International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2022): 7.942

Optimizing Inventory for Manufacturing Efficiency: A Data Science Approach to Balance Supply and Demand

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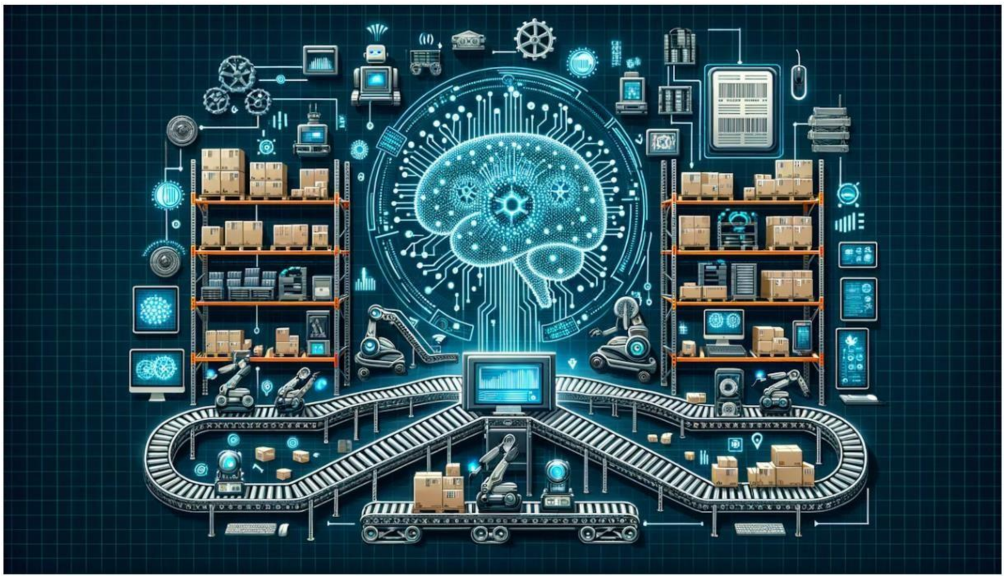
Abstract: ***Effective inventory management plays a critical role in sustaining operational efficiency and profitability within the dynamic realm of manufacturing where maintaining a delicate balance between supply and demand is paramount. Based on our supply chain project experience, we observed that major manufacturing companies might hold inventory of up to a month (30 days). Moreover, un - optimized buffers created for safety stock, these companies may end up with 80% more safety stock than required for manufacturing. This can negatively influence cash flow, as money is stuck in assets that generate low returns. Investing in assets with better returns can create opportunities for companies and reduce potential losses. Conversely, stockouts pose risks of lost sales, diminished customer satisfaction, and increased expenditures linked to order expediting and emergency shipments. This paper aims to shed light on the pivotal role of inventory optimization using a novel data science - based technique.***

Keywords: Inventory Optimization; Supply Chain Management; Machine Learning; Deep Learning; Review; Analysis; Enabling Safety Stock; Forecasting; Ordering System Enhancement

1. Introduction

Inventory takes many forms, ranging from raw materials to finished goods. While holding large amounts of inventory enables a company to be responsive to fluctuations in customer demand, there are associated costs. Inventory can therefore have conflicting priorities for different areas within the organization.



Inventory control is a key aspect of almost every manufacturing and/or distribution operation business. The ultimate success of these businesses is often dependent on their ability to provide customers with the right goods, at the right place, at the right time.

The role of inventory management is to coordinate the actions of all business segments so that the appropriate level of stock maintained to satisfy customer demand.

In order to do this, a process of optimization is required to allocate resources in the most effective way to satisfy competing requirements and goals.

Inventory optimization takes inventory management to the next level, providing a more dynamic and holistic approach which allows managers to assess various signals in the supply chain that may be relevant.

2. Methodology

The Duality of Inventory: A Fine Interplay between Cost and Revenue Optimization.

The delicate balance required to maintain optimal safety stock levels becomes a double - edged sword, significantly influencing the top and bottom lines of industrial operations. Suboptimal safety stock maintenance presents following challenges:

Understocking Woes:
This phenomenon, marked by insufficient stock levels creates a shortfall in meeting customer demands results in stockouts, leading to expediting costs, loss of sales, and diminished customer satisfaction. The unrealized revenue potential and operational inefficiencies collectively cast a shadow on the top line, hindering revenue maximization.

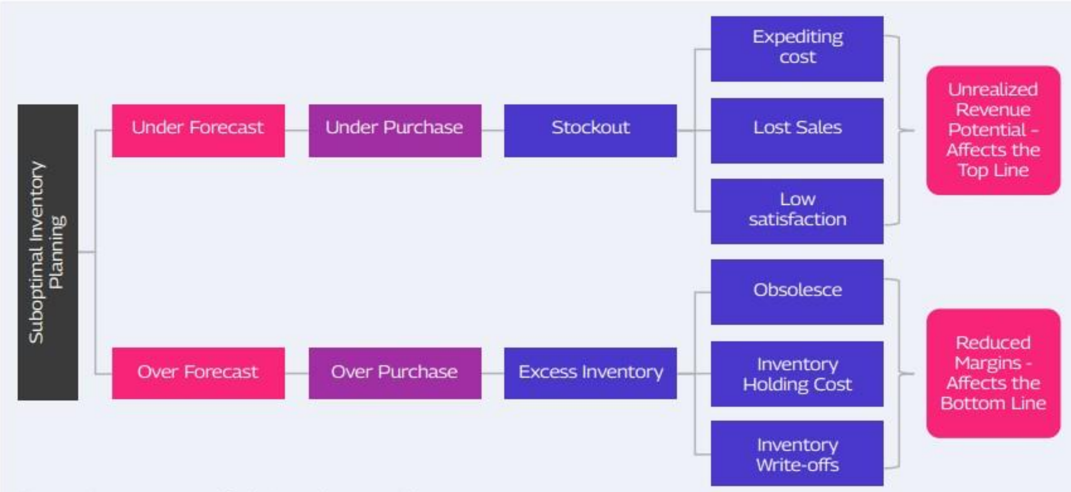


Figure 1: Business Impact of Sub-Optimal Inventory Planning

Overstocking Quandaries:
Conversely, the perils of overstocking, another facet of suboptimal inventory practices, manifest in the realm of excess. This situation leads to incurring costs associated with obsolescence, inventory holding, and write - downs. The impact resonates through decreased margins, affecting the bottom line. Financial resources tied up in excess inventory limit opportunities for better capital utilization and reduce overall profitability.

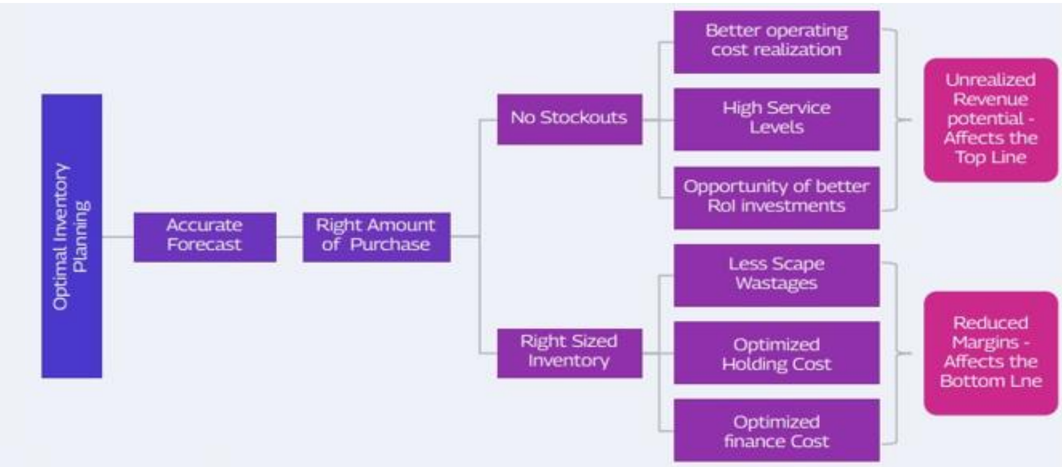


Figure 2:Business Impact of Optimal Inventory Planning

Striking the Harmonious Balance:
Efficient inventory management, which balances between overstocking and understocking, optimizes operational resilience and costs, elevates service levels, and improves returns on investments. It also reduces wastages and financial expenditures, thus enhancing overall profitability.

The Silver Lining of Balanced Inventory Management:
Navigating the intricacies of inventory planning, often deemed a double - edged sword, reveals its transformative power. When calibrated astutely, it serves not only as a guardian against potential losses but also as a catalyst for concurrent enhancements in both the top and bottom lines. Achieving this equilibrium emerges as the positive aspect in the dynamic realm of inventory optimization.

Steps to inventory optimization:

How should business leaders approach inventory optimization in the supply chain? The steps to follow are:
- Analysis of stock
- Forecasting
- Modelling and selecting stock policies
- Replenish stock

1) Analysis of stock:
Before doing any forecast, you need to understand the relationship between stock codes and the key issues of profit, revenue and service levels. In addition to any market segmentation, stock codes should be analysed in two dimensions – profitability, revenue or service frequency – to determine relative importance, and by behaviour to identify

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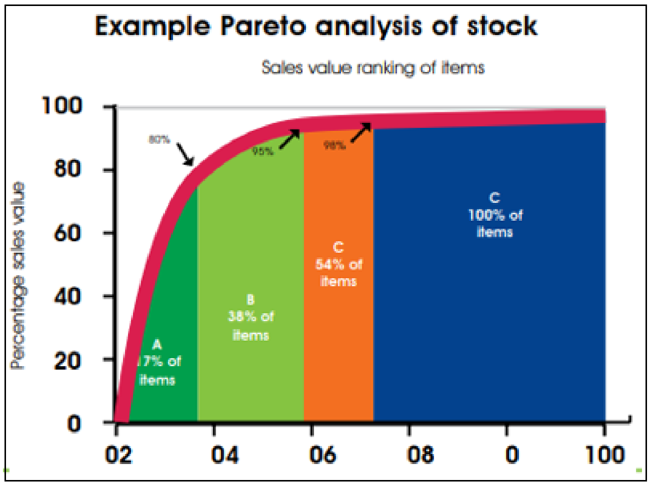
demand frequency and any historic demand patterns such as seasonality.

Classify stock codes according to some measure of usage. This will also show which stock items should be forecast.

a) Identify the relative importance of each stock code using a Pareto analysis (also known as the 80: 20 rule or an ABC analysis) based on revenue, profitability or service

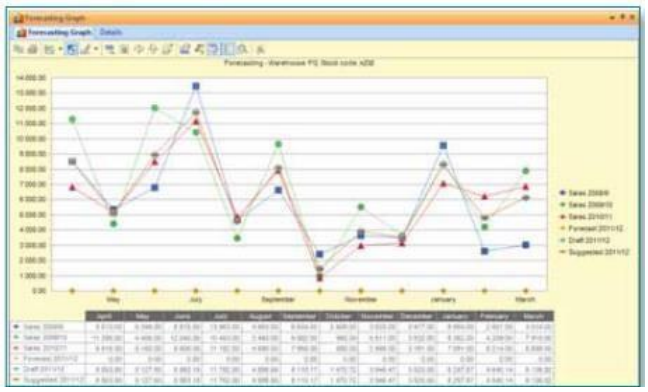


b) Understand the historic demand patterns. There are two parts to this:

- Do a Pareto analysis based on hits (frequency of demand). This indicates How important customer service is for the item, identifies if it has erratic Demand patterns, and gives an indication of its forecast ability.
- Analyze the time series to identify seasonality or other repeating patterns.

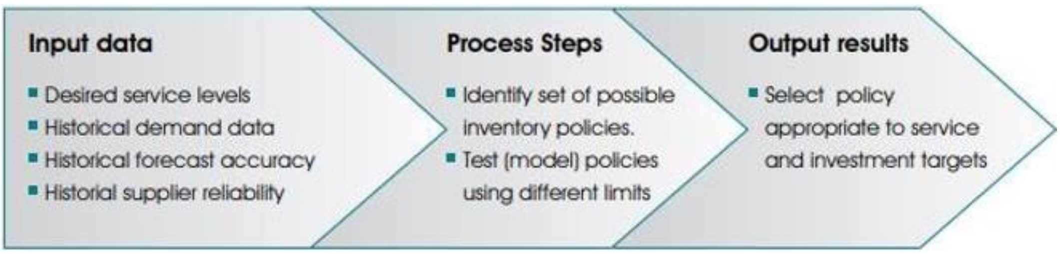
Because of this analysis, all stock codes that have service levels should classified.

2) Forecasting:
Having identified which stock items will be forecast, the forecasting process allows the organization to determine the main driver of the inventory planning process – the estimate of customer demand. The importance of this process cannot be understated and its success should be measured through a suitable measure of forecast accuracy. For good reason, high forecast accuracy is often considered the holy grail of supply chain management.



3) Modelling and selecting stock policies:

A stock policy encapsulates the rules for determining how much stock held to meet expected demand. Modelling the effect of a policy provides feedback on whether it can meet the competing requirements of pushing up service levels while lowering inventory.



The key outcomes of a policy are safety stock and cycle stock. These two settings establish the minimum and maximum inventory quantities per product targeted to meet expected demand at an appropriate level of service. The groups determined in Step 1 above will have different policies to provide the service and investment targets deemed appropriate for each group.

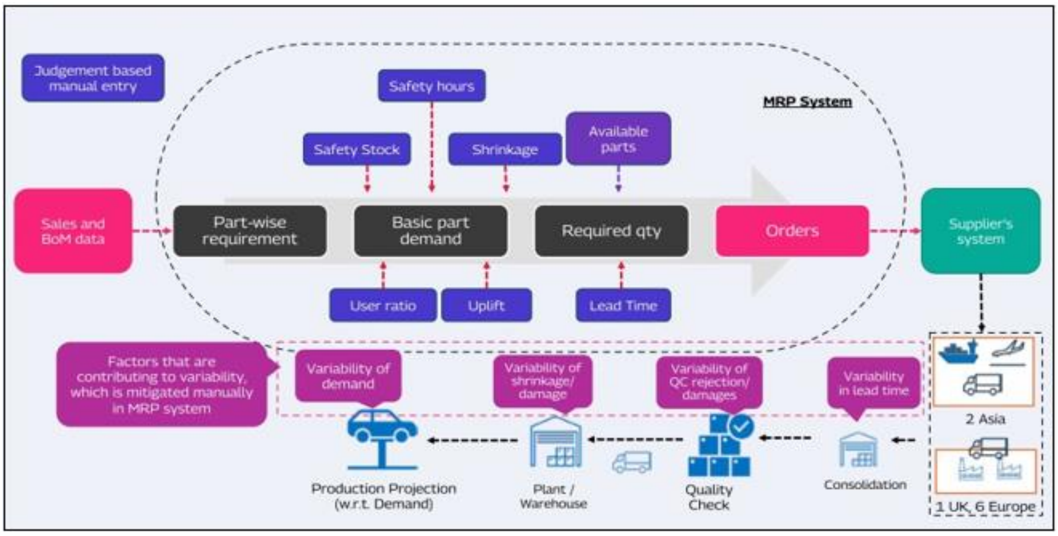
The process for determining an appropriate inventory optimization policy is summarized below.

4) Replenish to the plan:
The plan is defined by the combination of the forecast and the policy. The key discipline of managing to the plan and only deviating by exception is an often - overlooked component of optimizing inventory.

Manual Variables in the Existing Process:

Evolution of Inventory Management: A Historical Lens
In the annals of inventory management, traditional

approaches often relied on manual variables, weaving a labyrinth of complex decision - making. This section casts a discerning eye on the historical landscape, spotlighting the multifaceted manual variables that once governed the buffer inventory stock.



- **Safety Stock as a Blanket Variable:** Legacy systems used a fixed safety stock based on production schedules, providing predictability but lacking adaptability to dynamic market demands.
- **Safety Hours:** An additional layer of safety was introduced through safety hours, indicating the duration for which a safety stock was expected to be retained.
- **Shrinkage Percentage:** Shrinkage, a perennial concern, was addressed through a fixed percentage addition to the basic part requirement.
- **Uplift Factor:** An uplift factor added a layer to the stock, anticipating unforeseen fluctuations.
- **User Ratio:** The user ratio allowed for customization in determining the buffer stock.
- **Lead Time:** Lead - time was manually factored into the stock decision. Its deterministic nature often lagged real - time changes, influencing the agility of the overall system.
- **Static Service Level:** The application of a standardized service level across all parts uniformly.

Unravelling Inefficiency: A Plethora of Buffer Variables

The existing system, in contrast to the risk pooling strategy, used numerous buffer variables contributing to 80% safety stock, which required meticulous tracking and posed challenges. This approach, although aimed at precision, led to inefficiencies in resource allocation and data management. Upcoming sections will discuss a machine - learning model's streamlined approach that replaces manual variables, improving efficiency and accuracy in inventory optimization.

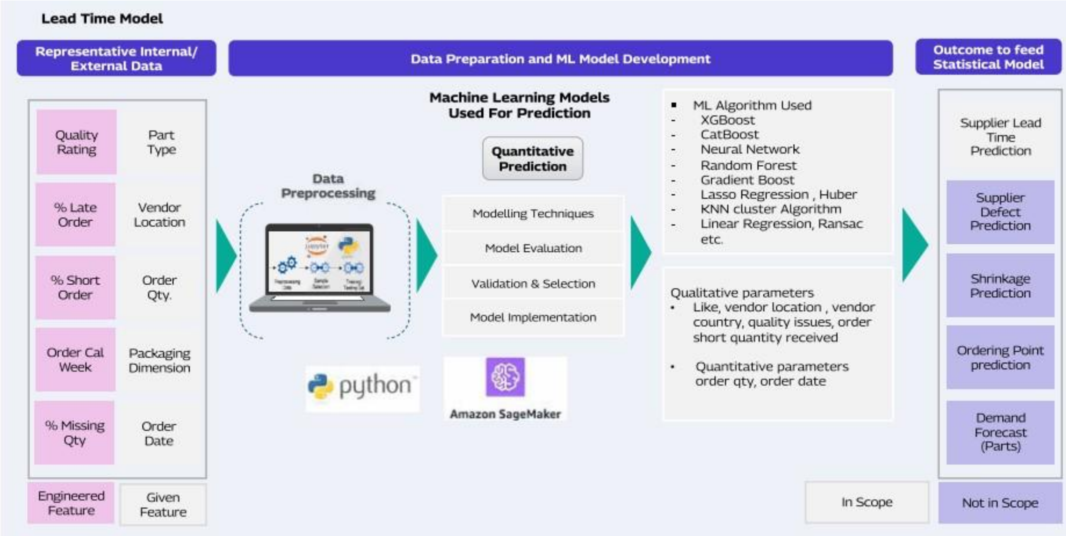
Bespoke Approach for Safety Stock Calculation: Pioneering Precision

Standard Kings Formula vs. Bespoke Approach

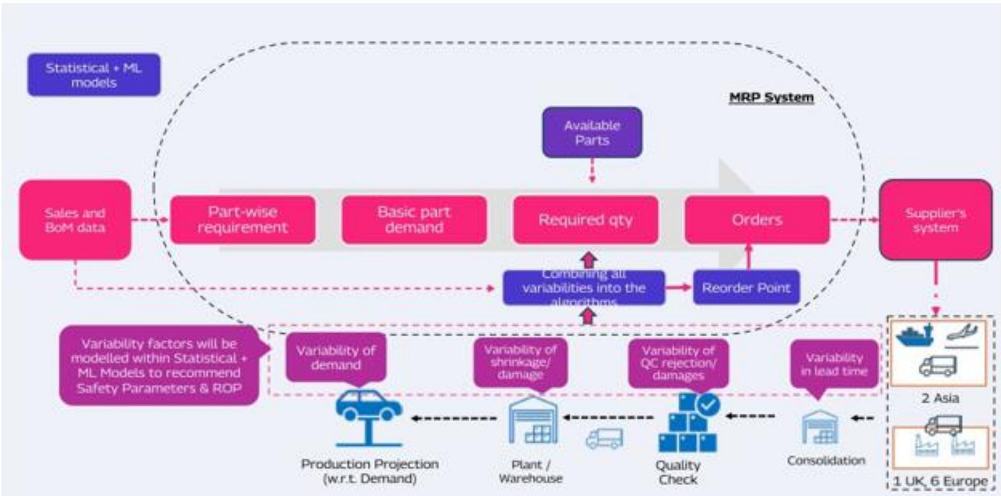
Decoding the Standard: The traditional realm of inventory management often bowed to the authority of the standard Kings formula—a method anchored in the normal distribution of demand. This venerable approach, while foundational, faced limitations in swiftly adapting to evolving market dynamics.

Bespoke Brilliance: Our bespoke approach breaks free from the shackles of historical averages. Instead of tethering safety stock to past demand patterns, we harness the power of future - ready projections.

a) **Future - Ready Demand Projections**: In stark contrast to traditional models rooted in historical consumption averages, our machine - learning model embraces the future. Future - ready demand projections become the cornerstone; steering inventory decisions based on the latest market forecasts.
b) **Forecast Error Sensitivity:** The bespoke approach acknowledges the inherent uncertainty in forecasting. To counteract the ripple effects of forecast errors, our model dynamically adjusts safety stock, ensuring a robust buffer against unforeseen discrepancies between projections and actual demand.
c) **Machine Learning Model for Lead Time Prediction:** The model revolutionizes lead - time prediction, a crucial inventory variable, by using machine - learning algorithms. It factors in variables like order quantity and source country, creating a predictive model that overcomes historical data limitations.



d) **Following the MLOps approach (3) (4):** We started with understanding the data and business imperatives, processed the data through cleaning and imputations, removed contradictory data points, and created several features for the ML model. We used various ML algorithms, from simple to complex, tested the outcomes with robust evaluation techniques, and achieved 91% accuracy.



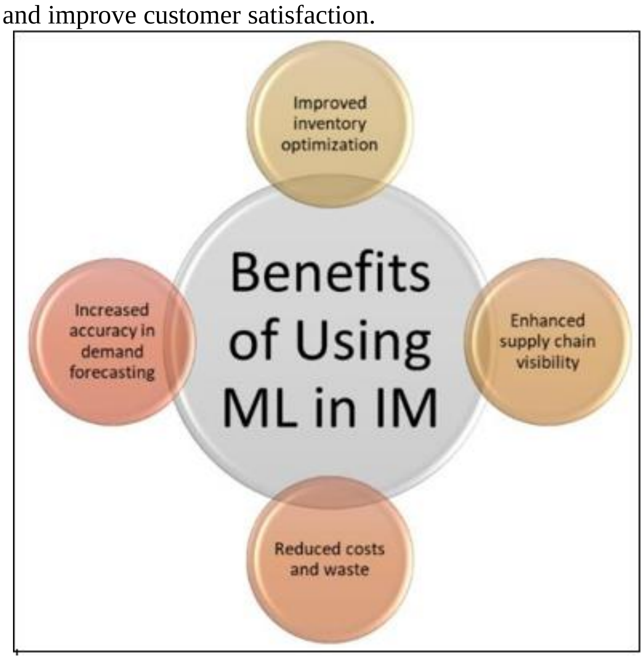
e) **Dynamic Service Level Calculation:** Ditching the one - size - fits - all approach, our model ushers in a new era of service level calculation by adopting a dynamic methodology.

f) **Shrinkage Compensation: Enhancing Resilience:** In our bespoke model, we go beyond conventional considerations by incorporating shrinkage compensation. Shrinkage, a critical aspect often overlooked, is addressed through a meticulous analysis of consumption patterns over the last six months.

g) **Innovative Variance Approaches for Demand and Lead Time:** Variance, the silent harbinger of unpredictability, is harnessed innovatively in our model by fusing past uncertainties with future projections.

Benefits of Using Machine Learning in Inventory Management:

Using machine learning in inventory management offers several benefits to businesses. One of the most significant benefits is improved demand forecasting. Machine learning algorithms can analyse historical sales data, market trends, and other variables to accurately forecast demand. This can help businesses optimize inventory levels, reduce stock outs, and improve customer satisfaction.



Traditional inventory management methods often rely on reactive approaches, using historical data and intuition to make inventory decisions. This approach can be time - consuming and prone to errors, leading to stockouts or overstocks. Machine learning algorithms, on the other hand, can analyze large amounts of data in real - time, enabling proactive inventory management. This helps businesses adjust inventory levels and reorder

Points based on actual demand, which results in optimal inventory levels and reduced carrying costs.

Another benefit of machine learning in inventory management is real - time inventory optimization. Machine learning algorithms can continually analyze supply chain data and adjust inventory levels and reorder points in real - time based on changing demand and supply conditions. This ensures that inventory levels remain optimal, reducing stock outs and overstocks. Real - time inventory optimization can also help businesses reduce waste by ensuring that inventory levels are not unnecessarily high.

Machine learning can also help businesses optimize inventory across multiple locations and supply chain partners. Traditional inventory management methods may have limited visibility into supply chain and demand fluctuations, resulting in suboptimal inventory levels and higher carrying costs. However, machine - learning algorithms can provide real - time visibility into supply chain data, allowing businesses to optimize inventory levels and reorder points across multiple locations and partners.

This can result in more efficient use of resources and lower carrying costs. Machine learning can also help businesses reduce the risk of stock outs and overstocks. By accurately forecasting demand and adjusting inventory, levels and reorder points in real - time, businesses can ensure that they have the right products in stock when customers need them. This can help businesses reduce the risk of stock outs, which can damage customer satisfaction and result in lost sales. At the same time, machine - learning algorithms can also help businesses avoid overstocks, which can tie up capital and increase carrying costs.
Finally, using machine learning in inventory management can help businesses make better decisions. Traditional inventory management methods often rely on static rules and heuristics, which can be limited in their ability to accurately predict demand and optimize inventory levels.

Machine learning algorithms, on the other hand, can analyse large amounts of data and identify patterns and trends that may not be immediately apparent to human analysts. This can help businesses make more informed decisions about inventory levels, reorder points, and supply chain partners, resulting in improved profitability.

Using machine learning in inventory management offers several benefits to businesses, including improved demand forecasting, real - time inventory optimization, optimization across multiple locations and partners, risk reduction, and better decision - making. Machine learning algorithms can analyze large amounts of data in real - time, enabling proactive inventory management and reducing the risk of stockouts and overstocks.

They can also help businesses optimize inventory levels across multiple locations and partners, resulting in more efficient use of resources and lower carrying costs. By enabling better decision - making, machine learning can help businesses improve profitability and gain a competitive edge in today's fast - paced business environment

3. Challenges of Implementing Machine Learning in Inventory Management

One of the primary challenges of implementing machine learning in inventory management is data quality. Machine learning algorithms require high - quality data to make accurate predictions and recommendations. However, many businesses struggle with data quality issues, such as incomplete or inconsistent data, data silos, and data bias.

These issues can significantly affect the accuracy of machine learning models, leading to suboptimal inventory decisions. Another challenge is the cost and complexity of implementing machine - learning algorithms. Developing and deploying machine - learning models can be time - consuming and require specialized expertise, which may be costly for smaller businesses.

Additionally, integrating machine learning algorithms into existing inventory management systems can be challenging, requiring significant changes to existing processes and infrastructure. Lack of understanding and trust in machine learning algorithms is also a challenge for some businesses. Traditional inventory management methods often rely on intuition and experience, making it challenging some employees to understand and trust the recommendations made by machine learning algorithms. This can lead to resistance to change and reluctance to adopt new technology. Finally, privacy and security concerns can be a challenge when using machine learning in inventory management.

Machine learning algorithms require access to sensitive data, such as sales data, customer data, and supplier data. Ensuring the security and privacy of this data can be a significant challenge, especially in industries with strict data privacy regulations. Implementing machine learning in inventory management presents several challenges.

Including data quality, cost and complexity, lack of understanding and trust, and privacy and security concerns. Addressing these challenges requires careful planning, collaboration between data scientists and domain experts, and a willingness to adopt new technologies and processes. However, the benefits of using machine learning in inventory management can outweigh these challenges, resulting in improved profitability and competitive advantage.

4. Conclusion

In conclusion, this review paper highlights the potential benefits and challenges of implementing machine learning in inventory management for increased profitability. Machine

Paper ID: SR241119090526 DOI: https://dx.doi.org/10.21275/SR241119090526

learning algorithms offer significant advantages over traditional inventory management methods.

Including increased accuracy in demand forecasting, improved inventory optimization, enhanced supply chain visibility, and reduced costs and waste. However, implementing machine learning in inventory management requires careful consideration of data quality, cost and complexity, lack of understanding and trust, and privacy and security concerns.

Despite these challenges, businesses can effectively leverage machine learning algorithms to optimize inventory decisions and improve overall supply chain performance by collaborating between data scientists and domain experts, adopting new technologies and processes, and prioritizing data quality and security. In doing so, businesses can achieve increased profitability and competitive advantage in the dynamic and ever - changing world of inventory management.

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