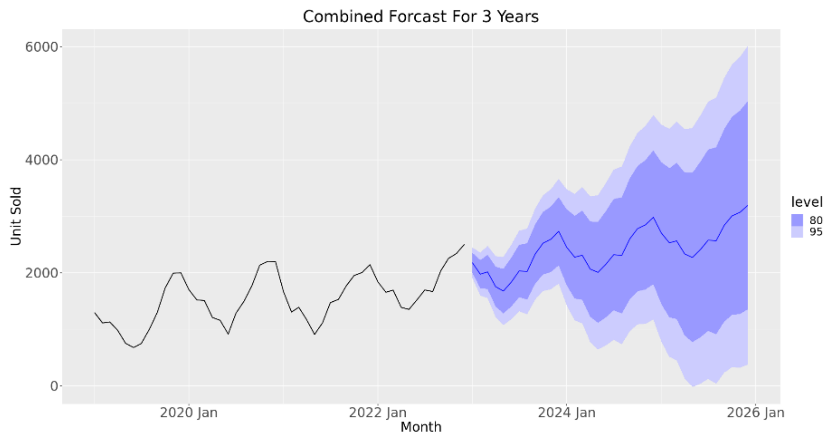

Figure 6. Combined forecast for three years

5.6 Continuous Improvement (Monitor)

Tracking signal is a crucial measure for evaluating the accuracy of forecasting models. It indicates whether there is any persistent bias in the forecasting process. The tracking signal is based on the provided data for the year 2022. The tracking signal (TS) is calculated by dividing the cumulative sum of errors (CSE) by the mean absolute deviation (MAD). A tracking signal close to zero suggests accurate forecasting, while a significant deviation may indicate a systematic error in forecasting. Figure 7 shows the tracking signal control chart for the year 2022. The control limits for the tracking signal have been calculated, with the lower control limit (LCL) at -3.75 and the upper control limit (UCL) at 3.75. The blue line is within the control limits, so the forecast is in control.

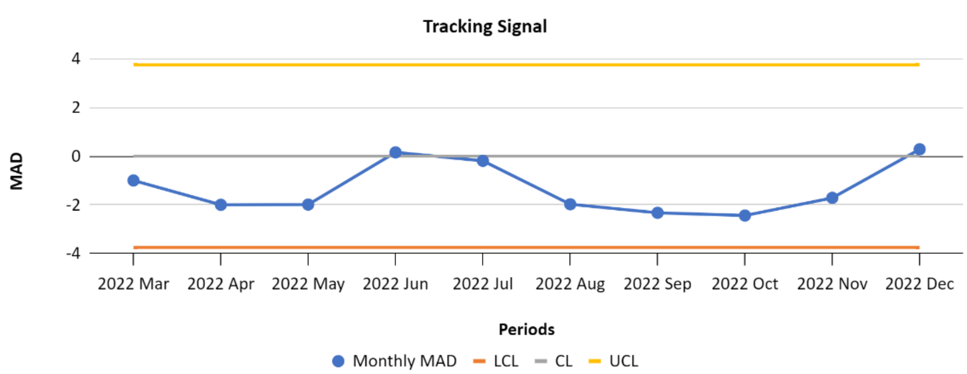

Figure 7. Tracking signal control chart

5.7 Capacity Expansion: Line Utilization and Annual Growth Rate (AGR)
The overall annual demand for the years 2023, 2024, and 2025 doesn't exceed the annual production rate, as shown in Table 7. The annual utilization rate for these years stands below 100%, reflecting the capacity of the production facility to meet the forecasted demand efficiently.

Table 7. Utilization and growth summary for the normal scenario

Year	Forecasted Demand	Capacity	Utilization	Growth Rate
2023	25,667	34138	75%	13%
2024	29,102	34138	85%	10%
2025	32,061	34138	94%	24%

5.8 Proposed Improvements
The team recommends using the proposed method, a combination of ARIMA that enhances accuracy by merging various model forecasts, resulting in minimizing errors to achieve 3.75%. In addition, use scenario-based forecasts due to the nature of long-term predictions. By evaluating multiple scenarios, firms can better prepare for uncertainty while mitigating associated risks. Furthermore, monitor the forecasting process monthly using the provided tracking signal as the base to confirm the model's validity. Optimize the production plan, which involves aligning forecasted demand with line utilization and determining ideal production volumes and schedules for different product formats. Consider an expansion in the five-year plan due to positive growth in demand while having 94% utilization in the normal state, which would result in a bottleneck in production after three years.

5.9 Validation
The forecast residuals' three-year correlogram plot shown in Figure 8 primarily stays inside the confidence intervals, proving that there is no discernible autocorrelation in the residuals, which indicates that the model has mostly caught the underlying structures in the data, indicating its predicting reliability. The distribution of the total forecast residuals over three years is shown by the histogram in Figure 8. The concentration of residuals close to zero highlights the model's overall dependability. The validity of the prediction intervals obtained from the model is further supported by this normal distribution.

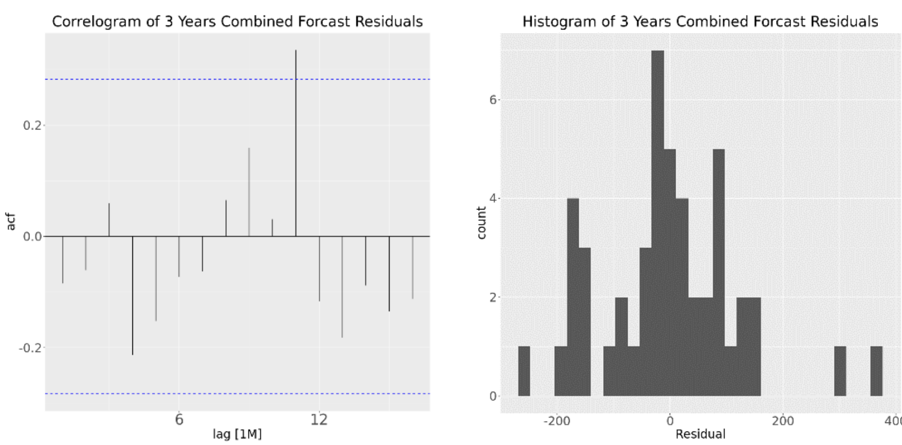

Figure 8. Residual diagnostics

6. Conclusion
In conclusion, this paper worked toward enhancing the forecasting processes for FMCG after Covid-19, improving demand planning, a crucial pillar of the operation department of any firm in today's competitive market, and the advantages that can be obtained from having a good demand plan are enormous. A tidy forecasting workflow methodology was implemented to address the current state and produce a better forecasting process. Several different forecasting methods were evaluated. Accordingly, the method that got the most accurate forecast is the combination ARIMA, and it was a better fit for the data in both MAPE and RMSE. Moreover, the tracking signal with ±3.75 MAD

control limits showed that the forecast is in process. Furthermore, looking at utilization, we can see the annual utilization for the standard scenario is less than a hundred, with 94% as the highest value in the last year. The project objective was achieved, including determining the best forecasting model and developing a monitoring process for forecasting through tracking signals, assessing the capacity over the next three years, and determining the need for expansion through utilization.

References

Armstrong, J., *Principles of Forecasting: A Handbook for Researchers and Practitioners*, 1st Edition, Springer, 2001.

Armstrong, J., *Long-Range Forecasting: From Crystal Ball to Computer*, 2nd Edition, Wiley, 1985.

Bates, J. M., and Granger, C. W., "The Combination of Forecasts.", *OR*, vol. 20, no. 4, p. 451, 1969, doi:10.2307/3008764.

Brockwell, P. and Davis, R., *Introduction to Time Series and Forecasting*, 3rd Edition, Springer International Publishing, 2016.

Clemen, R., "Combining Forecasts: A Review and Annotated Bibliography.", *International Journal of Forecasting*, vol. 5, no. 4, pp. 559–583, 1989, doi:10.1016/0169-2070(89)90012-5.

Cleveland, W., *Visualizing Data*, 1st Edition, At&T Bell Laboratories, 1993.

Cleveland, R., Cleveland, W., McRae, J. and Terpenning, I., "STL: A Seasonal-Trend Decomposition Procedure Based on Loess.", *Journal of Official Statistics*, vol. 6, no. 1, pp. 3–33, 1990. http://bit.ly/stl1990

Gardner, E., "Exponential Smoothing: The State of the Art—Part II.", *International Journal of Forecasting*, vol. 22, no. 4, pp. 637–666, 2006, doi:10.1016/j.ijforecast.2006.03.005.

Goldratt, E. and Cox, J., *The Goal: A Process of Ongoing Improvement*, 30th Edition, North River Press, 2014.

Heizer, J., Render, B. and Munson, C., *Operations Management: Sustainability and Supply Chain Management*, 14th Edition, Pearson, 2022.

Hyndman, R. and Athanasopoulos G., *Forecasting: Principles and Practice*, 3rd Edition, OTexts, 2021.

Hyndman, R. and Khandakar, Y., "Automatic Time Series Forecasting: The Forecast Package for R.", *Journal of Statistical Software*, vol. 27, no. 3, pp. 1-22, 2008, doi:10.18637/jss.v027.i03.

Hyndman, R. and Koehler, A., "Another Look at Measures of Forecast Accuracy.", *International Journal of Forecasting*, vol. 22, no. 4, pp. 679–688, 2006, doi:10.1016/j.ijforecast.2006.03.001.

Önkal, D., Sayım, K. and Gönül, M., "Scenarios as Channels of Forecast Advice.", *Technological Forecasting and Social Change*, vol. 80, no. 4, pp. 772–788, 2013, doi:10.1016/j.techfore.2012.08.015.

Unwin, A., *Graphical Data Analysis with R*, 1st Edition, Taylor & Francis, 2015.

Biographies

Ammar Y. Alqahtani, PhD, is an associate professor of Industrial Engineering at King Abdulaziz University in Jeddah, Saudi Arabia. He received his BS degree with first honors from the Industrial Engineering Department of King Abdulaziz University, Jeddah, Saudi Arabia, in May 2008. Being awarded with a full scholarship by the King Abdulaziz University (KAU), he received his MS degree in Industrial Engineering from Cullen College of Engineering, University of Houston. In September 2012, he started his PhD studies in Industrial Engineering at Proceedings of the 8th North American International Conference on Industrial Engineering and Operations Management, Houston, Texas, USA, June 13-16, 2023 © IEOM Society International Northeastern University, Boston, Massachusetts. He received his PhD degree in 2017. He has been employed as a faculty member by King Abdulaziz University since December 2008. His research interests are in the areas of environmentally conscious manufacturing, product recovery, reverse logistics, closed-loop supply chains (CLSC), sustainable operations and sustainability, simulation and statistical analysis and modeling with applications in CLSC and multiple life-cycle products. He has published two books, titled Warranty and Preventive Maintenance for Remanufactured Products Modeling & Analysis and Responsible Manufacturing Issues Pertaining to Sustainability. He has coauthored several technical papers published in edited books, journals and international conference proceedings. At Northeastern University, he won the Alfred J. Ferretti research award. He also received the 33rd Quality.

Ibrahim M.G. Khayat, a native of Saudi Arabia, is a driven and accomplished individual making waves in the field of Industrial Engineering. Currently a senior student at King Abdulaziz University. He has demonstrated a keen interest and aptitude for leveraging data to drive insights and decision-making. His academic journey is marked by notable achievements, including completing a Business Analytics Nanodegree from Udacity in 2022 and following it up with a Data Analytics Nanodegree, showcasing his commitment to staying at the forefront of technological advancements. His dedication to excellence was recognized when he emerged as the 1st winner at the Simio competition in May 2023, a testament to his proficiency and skill in the field of industrial simulation. Beyond the academic realm, his true passion lies in the realm of business analytics. His enthusiasm for dissecting data to extract meaningful insights reflects a natural curiosity and a strategic mindset. This passion has not only guided his academic pursuits but has also set the stage for a promising future in the dynamic world of data-driven decision-making.

Mohammed F. Hariri, a results-driven senior Industrial Engineering student, embraces dedication and continual learning. He showcased a strong passion and proficiency in utilizing data to derive insights. Complementing his education, he completed a Nanodegree in Business Analytics through Udacity & Misk Academy, mastering various data-focused software tools. He won the Simio competition in May 2023 in the field of industrial simulation, surpassing 125 global teams. This feat is a testament to his exceptional abilities and dedication. His genuine enthusiasm lies in entrepreneurship through exploring new possibilities and finding innovative ways to bring ideas to life. His curiosity fuels a desire to create impactful solutions within business and technology. This vision propels him towards a future where he envisions pioneering ventures, leveraging his industrial engineering and business analytics expertise. He seeks to revolutionize industries through creativity and forward-thinking strategies, driven by a passion for transformative innovation.

Mohammed H. Baggazi, A highly motivated and talented man, a senior industrial engineering student at King Abdulaziz University is making tremendous progress in the sector. He has continuously shown a keen interest in and a remarkable ability to learn new skills and apply them to the use of cutting-edge software to solve problems effectively. He has achieved a noteworthy feat during his academic career that demonstrates his devotion to being on the cutting edge of technical breakthroughs. He won first place in the renowned Simio competition in May 2023, demonstrating his constant devotion and skill in the field of industrial simulation. This outstanding accomplishment is evidence of his extraordinary skills and knowledge in the field of industrial simulation. His outstanding performance establishes him as a key player on the field in addition to showcasing his technical skill. He is in a position to have a big influence on the constantly changing field of industrial engineering. His capacity for technological adaptation and effective application makes him an invaluable tool for promoting well-informed decision-making. He is expected to make a lasting impact on the area and push new technologies across several industries as he keeps moving forward.

Yousef J. Bassyoni, born on February 9th, 1998, in Jeddah, Saudi Arabia, is a senior Industrial Engineering student at King Abdulaziz University, Saudi Arabia, embodying a relentless pursuit of academic excellence and innovation. With a consistent track record of scholarly achievement in Industrial Engineering principles, Yousef actively participates in team sports competitions like padel and volleyball, fostering teamwork and camaraderie among peers. A natural leader, he heads the Team Sports Association and holds an executive role in the Industrial Engineering Club, fostering unity and academic enrichment. Alongside his academic endeavors, Yousef lead "Ma'wana," a pioneering simulated real estate platform, challenging industry norms through innovation. Drawing from global experiences studying abroad in Canada and Australia, Yousef brings a unique perspective to tackle complex industrial challenges, driven by a vision to take part the consulting industry. His journey as a senior Industrial Engineering student reflects academic prowess, leadership, entrepreneurial spirit, and a global mindset, poised to redefine the future of industrial engineering.