Optimizing Manufacturing Supply Chains: A Time Series Approach for Demand Forecast

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BUSINESS PROBLEM

Impact of Inaccurate demand forecasting in face of global economic fluctuations and market uncertainties:

1. **Impact on Firms:** Inaccurate forecasts lead to stockouts, impacting production efficiency, customer satisfaction, and financial health of manufacturing firms.
2. **Impact on Suppliers:** Inaccurate forecasts lead to inventory surplus, tying up financial resources, causing financial strain and potentially damaging long-term business relationships within the industry.

BUSINESS PROBLEM

01 Stakeholder
Manufacturing sector – Welding machines

02 Industry feature
Relies on complex supply chain and specialized suppliers

03 Key Challenge
Vulnerability of supply chain due to Demand Volatility

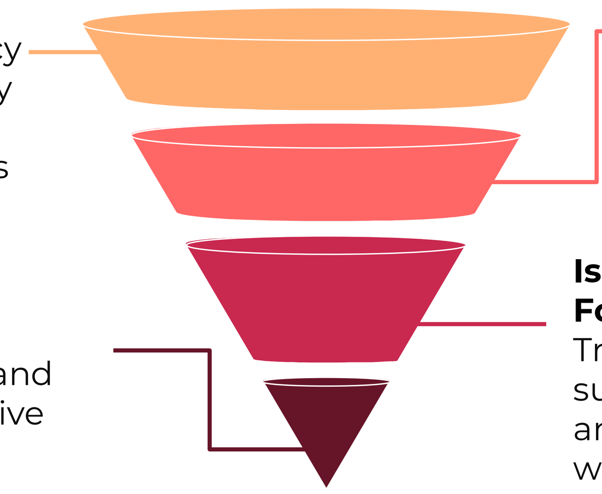
04 Solution focus
Accurate forecast of raw materials to avoid stockouts or surplus

POTENTIAL BENEFITS

- **10-15%`** Operational Cost Reduction
- **5-10%** Enhanced Service Levels
- **20-40%** Reduction in inventory levels and product obsolescence
- **5%** Increase in sales through streamlined inventory
- **10%** Improved customer responsiveness

ANALYTICAL PROBLEM

Develop and implement an advanced machine learning solution to accurately forecast the volatile demand for materials in the welding industry, overcoming the limitations of traditional forecasting methods.



Analytical Context
Enhance demand prediction accuracy in welding industry using advanced analytical methods

Challenge
Address complexities of forecasting for materials with diverse demand patterns and minimal correlation

Solution focus
Develop advanced machine learning and time-series predictive models tailored to strategic products

Issue with Traditional Forecasting
Traditional forecasting such as scenario analysis and stimulations struggles with sector's demand volatility

Success Metrics: Measuring decrease in variation between maximum and standard forecast before and after implementing new forecasting methods.

DATA SUMMARY

Key Columns

Vital columns for Forecast:
- Order Request Date
- Product ID
- Quantity Ordered

Additional tables for expansion to raw material level:
- Product Hierarchy
- Component Parts
- Supplier's Delivery Performance

Key data variables:
Purchase ID, Product ID, Quantity Ordered, Order Request Date, Order Delivery Date and In-House Production Time

Data Insights

Total No. of Rows & Columns **358K Rows & 19 Columns**	Material Rows **148K Rows**
Time Period of Order Request Date **2014/06/04 – 2023/12/22**	Time Period of Order Delivery Date **2014/01/15 – 2024/04/18**
Total Quantity Requested **350+**	Total No. of Distinct Materials **1305**

Relationship Between Tables:

Customer Order Details → Product Hierarchy → Component Parts → Supplier Delivery Performance

PROJECT METHODOLOGY

Objective: Identify the model that minimizes forecast errors and aligns with manufacturing firm operations.

Data Understanding
- Entity relationship diagrams
- Data dictionaries

Exploratory Data Analysis (EDA)
- Product segmentation
- Time Series decomposition
- Graphical visualization

Data Preprocessing
- Outlier & missing value treatment
- Master dataset creation
- Data transformation and Product Segmentation

Data Modelling & Validation
Create time series forecast, Evaluate Model Outcomes, to get Best Fit using dynamic selection box
- Holt Winter
- ARIMA
- Exponential Smoothing
- Prophet

Reporting & Insights
- Tableau dashboard
- Next purchase day and quantity
- Recommendations report

Forecast Extension
- Explode the finished product forecasts to raw material level

Data: reduced from 2022-2023 only to manage variation
Outlier Treatment: 19 outliers removed after consultation with the client
Missing Value Treatment: Assumed missing demand entries as zero.

DATA MODELLING

1. Volume - Variance Product Segmentation

Idea: Our modeling strategy employs a 2-D matrix to segment 1,305 products, with X-axis representing quantity ordered and Y-axis representing Coefficient of Variance. The products are categorized into four distinct segments.

This segmentation strategy is crucial for developing customized time-series and ML models considering mixed nature of products' demand:

1. **Low Volume Segments:** Advanced Time series models
2. **High Volume Segments:** Advanced ML models

Forecastability Matrix

Increasing variance (CoV) >>	Bottom 80%	Top 20%
1 (high)	Low Volume - High Variance, 67 materials (8.7%) — *Manage by Exception*	High Volume - High Variance, 24 materials (3%) — *Collaborate*
0 (low)	Low Volume – Low Variance, 554 materials (71.3%) — *Prioritize and Improve*	High Volume - Low Variance, 132 materials (17%) — *Automate*

Increasing volume (Qty sold) >>

2. Best Fit Approach Model

Advanced Time series models
1. Low Volume – Low Variance
2. Low Volume – High Variance

SARIMA, Holt Winter, Prophet

Advanced ML models
1. High Volume – Low Variance
2. High Volume – High Variance

Wave Net, CNN

Dynamic Selection box
Key Metrics: Use lowest WMAPE to select the best model for each material

$$WMAPE = \frac{1}{\sum_{i=1}^{n} A_i} \sum_{i=1}^{n} |A_i - F_i|$$

- A_i as the actual quantity for month i
- P_i as the predicted quantity for month i
- n is the total number of months considered

Model Outputs
Standard Forecast and Standard deviation

Calculating Model Improvement Factor (MIF)

$$\frac{\text{Abs}[\text{ Avg. WMAPE}_{\text{Current}} - \text{Avg. WMAPE}_{\text{New}}]}{\text{Avg. WMAPE}_{\text{Current}}}$$

Calculating Maximum Forecast

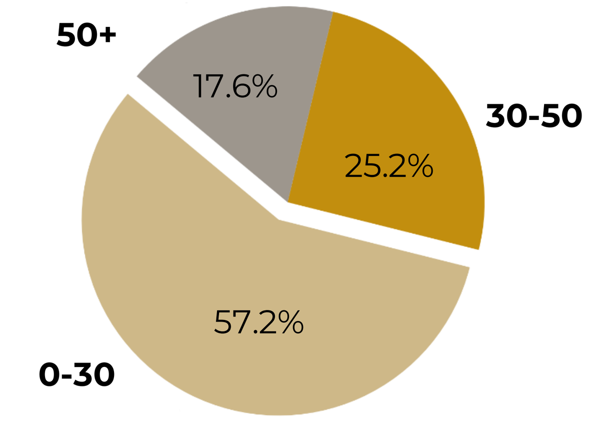
$$\text{Max}\{\text{Std. Forecast} + 1.65 * \text{Std. Deviation} * (1\text{-MIF}),\ 2 * \text{ Std. Forecast }\}$$

Steps to calculate Max. Forecast
1. Calculate MIF, which capture improvement factor of the new model over current model
2. Apply MIF to the 90% Confidence Interval (CI) estimate of Std. forecast

Final Output
Standard Forecast and Max. Forecast (90% CI)

MODEL RESULTS

Distribution of Materials by WMAPE Range

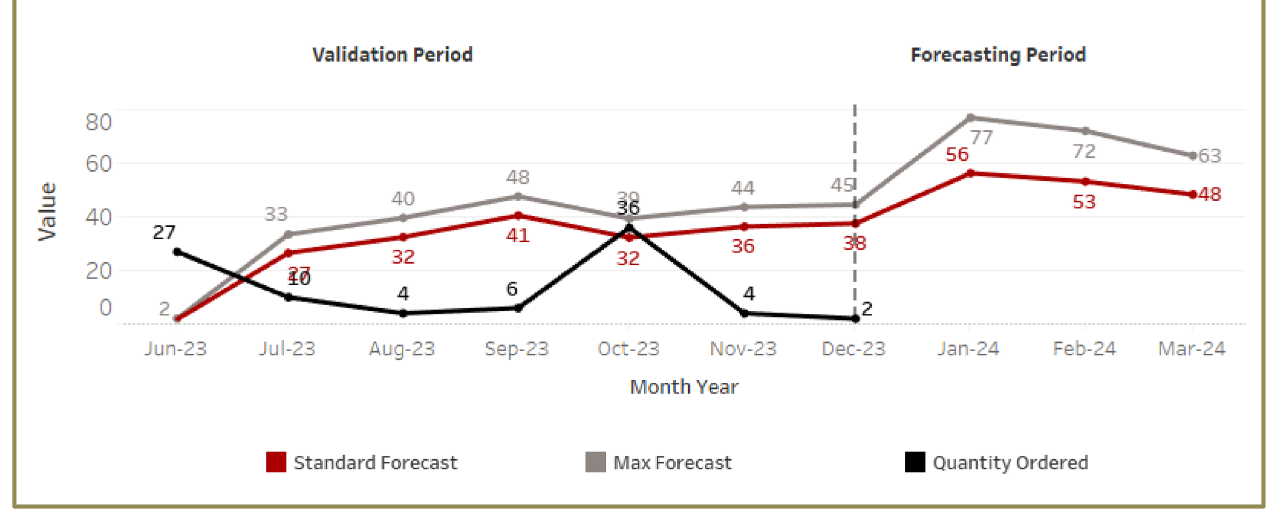


Overall Average WMAPE: 0.44

WMAPE Range	# of Materials	Distribution
0-30	143	57.20%
30-50	44	17.60%
50+	63	25.20%

Training data: 2.5 years
Validation data: last 6 months

Ordered vs Forecasted Graph



To further refine these forecasts, it may be beneficial to:

- Implement rolling forecast model that periodically updates and extends the training dataset.
- Explore reasons behind the higher WMAPE for certain materials and adjust model or data treatment accordingly.
- Consider integrating more sophisticated techniques like machine learning or ensemble that capture complex patterns better.

LIFE CYCLE MANAGEMENT

- The gap between the standard and maximum forecasts for the final product was successfully reduced by up to 50%.
- Achieved effective categorization of the products into various segments based on their forecastability
- Cut down the time required for future demand computation (transitioning from Excel to Python) by 80%, enhancing operational efficiency
- Model Maintenance: Ongoing monitoring for the model's performance against key metrics, with alerts deviations from acceptable thresholds

AUTHORS