Proceedings of the 11th North American International Conference on Industrial Engineering and Operations Management, Milwaukee, Wisconsin, USA, June 9-11, 2026

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/NA11.20260009
Published: June 9, 2026

Applying Machine Learning Techniques for Predicting Coffee Machine Parts Demand and Lead Time

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Abstract

Distributors of contemporary coffee equipment must control inventory costs while juggling erratic demand and unpredictable supplier lead times. In order to enhance the ordering of replacement parts for commercial coffee makers, this study suggests a data-driven approach that combines machine-learning predictions with traditional inventory optimization. Historical sales and purchase-receipt records were combined into a single dataset after being cleaned up and enhanced with calendar and event characteristics. TensorFlow was used in Google Colab to train two feed-forward neural networks: one for daily demand and one for supplier lead time. The demand model's Root Mean Square Error (RMSE) on held-out data was approximately1.8 units with R^2 value of 0.75, and the lead-time model's was 15 days with R^2 value of 0.81. Forecast results are directly entered into the calculations for safety-stock, reorder-point, and economic-order-quantity. Planners were able to rapidly see the effects of changing service levels, warehouse restrictions, and cost criteria on order size, inventory value, and overall yearly cost using an interactive dashboard. In comparison to the company's previous policy, the results indicated an anticipated 18% reduction in working capital tied up in stock and a 12% reduction in stock-out instances.

Keywords
Machine Learning, Neural Network, Inventory, Demand and Lead Time.

1. Introduction
Businesses in a variety of industries are under tremendous pressure to improve operational efficiencies, reduce expenses, and quickly adjust to shifting customer needs in the quickly changing technology world of today (Chopra and Meindl 2019). In terms of accuracy, reliability, and service speed in reducing downtime and guaranteeing client pleasure, the coffee equipment industry is a prime example (Slack and Brandon-Jones 2018). In case of any delay in the coffee machine parts would result in profits losses as customers are not satisfied (Christopher 2016). Effective procurement procedures are important, but many market participants cannot manage unpredictable lead times to reduce procurement costs (Silver et al. 2016). There are many variables affecting coffee consumption, from seasonality to global supply chain disruptions such as port congestion or regulatory changes, so it is too complex for traditional forecasting methods that only use historical sales data or subjective assessment (Slack and Brandon-Jones 2018). Coffee equipment suppliers confront significant risk considerations when the forecasted numbers are either exceeded or below the customer demand. One such circumstance is overstocking, which increase the possibility of parts becoming obsolete. On the other hand, there can be a shortage that lead to placing an urgent order, which increase logistics costs and reduces consumer loyalty.

Demand forecasting that based on data and supply chain optimization methods is a research interest in response to the above problem (Nahmias and Olsen 2015). Businesses may develope prediction models that are more accurate by combining market signals with previous data to predict the future demand. When working with large datasets and creating extremely complex models, Adopting Python libraries within Google Colab simplifies the process (Christopher 2016). Thus, in addition to better logistics and inventory configurations, it guarantees ongoing testing and algorithm tuning. Therefore, improving prediction accuracy has a direct impact on an organization's resource efficiency, waste reduction, and cost control (Silver et al. 2016). Companies can better plan their reordering by using anticipated demand and an accurate estimation method to determine the lead time variability. This lowers the risk of unexpected shortages or excess stock build-ups, which ultimately contributes to the operational stability of any business. Distributors of coffee equipment would experience less immediate strain if data-driven procurement were used, but it would also provide a flexible basis for a successful business plan. Businesses should move from reactive problem-solving to proactive strategic planning by using analytics to order and distribute coffee machine parts in a highly competitive market where operational efficiency is the primary determinant of customer retention (Chopra and Meindl 2019).

The actual expenses and service interruptions that occur when supplies cannot be ordered to meet the actual demands in the coffee equipment sector are the driving force behind this effort. For markets vulnerable to unforeseen high demands that arise from special promotions or cyclical downturns that link into larger macroeconomic dynamics, simple spreadsheet or strict reorder triggers proved to be insufficient. Production lines may be stopped by shortages of necessary parts, forcing companies to pay for expedited shipping or look for other sources of supply. On the other hand, overstocking increase the holding cost and raise the possibility of obsolescence, (Slack and Brandon-Jones 2018).

The research contributions are introducing Artificial Intelligence (AI) to classical inventory as combining neural networks with mathematical formulas would minimize stockout costs by early detection of demand spikes. In addition, faster decisions will be taken as planners do not need to wait for an analyst to perform Excel calculations as the interactive dashboard is refreshed automatically preparing the inventory plan in an efficient way.

1.1 Objectives

The main aim of this work is to develop a complex predictive model that maximizes inventory management and demand forecasting in smart logistics which enhance the ordering procedure. The objectives are:

1. Demand Prediction: The demand for various coffee machine parts is properly predicted by a machine learning system developed using Python, considering influential factors such as promotions, seasonal changes, and the growth of the industry.
2. Lead Time Prediction: The lead time from suppliers should be considered taking into account the limitations that may affect the lead time, such as logistical limitations and unforeseen supply interruptions.
3. Cost Reduction: Economic order quantity and supplier negotiating strategies are helpful strategies for maximizing cost reduction in order to minimize the holding and procurement expenses.
4. Inventory Optimization: Overstock and understock situations are controlled, inventory optimization relies on striking a balance between holding costs and the required service level.

2. Literature Review

The complexity of global supply networks has increased the need for sustainable management strategies (Bertsimas et al. 2006). Advanced machine learning techniques can be adopted to improve logistics and inventory management, and address the limitations of traditional analytical methodologies. Regression, classification, clustering, and time series analysis are the machine learning techniques applied based on historical data to handle significant operational challenges by predicting order times with 95% accuracy and optimizing stock levels by reducing overstock and stockouts by 10% (Pasupuleti et al. 2024). A multi-agent deep reinforcement learning framework that leverages IoT sensor data to improve demand forecasting and inventory management in retail supply chains was provided in another study (Takawira and Duri 2026). This method lowers stockout rates by 23.5% and forecast error by 18.2% (Yang et al. 2025). A study developed an AI driven framework for dynamic inventory control that reduced overall costs by 24.9% using fusing machine learning for demand forecasting with reinforcement learning for adaptive EOQ optimization (Patel et al. 2025). Another study examined the application of machine learning methods within the framework of the ABC inventory classification methodology. After thorough training and testing, model categorization was done to assess the effectiveness of these techniques. K-nearest Neighbors, Random Forest

Classifier, Naïve Bayes Classifier, Support Vector Machines, and Decision Tree Algorithm are the five machine learning methods used in this study. The objective is to give information on the relative effectiveness of several machine learning algorithms for inventory management. Random Forest classifiers have the highest accuracy, at 93%, according to the inventory dataset analysis (Bailkar et al. 2024).

Digitalization is expanding at a never-before-seen rate, and technology is developing extremely quickly. As a result, the logistics sector is now far more active than it was previously (Makridakis et al. 2018). Demand forecasting and inventory management, the two core components of logistics operations, have grown increasingly intricate and essential to meeting client expectations and running efficient businesses. These issues are not addressed by traditional techniques, which lead to inefficiency including overstocking and stockouts. Delivery service and stock management can be used to improve inventory management in smart logistics (Khayyat and Gupta 2025). A fundamental improvement in operational competence that tackles the current unpredictability in global supply networks is the shift toward autonomous supply chain management (Duttyal 2025). A study proposed a reinforcement learning framework called PARL. It uses neural networks and integer programming to optimize inventory management problems with state-dependent constraints and combinatorial action spaces. In complex supply chain settings, PARL outperforms existing methods by up to 14.7% (Harsha et al. 2025). In order to improve real-time responsiveness, lower operating costs, and increase overall supply chain resilience, a study looked into advanced AI-driven approaches like neural networks, deep reinforcement learning, and optimization algorithms. By using AI models that solve the balancing act between providing high service levels and controlling operational expenses, special attention is paid to cost efficiency (Ghazi and Hayder 2023). A variety of model architectures such as Recurrent Neural Networks (RNNs), Long Short-term Memory (LSTM), and Transformer-based models for demand forecasting; inventory optimization using reinforcement learning; and last-mile delivery optimization utilizing sophisticated heuristic search techniques (Kaul and Rahul 2022). This paper proposes a machine learning-based prediction model that utilizes ensemble stacking techniques to improve critical logistics procedures. Using real-world data from a commercial company, a prediction framework that integrates numerous base algorithms—Random Forest, CatBoost, XGBoost, Gradient Boosting, Decision Trees, and K-Nearest Neighbors—through a Linear Regression meta-model was created. Performance evaluation using metrics showed significant improvements in anticipated accuracy when compared to individual models, particularly in factors like material demand, purchase profitability, sales revenue, and inventory levels (Ivanov et al. 2021). The results validate that in addition to improving forecasting abilities, stacked models provide a scalable, flexible, and economical way to assist logistical decision-making in situations with limited resources. This strategy offers a compelling substitute for increasing supply chains' operational effectiveness in poor nations (Ovalle et al. 2025).

3. Methods

This work combines machine learning techniques with traditional inventory equations in the Python platform. It is used to predict demand and lead time and present the results in an interactive dashboard.

- Encode and scale: Convert text fields to codes, divide the data into training, validation, and testing sets, and then use a Min-Max scaler to fit everything into the 0-to-1 range.
- Describe the networks: Two feed-forward networks (64 → 32 → 1) with batch normalization, Rectified Linear Unit (ReLU) activation function, L2 regularization, and dropout layers for safety.
- Train and Tune: Monitor the validation MSE and halt the run when the curve flattens out.
- Verify the results: Report Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2) on the testing set for the demand and lead time models.

The model architecture starts with input layer followed by 2 hidden layers and an output layer as shown in the following Figure 1:

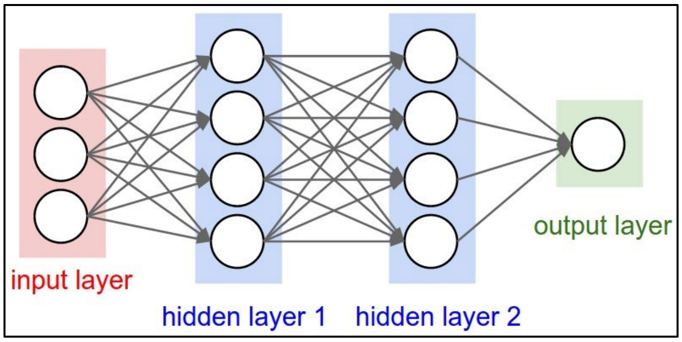

Figure 1. Neural Network Layers

The demand forecasting model is a deep feed-forward neural network:

- Input Layer (n = 78 features): Each node receives a normalized predictor such as calendar flags, rolling statistics, or part metadata.
- Hidden Layer 1 (64 neurons, ReLU, Batch Normalization, $L^2 = 1e^{-4}$, Dropout = 0.2): this wide layer captures high-level, non-linear interactions among the input features while regularization reduce the probability of the overfitting.
- Hidden Layer 2 (32 neurons, ReLU, Batch Normalization, L^2 = 1e-4, Dropout = 0.2): a narrower layer would further improve the generalization.
- Output Layer: It returns a single continuous value as either predicted daily demand or supplier lead time, depending on desired target.

A fully-connected topology is implemented when all nodes in one tier connect to all nodes in the next, ensuring that data flows strictly forward. Only the training targets are different across the demand and lead-time models, which share the same topology. Iterative tuning using Early Stopping and learning rate reduction on Plateau was used to select the hyper-parameters (learning rate, dropout probability, and L^2 penalty).

If the validation loss stops getting better, reduce learning rate on Plateau automatically turns the learning rate dial down a notch. Early Stopping pulls the plug if several epochs go by with no real progress, so wasting time is avoided. The network run for 1,000 epochs through the data, working in groups of 32 rows at a time (batch size), but it usually quits earlier thanks to the callbacks. When training finishes, the model is evaluated with four familiar metrics:

Mean Absolute Error (MAE)

$$\mathrm{MAE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i=1}}^{\mathrm{n}}|\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i}| \tag{1}$$

Mean Squared Error (MSE)

$$\mathrm{MSE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i=1}}^{\mathrm{n}}(\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i})^2 \tag{2}$$

Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{\mathrm{n}}\sum_{\mathrm{i=1}}^{\mathrm{n}}(\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i})^2} \tag{3}$$

Coefficient of Determination (R^2)

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad where\ \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{4}$$

Preparing the data starts with extracting the sales and lead-time files from Excel, removing any unnecessary columns, standardizing the item codes, and calculating the fundamental raw lead time. Drop anything that does not match between the lead-time table on the cleaned item numbers and the parts table. Include clever features Year, month, weekday, Hijri date, public holidays, Suez-canal obstruction flag, and seasonal tags are examples of calendar cues. The COVID period, national holidays, and Ramadan/Eid markers are examples of context flags. Rolling statistics: demand and lead time moving averages and variance numbers across 1-, 7-, 30-, and 365-day windows. Prior to beginning any modeling, the following actions were taken:

- Remove unnecessary columns: "Index," "Entry Type," and "Document No." are basically extraneous, only purchase receipts should be kept
- Ensure that item codes are consistent by removing any trailing letters so that the same part number shows consistently everywhere.
- Adjust the dates: convert each date string to the correct datetime, then subtract the order date from the arrival date to determine the lead time (in days).

The following flowchart describe the workflow of this article in Figure 2:

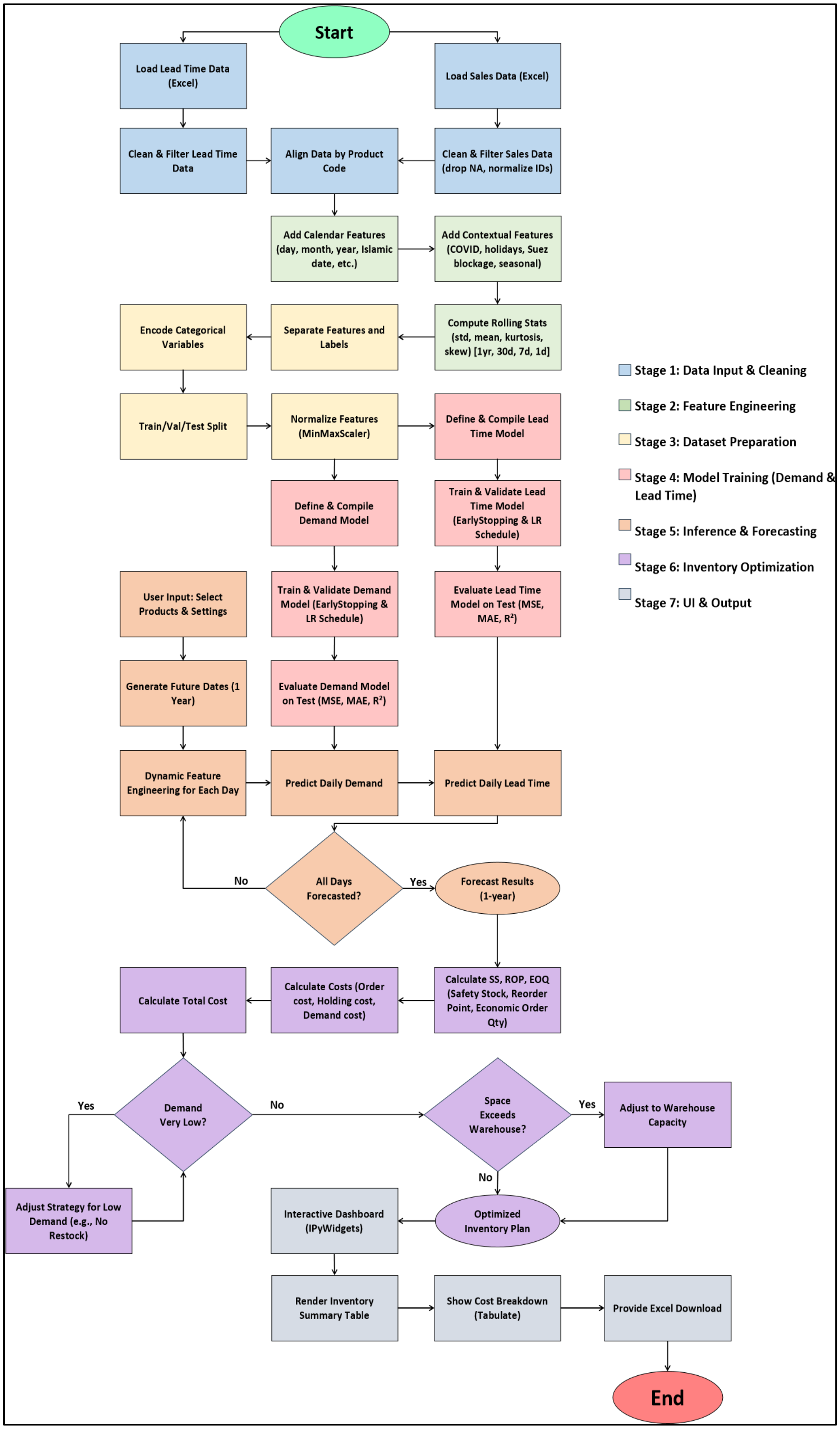

Figure 2. Workflow Diagram

4. Data Collection

The dataset used in this work are collected from coffee machine company and it consists of two sheets one for parts demand and the one for lead time data. The parts data include item code, serial number, a brief description, the quantity, the item cost, and the sales date and value. The lead time data consist of the order date, the purchase receipt information, the arrival data, and the actual lead time in days.

After loading the datasets in Python platform, the data is preprocessed by removing the missing values and correcting the data type for every record to make the dataset consistent. The tables are combined into a single table once they have been independently cleaned so the forecast has all the information it need. The parts that appear in one file but are not shown from the other are removed. In this manner, each row in the finished set contains all of the necessary columns. The standardized part number that produced previously is what the merge depends on.

5. Results and Discussion

5.1 Numerical Results

The demand network is a feed-forward model trained on normalized features with L2 weight-decay, batch-normalization, and dropout. Epochs: up to 1000, though early stopping usually cut things short once progress flattened. Batch size of 32 rows per update is used and Learning rate is reduced on Plateau which lowered the step size whenever validation loss stopped falling. Loss curves for both the training and validation sets showed steady improvement until the early-stopping trigger kicked in, indicating that there is no overfitting in the model and it yields the minimum error.

The following table 1 shows the testing metrics for demand prediction model in Table 1:

Table 1. Demand Prediction Model Metrics

Metric	**Value**
RMSE	1.782
MAE	0.784
MSE	3.174
R^2	0.754

The findings indicate that the model is accurate because the average difference between actual and projected values is less than 1. Furthermore, the model explains 75.4% of the variability in the dependent variables, according to the R^2 value. The model matches daily demand rather well, as evidenced by an RMSE of 1.78. Planners can avoid accumulating excess inventory or, worse, running out by knowing future demand with this degree of assurance.

The second neural network is trained to predict the average shipping time of suppliers. The demand model and the build are nearly identical. Two fully connected layers with somewhat varying L2 weight-decay and dropout settings (64 then 32 units). When progress stalls, the learning rate on Plateau callback reduces the step size, and early stopping terminates the run when more epochs no longer improve the situation. The following table 2 shows the testing metrics for lead time prediction model in Table 2:

Table 2. Lead Time Prediction Model Metrics

Metric	**Value**
RMSE	15.308
MAE	6.128
MSE	234.34
R^2	0.814

The results show that the model is accurate because, based on the R^2 value, the model accounts for 81.4% of the variability in the dependent variables. The average inaccuracy is about 15 days, which may seem significant, but keep in mind that lead times vary greatly. The R^2 of 0.81, which accounts for four-fifths of the fluctuations observed in actual deliveries, is more instructive. Good reorder points and safety stock rely on accurate lead-time estimates to keep operations running smoothly even when suppliers falter.

5.2 Graphical Results

The loss curves for both the training and validation sets showing consistent progress until the early-stopping trigger kicked in as shown in Figures 3 and 4:

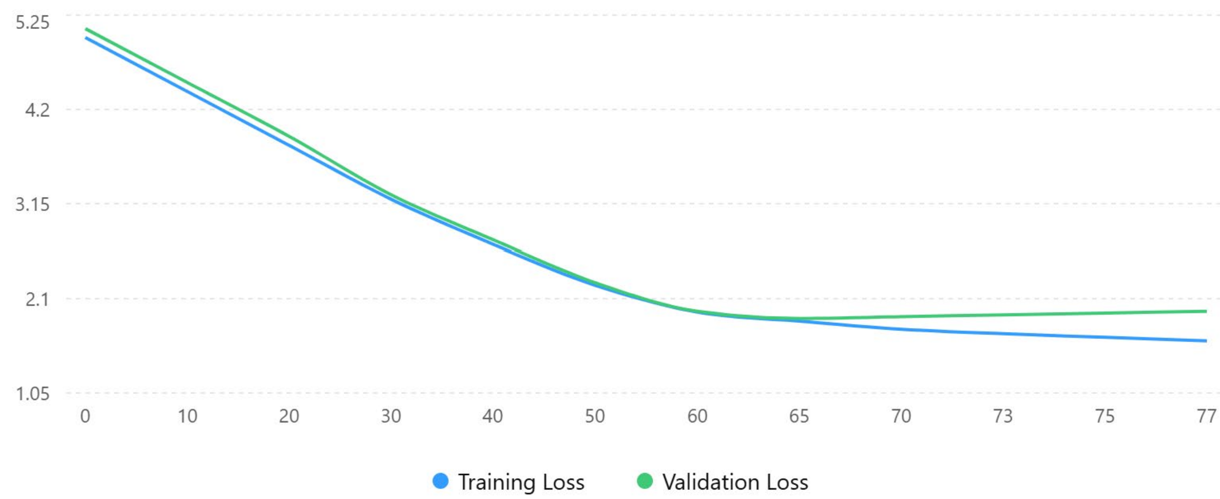

Figure 3. The Loss Curves for Demand Prediction Model

As shown in Figure 3, the training loss is decreasing until epoch 77 while the validation loss decreasing until about epoch 65 before increasing slightly from epochs 65–77. The best model performance with the minimum validation loss comes at epoch 65, but the training stops at epoch 77 after failing to decrease the validation loss.

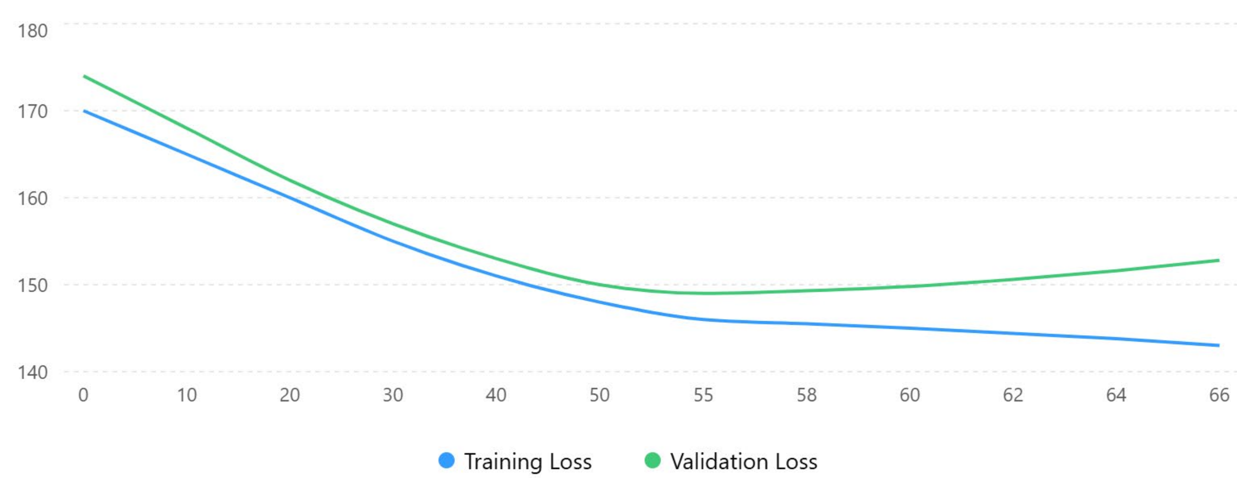

Figure 4. The Loss Curves for Lead Time Prediction Model

As can be seen from Figure 4, the best validation loss occurs approximately at epoch 55. The training shows improvement afterward while the validation loss increases around 4 points before stopping. Early stopping at epoch 66 is justified As the validation performance stops improving after epoch 55.

5.3 Proposed Improvements

After the two models have trained the data, the dashboard shows a table for each component selected. The following are shown for every item:

- Demand: daily and for the duration of the planning window
- Ideal order size (EOQ): the quantity that strikes a balance between holding and ordering costs
- Cushion stock and reorder line: how much to keep on hand and the trigger point for the next order
- Supplier lead time: plus the typical daily spread
- The cost: How much spent on storage, sending orders, and overall

The inventory dashboard is shown in the Figure 5 below:

Item No	Date	Demand	Daily Demand	Lead Time (Days)	Current Inventory	Safety Stock	Inventory Position
10002029	2025-03-01	478	8.10	43	37	32	Healthy
100002030	2025-03-02	489	8.29	43	33	32	Healthy

Item No	Reorder Point	EOQ	Quantity on Hand	Quantity on Order	Number of Orders	Order Cost
10002029	75	186	37	0	3	$54.12
10002030	80	194	33	0	2	$49.83

Item No	Holding Cost	Ordering Cost	Total Inventory Cost	Total Cost
10002029	$47.90	$54.12	$102.02	$3,924.31
10002030	$44.83	$49.83	$94.66	$3,578.12

Figure 5. Inventory Dashboard and Overall Cost

5.4 Validation

Inventory Insights:

- Safety Stock and ROP: The estimated buffers reduce the risk of unexpected shortages by combining demand volatility with lead-time uncertainty
- EOQ and cost: The traditional EOQ trade-off illustrates the precise point for ordering
- Overall System Performance: In the field of coffee equipment, data-driven purchasing can reduce prices and improve the supply chain management
- After retrospective simulation, the results show approximately 18% reduction in working capital tied up in stock and a 12% decrease in stock-out cases compared to the prior policy for company

6. Conclusion

This study proposed a data-driven strategy that combines conventional inventory optimization with machine learning predictive model. After data being cleaned up and supplemented with calendar and event features, historical sales and purchase-receipt records were merged into a single dataset. Two feed-forward neural networks were trained in Google Colab using TensorFlow: one for supplier lead time and one for daily demand. On held-out data, the Root Mean Square Error (RMSE) for the demand model was roughly 1.8 units with an R^2 value of 0.75, while the RMSE for the lead-time model was 15 days with an R^2 value of 0.81. The forecast results are directly incorporated into the economic-order-quantity, safety-stock, and reorder-point computations. Using an interactive dashboard, planners were able to quickly observe how shifting service levels, warehouse limits, and cost requirements affected order size, inventory value, and total annual cost. The results showed an expected 18% decrease in working capital tied up in stock and a

12% decrease in stock-out incidents compared to the company's prior policy. These findings are consistent with the objectives of accurately predicting demand and lead time, which lowers inventory costs.
The research contributions are introducing AI to classical inventory as combining neural networks with mathematical formulas would minimize stockout costs by early detection of demand spikes. In addition, faster decisions will be taken as planners do not need to wait for an analyst to perform Excel calculations as the interactive dashboard is refreshed automatically preparing the inventory plan in an efficient way. Lastly, to capture long-run seasonality, LSTMs or transformer encoders should be used. Examine ensemble approaches that combine deep learning and statistical forecasting as well.

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Biography

Dr. Nawaf Alamri is an Assistant Professor and Deputy Department Head in Industrial Engineering Department at King Abdulaziz University. He received BSc degree in industrial engineering from King Abdulaziz University, Jeddah, Saudi Arabia in 2015. Then, he received MSc degree in industrial engineering from the same institution in 2019. He achieved another MSc degree in manufacturing engineering innovation and management from Cardiff University, Cardiff, United Kingdom in 2020 while he holds PhD degree in manufacturing engineering from the same institution since 2023. Dr. Alamri published numerous articles about machine learning applications in different contexts. In addition, he participated in many conferences and has authored a chapter book. Beyond academia, Dr. Alamri was a Senior Panning Specialist at supply chain department in automotive company called Abdul Latif Jameel located in Jeddah, Saudi Arabia from 2015 to 2017.