# Integrating Demand Forecasting & Inventory Management in Food Manufacturing Industry: Hierarchical Forecasting Approach

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# DECLARATION OF ORIGINALITY

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## STATEMENT OF THE SUPERVISOR

The candidate has carried out research for the Degree of MSc in Major Component of Research under my supervision.

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# ABSTRACT

This study focuses on production planning in the food manufacturing industry utilizing hierarchical forecasting in order to enhance demand prediction for products that share a common core ingredient. Creating strategic supply chain techniques that maximize resource allocation and production efficiency requires accurate demand predictions for this ingredient. The study aims to increase forecast accuracy in order to improve predictions at various operational levels. The study considers two scenarios: (1) forecasting the aggregated total demand for the common ingredients of all five products and (2) forecasting the demand for the common ingredients of each product individually and then summing the results. Following an exploratory data analysis to understand the dataset's characteristics, both statistical and machine learning (ML) methods are utilized. The statistical methods, including SARIMA and Prophet, serve as benchmarks, while ML models, including LR, SVR, RF, and XGBoost, are employed to enhance forecasting accuracy. Reconciliation methods such as bottom-up, MinT, and OLS are evaluated, with the base forecast serving as a benchmark. The dataset exhibits sudden spikes and drops, where the spikes impose an additional penalty cost and adversely impact forecasting accuracy. To address this, the study adopts a dual approach: retaining the original dataset in one instance and creating an anomaly-free dataset in another. Results demonstrate that the XGBoost model, combined with MinT reconciliation, outperforms other reconciliation techniques across all products and hierarchical levels. The forecasting process was applied to two datasets: one with the original data and the other after anomaly removal. This research underscores the critical role of data preprocessing in the forecasting process, particularly the value of anomaly detection in improving forecasting accuracy. Key findings reveal that forecasting the aggregated demand for the common ingredients of all five products outperforms the individual forecasting and summation approach for the selected industry case. Moreover, this study aids a middle-scale local food manufacturer by integrating academic insights with industry practices. The results have significant implications for enhancing production efficiency, reducing inventory costs, and improving supply chain resilience in the food and beverage sector.

Keywords: Hierarchical forecasting, demand forecasting, production planning, anomaly detection, reconciliation techniques

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## LIST OF ACRONYMS

| | |
|---|---|
| AMSE | Absolute Mean Scaled Error |
| AB | Adaptive Boosting |
| AI | Artificial Intelligence |
| ANN | Artificial Neural Network |
| Auto ARIMA | Auto Autoregressive Integrated Moving Average |
| Auto ETS | Auto Error-Trend-Seasonality |
| AR | Autoregressive |
| ARIMA | AutoRegressive Integrated Moving Average |
| ARMAX | AutoRegressive Integrated Moving Average with eXplanatory variables |
| ARMAE | Average Relative Mean Absolute Error |
| AvgRelMAE | Average Relative Mean Absolute Error |
| AvgRelMSE | Average Relative Mean Squared Error |
| ARMAPE | Average Relative Means Absolute Percentage Error |
| ARMSE | Average Relative Means Squared Error |
| BP-ANN | Backpropagation Artificial Neural Networks |
| BiLSTM | Bidirectional LSTM |
| BOM | Bill Of Materials |
| BU | Bottom Up |
| CMA | Center of Moving Average |
| CPSO | Cloud Particle Swarm Optimization |
| CHF | Conditional hierarchical forecasting |
| CWT | Continuous Wavelet Transform |
| CNN | Convolutional Neural Network |
| CTFF | Cross-Temporal Forecasting Framework |
| CUB | Cubist |
| DES | Double Exponential Smoothing |
| DTDBU | Dynamic top-down bottom-up |
| ETS | Error-Trend-Seasonality |
| ES | Exponential Smoothing |
| EWMA | Exponentially Weighted Moving Average |
| XGBoost | Extreme Gradient Boosting Regressor |

| | |
|---|---|
| ELM | Extreme Learning Machine |
| GMM | Gaussian Mixture Model |
| GPR | Gaussian Process Regression |
| GARCH | Generalized Autoregressive Conditional Heteroskedasticity |
| GA | Global Average |
| GBM | Gradient Boosting Machine |
| GBR | Gradient Boosting Regressor |
| GridSearchCV | Grid Search Cross-Validation |
| SARIMA-QR | Hybrid SARIMA and Quantile Regression |
| IoT | Internet of Things |
| KNN | k-Nearest Neighbors |
| LASSO | Least Absolute Shrinkage and Selection Operator |
| LightGBM | Light Gradient Boosting |
| LightGBM | Light Gradient Boosting Machine Regressor |
| LR | Linear Regression |
| LSTM | Long Short-Term Memory |
| ML | Machine Learning |
| MPS | Master Production Schedule |
| MRP | Material Requirements Planning |
| MAE | Mean Absolute Error |
| MAPE | Mean Absolute Percentage Error |
| MASE | Mean Absolute Scaled Error |
| ME | Mean Error |
| MPE | Mean Percentage Error |
| MRAE | Mean Relative Absolute Error |
| MSE | Mean Squared Error |
| MA | Moving Average |
| MLP | Multilayer Perceptron |
| MLP-NN | Multiple Layer Perceptron-Artificial Neural Network |
| NB | Naive Bayes |
| NPV | Negative Predictive Value |
| NAR | Non-linear AutoRegression model |
| NAR | Nonlinear Autoregressive |
| OLS | Ordinary Least Squares |

| | |
|---|---|
| PLSR | Partial Least Squares Regression |
| PPV | Predictive Value |
| RF | Random Forest |
| RNN | Recurrent Neural Network |
| Reg-ARMA | Regression-Autoregressive Moving Average |
| RMAE | Relative Mean Absolute Error |
| RR | Ridge Regression |
| RMSE | Root Mean Square Error |
| RMSSE | Root Mean Sum of squared Scaled Error |
| SARIMA-MLR | SARIMAX using Multiple Linear Regression |
| SARIMA | Seasonal AutoRegressive Integrated Moving Average |
| SARIMAX | Seasonal Autoregressive Integrated Moving Average with external variables |
| NNET | Single-Layer Perceptron Feedforward Neural Networks |
| SEM | Structural Equation Modelling |
| SVM | Support Vector Machine |
| SVR | Support Vector Regression |
| SVMl | Support Vector Regression with Linear Basis Function Kernels |
| SVMr | Support Vector Regression with Radial Basis Function Kernels |
| SMAPE | Symmetric Mean Absolute Percentage Error |
| TD | Top Down |
| WLS | Weighted Least Squares |
| XGB | Xtreme Gradient Boosting |

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