INVENTORY OPTIMIZATION

Intelligent decision-making powered by AI ensuring smarter purchasing and reduced costs.

contact@thedecisioninc.com
www.thedecisioninc.com

DATA QUALITY DRIVES RESULTS

Before diving into any results or analysis, it's crucial to acknowledge that the quality of results is only as good as the data we begin with. Well-representative, clean, and contextually rich data lay the foundation for reliable outcomes. No algorithm can compensate for biased, incomplete, or noisy data.

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EVALUATION METRICS

R-squared

- $R^2 = 0$: The model cannot explain any variation in the output based on the inputs, it's no better than guessing.
- $R^2 = 0.5$: The model explains 50% the variation in the output; the rest may be due to factors not included or natural randomness.
- $R^2 = 1$: The model perfectly explains all variation in the output using the input variables.

RMSE

- Measure the differences between values predicted by a model and the values actually observed.
- RMSE is expressed in the same units as the actual variable, so an RMSE of 10 would indicate that, on average, the predicted values deviate 10 units from actual data.
- A lower RMSE signifies a better model fit, with smaller errors between predicted and actual values.

DATA CONTEXT

- The R^2 scores and RMSE that are discussed in the upcoming slides are obtained using weekly demand data retrieved from Kaggle, consisting of 76 warehouses, each having nearly 28 items.
- Lead times, holding costs, and ordering costs were synthetically generated using defined logic in code.
- The analysis was based on a 95% service level (5% risk of stockout).
- Results are expected to improve with more focused, granular datasets.

PROBLEM STATEMENT

Inventory mismanagement often leads to critical issues such as overstocking and stockouts, disrupting supply chain efficiency.

OverStocking

- High Holding Cost
- High Ordering Cost

Stockouts

- Lost Sales
- Customer Dissatisfaction

OBJECTIVES

Data-Driven Restocking Decisions

Restocking quantities are optimized using Economic Order Quantity based on forecasted sales, while Re-Order Point determines the ideal reorder timing which ensures inventory is replenished precisely, eliminating stockouts and associated costs.

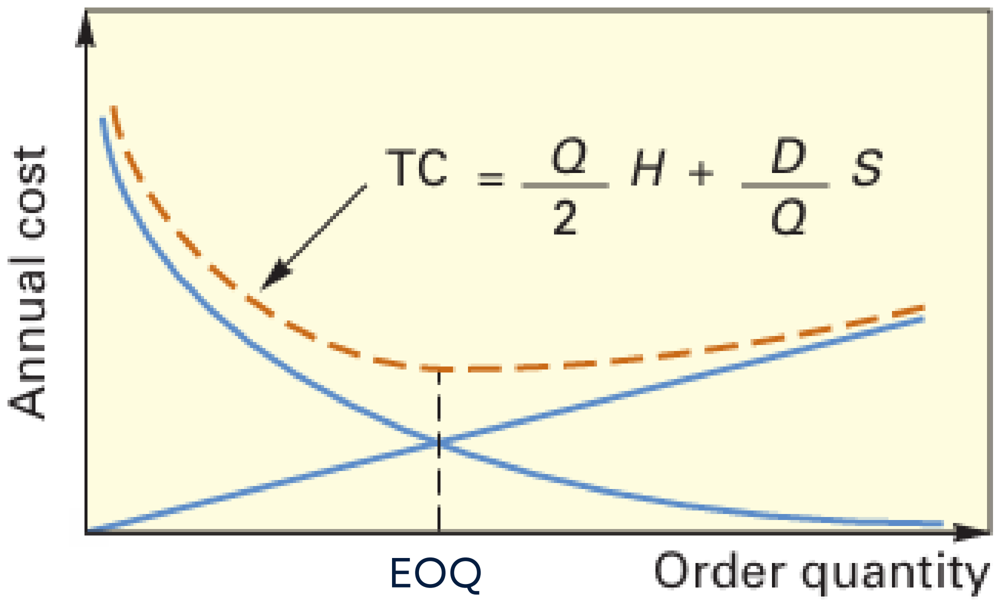
Improve Stock Availability

Re-Order Point guarantees that the stock is always available exactly when it is needed, enhancing efficiency and preventing shortages.

Minimize Holding & Ordering Cost

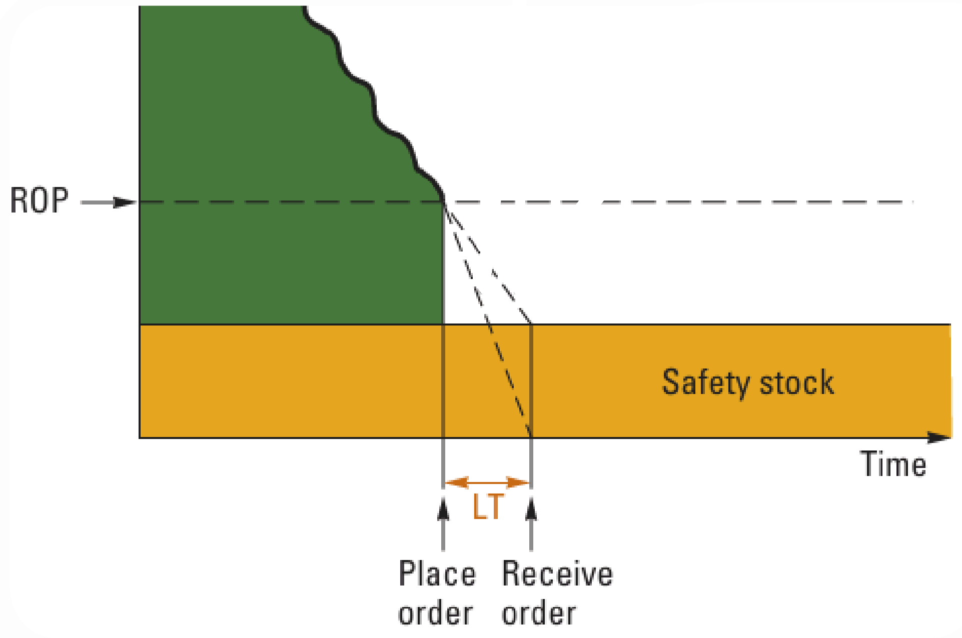
Economic Order Quantity based on the forecasted sales will result in minimized holding and ordering costs.

MODULES



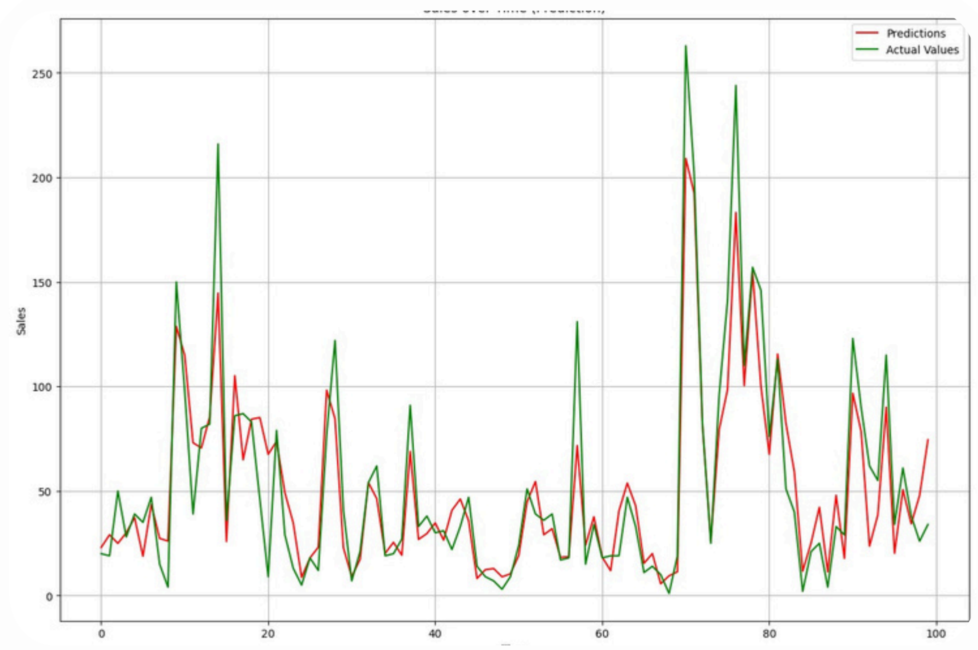
Economic Order Quantity

To minimize the sum of the costs of holding inventory and ordering inventory.



Re-Order Point

To order EOQ at the right time to prevent stockouts.

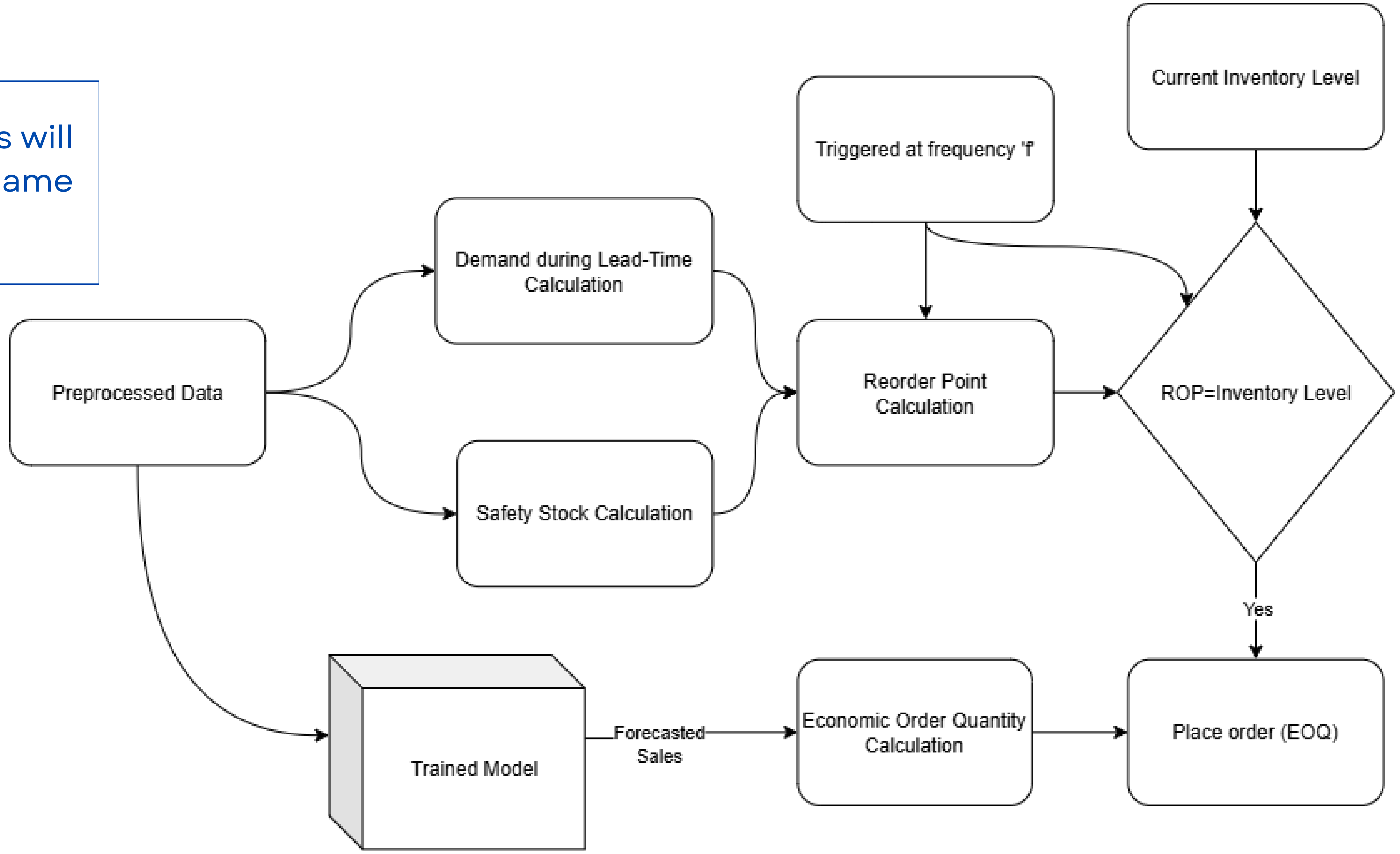


Demand Forecasting

To make EOQ data-driven, demand forecasting ensures optimal order quantities based on actual demand patterns.

FLOWCHART

Note: All the calculations will be performed at the same frequency 'f'



CHOOSING THE OPTIMAL INVENTORY REVIEW CYCLE

$$\text{Coefficient of Variation (CoV)} = \frac{\text{Standard Deviation of Demand}}{\text{Average Demand}}$$

CoV Measures demand variability relative to average demand.

- Higher CV (closer to 1) → Unpredictable demand → More frequent model runs
- Lower CV (closer to 0) → Stable demand → Less frequent optimization needed

Note: As High CoV signals highly variable demand, it indicates lower forecastability and the need for advanced forecasting approaches.

INSIGHTS

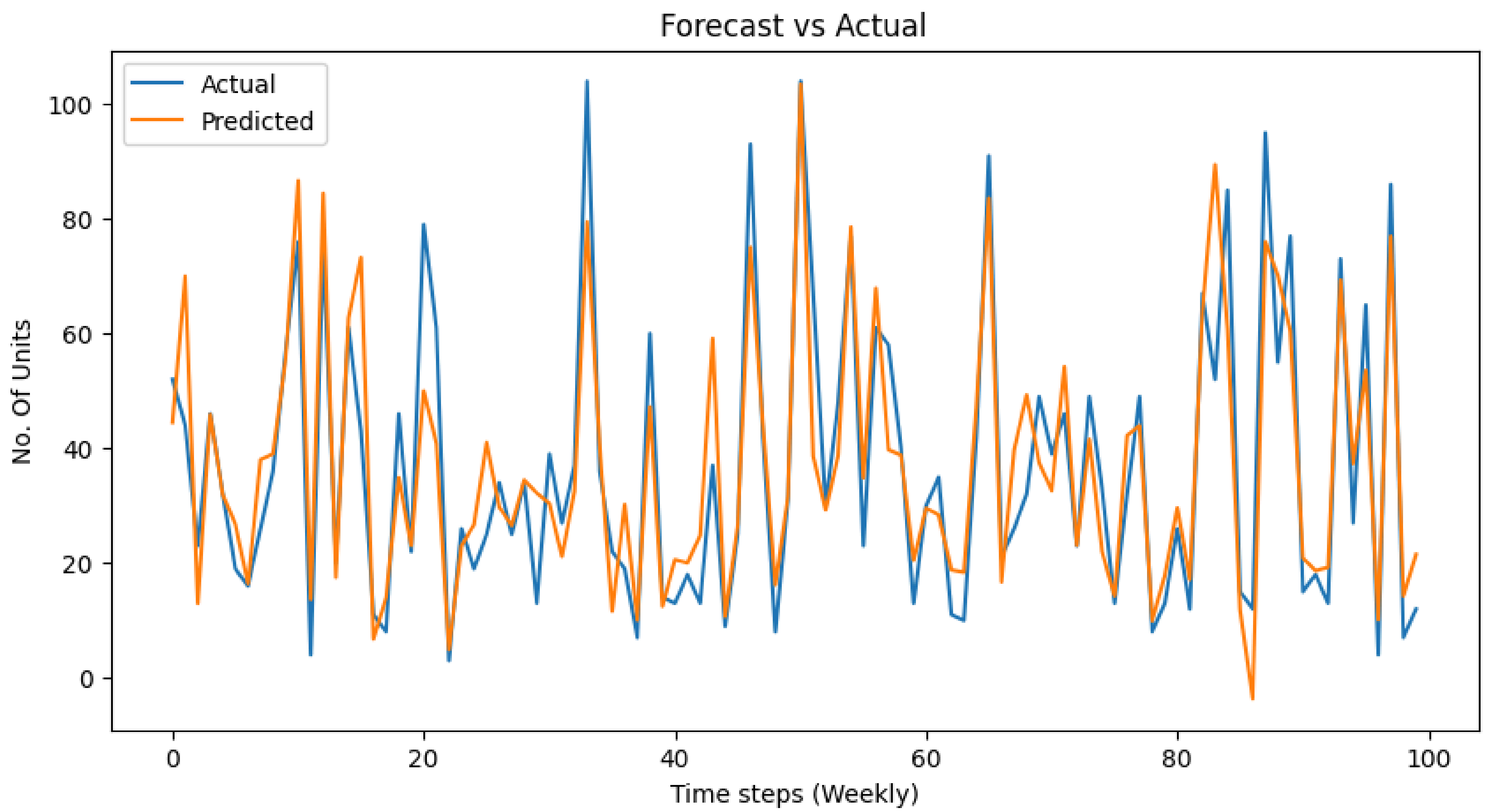


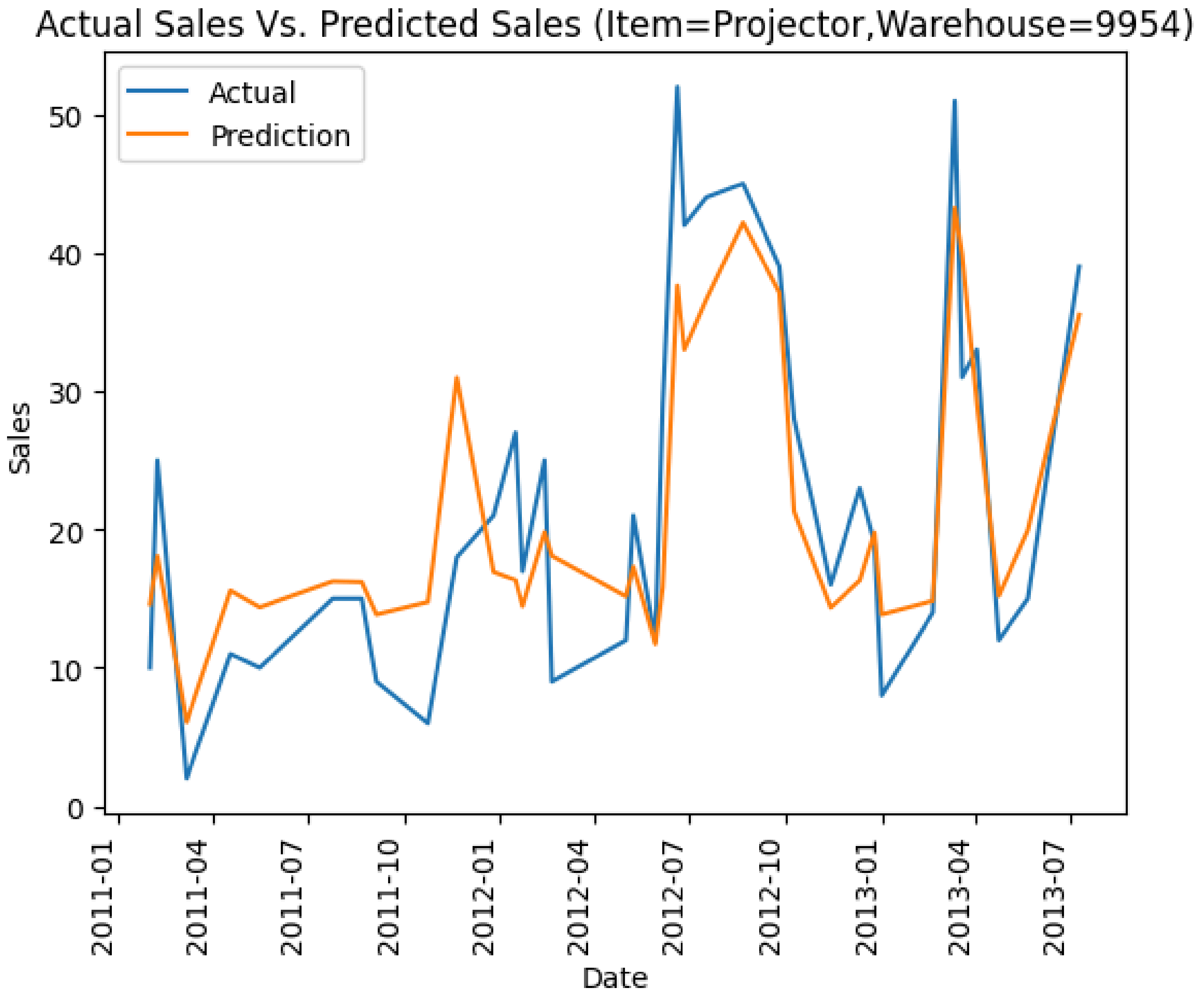
Fig. The graph shows forecasted demand using test data obtained via a trained neural network with an RMSE of 11.0 and an R^2 score of 0.79.

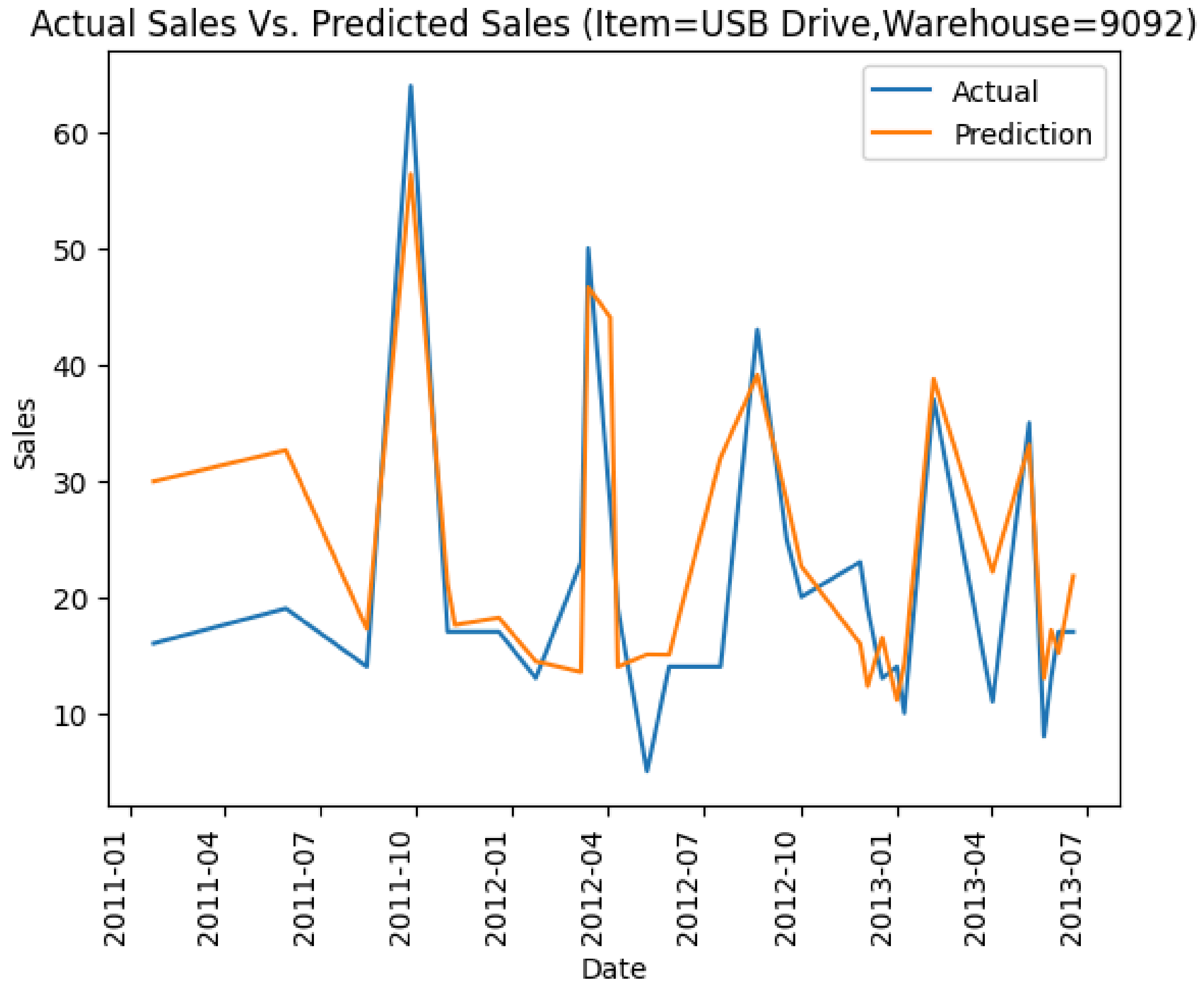
The forecasted plots shown on the current and subsequent slides are the model's predictions on the test data (hold-out sample).

INSIGHTS

- The item names shown in the next slide are self-assigned labels for clarity and ease of interpretation. In the original dataset, item identifiers were numeric codes.
- The results are derived from a model trained on consumer-driven market data, but they also apply to industrial-driven markets.
- The data was split into 80% train data and 20% test data (the splitting is in chronological order).
- The model was trained on 76 warehouses with 28 items each, handling many variables. Even so, results closely follow actual patterns and are expected to improve with fewer variables.

INSIGHTS

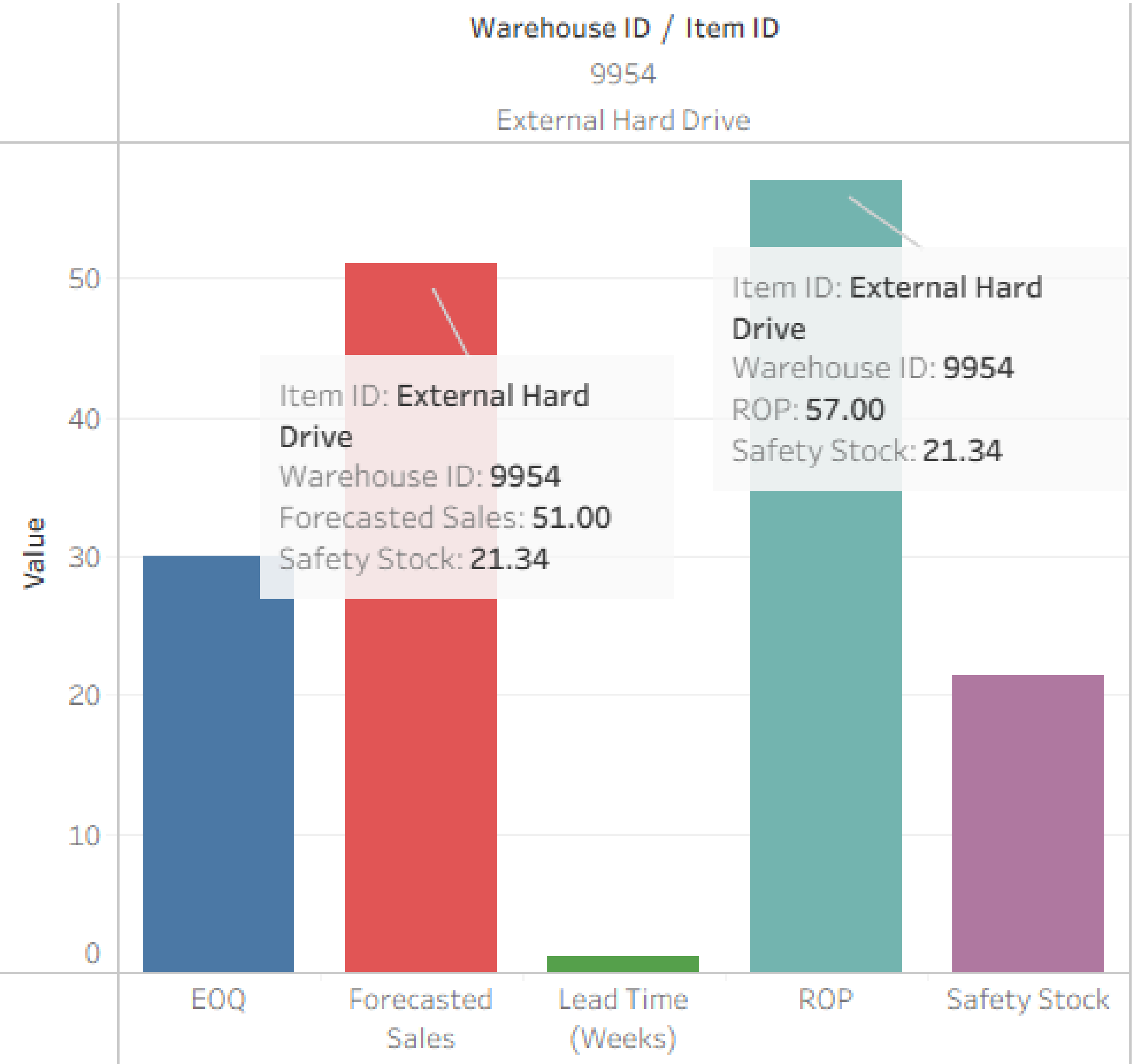

Actual Sales Vs. Predicted Sales (Item=Projector,Warehouse=9954)
Actual
Prediction
Sales
Date
0
10
20
30
40
50
2011-01
2011-04
2011-07
2011-10
2012-01
2012-04
2012-07
2012-10
2013-01
2013-04
2013-07


Actual Sales Vs. Predicted Sales (Item=USB Drive,Warehouse=9092)
Actual
Prediction
Sales
Date
10
20
30
40
50
60
2011-01
2011-04
2011-07
2011-10
2012-01
2012-04
2012-07
2012-10
2013-01
2013-04
2013-07

INSIGHTS

Fig: ROP based on forecasted demand during lead time, illustrating how service level (95%) impacts safety stock and consequently the overall reorder point.

INSIGHTS



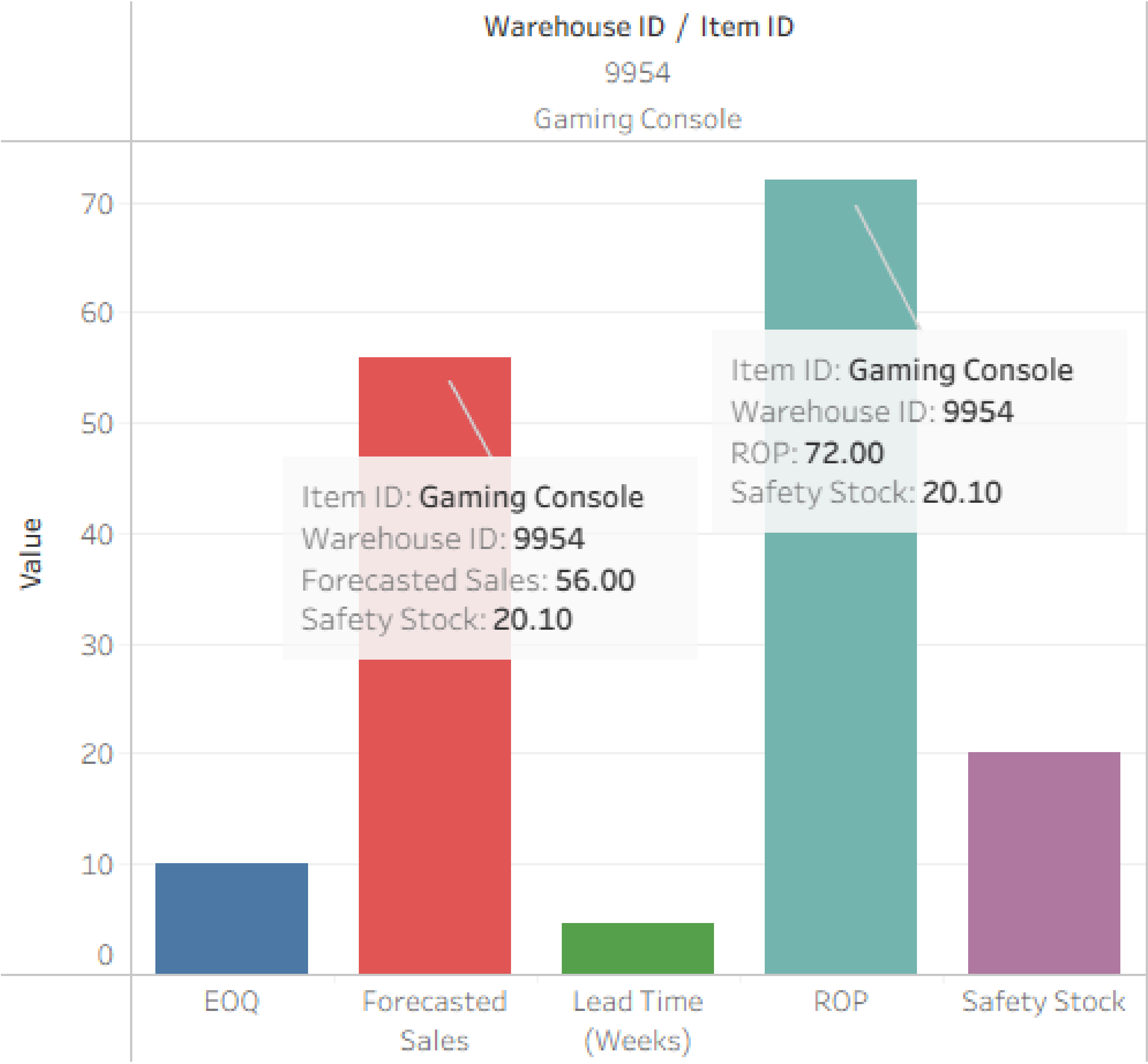


Fig: ROP based on forecasted demand during lead time, illustrating how service level (80%) impacts safety stock and consequently the overall reorder point.

INSIGHTS

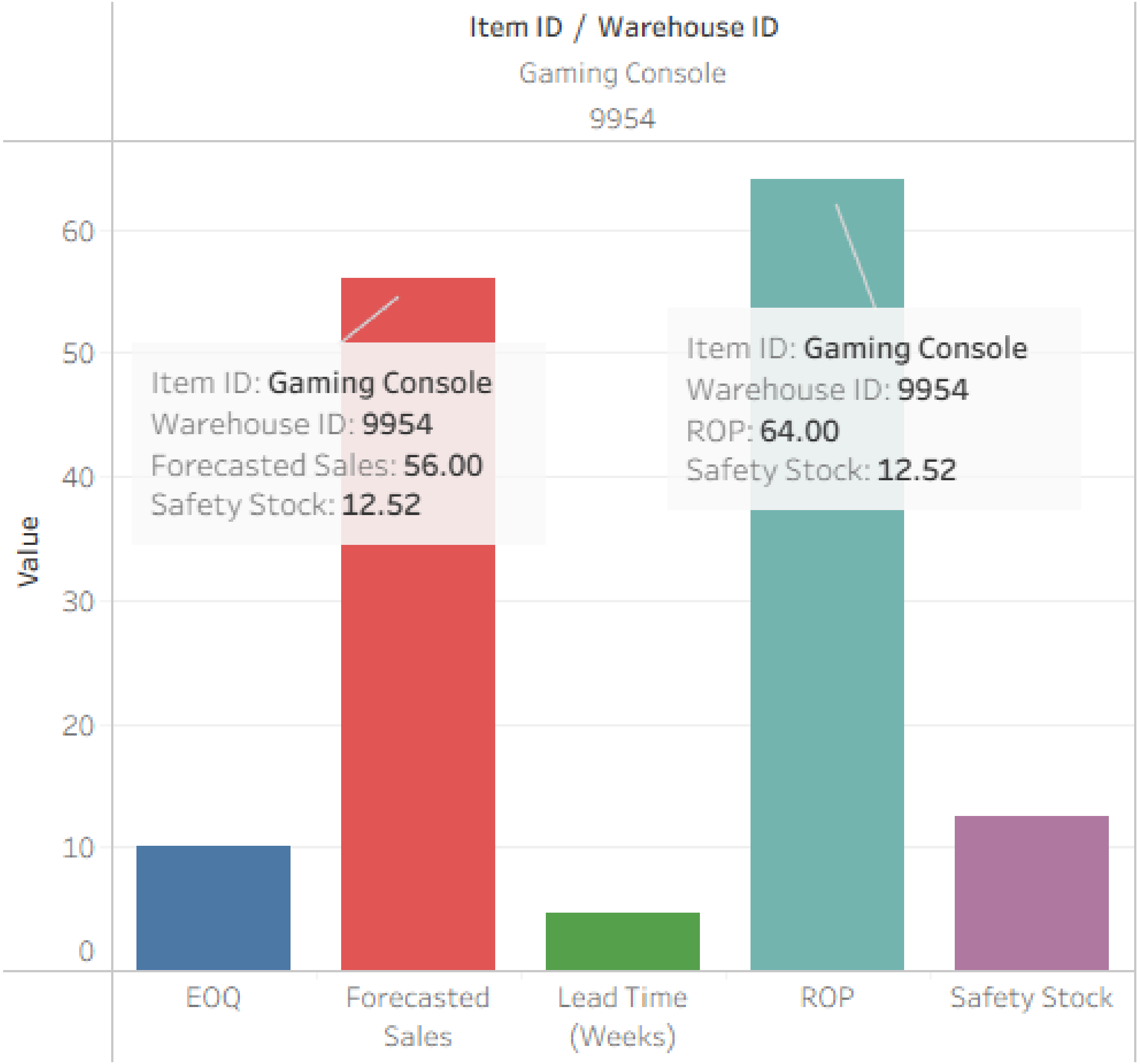


Fig: ROP based on forecasted demand during lead time, illustrating how service level (70%) impacts safety stock and consequently the overall reorder point.

INSIGHTS

- As seen in the previous slides, lowering the service level reduces the safety stock, bringing the Reorder Point (ROP) closer to the forecasted sales during lead time. This means less buffer inventory while waiting for replenishment.

- In the last slide (External Hard Drive), the side-by-side bar plot shows ROP < Forecasted Sales, indicating a risk of lost sales. This highlights the importance of selecting a service level aligned with business priorities, balancing cost and availability.

INSIGHTS

Item ID	Warehouse ID	Order Quantity	Current Inventory Level
Camera	9954	39	96
E-Reader	9954	24	23
External Hard Drive	9954	30	77
Gaming Console	9954	10	91
Graphics Card	9954	23	26
Headphones	9954	13	43
Keyboard	9954	73	119
Monitor	9954	18	131
Mouse	9954	45	109
Projector	9954	22	73
Smartphone	9954	29	74
Smartwatch	9954	35	36
Speaker	9954	88	171
Tablet	9954	21	19
TV	9954	55	104
USB Drive	9954	15	33
VR Headset	9954	40	45

This table is generated daily and indicates that the current inventory level for the specified item and warehouse has dropped to the Reorder Point (ROP), triggering the need to place a replenishment order. The suggested order quantity corresponds to the Economic Order Quantity (EOQ), ensuring a cost-effective restocking decision.

MATHEMATICAL BASIS OF THE MODEL

The model deals with all four reorder point (ROP) scenarios as discussed below:

Sr. No	Lead Time	Demand	Formula
1	Constant	Constant	$\text{ROP} = \begin{matrix}\text{Expected demand} \\ \text{during lead time}\end{matrix} + z\sigma_{d\text{LT}}$
2	Constant	Variable	$\text{ROP} = \bar{d} \times \text{LT} + z\sigma_d\sqrt{\text{LT}}$
3	Variable	Constant	$\text{ROP} = d \times \overline{\text{LT}} + zd\sigma_{\text{LT}}$
4	Variable	Variable	$\text{ROP} = \bar{d} \times \overline{\text{LT}} + z\sqrt{\overline{\text{LT}}\sigma_d^2 + \bar{d}^2\sigma_{\text{LT}}^2}$

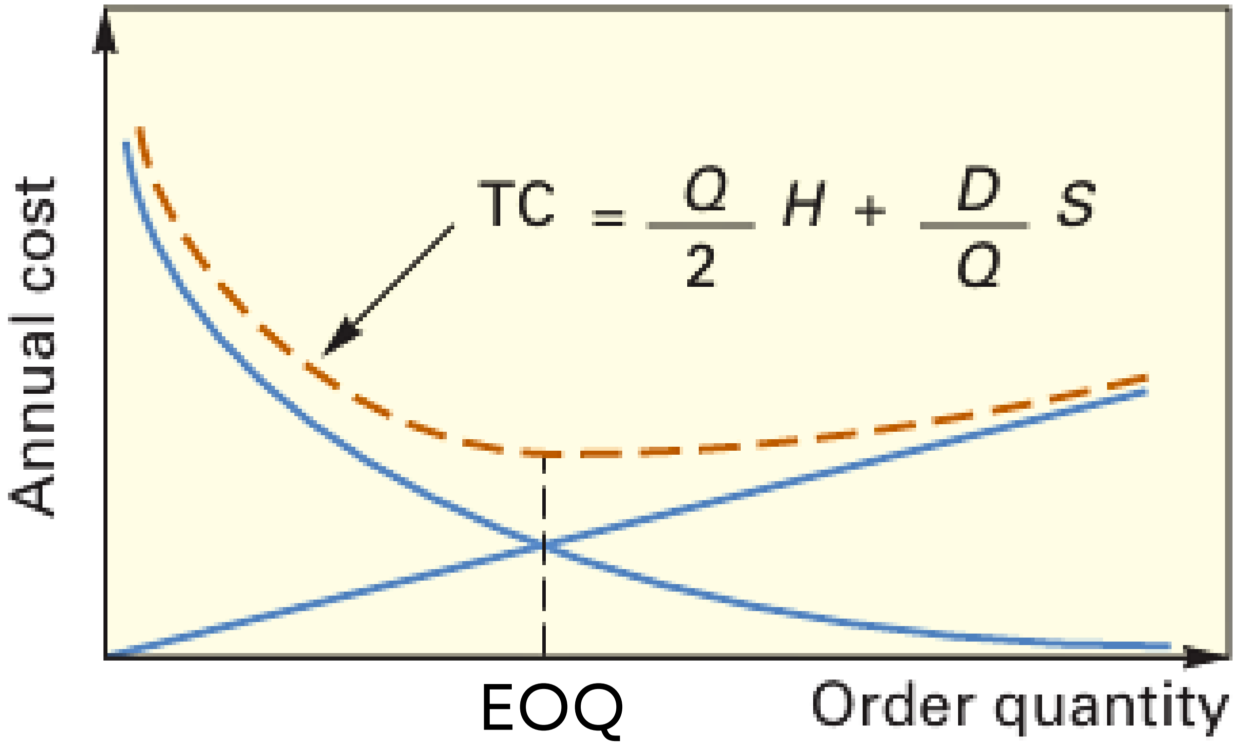
Note:

- The bar notation indicates that the average value is to be used.
- σ denotes Standard Deviation.
- z is the z-score corresponding to the desired service level.
- d and LT are demand and Lead Times, respectively.

MATHEMATICAL BASIS OF THE MODEL

The Economic Order Quantity (EOQ) model determines the optimal amount to order by minimizing total inventory costs. In our approach, EOQ is driven by forecasted sales (D) to ensure that inventory aligns with actual demand. The formula gives the order quantity that minimizes holding (H) and ordering (S) costs:

$$\mathrm{EOQ} = \sqrt{\frac{2 \times S \times D}{H}}$$



BUSINESS VALUE

1 Minimized Inventory's Cost

The model balances ordering and holding costs to achieve the lowest possible total inventory cost, leading directly to stronger financial performance.

2 Better Inventory Planning

ROP and EOQ driven by forecasted sales enable precise planning of what, when, and how much to order, reducing uncertainty and ensuring the right products are always available at the right time.

3 No Guesswork

All decisions are backed by data and inference, not intuition or static rules, eliminating the trial-and-error approach, reducing human error, and ensuring every restocking action is justified by real demand patterns.

4 Scalable to Multiple Warehouses

The EOQ and ROP framework is adaptable to any number of locations. Each warehouse can operate with customized parameters while following a unified strategy, enabling consistent performance across the entire supply chain

TIMELINE

Note: The user interface phase will be implemented at the client's request.

Data Preparation

Gathering raw data from the source and cleaning, transforming, and structuring it to make it reliable and ready for model development

Implementation

Select a suitable modeling technique. The chosen model is then trained, validated, and tuned to best capture the underlying patterns in the data

Validation

Validate the results by testing on hold-out sample (test data).

User Interface

Designing User Interface either by using tools like PowerBi, Grafana to create dashboards or from scratch.

DEPLOYMENT PATHWAYS

The deployment methods are broadly categorized into following stated below, though the choice of deployment method depends on client’s desired level of automation and scalability.

Deployment Methods

Local Deployment

Cloud Based Deployment

Remote Server Deployment

DEPLOYMENT PATHWAYS

Among the available deployment options, the method that best aligns with the client's priorities will be adopted.

	Local Deployment	Remote Server Deployment	Cloud Based Deployment
Working	The application will be installed and run directly on the client's machine.	The application will be deployed on a dedicated server and accessed via a private link or VPN.	The application will run on secure cloud servers accessed via the web or API.
Advantages	• Full data privacy • No waiting for server responses.	• Minimal client setup • Multi-user ready • Security configurable • Setups, updates, and scaling can be handled remotely.	• Data can be secured with encryption • Setups, updates, and scaling can be handled remotely.
Disadvantages	• Needs to be updated manually. • For multiple users' access, Installation on each device is required.	• Requires constant internet • Dependent on server speed and the user's internet. • Requires ongoing server hosting fees.	• Downtime Risks (due to cloud provider outages) • Complex Initial configuration • Data being stored and processed on third-party servers can raise compliance and trust issues

HOW CLIENT WILL USE THE MODEL

Uploading Sales Data

The client should have the following three files:

- Historical & current sales data
- Lead Time data
- Holding and Ordering Cost data

Depending on your chosen deployment type:

- For local deployment, that file will be placed by the client in the same directory as the model.
- For cloud or remote deployment, that file will have to be uploaded to the designated cloud storage or interface.

Frequency Setting

The client can configure how often the model runs:

- Daily, Weekly, or Custom Intervals

At the selected frequency, the model will run to detect whether the Reorder Point (ROP) is reached and automatically calculate the optimal quantity to reorder (EOQ).

Output

The model generates a file containing:

- Items that have hit their ROP with date and warehouse location (if applicable)
- Recommended quantity to order
- The file will be saved to a client accessible directory or cloud folder.

DATA REQUIREMENT FOR MODEL CUSTOMIZATION

To tailor this solution specifically for the client's business needs, access to the historical sales data will be required. This data is essential for:

- Training the model on patterns unique to your products, seasonality, and customer behavior.
- Improving Forecast Accuracy by aligning predictions with the real-world trends.
- Ensuring the relevance of the model outputs to the inventory, lead times, and demand cycles.
- Forecasting requires predictor variables (inputs). For the customized model, these inputs will be provided by the client, as they best understand the factors influencing their sales.

Data Privacy Assurance: All shared data will be handled with strict confidentiality, used only for model training and evaluation purposes, and stored securely in compliance with data protection practices.

THANK YOU