# Predict then Optimise for Inventory Management


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**Abstract** Inventory management plays a vital role in organizations. Once inventory is efficiently and effectively managed, the service supplied to customers ultimately improves and costs can be controlled. We use a prediction model to develop multiple potential futures, from which efficient inventory decisions can be made using stochastic optimization.


## Background

Effective inventory management by manufacturers and suppliers is fundamental to achieving acceptable customer service levels, while controlling the cost of procuring and holding stock as a buffer against uncertain demand [1, 2]. Inventory management address the question of when an order should be placed and the quantity that should be ordered. We investigate the combination of demand prediction models with stochastic optimization, to develop inventory management policies that are able to take into account more accurate predictions of future sales to reduce overall inventory costs. We evaluate several forecasting methods: naive forecasting using a normally distributed approximation; LightGBM (Light Gradient Boosted Machine), [3]; and a seasonal demand forecast. These are used to create multiple forecasts of future demand, from which the optimal inventory replenishment decision (plan) is obtained by evaluating the deterministic equivalent ordering policy using stochastic optimization.

## Methodology

Our modelling assumes that during each (daily) replenishment cycle, the inventory level is calculated and a replenishment order is made, to be received after a specified lead time.

For the case of the **(Q, r)** model, the replenishment decision protocol applied during each inventory cycle is that if the inventory position is equal to or less than **r**, reorder point, then an order of size **Q** is placed, to be received after a specified lead time.

Stochastic optimization is used to make a replenishment decision based on forecast demand over a specified time window. For all models the optimization is performed iteratively, one day-at-a-time using a sliding time window of duration **W**. Beginning at the current time period, $t_0$, the optimal replenishment decision (plan) is made for each day over the interval $[t_0, t_0+W]$. However, only the replenishment decision for the current day, $t_0$, is implemented, and the remaining decisions discarded. The inventory cycle repeats, whereby $t_0$ is updated to the following period, and the process continues to evaluate the replenishment decision over the next **W** periods.

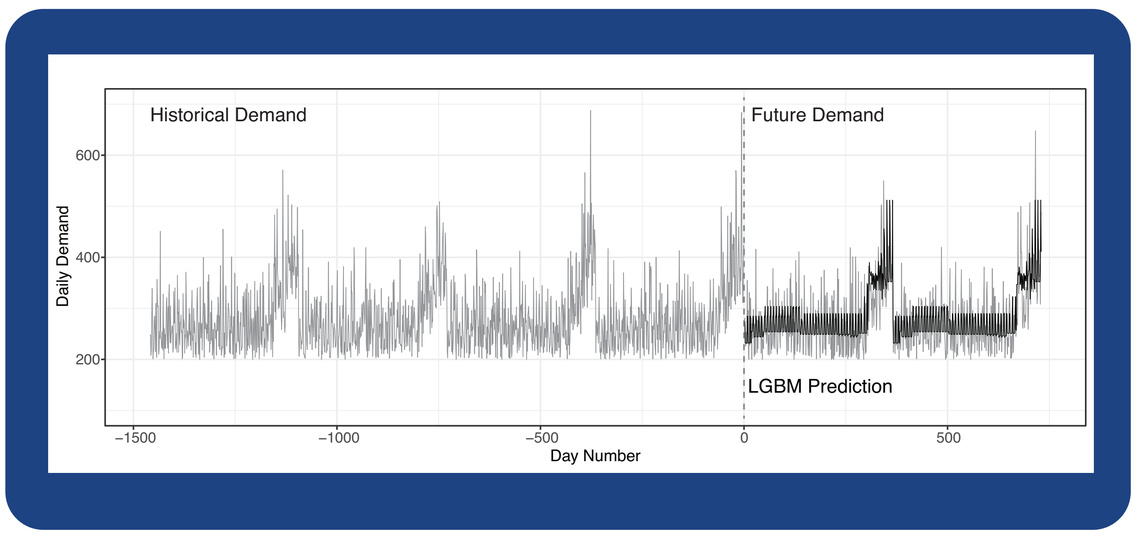


**Figure 1:** LightGBM forecast example showing historical and future demand (gray), and forecast (black).

## Results

Figure 1 shows how LightGBM makes accurate predictions of future demand that take into account seasonality, but with less variation than the actual data.

Table 1 shows the result of LGBM, Normal distribution, and seasonal distribution in comparison to (Q, r) model. Due to the accuracy of LGBM forecast, the operating cost of LGBM model is much lower than the other optimization approaches and (Q r) model.

In addition, the accurate forecast of demand of LGBM and Seasonal forecast leads to increased customer service level compared to the (Q,r) model. The (Q, r) model has a limited understanding of future demand. This results in greater average inventory on hand to minimize stockouts compared with prediction-based stochastic optimization.

Table 1: Average costs per day, reorder frequency and service level summary for each inventory management policy assuming a 30 day lead time, and using a 35, 60 and 120 day planning window for stochastic optimization.

| Model | (Q, r) | Normal | LGBM | Seasonal |
|---|---|---|---|---|
| **Review Period** | - | **120** | **120** | **120** |
| **Total cost** | 4186.99 | 4513.01 | **2639.73** | 2699.43 |
| **Reorder cost** | 1037.04 | 1111.11 | 1185.19 | 1185.19 |
| **Hold cost/Ave inv** | **2186.62** | 2934.23 | **1188.35** | 1294.30 |
| **Stockout cost** | 963.33 | 467.67 | **266.19** | 219.95 |
| **Not supplied** | 9.63 | 4.68 | 2.66 | 2.20 |
| **Order Frequency** | 9.64 | 9.00 | 8.44 | 8.44 |
| **Type 1 Service** | 0.97 | 0.98 | **0.98** | **0.99** |
| **Type 2 Service** | 0.97 | 0.98 | **0.99** | **0.99** |

## Conclusion

In this paper we show that we can substantially improve inventory management compared to traditional approaches by using more accurate predictions of future demand. The use of stochastic optimization to obtain efficient inventory management polices from forecast demand clearly results in lower cost solutions than those from the (Q, r) model by having a more accurate view of future demand. The stochastic optimization approach can be combined with any prediction method, under the caveat that we need to be able to generate multiple independent forecasts of the future.


FOR FURTHER INFORMATION
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