

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

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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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