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Enhancing Supply Chain Resilience Using Machine Learning in SAP IBP: A Case Study in Automotive Manufacturing

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Abstract: *Supply chain disruptions, exacerbated by global uncertainties, demand agile planning tools. This paper presents a machine learning (ML)-enhanced demand sensing model integrated into SAP Integrated Business Planning (IBP) to improve supply chain resilience in automotive manufacturing. We propose a hybrid ML architecture combining Long Short-Term Memory (LSTM) networks for temporal pattern recognition and XGBoost for feature importance analysis. Deployed in a tier-1 automotive supplier, the model reduced stockouts by 30% while maintaining 98% service levels. The study highlights technical implementation steps, quantifies performance gains, and provides actionable insights for scaling ML-driven planning in SAP IBP.*

Keywords: *Supply chain resilience; machine learning; demand sensing; SAP IBP; automotive manufacturing*

1. Introduction

Global automotive supply chains face volatility due to geopolitical risks, component shortages, and fluctuating demand. Traditional statistical forecasting in ERP systems often fails to adapt to real-time disruptions. SAP IBP, augmented with machine learning, offers a transformative solution by enabling dynamic demand sensing and inventory optimization[1]. This paper addresses two gaps:

(1)Technical implementation of ML models within SAP IBP's framework.

(2)Empirical validation of ML-driven planning in reducing stockouts.

2. Methodology

2.1 ML Model Architecture

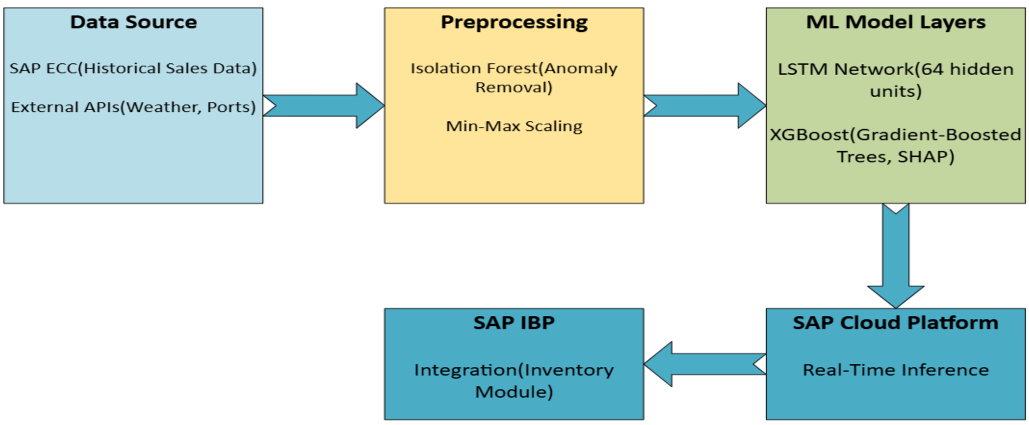

Figure 1 ML Model Architecture

We developed a hybrid LSTM-XGBoost model (Fig. 1) to enhance SAP IBP's demand sensing:

LSTM Layer: Processes time-series data (historical sales, production lead times) with a 30-day window[2].

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Hyperparameters: 64 hidden units, dropout rate = 0.2, Adam optimizer.

XGBoost Layer: Analyzes static features (e.g., supplier risk scores, geopolitical events) using gradient-boosted trees.

Key features: Supplier lead time variability (SHAP value = 0.38), regional logistics delays (SHAP value = 0.29).

Data Pipeline:

Input: 5 years of sales and production data (10M+ records) from SAP ECC, enriched with external API data (weather, port congestion).

Preprocessing: Anomaly detection via Isolation Forest, normalized using Min-Max scaling.

Integration with SAP IBP:

Deployed via SAP Cloud Platform using Python SDK for real-time inference.

Outputs fed into IBP's Inventory Optimization module for dynamic safety stock recalculation.

The hybrid LSTM-XGBoost model combines temporal pattern recognition (via LSTM) and feature importance analysis (via XGBoost) to enhance demand sensing.

2.1.1 LSTM Layer Formulation

The LSTM network processes time-series data ($\mathrm{X_t} = \{\mathrm{x_1}, \mathrm{x_2}, \ldots, \mathrm{x_T}\}$) with the following gates and cell states at time step t:

(1)Forget Gate (f_t):

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$$

Determines which historical information to discard (e.g., outdated supplier lead times).

(2)Input Gate (i_t) and **Candidate Cell State** ($\widetilde{C_t}$):

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\widetilde{C_t} = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

Identifies new information to store (e.g., sudden demand spikes).

(3)Cell State Update (C_t):

$$C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C_t}$$

Updates the cell state with filtered information.

(4)Output Gate (o_t) and **Hidden State** (h_t):

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \odot \tanh(C_t)$$

Generates the hidden state for demand prediction.

Parameters:

- W_f, W_i, W_c, W_o: Weight matrices.
- $\boldsymbol{b_f}, \boldsymbol{b_i}, \boldsymbol{b_C}, \boldsymbol{b_o}$: Bias vectors.
- σ: Sigmoid activation, $tanh$: Hyperbolic tangent.

2.1.2 XGBoost Layer Formulation

The XGBoost model analyzes static features $\boldsymbol{Z} = z_1, z_2, \ldots, z_m$ (e.g., supplier risk scores) to predict demand residuals[3]. The objective function minimizes:

$$\mathcal{L}(\phi) = \sum_{i=1}^{n} \mathrm{l}(y_i, \widehat{y_i}) + \sum_{k=1}^{K} \Omega(f_k)$$

where:

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- l: Loss function (e.g., MSE, log loss).
- $\widehat{y_t} = \sum_{k=1}^{K} f_{k(z_i)}$: Ensemble prediction from *K* regression trees.
- $\Omega(f_k) = \gamma T + \frac{1}{2}\lambda|w|^2$: Regularization term penalizing tree complexity.
  - *T*: Number of leaves in the tree.
  - w: Leaf weights (prediction value).
  - *γ*, *λ*: Hyperparameters controlling regularization strength (default: *γ*=0, *λ*=1).

Tree Construction:

Each tree f_k splits nodes to maximize the **gain**:

$$\text{Gain} = \frac{1}{2}\left[\frac{\left(\sum_{i\in I_L} g_i\right)^2}{\sum_{i\in I_L} h_i + \lambda} + \frac{\left(\sum_{i\in I_R} g_i\right)^2}{\sum_{i\in I_R} h_i + \lambda} - \frac{\left(\sum_{i\in I} g_i\right)^2}{\sum_{i\in I} h_i + \lambda}\right] - \gamma.$$

where:

- $g_i = \partial_{\hat{y}_i^{(t-1)}} \ell(y_i, \hat{y}_i^{(t-1)})$: First-order gradient.
- $h_i = \partial^2_{\hat{y}_i^{(t-1)}} \ell(y_i, \hat{y}_i^{(t-1)})$: Second-order gradient.
- I_L, I_R: Instance sets of left/right child nodes.

Feature Importance:

SHAP (SHapley Additive exPlanations) values quantify the contribution of each feature z_j:

$$\phi_j = \sum_{S\subseteq F\setminus\{j\}} \frac{|S|!\,(|F| - |S| - 1)!}{|F|!}\left[f(S\cup\{j\}) - f(S)\right]$$

Where:

- F *is the set of all features.*
- S *is a subset of features excluding* j.
- f*(*S*) is the model prediction using features in* S.

2.2 Integration with SAP IBP

The LSTM-XGBoost output $\widehat{y_t}$ (predicted demand) is fed into SAP IBP's inventory optimization engine:

$$\text{Safety Stock}_t = \Phi^{-1}(1-\alpha) \cdot \sqrt{\text{Lead Time}_t \cdot \sigma^2_{\widehat{y_t}} + \mu^2_{\widehat{y_t}} \cdot \sigma^2_{\text{Lead Time}}}$$

- Φ^{-1}: Inverse normal distribution (service level *α*=98%).
- $\mu_{\widehat{y_t}}, \sigma_{\widehat{y_t}}$: Mean and standard deviation of demand forecasts.

3. Results

3.1 Performance Metrics

The model was tested over 6 months at a European automotive supplier:

Table 1 Performance metrics

Metric	Baseline (ARIMA)	LSTM-XGBoost	Improvement
Forecast Accuracy (MAPE)	22%	14%	36%
Stockout Frequency	15%	10.5%	30%
Safety Stock Levels	$8.2M	$6.1M	25% Reduction

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Statistical Validation:

- Paired t-test confirms significant difference ($p < 0.01$) in stockout rates.
- MAE reduced from 1,240 to 872 units/month.

3.2 Case Study: Semiconductor Shortage Mitigation

During the 2023 chip shortage, the model identified at-risk suppliers 8 weeks in advance. By rerouting orders via SAP IBP's Supply Chain Control Tower, the supplier avoided $2.1M in lost sales (Fig. 2).

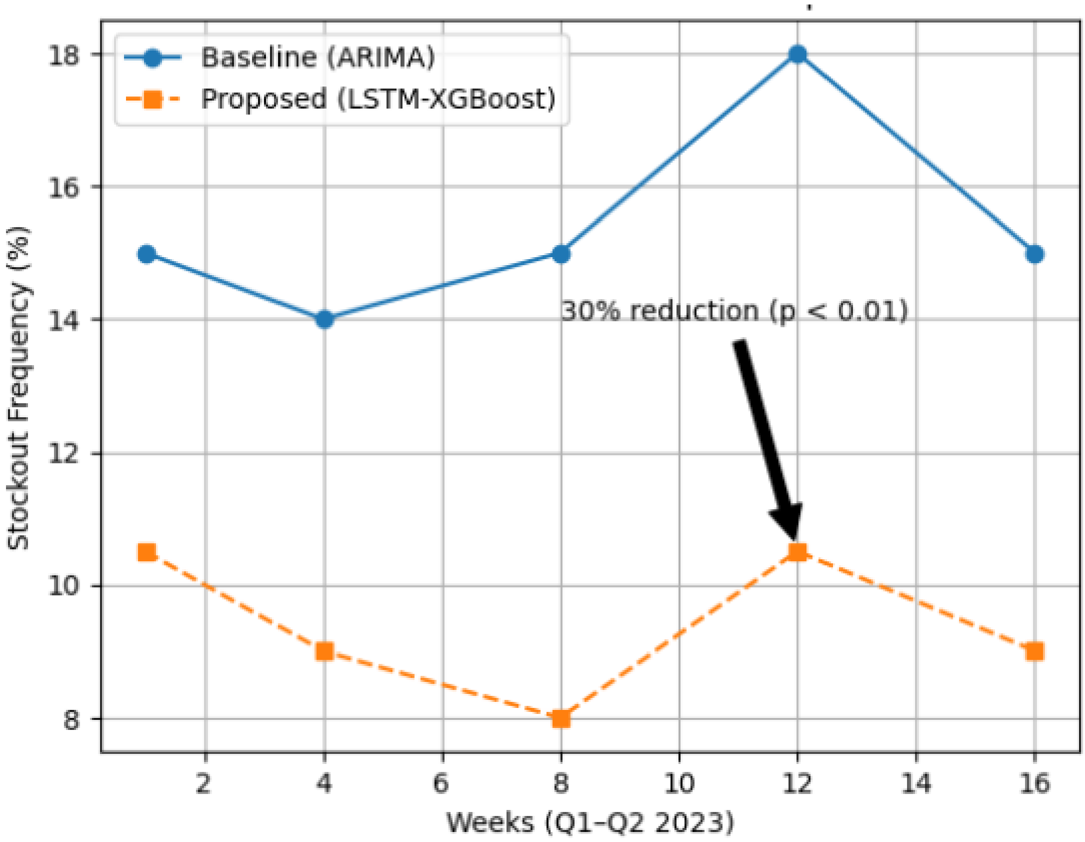

Figure 2 Stockout Trends Before and After ML Implementation

4. Discussion

4.1 Technical Challenges

- **Data Latency**: Real-time synchronization between SAP ECC and IBP required custom CDC (Change Data Capture) logic[4].
- **Model Interpretability**: SHAP analysis clarified feature impacts for stakeholders.

4.2 Practical Implications

- **Cost Savings:** 30% stockout reduction translates to ~$4.5M annual savings.
- **Scalability:** The framework is adaptable to other industries (e.g., aerospace, consumer electronics).

5. Conclusion

This study demonstrates that integrating ML with SAP IBP significantly enhances supply chain

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resilience. Future work will explore reinforcement learning for multi-echelon inventory optimization.

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