MRP•NEXUS: Intelligent Demand Forecasting and Inventory Optimization Using Machine Learning

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Abstract

The accurate demand forecasting and inventory optimization cannot be overstated when it comes to having efficient and smooth supply chain processes and reducing costs associated with inventory and risks connected with it. Inventory control systems that use traditional methods of operation depend on manual planning and separate forecasting process, which makes them ineffective in responding to dynamically changing demand patterns. In this paper, an intelligent decision support system is proposed by combining an ensemble machine learning algorithm with material requirements planning to enable forecasting and inventory optimization and detect conflicts in this process. The forecasted demand is then used to calculate Economic Order Quantity (EOQ), Safety Stock, and Reorder Point, whereas a conflict detection mechanism automatically detects important inventory states. The proposed framework has been developed as a web application with the help of Flask and SQLite, which supports forecasting, inventory tracking, and procurement planning in an interactive dashboard. The experimental analysis shows the accuracy of 91.3% with MAPE of 8.7% and MAE of 35.6, reflecting the efficiency of the framework for intelligent inventory management.

Keywords: MRP•NEXUS, Ensemble Demand Forecasting, Intelligent Inventory Optimization, Economic Order Quantity, Safety Stock Modeling, Supply Chain Decision Support, Inventory Conflict Detection, Retail Demand Analytics.

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1. Introduction

Demand forecasting and inventory optimization form the basis of contemporary supply chain management and help businesses stay stocked with the products while keeping their operating costs low. With the changes in consumer demand patterns, seasonal differences, and supply chain interruptions in the manufacturing, retail, and distribution industries, inventory management becomes more challenging by the day. The conventional MRP systems depend upon historical averages and pre-defined planning policies, which are not always capable of adjusting to changing situations. In such scenarios, an inaccurate estimate of demand can cause shortage of stock, overstocking, higher inventory costs, late procurement activities, and lowered customer satisfaction. The advent of historical data and smart analytical systems has paved the way for smarter supply chain management.

To address these challenges, an intelligent forecasting and inventory optimization needs to be established, which should be capable of forecasting the future demand as well as providing a reliable purchase plan. Instead of relying only on traditional statistical tools, machine learning will be able to discover nonlinear trends and other relationships existing in historical sales records. The combination of predictive analytics with such classical approaches of inventory management as EOQ, Safety Stock, and ROP will allow for automatic inventory management based on forecasted demand. Additionally, using automatic conflict detection allows detecting the shortage of stock, overstocking, problems with suppliers, and discrepancies in forecasts.

This research proposes MRP•NEXUS, an intelligent demand forecasting and inventory optimization framework, which is a combination of machine learning and automatic Material Requirement Planning. The methodological approach used in this research includes a weighted ensemble forecasting model, which uses Gradient Boosting Regressor, Random Forest Regressor, and Seasonal Decomposition. The obtained demand forecast will then be used by the MRP optimization engine to calculate EOQ, Safety Stock, and Reorder Point, while the inventory risk/conflict detection component will be constantly monitoring the inventory. The whole system is built as a web-based decision support system with Flask, SQLite, Scikit-learn, and Bootstrap as core technologies. The main purpose of this research is to increase the forecasting accuracy and automate the inventory planning process.

2. Literature Review

Effective supply chain management requires demand forecasting and proper inventory planning in order to minimize costs and sustain service quality. Conventional Material Requirements Planning (MRP) systems have the capability of supporting manufacturing and inventory operations based on a set of static parameters, which makes them inflexible in dealing with changing market environment. The contemporary approach is aimed at incorporating intelligence into forecasting and inventory decision-making processes [1], [2]. Time-series forecasting is commonly utilized for demand forecasting. The classical statistical models are successful in dealing with stable data, yet fail to cope with non-linear behavior and unexpected changes, which resulted in the use of data-driven models [3], [4].

Machine learning techniques, including gradient boosting and scaling of boosting algorithms, has increased the forecasting accuracy through nonlinear relationship modeling and effective processing of large amounts of data. They have an advantage over traditional models, particularly in the case of complicated and dynamic settings [5], [6], [7]. The ensemble learning approach helps forecasters to make predictions with high accuracy by combining several models.

Classical techniques such as EOQ and safety stock assist in balancing costs and service levels; however, inaccurate forecasts may lead to problems like the bullwhip effect. The integration of forecasting using machine learning algorithms with inventory models ensures better planning and less stockouts [9], [10]. Forecast evaluation techniques such as MAPE and MAE have been employed in order to evaluate the forecast accuracy [11].

2.1 Research Gap

Although previous studies achieved in demand forecasting via the use of statistical models, machine learning approaches, and ensemble learning methodologies, majority of the research in the field has been focused on forecasting and inventory optimization as two different issues. Moreover, conventional MRP systems operate under the deterministic approach to planning, which cannot easily adapt to dynamic changes in demand. Very few researches have combined ensemble machine learning-based forecasting with automatic MRP planning and inventory optimization via EOQ, Safety Stock, and Reorder Point calculations. Furthermore, limited attention has been paid to the creation of a full-fledged web-based system that will be able to make ongoing updates in forecasted data, optimize purchasing operations and detect any potential problems related to inventory. In order to eliminate such drawbacks, the proposed MRP•NEXUS framework combines weighted ensemble forecasting, automated inventory optimization and conflict resolution into a single system.

3. Methodology

3.1 Dataset Description

The proposed MRP•NEXUS model was tested using the M5 Forecasting – Accuracy dataset [12], which is freely available on Kaggle and frequently used in academic research for retail demand forecasting purposes. The database consists of historical sales data recorded on a daily basis for 3,049 items in 10 Walmart stores located in 3 different U.S. states for the period between 2011 and 2016 and consists of 30,490 time series in total. The dataset features item IDs, store details, sales records, calendars, promotions and selling prices. The features of the database are shown in Table 1.

Table 1. Characteristics of the M5 forecasting dataset

Parameter	**Description**
Dataset Name	M5 Forecasting – Accuracy
Source	Walmart Retail Sales
Data Provider	Kaggle M5 Forecasting Competition
Time Period	2011–2016
Duration	1,941 Days
Number of Products	3,049
Number of Stores	10
Number of States	3
Total Time Series	30,490
Data Frequency	Daily
Primary Attributes	Date, Item ID, Store ID, Department, Category, Sales Quantity, Calendar Events, Selling Price
Training–Testing Split	80:20

Prior to model development, missing values and duplicates were deleted in order to enhance the quality of the data. Past sales data was aggregated at the product level to generate demand time-series, while day, week, month, and year information were generated from calendar data to account for seasonality effects. Features related to lagged demand and rolling statistics were also created to maintain past purchase behavior and boost the accuracy of forecasts. The final dataset was then split into 80% training and 20% testing sets, which served as the input for the forecasting module.

The processed data forms the input for the forecasting module, and the forecasted demand is then used for inventory management purposes such as EOQ, SS, and ROP calculations in the proposed framework.

3.2 MRP•NEXUS System Architecture

The proposed MRP•NEXUS framework is designed on the basis of a three-layer architecture that incorporates intelligent forecasting and automation of inventory management processes. The architecture includes the Frontend Layer, the Application Layer, and the Data Layer and, as shown in Figure 1 below, helps in collecting and processing information as well as its storing. The design allows effective communication among the components of the system.

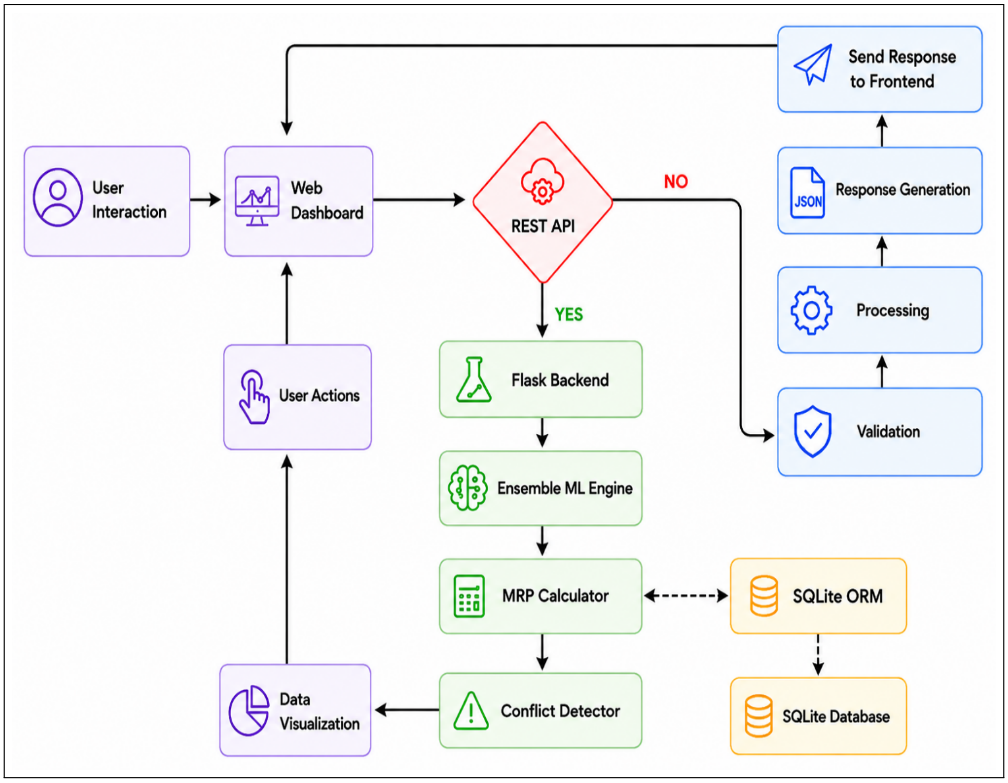

Figure 1. MRP•NEXUS processing workflow

The Frontend layer offers a user-friendly interface to control the products, sales, and forecasting process, whereas the Application layer offers pre-processing of data, demand forecasting, inventory optimization, and conflict monitoring based on intelligent modules proposed in the study. The Data layer keeps all the product details, sales history, forecasting outcome, inventory plans, and conflicts in an SQLite database, providing effective data storage and management techniques. These three layers create a comprehensive decision-making framework allowing real-time forecasting and inventory planning.

3.3 Ensemble Demand Forecasting

Demand forecasting module becomes the central analytics tool within the proposed MRP•NEXUS system. It uses sales data from M5 Forecasting dataset as an input source and preprocessed it in order to eliminate discrepancies and create time-series by arranging data in chronological order. Extracted temporal and statistical characteristics include month index, quarter, lagged values, moving averages, and trends in order to account for seasonal fluctuations and demand history.

To improve the forecasting performance, a weighting methodology is utilized by integrating Gradient Boosting Regressor, Random Forest Regressor, and Seasonal Decomposition algorithms. The latter have different features and properties of the demand data, which allows for enhancing the forecasting result through weighted integration of models' results.

Gradient Boosting Regressor builds an additive model using sequential minimization of the residuals from the last iteration. At each step, a new regression tree is trained on the negative gradient of the loss function to help increase the forecasting accuracy. The mathematical representation of the Gradient Boosting model is defined as

$$[F_m(x) = F_{m-1}(x) + \eta h_m(x)] \tag{1}$$

where,

- $F_m(x)$ = prediction at iteration mmm
- $F_{m-1}(x)$ = prediction from the previous iteration
- η = learning rate
- $h_m(x)$ = weak learner trained at iteration mmm

The Random Forest Regressor increases the robustness of predictions by taking an average of predictions made by many decision trees constructed using bootstrapping. This process involves estimating the demand separately in each tree and taking an average of predictions made by all trees, thus minimizing variance in predictions. The prediction from the Random Forest is expressed as

$$[\widehat{y}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b\left(x, \theta_b\right)] \tag{2}$$

where,

- $\widehat{y}(x)$ = predicted demand
- B = total number of decision trees
- T_b = prediction of the b_{th}decision tree
- θ_b = bootstrap sample used for tree construction

To capture periodic demand fluctuations, Seasonal Decomposition decomposes the demand data into two parts: the trend and the seasonal component. The trend captures the long-run pattern of demand, while the seasonal component captures the recurring changes related to monthly purchases. Seasonal demand can be represented as

$$[S(t) = T(t) \times SF(m)] \tag{3}$$

where,

- $S(t)$ = seasonal demand estimate
- $T(t)$ = trend component
- $SF(m)$ = seasonal factor for month m

Finally, the forecasts generated by all three models are combined together using the weighted ensembling technique. This method puts more emphasis on the model that generates lower forecast errors while training. The formula for the ensemble forecast is given as

$$[\widehat{y}_{\text{ensemble}} = 0.65\left(w_1\widehat{y}_{GB} + w_2\widehat{y}_{RF}\right) + 0.35\widehat{y}_{\text{Seasonal}}] \tag{4}$$

where,

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- $\widehat{y}_{GB}$ = Gradient Boosting prediction
- $\widehat{y}_{RF}$ = Random Forest prediction
- $\widehat{y}_{\text{Seasonal}}$ = Seasonal Decomposition prediction
- w_1, w_2 = adaptive model weights

The calculated demand forecast becomes the input for the inventory optimization model in which procurement quantities are calculated using EOQ, safety stock, and reorder point models.

3.4 Inventory Optimization

The forecasted demand obtained through the ensemble forecasting module is then applied to help in determining optimal levels for inventory planning and procurement. The suggested MRP•NEXUS model incorporates three popular methods of inventory management, which include Economic Order Quantity (EOQ), Safety Stock (SS), and Reorder Point (ROP) in order to achieve the optimal quantities of replenishment in keeping with the required service level.

Economic Order Quantity (EOQ) helps decide the best order quantity that balances ordering cost and inventory holding cost. The EOQ is calculated from the forecasted annual demand as

$$[EOQ = \sqrt{\frac{2D_aS}{H}}] \tag{5}$$

where,

- D_a = annual forecasted demand
- S = ordering cost per order
- H = annual holding cost per unit

The calculated safety stock serves as the buffer for the demand uncertainty and supply uncertainty. To ensure availability of the products throughout the process of demand variations and suppliers' lead time, the Safety Stock (SS) is determined as

$$[SS = Z \times \sigma_e \times \sqrt{L}] \tag{6}$$

where,

- SS = safety stock
- Z = service level factor
- σ_e = standard deviation of demand
- L = supplier lead time

The computed safety stock acts as a buffer against demand uncertainty and supply delays. Reorder Point (ROP) will indicate the inventory position when the order should be placed to avoid shortages. This can be calculated by

$$[ROP = \bar{d} \times L + SS] \tag{7}$$

where,

- ROP = reorder point
- $\bar{d}$ = average daily demand
- L = lead time
- SS = safety stock

The calculated EOQ, Safety Stock, and Reorder Point all together constitute the necessary inventory parameters needed for making appropriate procurement decisions. The optimal inventory values are then passed to the conflict detector for the purpose of monitoring any inventory-related risks or issues.

3.5 Conflict Detection and System Implementation

The proposed MRP•NEXUS system constantly tracks the inventory to detect possible risks that can impact the supply chain management. In the conflict detection component, inventory data is automatically analyzed based on EOQ, Safety Stock, and Reorder Point values to determine critical situations like low stock, competition among suppliers, forecast errors, and excessive inventory. Based on established decision criteria, the conflicts detected are then categorized by severity and alerts are issued for timely procurement and inventory management decisions.

The proposed architecture is realized a web-based decision support system based on the following technologies shown in Table 2. The application is designed in the Flask framework with Scikit-learn as a machine learning library, SQLite database, and Bootstrap with Chart.js for visualization. The workflow of the application is based on an automated execution process, according to which new entries in the sales are followed by demand forecasting, inventory optimization, and conflict detection processes performed automatically.

Table 2. Technology stack of the proposed MRP•NEXUS framework

Component	Technology
Backend Framework	Python 3.12, Flask 3.1
Machine Learning	Scikit-learn (Gradient Boosting Regressor, Random Forest Regressor)
Database	SQLite
Frontend	HTML5, CSS3, JavaScript, Bootstrap 5
Data Visualization	Chart.js 4.4
Feature Scaling	StandardScaler

4. Results and Discussion

4.1 Forecasting Performance

Table 3. Forecasting components of the proposed MRP•NEXUS framework

Method	Key Feature
Gradient Boosting Regressor [5]	Sequential tree-based learning for modeling nonlinear demand patterns and minimizing prediction errors.
Forest Regressor [7]	Ensemble decision-tree model that improves prediction stability and reduces overfitting.
Seasonal Decomposition [3]	Separates trend and seasonal components to capture recurring demand variations.
Proposed MRP•NEXUS Ensemble	Integrates Gradient Boosting Regressor, Random Forest Regressor, and Seasonal Decomposition through adaptive weighted ensemble learning to improve forecasting reliability and support inventory optimization.

The recent developments in demand forecasting show that ensemble machine learning and seasonal modeling lead to the improvement of forecasting accuracy. The gradient boosting regressor is sutable for modeling non-linear demand, the random forest regressor offers a stable forecasts while use of ensemble machine learning, and the seasonal decomposition algorithm helps capture seasonality in the past sales data [3], [5], [7]. Based on these new results, the

MRP•NEXUS framework is developed by utilizing all these techniques with adaptive weighting of the ensemble. The used forecasting models are listed in Table 3.

The accuracy of forecasting is depicted in Figure 2 as it presents the graphical demonstration of the output of the model. The analysis reveals that there is a very little deviation between the forecasted demand and the actual demand trend and thus, confirming the capability of the forecasting model in identifying the demand pattern.

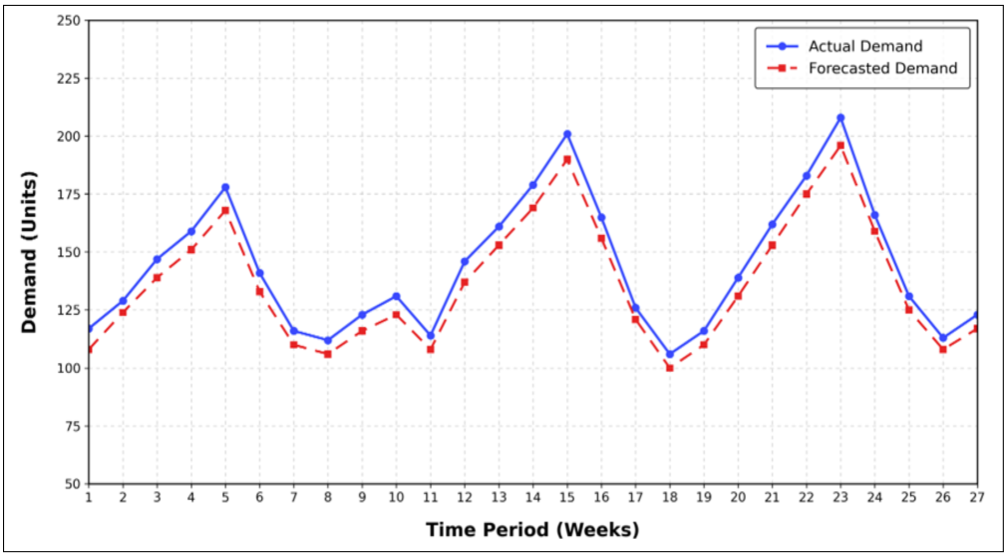

Figure 2. Forecasting performance of the proposed MRP•NEXUS framework

The forecasting performance of the proposed MRP•NEXUS Ensemble is illustrated in Table 4. The ensemble framework resulted in overall forecasting accuracy of 91.3%, while having MAPE and MAE equal to 8.7% and 35.6 units correspondingly, thus demonstrating good accuracy of forecasting and rather low level of forecasting error. It can be concluded that it is quite effective to utilize Gradient Boosting Regressor, Random Forest Regressor and seasonal decomposition within single ensemble framework, as it allows to perform accurate forecasting for demand.

Table 4. Forecasting performance of the proposed MRP•NEXUS framework

Model	**MRP•NEXUS Ensemble**
Accuracy (%)	91.3
MAPE (%)	8.7
MAE (Units)	35.6

4.2 Inventory Planning Results

The inventory planning parameters have been calculated based on the demand forecasts retrieved from the M5 forecasting-accuracy dataset [12]. In accordance with the forecasted demand values, the EOQ value, safety stock, and reorder point have been calculated for certain products. These inventory planning parameters are provided in Table 5, reflecting the ability of the proposed MRP•NEXUS framework to convert demand forecasts into procurement decisions while keeping inventory available and reducing possible risks related to inventory.

Table 5. Inventory planning results generated by the proposed MRP·NEXUS framework

Product ID	Forecast (6 Months)	EOQ (Units)	Safety Stock	Reorder Point	Inventory Status
ITEM_001	3,148	142	12	95	Healthy
ITEM_017	5,824	489	19	117	Healthy
ITEM_043	8,736	1,043	58	297	Healthy
ITEM_086	14,512	476	29	183	Reorder Required
ITEM_112	4,218	96	21	142	Critical

The computed inventory parameters support intelligent procurement by determining the most efficient order size and the correct replacement point for each item. The obtained status of the inventory allows grouping items depending on their state, thus providing an ability to define normal inventory, items that need replenishment, and critical inventory. The inventory analysis directly contributes to the functionality of the conflict detection module.

4.3 System Implementation

Implementation of the proposed framework is illustrated via the web-based dashboard as shown in Figure 3. It provides easy access to the information about products, inventory, and operation data. Thus, it enables continuous monitoring of inventory activities with the visual data representation.

Figure 3. Inventory management interface

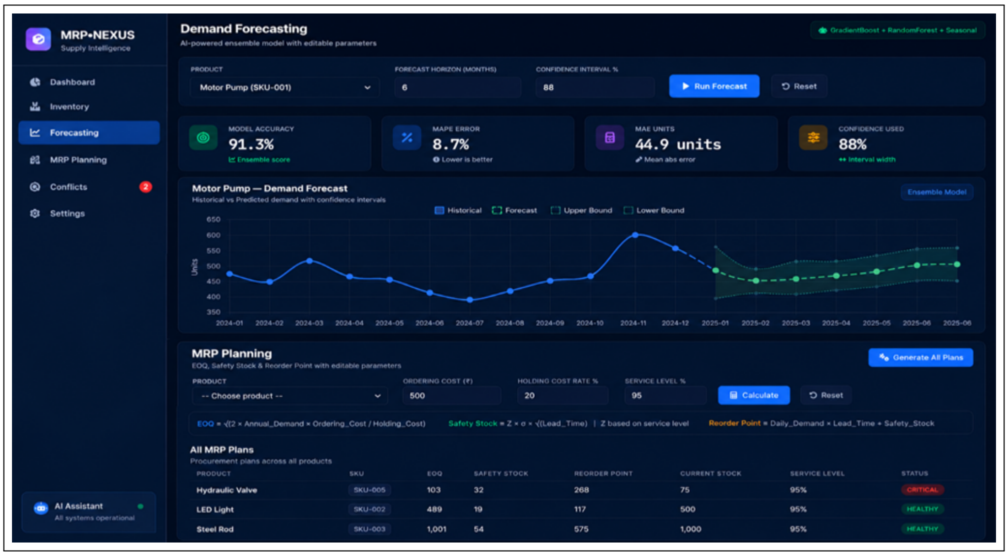

Figure 4. Demand forecasting and inventory planning interface

Modules for forecasting and inventory planning are shown in Figure 4, where the demand forecast generated is incorporated into the EOQ, Safety Stock, and Reorder Point calculations. This interface allows users to predict future demand and get immediate inventory planning by making the process of data-based procurement possible.

Operational feasibility of the proposed framework is highlighted in Figure 5, which gives an overview of the conflict detection mechanism. The proposed system constantly checks the conditions of the inventory and automatically detects operational challenges, including lack of availability of the inventory, forecast conflicts, and any other inventory-related problem.

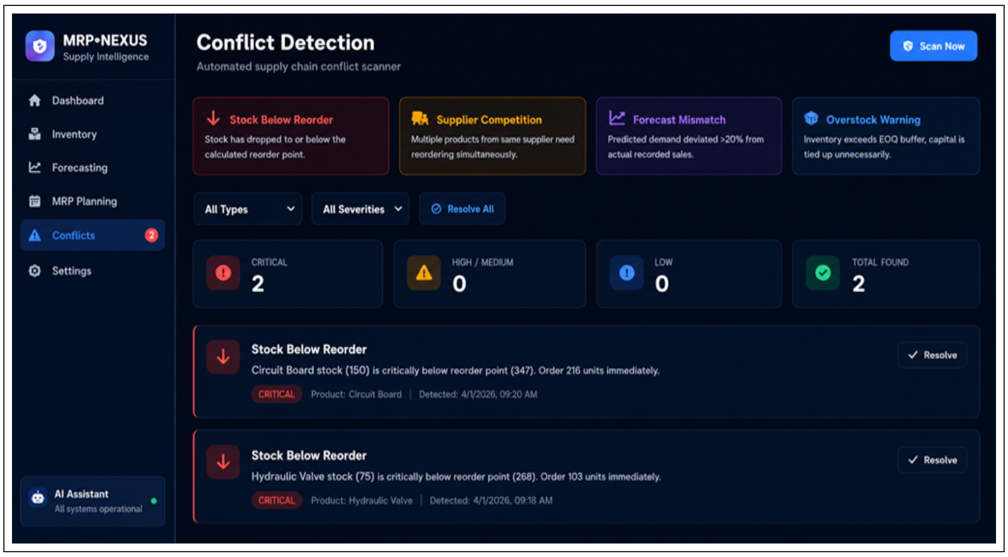

Figure 5. Inventory conflict detection interface

4.4 Discussion

The experiment results show that the developed MRP•NEXUS system is capable of integrating the techniques of demand prediction, inventory management, and conflict detection. The ensemble prediction method generates precise predictions that can be used to compute the inventory management parameters, while the built-in conflict detection approach can help identify possible problems related to inventory management. This web-based realization of the proposed framework demonstrates its practical applicability through real-time inventory tracking and decision-making support. Overall, the proposed framework increases planning effectiveness, decreases the reliance on human intervention during inventory management, and provides a solution that can be easily scaled up for intelligent material planning.

5. Conclusion and Future Work

This research presented MRP•NEXUS, an intelligent inventory planning system that incorporates demand forecasting, inventory optimization, conflict detection, and real-time monitoring into a single web-based decision support system. The intelligent inventory planning system makes use of ensemble machine learning and material requirement planning concepts to turn sales data into actionable inventory decisions. The integration of forecasting, optimization, and conflict detection makes inventory planning more efficient and minimizes human involvement. Modular architecture also contributes to increased scalability and easier deployment in retail, warehouse, and manufacturing environments. Future research will focus on the development framework by incorporating forecasting models using deep learning, integrating IoT real-time data, and deploying the framework in the cloud environment to facilitate distributed inventory management. In addition, the use of reinforcement learning in adaptive inventory control and using more sophisticated explainable artificial intelligence algorithms will increase the scalability and practicality of the framework in future intelligent supply chain management systems.

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