Forecasting Demand To Determine Minimum Inventory Levels

Christopher Grime

# Introduction ­

Minimum Stock Level (MSL) represents the minimum inventory quantity a company must maintain to ensure consistent operations without risking stock-outs or overstocking. Stock-outs occur when stock levels are insufficient to meet demand, leading to disruptions in operation. Overstocking happens when inventory levels exceed demand, increasing storage costs and potential waste. Estimating the MSL requires optimizing the balance between avoiding stock-outs and minimizing overstocking. Achieving this balance prevents operational disruptions and reduces unnecessary costs associated with excess on-hand inventory.

Accurate MSL estimation requires businesses to consider the average usage rate of stock and safety stock. The average usage rate is the quantity of inventory required to meet demand over a specified period. Safety Stock is a buffer to account for fluctuations in demand and supply chain uncertainties. In inventory management, maintaining "safety stock is an important topic in inventory management, and its main role is to meet the uncertainty of supply and demand"[4]. Calculating these variables can be challenging and may vary depending on the nature of the business. Specifically, a manufacturing and repairs company must account for customer demand, production materials, and repair parts. Accurate demand forecasting is essential to determining the optimal MSL. As noted, "Accurate demand forecasting guarantees suitable supply chain management and enhances customer satisfaction by preventing inventory stock-out" [1].

Traditionally, MSLs are calculated using methods that rely on historical data and statistical analysis. Such as using past demand patterns, lead times, and necessary service levels. As noted, "Spare parts inventory levels are often calculated based on certain historical data and forecasting models" [4]. Traditional methods, while reliable, are being replaced with more advanced methods, such as using machine learning in order to improve accuracy, especially in complex scenarios. "With the development of artificial intelligence, forecasting models based on AI techniques began to play an important role, such as machine learning, deep learning, support vector machine (SVM), back-propagation (BP) neural networks, and long short-term memory (LSTM)" [4].

Effective demand forecasting is crucial for optimizing inventory management. Accurate forecasting mitigates the risks associated with maintaining appropriate inventory levels. Given the growing complexity of supply chains, leveraging advanced techniques such as machine learning enables businesses to achieve greater adaptability, allowing them to learn and adjust automatically based on new trends. Improved demand forecasting paves the way for better decision-making and resource allocation, driving overall business success.

# Importance Of Demand For Minimum Stock Levels

A basic and standard formula for finding the Minimum Stock Level is:

This simple formula can be expanded into a slightly more complex version that highlights demand as a critical variable:

An explanation of the new variables:

* **Lead Time Variability** - This is the standard Deviation of lead times; for example, every order from vendor ships on a different timeline due to various factors such as supplier reliability, shipping delays, and production schedules. Accurate estimation of lead time variability is necessary for ensuring sufficient stock during the lead time.
* **Demand Variability** - Demand can also vary throughout lead time due to various influences. Estimating the demand variability assists in planning for changes in demand over the lead time and ensures the company will have sufficient stock during the lead time. As noted, "The main limitation of Auto-regressive integrated moving average (ARIMA) is that it assumes that the given time series is linear" [1], highlighting the complexity of accurately capturing demand variability. Furthermore, the unpredictable nature of demand is particularly pronounced for spare parts, as "only inspection reveals which parts are needed in each repair. Thus, demand for each spare part is unpredictable, forcing repair shops to keep large spare parts safety stocks" [5].
* **Z** - Represents the desired service level, indicating the probability that inventory will be sufficient during the lead time. A higher Z-score increases safety stock, improving the likelihood of avoiding stockouts

Several factors must be considered when determining demand. Demand is the most crucial factor for calculating MSL. Key factors that influence demand include:

* **Sales Trends** - Trends include general market trends, industry-specific trends, and seasonal trends.
* **Historical Demand Data** - Analyzing historical sales data is one way to help identify trends and help forecast future demand.
* **Economic Changes** - Larger economic conditions, especially in cyclical industries like airlines, can significantly alter the demand.
* **Special Events** - Promotions and anomalies can cause spikes in demand and need to be anticipated.
* **Repair Demand** - In industries that handle repairs, it is essential to consider the demand generated by the repair service. Forecasting demand must account for the parts needed for regular sales and the parts required for repairs. As observed, "the most challenging of these processes is making sure that the spare parts needed in the component repairs are available when we need them, while at the same time keeping inventory costs under control" [5].

Accounting for repair demand significantly complicates demand forecasting and MSL calculations. Repairs require several additional factors that must be considered to determine future demand accurately. For instance, the failure rates of components within each part need to be analyzed to project repair rates and the demand for those parts. Additionally, the time required to ship the broken part to the repair facility, the duration of the repair process itself, and the shipping time for the repaired part back to the customer must all be factored in. These additional variables mean a more comprehensive method for forecasting demand is required. As stated, "Moreover, the failure rate is often unknown either due to the absence of operational data at the time of initial provisioning, or due to the lack of data when changes to the environment occur" [2].

Accurately calculating demand is crucial for businesses to optimize inventory levels and avoid stock-outs and overstocking. As noted, "the overall inventory costs of these production systems are often very high and, therefore, any savings may be quite significant" [6]. Even minor improvements in accuracy can lead to substantial reductions in inventory storage costs, waste, and inventory inefficiencies. Demand forecasting is essential in industries with volatile demand, such as manufacturing and aerospace. Traditional demand forecasting methods rely on historical data and statistical models, making them most suitable for more straightforward, predictable, and stable environments. In more complex environments, a more modern approach is necessary. Modern improvements to traditional methods, such as ZIP-METRIC and Poisson-Bayes, attempt to account for complex situations by incorporating dynamic factors into forecasting. While these modern statistical methods are an improvement over traditional methods, machine learning and neural network approaches have greatly improved demand forecasting. These advanced techniques are effective for complex and highly volatile environments as neural networks can analyze massive datasets and uncover hidden relationships, significantly improving demand forecasting accuracy beyond the capabilities of traditional methods.

# Traditional Methodology

Traditional demand forecasting methods rely on historical data and statistical models to predict demand. These models are typically designed to work in straightforward and predictable environments. These statistical approaches assume that past trends can predict future demand. They have been widely used and work well in environments where demand follows a consistent and straightforward pattern. As noted, "These quantitative forecasting approaches tend to have certain data requirements and also have obvious advantages and disadvantages, such as an emphasis on model improvement to improve the prediction accuracy" [4]. These traditional patterns often fail in industries that experience more dynamic and volatile demand.

A few examples of the traditional methods are:

* **Auto-regressive integrated moving average (ARMIA)** - ARMIA models use historical trends to predict future trends using a blend of auto-regressive terms, moving averages, and integration steps. As previously mentioned, "the main limitation of ARIMA is that it assumes that the given time series is linear" [1], which can lead to inaccuracies in more complex scenarios. ARMIA models effectively predict demand in environments where demand follows a consistent cycle.
* **Exponential Smoothing** - A common technique to assign decreasing rates to older historical data and valuing newer historical data more. This helps the model react to newer data and trends, assuming those trends are gradual in nature. "Exponential smoothing methods are similar to moving average, except for the fact that predictions are obtained by considering weighted averages of past values in a time series" [3].
* **Poisson Processes** - A model used commonly in repair shops. The addition of predicting demand changes at random intervals helps with forecasting unusual demand and can be used when the historical data source is too small for other methods. It has been combined with a Bayes approach that significantly improves its accuracy.

These traditional methods are effective in industries that follow transparent and predictable trends. Their methodology is insufficient for industries with volatile demand, especially in industries that experience sudden shifts in trends. The complexity of demand forecasting is increased when the demand for repair parts is introduced, "In particular, studies of large-scale spare parts networks assume that demands for different spare parts are independent" [5]. There have been numerous improvements to these traditional methods in order to account for additionally complex inventory demands.

Example of modern updates to traditional methods:

* **ZIP-METRIC** - This method adjusts the traditional statistical models to account for fluctuating demand. It dynamically adjusts metrics to allow companies to factor in the volatility of demand.
* **Poisson-Bayes Methods** - The traditional Poisson process is blended with Bayesian statistics, allowing the model to update predictions as newer data becomes available. This method is suitable in quickly evolving industries where demand is constantly changing.

Statistical models provide a foundation for demand forecasting but often fail in complex or dynamic environments. These methods struggle with the volatile demand patterns experienced in aerospace, manufacturing, and repair services. Statistical models are primarily linear and fail to account for dynamic and unpredictable changes in demand. They especially fail in sectors such as aerospace and in repairs, which have irregular and sometimes sparse data.

As supply chains have grown more extensive and complex, traditional methods are becoming more inadequate for accurate demand forecasting. Modern approaches like machine learning and neural networks provide new ways to predict demand levels. These advanced approaches can process large amounts of data, uncover hidden patterns, and adapt to sudden changes, making them an excellent tool for forecasting volatile demand.

# Modern Machine Learning Methodology

Unlike traditional statistical-based methods, machine learning models can identify complex patterns in large datasets, making them valuable in demand forecasting. "These intelligent prediction techniques have played an important role in various industries due to their excellent data processing capabilities" [4]. Machine learning techniques adapt to changes in demand patterns over time and improve their accuracy. Machine learning can effectively model complexities unlike traditional statistical methods, which may struggle with nonlinear relationships. As noted, "neural networks have also emerged as an alternative tool for modeling and forecasting due to their ability to capture the non-linearity in the data" [3].

Neural networks are a type of machine learning model that is specifically designed to recognize patterns in data. Their ability to capture nonlinear data and model complex relationships found in-demand data makes them superior to traditional models.

There are several types of neural networks and several that are used in demand forecasting:

* **Recurrent Neural Networks (RNN)** - Designed for sequential data, which makes them useful for forecasting. As highlighted, "RNNs provide a short-term memory by storing the activations from each time step"[1], enabling them to model volatile demand effectively.
* **Long Short-Term Memory Networks (LSTMs)** - A specialized type of RNN that includes logic to allow the model to remember or forget certain information over time. An advancement in forecasting methods is reflected in the use of LSTMs: "An effective model based on the long short-term memory (LSTM) recurrent neural network was put forward to predict the requirement for maintenance of spare parts" [4].

In addition to RNNs and LSTMs, other neural networks, such as convolutional neural networks and Transformers, are also being studied for their use in demand forecasting.

Despite the many advantages of neural networks, they also present challenges to companies that leverage these solutions. Neural networks require a large amount of training data; this data may be difficult for small or new businesses to gather. One possible solution is to supplement training data when it comes to repairs. As noted in one study, "Estimates of future repair volumes are obtained using standard forecast techniques and improved using expert knowledge" [5]. This method not only supplements the data, but can help better inform the model. Additionally, training the neural network can be computationally complex and expensive. As noted, "the simulation of a single replication of a system with only 5,000 nodes for 100 periods may take about an hour" [6], highlighting the significant computational requirements involved, especially when considering that a larger system could have training data involving tens of thousands or even hundreds of thousands of nodes. Advanced optimizations can be performed to combat the high computational cost of training the neural networks, as described by Ding, who "improved the BP neural network model based on the Adam optimization method to forecast the demand for materials…" [4]. Adam optimization helps track and fix mistakes the model is making in predictions. The computational power to train these models is expensive; however, as the cost of processing power decreases, this barrier becomes less of an obstacle.

Additionally, neural networks can be sped up and optimized using genetic algorithms. Integrating techniques such as L1-regularization can also help reduce model complexity by "forcing the solution of the optimization problem to be sparse" [6], enhancing both the speed and accuracy of the model. Furthermore, "a double-level combination forecast model can obtain a superior final result by automatic optimization combination of multiple models" [1].

In summary, machine learning models, particularly neural networks, offer significant advantages over traditional statistical approaches to demand forecasting. The downsides of neural networks can be reduced through well-researched advanced optimization techniques. Integrating neural networks is a promising solution for businesses aiming to optimize inventory management practices, especially in industries with complex and volatile demands.

# Neural Network Implementation Approach

Implementing a neural network to create demand forecasts for parts involves several critical stages. This process ensures that the model can accurately predict demand, optimize inventory levels, and ultimately support the forecasting needs of the business.

Multiple data sources are essential for creating an accurate forecasting model:

* **Historical sales data** - This dataset should capture the quantities sold over a defined period. This data allows the model to recognize patterns in past sales trends.
* **Mean Time Between Failure data (MTBF)** - MTBF data allows the model to make predictions based on the failure rates for parts. Failure data greatly influences demand when repairs must be accounted for when forecasting demand.
* **Repairs data** - Historical data for which repairs have been made over time and what components were required is required. As highlighted, "to improve the model's prediction accuracy, this study fully considers the factors that have direct and indirect effects on the [Remaining Useful Life] of equipment" [4]. It is essential to consider any other data points that might influence repair demand.
* **Sales forecasting data** - Projections of future sales help the model predict future trends.

These datasets should be consolidated into a time-series format, where each time step (day, week, or month) includes relevant variables such as total sales, quantities of parts needed for both new production and repairs, estimated MTBF for those parts, and any known factors that affect demand during that time period.

Before training the model, it is essential to preprocess the consolidated data. Reprocessing steps include:

* **Normalization** - Scaling the data to a standard range ensures no feature disproportionately influences the model's predictions. "Data cleaning and normalization are the two essential data preparation tasks which will be applied to prepare data for forecasting tasks" [1].
* **Handling Missing Data** - Missing values can lead to inaccuracies. Techniques such as interpolation, forward filling, or statistical methods can help address gaps in the dataset.
* **Feature Engineering** - This includes creating lag features (values from previous time steps that provide context for the RNN's predictions). For instance, forecasting demand for spare parts, including the sales from the past week as an additional feature, can help the model learn trends over time.

The implementation can first be completed with a simple RNN. An RNN is identified as an optimal choice, but "Unlike in feedforward ANNs, the connections between nodes in an RNN establish a cycle which allows signals to move in different directions" [1]. Later, more advanced models, such as an LSTM network, can be implemented, An LSTM should be considered due to their ability to capture long-term dependencies and mitigate issues related to vanishing gradients. Training the model to find network parameters that solve the optimization problem is essential in implementing the RNN [1]. Various optimization methods, such as Adam, should be explored during the training phase to enhance the model's performance. Additionally, uncertainty in the data can be accounted for by integrating confidence levels into the predictions. The performance and accuracy must be evaluated before the RNN is deployed.

Once deployed, the RNN is configured to retrain as new data becomes available, allowing the model to adapt to changing demand patterns and improve its forecasting accuracy over time.

By following these stages, an RNN can be effectively implemented for demand forecasting. The neural network will remain responsive to market demands and optimize its inventory management processes as it is continually used. The model must handle a vast amount of parts and forecast demand precisely.

# Conclusion

In conclusion, determining Minimum Stock Levels (MSL) is crucial for companies, especially in industries with highly variable demand, such as manufacturing and repair services. While traditional forecasting methods offer a foundational approach for estimating MSL, they are increasingly inadequate in the face of growing supply chain complexity. These conventional methods struggle to deliver the accuracy needed to optimize inventory levels in dynamic environments.

The shift toward modern approaches, particularly machine learning and neural networks, represents a significant advancement in demand forecasting. As demonstrated, "the results of the experiments showed that traditional statistical methods such as ETS and ARIMA yield weak performance in comparison to [machine learning and neural networks]" [1]. These advanced techniques are better equipped to handle rapid changes in demand patterns than traditional methods, leading to more accurate stock levels and reducing the risks of stock-outs and overstocking.

These advanced techniques can manage rapid changes in demand patterns, leading to more accurate stock levels and reducing the risks of stock-outs and overstocking. Implementing modern forecasting methods is essential for companies to stay agile, continuously adapt to shifting market conditions, and maintain operational efficiency.

# Citations

1. Abbasimehr, H., Shabani, M., & Yousefi, M. (2020). An optimized model using LSTM network for demand forecasting. \_Computers & Industrial Engineering\_, \_143\_, 106435. [[https://doi.org/10.1016/j.cie.2020.106435](https://doi.org/10.1016/j.cie.2020.106435)](https://doi.org/10.1016/j.cie.2020.106435%5D(https://doi.org/10.1016/j.cie.2020.106435))
2. Babai, M. Z., Chen, H., Syntetos, A. A., & Lengu, D. (2021). A compound-Poisson Bayesian approach for spare parts inventory forecasting. \_International Journal of Production Economics\_, \_232\_, 107954. [[https://doi.org/10.1016/j.ijpe.2020.107954](https://doi.org/10.1016/j.ijpe.2020.107954)](https://doi.org/10.1016/j.ijpe.2020.107954%5D(https://doi.org/10.1016/j.ijpe.2020.107954))
3. Dombi, J., Jónás, T., & Tóth, Z. E. (2018). Modeling and long-term forecasting demand in spare parts logistics businesses. \_International Journal of Production Economics\_, \_201\_, 1-17. [[https://doi.org/10.1016/j.ijpe.2018.04.015](https://doi.org/10.1016/j.ijpe.2018.04.015)](https://doi.org/10.1016/j.ijpe.2018.04.015%5D(https://doi.org/10.1016/j.ijpe.2018.04.015))
4. Tang, B., Ma, Z., Zhang, K., Cao, D., & Zhang, J. (2022). Substation equipment spare parts’ inventory prediction model based on remaining useful life. \_Mathematical Problems in Engineering\_, \_2022\_(1), 3396850. [https://doi.org/10.1155/2022/3396850](https://doi.org/10.1155/2022/3396850)
5. van Jaarsveld, W., Dollevoet, T., & Dekker, R. (2015). Improving spare parts inventory control at a repair shop. \_Omega\_, \_57\_(B), 217-229. [[https://doi.org/10.1016/j.omega.2015.05.002](https://doi.org/10.1016/j.omega.2015.05.002)](https://doi.org/10.1016/j.omega.2015.05.002%5D(https://doi.org/10.1016/j.omega.2015.05.002))
6. Wan, T., & Hong, L. J. (2022). Large-scale inventory optimization: A recurrent-neural-networks-inspired simulation approach. \_arXiv\_. [https://arxiv.org/abs/2201.05868](https://arxiv.org/abs/2201.05868)