IŞIK UNIVERSITY

Faculty of Engineering

Department of Industrial Engineering

"Forecasting Methods in Supply Chain"

Project Report

INDE4313.1

Supply chain management

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1) Introduction:

In today's highly competitive and fast-paced global economy, effective decision-making in the supply chain is critical for companies to maintain profitability and efficiency. A well-functioning supply chain ensures that the right products are available at the right time and place, minimizing costs while meeting customer demand. One of the key challenges in managing a supply chain is demand forecasting, which helps predict future product demand and enables businesses to plan and manage their resources effectively.

Forecasting plays an essential role in the supply chain by providing valuable insights that inform production, inventory management, and distribution strategies. By leveraging various forecasting methods, businesses can reduce the risks associated with stockouts, excess inventory, and missed sales opportunities. Effective forecasting models allow companies to optimize their supply chain operations, ensuring a balance between supply and demand.

This report focuses on the application of forecasting methods in the supply chain, specifically applying these techniques to Nissan car sales data. The analysis uses historical sales data to explore forecasting models such as moving averages, exponential smoothing, and trend analysis. By doing so, the report highlights the importance of accurate sales forecasting for optimizing production schedules, managing inventory, and improving logistics operations in the automotive industry.

Through this analysis, the report aims to provide a comprehensive understanding of how forecasting methods can be applied to supply chain management, with a focus on Nissan's sales data and the resulting benefits for operational performance.

2) Data Collection:

For this project, the primary data used consists of global Nissan car sales from 1995 to 2025. This dataset provides the total number of Nissan vehicles sold worldwide each year, offering valuable insights into the trends, fluctuations, and overall performance of Nissan in the global market over a period of 31 years.

Data Format

The dataset is organized in a straightforward tabular format, with the following columns:

- **Year:** Represents the year corresponding to the sales data.
- **Nissan_Global_Sales:** Denotes the total number of cars sold globally by Nissan in that specific year.

The dataset spans from 1995 to 2025, offering a comprehensive view of Nissan's sales performance on a global scale.

Data Sources

The data was collected from reliable and reputable sources, including:

- **Official Nissan Sales Reports:** The primary source of the data is Nissan's investor **relations website**, which publishes comprehensive annual reports on global car sales.
- **Third-Party Industry Websites:** Additional data was sourced from Best Selling Cars Blog and Good Car Bad Car, both of which aggregate and publish global sales data for major automotive manufacturers, including Nissan.

These sources were chosen to ensure accuracy, transparency, and credibility in the dataset.

Sources

- https://www.best-selling-cars.com/brands/2024-full-year-global-nissan-worldwide-car-sales-by-region-and-model/
- 2024 Full Year Global: Nissan Worldwide Car Sales by Region and Model

Data Preparation and Preprocessing

To prepare the data for forecasting and analysis, the following steps were taken:

- **Aggregation:** The data provided was already aggregated on an annual basis, making it suitable for time-series forecasting models.
- **Data Cleaning:** The dataset did not contain any missing values, so no imputation or further cleaning was required.
- **Standardization:** The data was consistent across all years, and no further normalization steps were necessary.

Assumptions and Limitations

- **Market Stability Assumption:** The analysis assumes that the market conditions for Nissan have remained relatively stable, with no significant global disruptions (such as economic crises or pandemics) that drastically impacted sales. While factors such as the COVID-19 pandemic may have affected sales in some years, these external influences were not specifically incorporated into the dataset.
- **Global Data:** This dataset provides global sales figures, but it does not break down sales by specific regions or car models. Having access to regional or model-specific data would allow for deeper analysis and more targeted insights.
- **Revenue Data:** While sales figures are available, detailed revenue information for each year was not included in the dataset. However, the total sales figures serve as a strong basis for forecasting.

Benefits for Supply Chain and Forecasting

The global Nissan car sales data plays a crucial role in forecasting future demand and supporting supply chain management. By analysing historical sales trends, this dataset can provide significant benefits in the following areas:

1. **Demand Forecasting:** Using forecasting models such as moving averages and exponential smoothing, we can predict future sales trends. This helps in anticipating demand and making informed decisions regarding production schedules and inventory management.
2. **Production Planning and Inventory Management:** Accurate sales forecasts allow Nissan to align its production capacity with expected demand, reducing the risk of overproduction (leading to excess inventory) or underproduction (leading to stockouts). This enhances operational efficiency and cost management.

3. **Market Insights and Strategy Adjustments:** The dataset reveals long-term trends in global sales, providing insight into market dynamics, consumer behavior, and regional variations. These insights can inform strategic decisions, such as entering new markets or adjusting product offerings to align with shifting demand patterns.

3) Methodology

The methodology of this study focuses on the application of time series forecasting techniques to analyze and predict Nissan's global vehicle sales. The ultimate goal is to understand how forecasting can enhance supply chain decision-making. This section outlines the systematic approach taken to prepare the data, apply forecasting methods, and assess their effectiveness within the context of supply chain operations.

3.1 Research Design

This project adopts a quantitative, data-driven research approach centered on historical sales data. By analyzing past trends, we aim to construct a forecast model that can project future demand, supporting inventory, production, and logistics decisions across the supply chain.

3.2 Data Source and Scope

The dataset consists of annual global sales data for Nissan vehicles from 1995 to 2025. Data was collected from publicly available and reputable sources such as Nissan's investor relations reports and independent automotive industry websites. The data includes two key variables:

- Year (1995–2025)
- Nissan_Global_Sales: Total number of units sold globally per year

This time series format is suitable for trend-based and smoothing forecasting models.

3.3 Forecasting Techniques Used

To evaluate the effectiveness of basic forecasting methods in supply chain applications, the following model was applied:

- Naïve Forecasting Method: This method assumes that the forecast for the upcoming period will be the same as the last observed value. It serves as a simple but powerful baseline model.

which allows us to establish a benchmark for forecasting accuracy without introducing model complexity. The choice of the naïve method was intentional due to its simplicity and interpretability,

- Winter's Forecast Methods: This method incorporates level, trend, and seasonality components to generate more accurate forecasts for time series data. Specifically, the multiplicative version is suitable when seasonal effects vary proportionally with the series level. Winters' method offers a more advanced approach compared to simpler models, enabling improved forecasting accuracy in data exhibiting clear seasonal and trend patterns. The choice of this method was deliberate to capture the complex dynamics in vehicle sales data while maintaining a structured and interpretable model framework.

3.4 Forecast Horizon

The model was used to forecast annual sales from 1996 through 2025, using the actual data from 1995 to 2024 as input. This created a rolling forecast, where each prediction is based on the immediately preceding year.

3.5 Performance Evaluation Metrics

To assess the accuracy and reliability of the forecasts, three standard error metrics were calculated:

- Mean Absolute Error (MAE): Measures the average magnitude of forecast errors in the same unit as the data (number of vehicles).
- Mean Squared Error (MSE): Emphasizes larger errors by squaring the differences.
- Mean Percentage Error (MPE): Indicates average forecast error as a percentage of actual sales, allowing scale-independent evaluation.

These metrics provide insight into how well the model captures sales trends and where it may fall short.

3.6 Tools and Software

All data analysis and visualization were conducted using Microsoft Excel, which provided sufficient functionality for time series plotting, applying moving averages, and calculating error metrics.

3.7 Integration with Supply Chain Analysis

The forecasts generated from the above methods were integrated with supply chain planning scenarios. Each stage of Nissan's supply chain, supplier sourcing, raw material procurement, manufacturing, assembly, distribution, dealership, marketing, and after-sales service, was evaluated considering the forecast results. This integration enabled us to explore how Predictive analytics informs critical operational decisions, from production schedules to reverse logistics.

4) Literature Review

- Supply chain forecasting Collaborative forecasting supports supply chain management

Authors: Marilyn M. Helms Dalton State College, Dalton, Georgia, USA Lawrence P. Ettkin University of Tennessee

This study investigates the role of collaborative forecasting in improving supply chain performance by fostering information sharing between partners. The authors emphasize that integrating customer input and supplier data into forecasting processes enhances demand accuracy, reduces inventory levels, and improves responsiveness. Real-world insights from Brach and Brock Confections illustrate how collaborative forecasting aligns production with market needs, lowers costs, and strengthens supplier–retailer relationships.

- Demand forecasting in supply chains: a review of aggregation and hierarchical approaches

Authors M. Zied Babai, John E. Boylan & Bahman Rostami-Tabar To cite this article

This paper reviews aggregation and hierarchical forecasting methods in supply chains, highlighting their impact on forecast accuracy and decision-making across multiple levels. The authors compare top-down, bottom-up, and middle-out approaches, discussing their suitability for different supply chain structures and data availability. Emphasis is placed on how aggregating demand across products, regions, or time horizons can reduce forecast error and improve planning efficiency. The review also addresses recent advances in cross-sectional and temporal hierarchies, offering guidance on model selection and implementation.

- Review and analysis of artificial intelligence methods for demand forecasting in supply chain management

Authors: Mario Angos Mediavillaa *, Fabian Dietricha,b, Daniel Palma,c a Reutlingen University, Alteburgstr

This study reviews the application of artificial intelligence (AI) techniques—such as machine learning, neural networks, and deep learning—in demand forecasting for supply chain management. The authors analyze how AI models outperform traditional forecasting methods by capturing complex nonlinear patterns and improving predictive accuracy. The paper categorizes AI approaches based on data type, forecast horizon, and supply chain tier, and highlights challenges such as data quality, model interpretability, and implementation complexity. The review concludes that AI holds significant potential for enhancing forecast precision and supporting real-time supply chain decision-making.

- The Effect of Collaborative Forecasting on Supply Chain Performance

Authors: Yossi Aviv Olin School of Business, Washington University, St. Louis, Missouri 63130

This paper examines how collaborative forecasting between supply chain partners impacts overall supply chain performance, particularly in terms of inventory levels, service rates, and cost efficiency. The author presents analytical models showing that information sharing and coordinated forecasting decisions lead to reduced demand uncertainty and improved alignment between supply and demand. The study highlights the strategic value of collaboration, especially in environments with volatile or uncertain demand, and offers guidelines for designing incentive-compatible forecasting systems.

- The Impact of Supply Chain Performance on Cost Reduction Case Study: Nissan Motors Egypt

Authors: Aya ELGarhy Collage of International Transport and Logistics, Arab Academy for Science, Technology and Maritime Transport (AASTMT), Cairo, Egypt

This case study investigates how enhancing supply chain performance can lead to significant cost reductions at Nissan Motors Egypt. The author examines key supply chain dimensions such as procurement efficiency, supplier relationships, inventory management, and logistics coordination. Findings indicate that optimizing these areas through performance monitoring and process integration leads to reduced lead times, lower inventory costs, and improved overall operational efficiency. The study highlights the strategic importance of supply chain excellence in achieving cost competitiveness in the automotive sector.

5) Data and variables

Descriptive statistics:

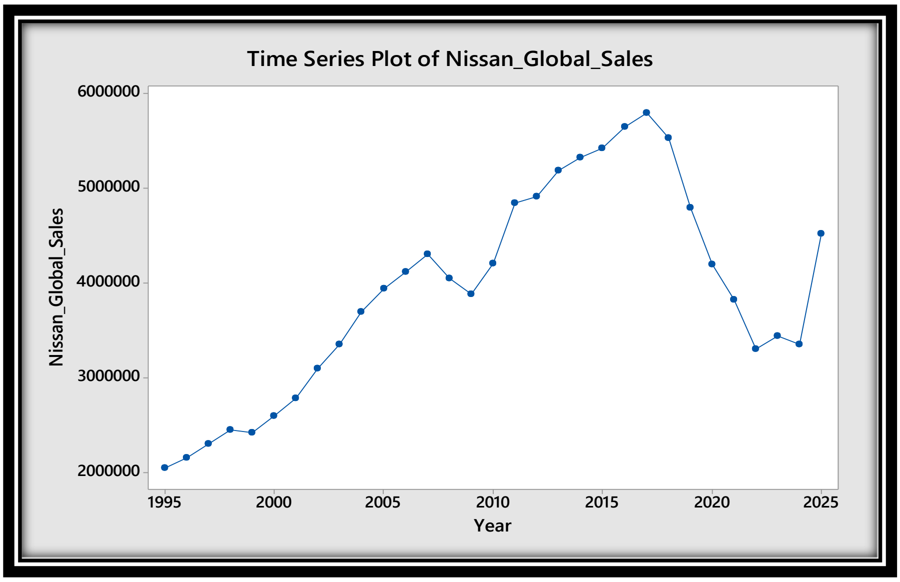
Descriptive Statistics: Nissan_Global_Sales

Variable	N	N*	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3
Nissan_Global_Sales	31	0	3919186	198861	1107213	2050078	3100000	3940000	4845341

Variable	Maximum
Nissan_Global_Sales	5790252

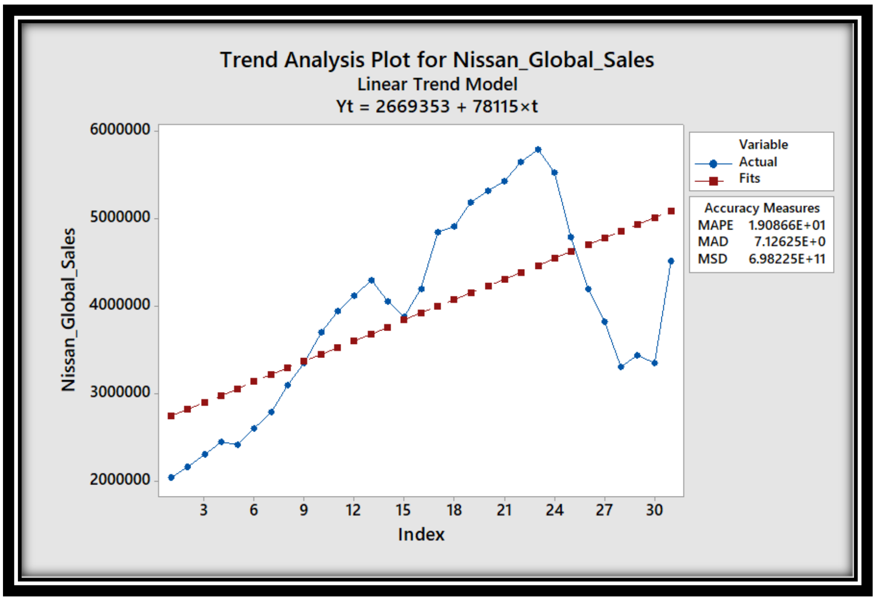
The descriptive statistics for Nissan_Global_Sales over 31 years show an average of approximately 3.9 million units sold annually, with a standard deviation of 1.1 million, indicating considerable variability. Sales ranged from a minimum of 2,050,078 to a maximum of 5,790,252 units. The median sales figure was 3,940,000, with the first quartile (Q1) at 3,100,000 and the third quartile (Q3) at 4,845,341.

Time series plot:



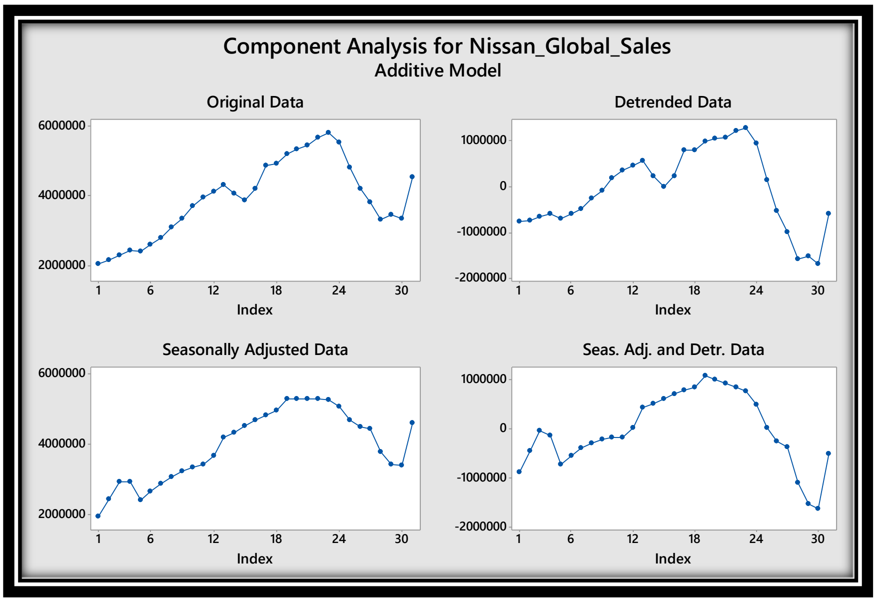
The time series plot of Nissan_Global_Sales from 1995 to 2025 shows a general upward trend until 2017, peaking at over 5.9 million units. After 2018, sales declined sharply likely due to market saturation or external shocks such as the COVID-19 pandemic. A recovery is observed after 2022, indicating a potential rebound in global demand. The pattern reflects both growth phases and demand volatility in the automotive sector.

Trend Analysis Plot for Nissan_Global_Sales



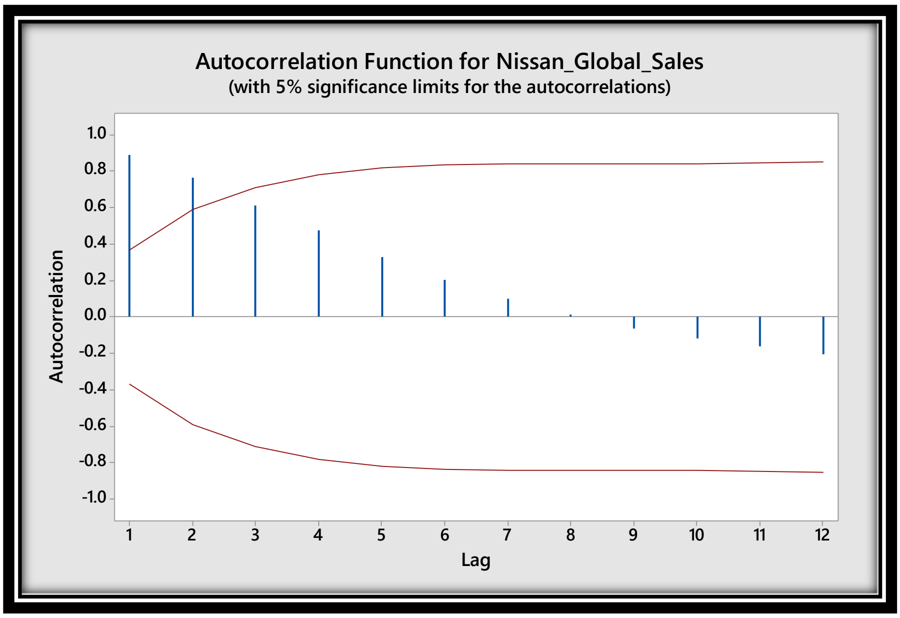
The trend analysis plot for Nissan_Global_Sales applies to a linear model: Y*t*=2,669,353+78,115×*t*. While the fitted line shows a steady upward trend, the actual data fluctuates significantly, especially after 24 years. The high MAPE (19.09%) and large MAD and MSD values indicate that the linear model fails to accurately capture recent volatility and downturns, suggesting that a nonlinear or segmented model might be more appropriate.

Component Analysis for Nissan_Global_Sales



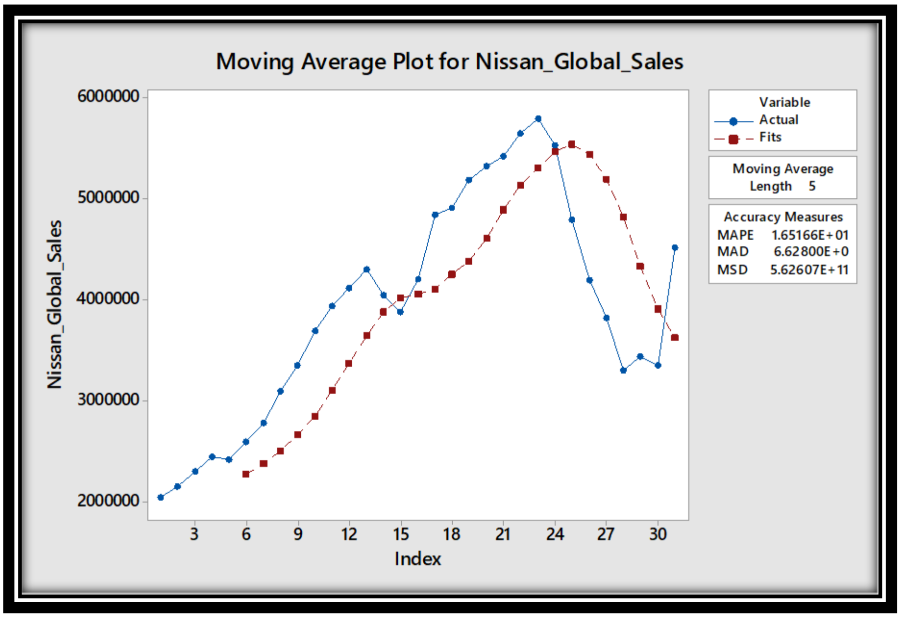
The component analysis breaks down Nissan’s global sales into trend, seasonal, and irregular components. The data shows overall growth with a sharp decline after index 24. After removing trend and seasonality, significant irregularities remain, highlighting volatility and external shocks in recent years.

Autocorrelation Function for Nissan_Global_Sales



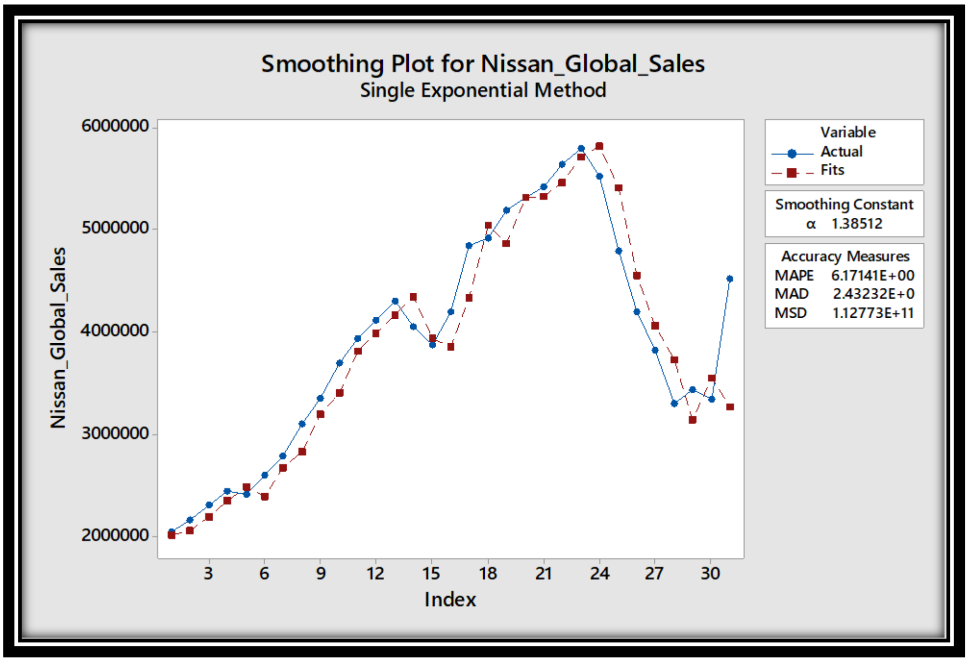
The autocorrelation plot shows strong positive correlation at lower lags, especially lag 1, indicating a strong dependency on previous years' sales. Correlation gradually declines with increasing lags, suggesting a persistent but decreasing trend over time. Most early lags are above the 5% significance level, confirming statistical relevance in short-term forecasting.

Moving Average Plot for Nissan_Global_Sales



The moving average plot (5-year span) smooths short-term fluctuations, revealing the overall trend more clearly. The fitted values closely follow the actual data during stable periods but lag behind during sharp rises or declines. With a MAPE of 16.5%, the model provides reasonable accuracy, though its responsiveness decreases during high volatility phases.

Smoothing Plot for Nissan_Global_Sales



The smoothing plot using the Single Exponential Method for Nissan_Global_Sales shows that the fitted values closely follow the actual data, especially during stable growth periods. With a smoothing constant α=1.3851\alpha = 1.3851α=1.3851, the model reacts relatively quickly to changes. The low MAPE (6.17%) and MAD indicate strong forecast accuracy, making this method suitable for short-term demand estimation in supply chain planning.

6) Forecasting Methods

Naïve Forecasting Method

Year	Nissan_Global_Sales	Forecast	Error	|Error|	|Error|^2	Error %
1995	2050078					
1996	2162200	2050078	112122	112122	1.2571E+10	5.19%
1997	2310043	2162200	147843	147843	2.1858E+10	6.40%
1998	2450000	2310043	139957	139957	1.9588E+10	5.71%
1999	2420013	2450000	-29987	29987	899220169	1.24%
2000	2600000	2420013	179987	179987	3.2395E+10	6.92%
2001	2790001	2600000	190001	190001	3.61E+10	6.81%
2002	3100000	2790001	309999	309999	9.6099E+10	10.00%
2003	3350032	3100000	250032	250032	6.2516E+10	7.46%
2004	3700456	3350032	350424	350424	1.228E+11	9.47%
2005	3940000	3700456	239544	239544	5.7381E+10	6.08%
2006	4120147	3940000	180147	180147	3.2453E+10	4.37%
2007	4300123	4120147	179976	179976	3.2391E+10	4.19%
2008	4050022	4300123	-250101	250101	6.2551E+10	6.18%
2009	3880000	4050022	-170022	170022	2.8907E+10	4.38%
2010	4200000	3880000	320000	320000	1.024E+11	7.62%
2011	4845341	4200000	645341	645341	4.1647E+11	13.32%
2012	4914212	4845341	68871	68871	4743214641	1.40%
2013	5188398	4914212	274186	274186	7.5178E+10	5.28%
2014	5318734	5188398	130336	130336	1.6987E+10	2.45%
2015	5423192	5318734	104458	104458	1.0911E+10	1.93%
2016	5642383	5423192	219191	219191	4.8045E+10	3.88%
2017	5790252	5642383	147869	147869	2.1865E+10	2.55%
2018	5522548	5790252	-267704	267704	7.1665E+10	4.85%
2019	4791600	5522548	-730948	730948	5.3428E+11	15.25%
2020	4198806	4791600	-592794	592794	3.514E+11	14.12%
2021	3820543	4198806	-378263	378263	1.4308E+11	9.90%
2022	3305204	3820543	-515339	515339	2.6557E+11	15.59%
2023	3442145	3305204	136941	136941	1.8753E+10	3.98%
2024	3348687	3442145	-93458	93458	8734397764	2.79%
2025	4519600	3348687	1170913	1170913	1.371E+12	25.91%

MEAN	ME	MAE	MSE	MPE
3899172	82317.4	284225.1333	1.3599E+11	0.07174221

In this study, the Simple Naïve Forecasting method was applied to forecast Nissan's global vehicle sales from 1996 to 2025 using historical sales data from 1995 to 2024. This method assumes that the best prediction for the current year is simply the actual value from the previous year. For example, the forecast for 1996 was based directly on the actual sales figure from 1995, and this approach was applied to all subsequent years.

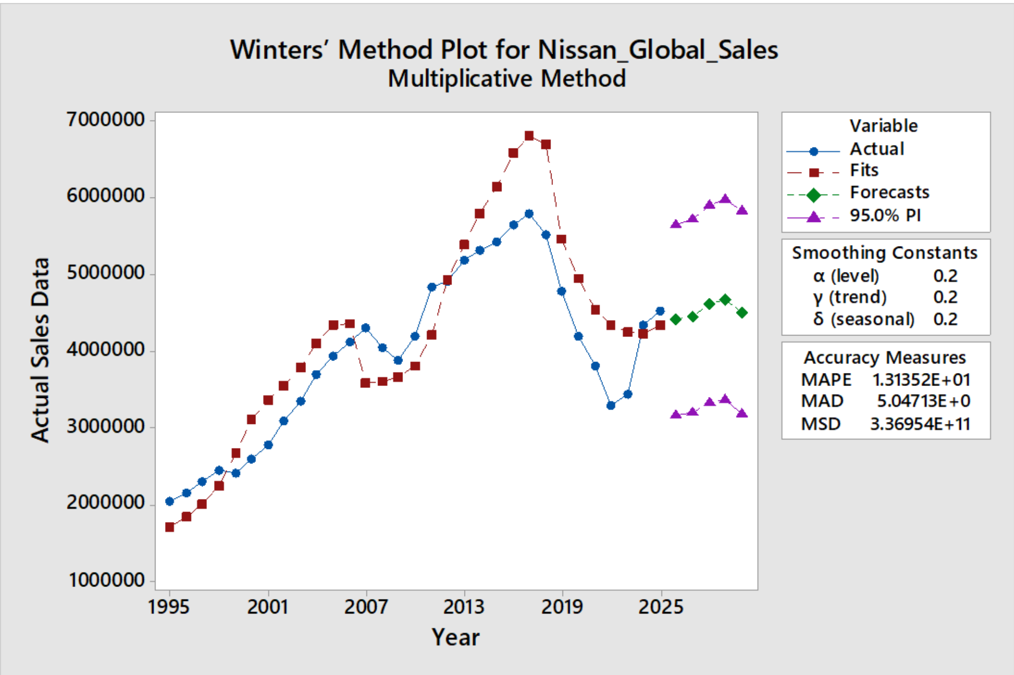
This forecasting technique was chosen for its simplicity and its effectiveness as a baseline model. Although it does not account for trends or seasonal patterns, it provides a useful benchmark for evaluating more advanced forecasting methods in future studies.

To assess the accuracy of the forecasts, several error metrics were calculated:

- **Mean: 3899172**
- **Mean Error (ME):82317.4**
- **Mean Absolute Error (MAE):** 284225.13
  This indicates that, on average, the forecasted values differed from the actual sales by around 284,000 units per year.
- **Mean Squared Error (MSE):** 1.3599E+11
  The large MSE value reflects the presence of some years with significant forecasting errors, especially in periods of high fluctuation or external disruption.
- **Mean Percentage Error (MPE):** 7.17%
  This shows that the average forecast error is about 7.17% of the actual sales, which is considered a moderate error rate in long-term forecasting contexts.

These results highlight that while the naïve method provides a quick and easy forecast, its accuracy is limited, especially in years with unexpected changes in sales. However, it still offers valuable insights for basic demand estimation and supply chain decision-making — such as inventory planning, production scheduling, and capacity allocation.

Winter’s Forecasting Method



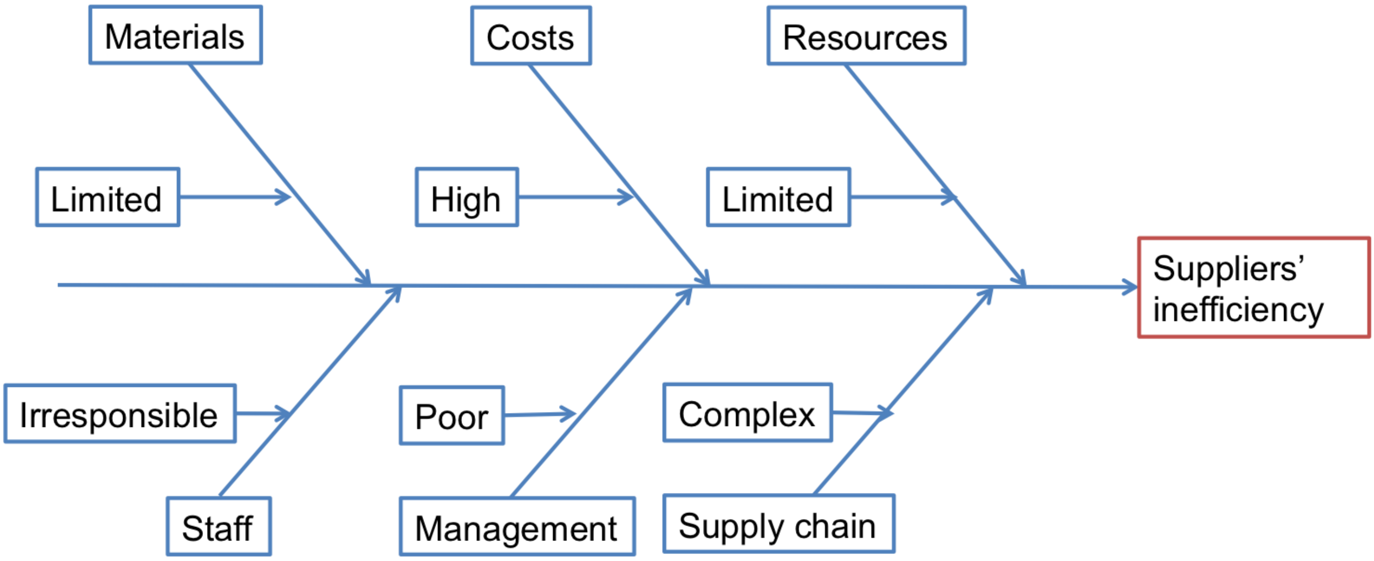
Winters' Method Plot for Nissan Global Sales using the multiplicative version of the Holt-Winters exponential smoothing method, which is ideal when seasonal variations are proportional to the level of the series.

Forecasts

Period	Forecast	Lower	Upper
2026	4413190	3176667	5649713
2027	4460316	3204421	5716212
2028	4614338	3336842	5891833
2029	4670900	3369688	5972113
2030	4508708	3181775	5835641

The table you provided shows the forecasted global vehicle sales for Nissan from 2026 to 2030 using the Winters' Multiplicative Method. It includes point forecasts as well as 95% prediction intervals (PI), giving a range within which actual sales are expected to fall with high confidence.

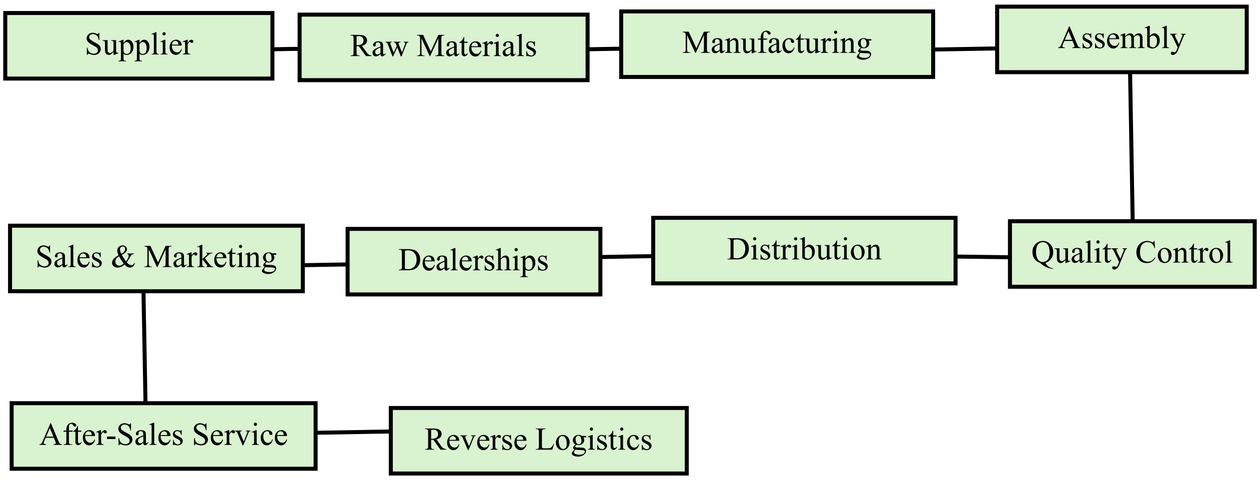
7) Supply Chain Implications of the Forecasting Results



The (fishbone) diagram identifies the root causes of suppliers' inefficiency.

- **Materials**: Limited availability affects timely supply.
- **Costs**: High costs reduce competitiveness and flexibility.
- **Resources**: Limited resources constrain supplier capability.
- **Staff**: Irresponsible behavior can delay operations.
- **Management**: Poor leadership leads to disorganization.
- **Supply Chain**: Complexity causes coordination problems.

The diagram highlights how interrelated operational factors contribute to inefficiencies in the supply chain.



Nissan's supply chain is a complex network of activities, starting from raw materials procurement to delivering vehicles to customers. Forecasting plays a pivotal role in optimizing this supply chain, allowing Nissan to meet market demand while minimizing excess inventory and reducing costs. Below is an overview of the various stages in Nissan's supply chain, along with the impact of forecasting, supported by numerical examples drawn from the sales data**.**

1. Supplier

Suppliers provide raw materials and components such as engines, tires, and electronics. Ensuring the availability of these materials is crucial for manufacturing operations.

Impact of Forecasting: By forecasting vehicle demand, Nissan can predict the number of components it will need from suppliers. This allows suppliers to optimize their production schedules to meet Nissan's requirements.

Example: Based on the forecast of 4,220,000 units for 2010 (compared to actual sales of 4,200,000), Nissan can inform its suppliers in advance, ensuring they have sufficient raw materials and components to meet production needs without delays.

2. Raw Materials

Raw materials such as steel, rubber, and plastic are used in manufacturing vehicle components. Proper procurement planning ensures there are no shortages or overstocking.

Impact of Forecasting: Forecasting vehicle production helps Nissan estimate raw material requirements and make bulk purchases to avoid material shortages.

Example: If the forecast for 2021 is 3,820,543 vehicles, Nissan can plan for the required raw materials in advance, ensuring that suppliers provide materials at the right time without the risk of overstocking or delays.

3. Manufacturing

Manufacturing involves assembling various parts into completed vehicles. Efficient scheduling of this process is vital to reduce costs and meet deadlines.

Impact of Forecasting: Accurate sales forecasts allow Nissan to align its manufacturing schedules with expected demand, reducing downtime and ensuring machines are used efficiently.

Example: With a forecast of 5,424,192 vehicles in 2015, Nissan can optimize its factory capacity to produce these vehicles without overloading the manufacturing lines or causing delays, preventing a situation where too few or too many cars are produced.

4. Assembly

In the assembly phase, the components are put together to form complete vehicles. A smooth assembly process depends on a steady supply of parts and timely coordination.

Impact of Forecasting: By predicting future demand, Nissan can prioritize assembly lines for high-demand vehicles, reducing the risk of bottlenecks.

Example: In 2016, the forecast was 5,642,383 vehicles, which helps Nissan determine which models to prioritize in the assembly lines to ensure they meet market demand.

5. Quality Control

Quality control ensures that each vehicle meets safety and performance standards. It's essential for maintaining customer trust and brand reputation.

Impact of Forecasting: Forecasting helps Nissan plan for additional quality checks when production volumes increase. This ensures that vehicles produced meet quality standards even when production scales up.

Example: For a forecast of 5,790,252 vehicles in 2017, Nissan can allocate additional resources to quality control to accommodate the larger volume, ensuring that there are no compromises in vehicle quality.

6. Distribution Centres

Distribution centres manage the storage and transportation of vehicles to dealers. Efficient logistics reduce costs and delivery time.

Impact of Forecasting: Accurate forecasts allow Nissan to strategically place vehicles in distribution centres based on expected demand in different regions, improving delivery times and reducing storage costs.

Example: Based on a forecast of 4,791,600 vehicles in 2019, Nissan can distribute vehicles more efficiently across its regional centres, ensuring that dealerships have the right inventory mix to meet customer demand without overstocking.

7. Dealerships

Dealerships are the point of sale for customers. Efficient inventory management at dealerships ensures that the right vehicles are available for customers when they need them.

Impact of Forecasting: Forecasting helps dealerships stock vehicles that align with customer preferences in specific regions. This avoids both stockouts and excess inventory.

Example: With a forecasted demand of 4,220,000 vehicles for 2020, dealerships can prepare accordingly, focusing on popular models and configurations to maximize sales.

8. Sales and Marketing

Sales and marketing drive vehicle demand through advertising and promotional activities. Accurate sales forecasts help plan marketing strategies.

Impact of Forecasting: Forecasts give the marketing team the data they need to focus their campaigns on the right models and regions, ensuring that promotional efforts are aligned with demand.

Example: With a forecast predicting 5,424,192 vehicles in 2015, the marketing team can target campaigns towards popular models like sedans and electric vehicles, adjusting the focus based on the forecast.

9. After-Sales Service

After-sales service, including repairs and spare parts, ensures customer satisfaction and long-term brand loyalty.

Impact of Forecasting: Forecasting allows Nissan to anticipate the need for spare parts and service based on vehicle sales. This ensures the availability of parts when required.

Example: If the forecast for 2015 indicates a high sales volume, Nissan can ensure a larger stock of essential parts for popular models like the Nissan Altima to address customer service needs.

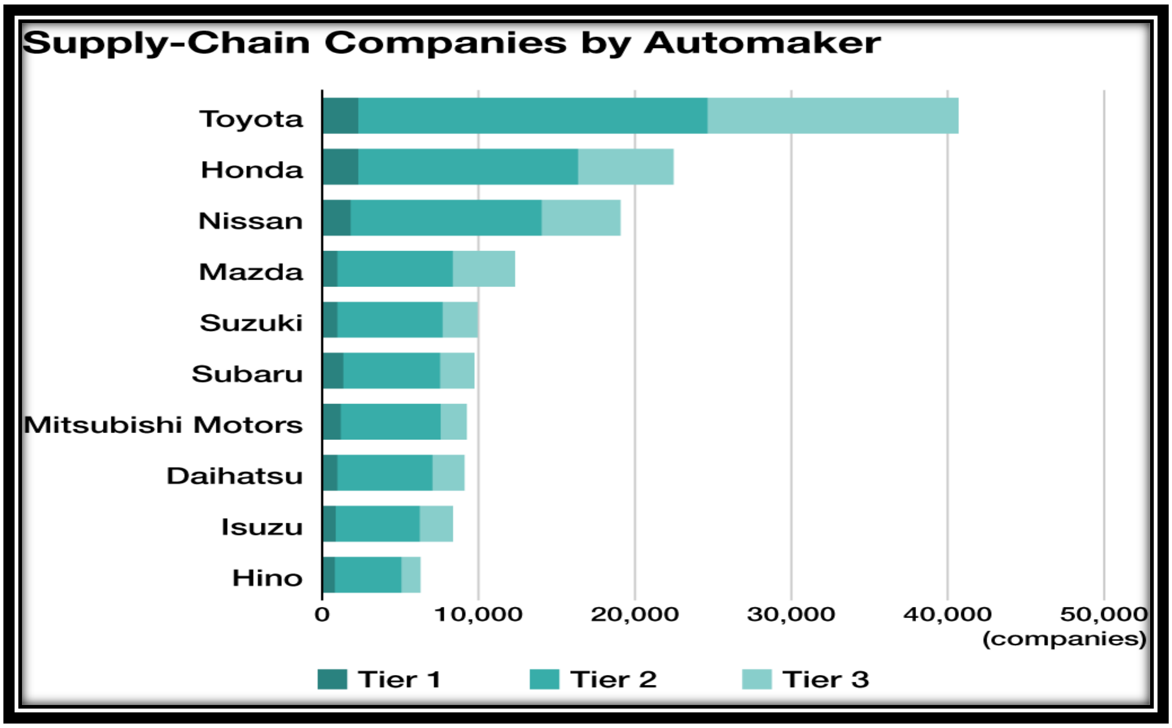
10. Reverse Logistics

Reverse logistics deals with returns, such as warranty claims, repairs, or vehicle recycling. Proper management reduces costs and customer dissatisfaction.

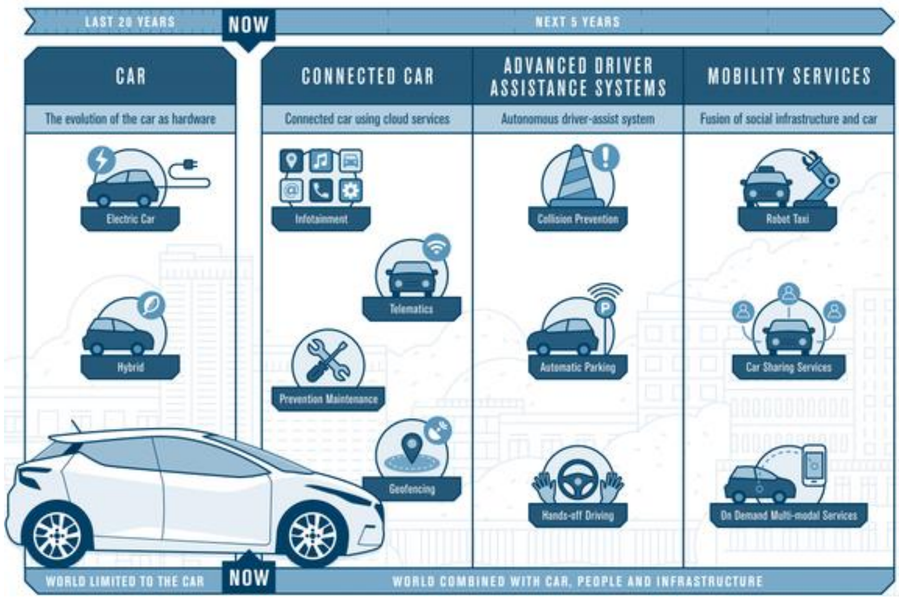
Impact of Forecasting: Forecasting helps Nissan anticipate returns and plan accordingly to manage potential recalls or warranty claims efficiently.

Example: If the forecast predicts a higher return rate for a specific model in 2020, Nissan can prepare its reverse logistics team to handle the influx of returns, reducing turnaround times and improving customer satisfaction.

❖ How does the forecast methods effect on the supply chain management?



The Forecasting methods makes Nissan company supplier in Top 3 comparing with other cars companies like Mazda, Suzuki, Mitsubishi…



And here it shows how the forecast for 20 years data effect on the next year either in supply chain management or Quality Control or even in improving the services demand

8) Conclusion:

In this report, we have explored the significance of forecasting within Nissan's supply chain, particularly through the application of the simple naïve forecasting method. By analysing historical sales data from 1995 to 2025, we demonstrated how sales predictions can help optimize various stages of the supply chain, from procurement and manufacturing to distribution and after-sales service.

Through the use of forecasting, Nissan can align its production capacity with market demand, manage raw materials efficiently, ensure the right inventory levels at dealerships, and coordinate logistics to avoid delays. Furthermore, accurate sales forecasts enable better decision-making in areas like marketing, production planning, and even reverse logistics, improving overall operational efficiency and customer satisfaction.

By examining key metrics such as the Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Percentage Error (MPE), we evaluated the performance of the forecasting model and provided insights into the potential areas for improvement. The forecasted figures allowed us to understand how sales trends impact capacity management, logistics, and inventory control, providing a roadmap for Nissan to adapt to changing market conditions.

In conclusion, accurate forecasting is a vital tool for enhancing supply chain operations, enabling Nissan to respond proactively to demand fluctuations while optimizing costs and maximizing customer satisfaction. The insights gained from this analysis not only benefit Nissan's internal processes but also contribute to the overall competitiveness and sustainability of the company in the global automotive market.

THANK YOU ❤

PROF: Sonya javadi