Empirical Evaluation of an Integrated Forecast to Inventory Planning Tool for Retail Service Levels and Inventory Efficiency

MSc Research Practicum
MSc. Data Analytics

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MSc Project Submission Sheet

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Research Practicum
Empirical Evaluation of an Integrated Forecast to Inventory Planning Tool for Retail Service Levels and Inventory Efficiency

Your Name/Student Number	Course	Date
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Empirical Evaluation of an Integrated Forecast to Inventory Planning Tool for Retail Service Levels and Inventory Efficiency

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Abstract

Retailers are challenged to ensure that they offer high service levels at a minimal inventory cost. The project gives an empirical assessment of an integrated forecast-to-inventory planning tool in a retail setting. The tool is an integrated workflow of a combination of demand forecasting techniques and services-level-based optimization of inventory, executed through a business intelligence dashboard. This project uses the recommendations of the tool and compares them with the current planning practices with a large number of SKU-store combinations using historical sales data and simulation. As the results demonstrate, the combined method can significantly enhance the service levels (cycle service level and fill rate) without the corresponding increase in average stock, which means the inventory efficiency improvement. The number of stockouts was decreased significantly and more so with highly variable products where the current heuristic system under-stocked. Such results indicate that the improved congruence between forecasting and inventory decisions can improve inventory performance in retail environments like the one under analysis. The project will attempt to bridge the gap between analytical work and managerial practice by prototyping an effective tool that will combine demand forecasting, inventory control, and interactive decision support.

Keywords: Demand forecasting; Inventory management; Service level

1 Introduction

The operational decisions that retailers have to make on a regular basis are decisions made under uncertainty conditions especially when deciding on the most appropriate inventory quantities to meet customer demands. The effects of stockouts are high; lack of the product will reduce sales and customer loyalty, and it is estimated in the global industry that almost 1 trillion of revenue is lost every year due to inventory shortages (Kim, Knight, and Mitrofanov, 2024). On the other hand, high inventories tie up working capital and create high carrying costs, which creates expensive markdowns and decreasing profitability. To balance these two conflicting forces that guarantee high service levels and control inventory expenses, it will be necessary to properly forecast demand and develop advanced replenishment policies (van der Haar et al., 2024).

Although there is substantial advancement in methodologies of forecasting and inventory control, these functions are usually applied individually in the retail organizations. Forecasters usually produce demand projections without regard to the way these are used to guide inventory policies, and planners use heuristic guidelines to establish reorder points and order quantities. This decoupled estimate-then-optimize method is suboptimal: in fact, as van der Haar et al. have demonstrated, an increase in forecast accuracy does not always lead to better inventory performance, due to the asymmetric cost of stockouts and overstocks.

Inventory control parameters are not updated systematically as well as forecasts are improved, then organizations may not achieve desired service or cost goals.

There are also some established practices in the industry that make it very difficult to perform operationally. The forecasts and replenishment rules tend to be isolated and this leads to the failure to take advantage of better predictive information. Conventional models assume that demand is distributed in a static manner ignoring seasonal changes, promotions, and changing market trends, and thus systematic forecast errors and inappropriate safety stock policies are experienced. Besides, the majority of practitioners continue to use straightforward statistical methods, like exponential smoothing, despite being clearly demonstrated that machine learning methods that utilize extensive data sets involving promotional activities and external indicators are more precise and efficient. Lastly, behavioral studies point out that cognitive biases and goal framing may be used to affect managerial choices during replenishment. Managers driven by cost-minimization objectives (represented by loss avoidance) also order more inventory and have lower stockout rates than profit-maximizing managers (represented by gain seeking), and are influenced by trust in automated recommendations further (Kosgoda et al., 2024).

The advantages of integrated and data-driven methods are operational and financial and are proven by the recent works. Wellens et al. (2024) showed that decision-tree based forecasting model with built-in explanatory attributes led to a decrease in the forecast error by 11.5, improvement in service level by 0.7, and lowering inventory cost by 12.5 percent than their classical counterparts. In the meantime, van der Haar et al. (2024) discovered that the use of machine learning methods that directly forecast quantities of orders might be as effective as heuristic policies, particularly in non-stationary, feature-driven demand models. Behavioral experiments also prove that loss-framed performance objectives and confidence in analytics platforms can result in significant cost reductions and service enhancements.

The existence of these gaps and new solutions highlights the importance of a single analytics. The forecast-to-inventory systems are integrated, and the demand estimation is tightly connected with the replenishment optimization, which provides dynamic adjustment of the stocking policies and the business goals at the SKU-location level. Such integrated systems can be used to help planners set adaptive targets of service and reorder points by using real-time information on sales, promotions, and trends, as opposed to the inflexibility of the old systems that use manually maintained safety stocks.

Research Question:

Compared with current planning practice in the focal retailer, how does an integrated forecast-to-inventory planning tool affect (i) cycle service level (CSL), (ii) fill rate, and (iii) average on-hand inventory at the SKU–location level?

Hypotheses :

- **H0:** The cycle service level (CSL) and fill rate in the current planning practice and in the integrated forecast-to-inventory planning tool have no statistically significant difference.
- **H1:** The use of the integrated forecast-to-inventory planning tool is statistically significantly related to a statistically significant improvement in cycle service level (CSL) and/or fill rate over the existing planning practice.

Proposed Solution:

The proposed project is a proposal of an integrated decision-analytics tool created on the Microsoft Power BI platform to assist in automated suggestions regarding retail inventory replenishment. This system is a combination of a group of demand forecasting algorithms, service-level-based inventory control logic, which produces recommended safety stocks, reorder points, and order quantities. The prototype tool will also attempt to connect operational decisions and explicit cost-service trade-offs by combining forecasting and inventory policy decisions into a unified and auditable process.

Interactive dashboards will enable the planners to do what-if analysis and include exploring alternative forecasting model, changing service targets or lengthening lead times. The planners are then able to assess how such changes will affect inventory and service results. Such scenario ability can assist in enhancing the visibility of decisions, build user confidence and promote the steady adherence to policies, and may even result in increased service levels at the same or reduced inventory investment.

The project makes contributions to applied research and managerial practice that include evidence in the form of cases of the effect of integrated analytics on performance, behavioural factors of automated decision-support adoption, and operationalisation of advanced analytic tools in a practical retail planning situation.

2 Related Work

The problem of retail inventory optimization has always been critical to the operations management literature and that is why a vast amount of literature has been developed. The following overview of the latest findings that are of specific importance to the current research scope is the combination of demand forecasting and inventory management, the application of predictive methods in retail demand, decision support systems in supply chain, and the gap that has been identified to exist between the theoretical knowledge and practice of managers.

2.1 Importance and Background:

The traditional inventory management systems may be very ineffective when the demand fluctuates and the lead times are long enough (van der Haar et al., 2024). Periodic review and experience-based judgment are rather inefficient to be used in these cases. Seasonal peaks, promotions, and unexpected surges make the forecasting difficult and can lead to managers overstocking in case of shortages, or understocking and being out of stock. These are challenges which are well documented in academic research. As an illustration, fashion retailers usually need to make orders at minimum 6 months before, and it is not easy to make correct long-term predictions (Kamran-Disfani and Mantrala, 2024). Practically, most retailers still possess siloed forecasting and inventory operations; the improvement of the integration of those operations is perceived as one of the means to stimulate improved performance (van der Haar et al., 2024). Recent studies have tried to address the issue through machine learning prediction technique to behavioral interventions to improve ordering decision. However, the application of advanced models in industries is not common, sometimes due to lack of simplicity or user friendly implementations. The significance of the given project is that it transforms state of the art techniques into a dashboard that can be easily used by the retail decision-makers. The suggested tool will democratize high-level inventory optimization analytics using a popular business intelligence platform (Power BI) that would offer real-time data-driven decision-making and predictive analytics (Yerra, 2025).

2.2 Integrating Forecasting and Inventory Control

Traditionally, the issues of demand forecasting and inventory decisions have been discussed as two independent matters, but it is often the case that poor results are observed when naive forecasts are used in inventory models. The importance of integration is demonstrated by van der Haar et al. (2024) as they mention that the integration of demand forecasting and inventory control has been a thorn in the flesh of the forecasting and inventory communities. Their article suggests the use of supervised machine learning with custom loss functions that reduce the inventory measures directly as a part of the prediction process. They also managed to make extraordinary improvements in performance by considering inventory costs in their forecast model. The combined approach was as effective or even more effective than the best extant inventory heuristics in the case of lost-sales, perishable goods, and dual-sourcing (van der Haar et al., 2024). This implies that stocking decisions can be significantly improved by setting the goals of forecasting to match inventory performance goals (e.g. service level or cost). The present project is based on this idea of integration; the integrated tool will not create the demand forecasts out of thin air but will apply the forecasts to calculate the best reorder quantities and safety stocks as a part of one system.

2.3 Advanced Forecasting Techniques in Retail:

A good stocking strategy is founded on precise demand forecasting. Recent literature suggests that there is a move towards machine learning and hybrid models to model multifaceted retail demand patterns (which can be seasonal, promotional, and random spikes). To provide an example, Rakholia et al. (2024) present a data-driven approach to inventory optimization, which is a combination of demand forecasting based on machine learning with sophisticated inventory models. Their approach has a random forest forecasting model (using the previous sales, seasonality factors, and external drivers) as an input in an Economic order quantity (EOQ) formula that uses better safety stock calculations. The result was a scalable system that could reduce drastically overstock and out-of-stock cases, which can be proven by the scenarios simulation of seasonal peaks and unexpected surges (Rakholia et al., 2024). This is in line with other studies that have made AI-based predictions and standard inventory models to act as essentially new wine in old wineskins to come up with the best of the two worlds. Scholars have explored unusual forecasting instruments in a similar setting in the context of fashion retailing: crowdsourcing has been experimented as a forecasting technique. Kamran-Disfani and Mantrala (2024) discovered that the predictions of demand by crowdsourcing of a large pool of consumers were more precise compared to predictions by professional fashion customers. It is worth noting that the heterogeneity of the crowd (the variation of income levels and shopping patterns of the individuals) was more effective in making correct aggregate forecasts since individual error is likely to cancel out. Also, they observed decreasing returns to accuracy gains once the crowd size went past 100 people (Kamran-Disfani and Mantrala, 2024). This observation underscores the importance of utilizing more and heterogeneous sources of information the so-called wisdom of crowds in addition to traditional time-series algorithms. The definite forecasting methods involved in the design of the integrated tool will be based on the features of demand of the corresponding products. As a case in point, seasonal ARIMA or Prophet could be appropriate when dealing with fast-moving goods, but Croston approach or a bespoke machine learning model may be required when dealing with intermittent-demand goods all in a bid to enhance the accuracy of forecasting and, in extension, stocking.

2.4 Behavioral Factors in Ordering Decisions:

Interestingly, human decision-makers do not necessarily act per the optimal policies, despite the presence of advanced analytics, which is also a common occurrence in the behavioral operations research. This phenomenon is typical of the classic Newsvendor model: people will over-order in low-margin situations and under-order in high-margin situations due to risk aversion and biasness. Protopappa-Sieke et al. (2019) tested the influence of ordering behavior under different periods of the introduction of retail promotions (modeled by budget cycles). They established in a controlled laboratory environment that the subjects were prone to lowering their order-up-to levels at the budget cycle conclusion consequently, creating a cyclic trend of inventory levels ostensibly due to shortsightedness of the subjects towards future budget cycles (Protopappa-Sieke et al., 2019). Such shortsighted behavior can destroy even well-thought-out plans to stocking. On the same pattern, cognitive limitations may intensify the bullwhip effect (the increased variability of demand further up a supply chain). Haines et al. (2016) found out that merely increasing the volume of information (i.e. having point-of-sale demand information) is not always enough to eliminate the bullwhip effect but rather the result of this process is determined by the effectiveness with which decision-makers make use of the information. Their study added to the metacognitive viewpoint and proved that those who comprehended cause-and-effect in the supply chain were much more effective in damping the fluctuations in orders (Haines et al., 2016). These findings indicate that there is a massive gap that can be addressed by decision support tools: to guide and teach the user to make a better decision. The proposed integrated tool will also contribute to the scenario analysis interface enabling the end-user to visualize the results of different scenarios (e.g. what happens when the demand doubles or the lead time is longer than the forecast is). This aspect should minimize guesswork of the planners and possibly eliminate biases. With that, the tool can be used as a what-if advisor simulating the scenarios thus making the decision-making process more organized, not based on gut feeling.

2.5 Analytics and Business Intelligence in Supply Chain:

Big data systems and business intelligence have developed to be part of the way companies operate. Real time analytics, especially in inventory management, is one of the areas that have been given a lot of attention. In a case study, Yerra (2025) reports that Power BI dashboards were worth the investment: firms that implemented such dashboards reported increased efficiency, decision-making, and risk of operations when utilizing them in the inventory management. The direct relation of the Power BI with the live database or ERP system enables the managers to detect the stock issues and take the corrective measures in real time before the end-of-day reports are created. The rich visualizations and the drill-down features also allow the easy determination of the trends or anomalies in sales or stock levels. Similar works in information systems have highlighted the strategic significance of data-driven decision-making. As an illustration, Doering and Suresh (2016) came up with the notion of Forecasting Management Competence, which is basically the capability of a firm in its control of the forecasting process. Their research attributed the competence to performance results: the companies that invested in the improved forecasting tools, training, and integration demonstrated higher inventory turnover and service. This observation also justifies the necessity of solutions that incorporate the mighty demand-planning analytics into day-to-day operations. Higher-level strategic decisions can also have an effect on inventory performance. The analysis of Qian et al. (2024) indicates that the effect of product range diversification and international expansion is strong on the efficiency of inventory. They emphasize the fact that inventory strategy should be consistent with business strategy, therefore, a well-differentiated retailer can afford to use more sophisticated, segmented stocking policies.

2.6 Research Gap:

Although the scholarly literature has developed demand forecasting and inventory optimization to a very high level, there remains a major gap in converting the models into available practical tools to the retail practitioners. Most of the available models are still restricted to the academic prototypes or simulations and demand specific expertise, which makes them less applicable in the real world. This means that retail managers tend to still be operating with siloed, heuristic-driven practices that fail to harness the power of the current predictive and optimization technologies.

In addition, past studies have largely concentrated on enhancing the accuracy of algorithms or cost reduction independently without combining them into a unified, easy-to-use decision-support system that can be implemented in real-time. The literature points out the significance of such integration but provides minimal practical applications that integrate demand forecasting, inventory management and business intelligence into an operational context.

This is particularly a notable gap in the wake of the emergence of data-driven decision-making in the supply chain management. The inability to implement an innovative practice is prevented by the absence of intuitive and scalable instruments that democratize advanced analytics through user-friendly interfaces (e.g., Power BI). Such a gap can be addressed in a transformative way, as it would allow connecting predictive analytics and operational decision-making in a seamless way in an accessible way.

3 Methodology

3.1 Research Design and Framework:

The research was quantitative and simulation-based, taking the form of comparative research in order to compare an integrated forecast-to-inventory planning tool with the current practice in planning by the focal retailer. The main research question will be how the tool influences the level of cycle service (CSL), fill rate, and average on-hand inventory at SKU-location level compared to practice, with the hypotheses on whether the difference is statistically important. The secondary questions are concerned with the dispersion of forecast error to safety stock and CSL, intermittent demand treatment, service-inventory Pareto frontier, and the behavioural aspect of planner adherence.

The study was based on a design-science reasoning: initially, an analytics artefact (the integrated tool) was created, and its effect was measured empirically. The tool connected the demand forecasting and inventory control to one workflow carried out in Power BI where Python was utilized to forecasting and simulation procedures, and Excel was utilized to handle data and certain inventory calculations. This corresponds to the literature demands to combine forecasting and inventory decisions instead of viewing them as distinct operations (van der Haar et al., 2024; Rakholia et al., 2024). The conceptual workflow was based on data extraction and cleaning, estimating the forecasting model, calculating inventory parameters, simulating inventory behavior with alternative policies, and statistically comparing the results of performance.

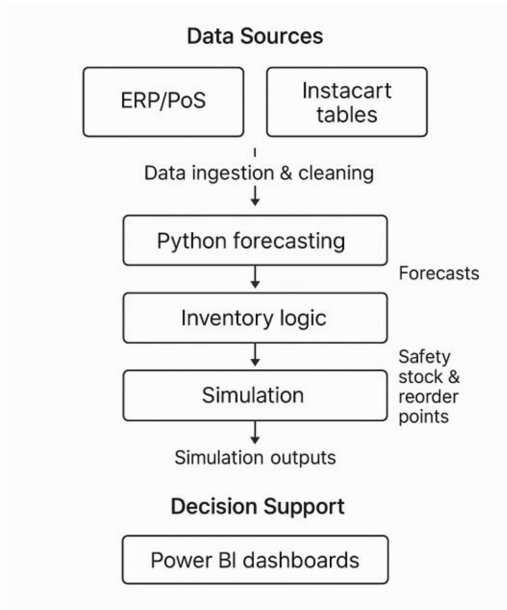

Figure 3.1 – Overall research design framework

3.2 Data Sources and Preparation:

The empirical model employed historical transactional data of the target retailer, including sales per SKU-location, recorded inventory position, lead-times and simple product characteristics during a recent multi-month time. The ERP and point-of-sale systems of the retailer exported these data into Excel and then to Python where they were processed.

Data cleaning involved dropping or fixing of apparent errors (negative sales, duplicate records), consistency of units of measure, and matching sales and inventory records on the same calendar. The sales were also put together into a time bucket of a week to make forecasts and inventory modelling, which is consistent with the planning cycle of the retailer and to average the high-frequency noise.

The demand pattern was a characteristic of each SKU-location time series. The average inter-demand interval and the squared coefficient of variation are some of the measures calculated to classify series as smooth, erratic, intermittent or lumpy in accordance with intermittent demand literature (e.g. Croston, 1972; Syntetos and Boylan, 2005; Teunter, Syntetos and Babai, 2011). This segmentation was used in deciding the forecasting model, as well as the analysis of the research questions on intermittent items.

This was followed by the division of the data into training and test periods. Forecasting models were fitted to the training part (the previously described part of the horizon), where the later part of the horizon was both the out of sample forecast evaluation set and the demand input to inventory simulations. The test period was not used to estimate the model in order to maintain time realism. The entire preprocessing was coded in Python so as to be reproducible.

3.3 Forecasting and Inventory Models

3.3.1 Forecasting Models

The tool also used an integrated model portfolio instead of an individual forecasting approach, as it is also shown that various patterns of demand respond to various techniques (Wellens et al., 2024; van der Haar et al., 2024).

Because a simple benchmark forecast (e.g. moving average or same-period-last-year) is a common proxy of current practice, it was used to model the heuristic planning of the retailer, which is noteworthy since most retailers are observed to make use of simple rules despite the existence of more sophisticated approaches (Kamran-Disfani and Mantrala, 2024).

In the case of smooth and higher-volume series, classical time-series models were used, such as seasonal ARIMA, exponential smoothing versions, and estimated with standard methods in Python in the statsmodels package. Prophet-style decomposable models were also tested on series that were clearly seasonal or trend-following, as has become recent practice in retail forecasting.

A machine learning model (random forest) based on a tree was used to utilize more rich feature sets, with inputs being lagged demand, calendar effects and promotion indicators, as shown by the data-driven models reported by Rakholia et al. (2024) and Wellens et al. (2024). Cross-validation was used to tune a model hyperparameter on the training set.

In the case of intermittent demand SKUs, the approach of Croston and its improvements (SBA, TSB) was adopted that individually predicts non-zero-size demand and the inter-demand interval (Croston, 1972; Syntetos and Boylan, 2005; Teunter, Syntetos and Babai, 2011). Parallel to this, a variant of machine learning that computes the occurrence of demand classes and the size conditional on that occurrence was built, responding to research question on cost-optimal approaches to intermittent items, to accommodate.

On the test period, the models were also assessed using standard accuracy metrics like MAPE, although inventory performance also defined the choice of model in the integrated tool, which is in line with the integrated forecast-inventory reasoning (van der Haar et al., 2024).

3.3.2 Inventory Control Logic

Inventory policies were modelled a continuous-review (r, Q) policy on SKU-location level. In the case of the integrated tool, the reorder point r was taken as demand during the lead time plus safety stock:

$$r = D^{\wedge}L + z\sigma L$$

where $\widehat{D}_L$is the forecast of demand during lead time, $\sigma_L$is the estimated standard deviation of lead-time demand derived from forecast residuals, and z is the normal safety factor corresponding to the target CSL (e.g. 1.645 for 95%). In the case of intermittent series, non-normal lead-time demand distributions were taken through Croston-type models. This directly connected forecast error with the necessary safety stock, answering research question on the propagation of errors.

The order quantity Q was calculated as a lot-to-lot order replenishment to a target value or an economic order quantity (EOQ) style calculation in which parameters of ordering and holding costs were known, which is aligned with integrated ML-EOQ methods (Rakholia et al., 2024). Practical constraints (e.g. case pack sizes) were added to many of the items by rounding Q to practical multiples.

The current practice (policy) was reformulated based on observed ordering behaviour and recorded rules of planners (e.g. heuristics of weeks of cover) that were approximated as fixed reorder points and quantities to replicate past inventory behaviour.

All the inventory calculations were written in Power BI through DAX and Python with formulas being validated and documented in Excel, which gives transparency and auditability to the planners (Yerra, 2025).

3.4 Experimental Setup and Evaluation Procedure

The assessment was based on discrete-time simulation to recreate inventory dynamics with both the current practice and tool-based policy. The SKU-location per period was the unit of analysis. The simulation used the same initial stock and used the historical demand within the test horizon in each SKU-location.

In the baseline scenario, the recreated current practice policy dictated when and in what quantity to order. Forecasts were made every period in the tool scenario, new r and Q were computed and the replenishment decisions were made according to the integrated policy. The lead times of suppliers and other operational limits were maintained the same in both cases.

In order to answer Secondary RQs, further what-if conditions were modeled, such as the surging demand and lead-time extension, which are the characteristics of non-stationary and risky environments identified in the literature (van der Haar et al., 2024; Kim, Knight and Mitrofanov, 2024). Both policies were subject to the same scenarios and therefore could be directly compared in terms of their robustness.

Python was used to simulate and do metrics calculation which were then loaded to Power BI to be visualized. This pipeline reflected the way this tool would work in practice and made sure that the results could be directly interpreted by the planners.

3.5 Performance Metrics and Statistical Analysis

The main research question was reflected in three main performance metrics:

Cycle Service Level (CSL): ratio of replenishment cycles which are nonstockout.

Fill Rate: percentage of the total volume of the demand that is met out of the stock.

Average On-Hand Inventory: time-averaged inventory as proxy of stock investment.

In the case of intermittent items, a cumulative relevant cost measure of holding and lost-sales costs was also calculated in research question based on cost parameters that were negotiated with the retailer and are also in line with previous studies on inventory-oriented forecast evaluation (e.g. Babai et al., 2019).

The differences between CSL, fill rate and average inventory of tool and baseline in each SKU-location were calculated. The difference between the mean differences and zero was tested using paired t-tests (a = 0.05). In situations where the normality of differences was questionable, a non-parametric test of robustness was applied as the Wilcoxon signed-rank test. These tests were concerned with the null hypothesis of no difference (H0) and the alternative of improved service under integrated tool (H1).Demand-based subgroup analyses were also done to determine whether the benefits were concentrated in high-variability or intermittent SKUs.

3.6 Validity, Reliability and Ethical Considerations

Internal validity was also increased with the same demand sequences, lead times as well as initial conditions in both policies such that any differences in performance could be explained by the planning approach. The standard and well-defined metrics of service and inventory commonly used in the research on retail inventory were employed to support construct validity (e.g. CSL, fill rate) (van der Haar et al., 2024; Wellens et al., 2024). External validity can only be applied to the similar retail setting, yet the presence of different SKU types and stresses scenarios enhances analytical generalisability of the results.

The support of reliability was in the form of scripted data preparation, Python model estimation and simulation, which meant that the entire pipeline could be re-executed using the same inputs to replicate the results. The main parameters (i.e. cost assumptions, service targets) were sensitivity analysed to ensure that conclusions were valid to sensible changes.

In terms of ethical considerations, anonymised operational data were only considered; no data that identified the customers were processed. Reporting was anonymous on the retailer and individual SKUs. The feedback that planners provided regarding the Power BI dashboards was informal and was only provided in aggregate form. The research met institutional requirements of data protection and research ethics, such as GDPR requirements where necessary.

4 Design Specification

The integrated forecast-to-inventory forecasting tool was developed as a retail analytics decision-support system that connects the demand forecasting with the inventory control in a single continuous pipeline. The architecture of the system was based on Microsoft Power BI as the main platform with embedded Python scripts to perform enhanced analytics and Excel to handle and validate the data. This design followed a design-science method: an analytics artefact was developed and tested, which is consistent with literature suggestions of rigidly combining forecasting and replenishment decisions. This was aimed at facilitating dynamic alignment of stocking policies with demand forecasts, such that the planners would have high service levels (CSL) at the cost of efficient inventory investment.

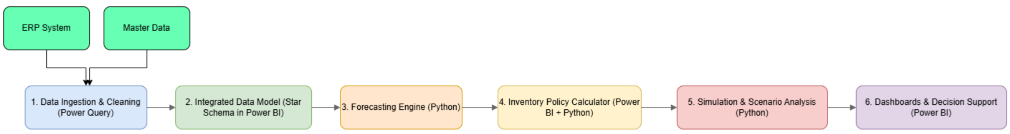

Figure 4.1 – Integrated Forecast-to-Inventory Workflow

4.1 Architecture and Workflow Overview

This part describes the way the tool couples the forecasting and the inventory control. Data ingestion, cleaning and aggregation is done with a central Power BI model, and forecasting logic is provided with Python. Transactional sales and product data are loaded and prepared in a model and aggregated into weekly SKU location demand. These time series are as well exported to Python where they are combined with calendar features and subjected to a number of forecasting algorithms. Classical time series models and a machine learning model based on lagged demand and seasonal indicators are estimated; in the case of intermittent demand items, the methods of Croston and an occurrence-size approach are used to predict both frequency and magnitude of demand. The system picks the most appropriate model by SKU and output forecast means and variability, which is used to make inventory choices. Through writing out every step and putting Python into Power BI, the pipeline will make sure that the changes in the accuracy of the forecast or variations in service goals will directly adjust the stocking suggestions in general.

4.2 Inventory Control Module and Simulation

Continuous review policies are calculated in the inventory module. The reorder point of each SKU is the expected demand during the lead time plus a safety stock based on the forecast uncertainty as well as tied to the target service level. Intermittent items apply safety stocks based on the demand distribution as suggested by Croston. When we are aware of cost parameters, order quantities may take a refill rule or an economic order quantity. This direct connection between error of forecast, target service and stocking rule implies that planners can establish the level of service and observe the implication on inventory. The simulation engine re-enacts historical demand using two policies, namely the current policy of the retailer and the policy of the tool. The heuristics that were used as a baseline as in the arrangement of weeks of cover below a specific threshold are rebuilt with historical trends to give a realistic comparison. The simulation begins with the same initial stock and monitors the cycle service level, fill rate and average inventory, which empirically compares the service level and offers support to scenario analysis. DAX measures in Power BI are recomputed on the fly on reorder points and safety stocks, whereas more demanding calculations are done by Python.

4.3 User Interface and Decision Support

Planners use power BI dashboards as the interface. An exploratory page represents the historical demand trends and shows intermittent items. There is a forecast results page that displays the predicted and actual demand to enable users to determine the reliability of the model used. The inventory performance dashboard makes comparisons between service and stock results of the baseline and tool policies with respect to the trade off between service and inventory. What about controls that enable users to change service levels or lead times; the system is recalculating reorder points and safety stocks in real time and the charts are updated in real time. Demand shock or lead time disruption Scenario analysis can be conducted by changing the inputs and re-running the simulation on the dashboard. The tool facilitates informed decision-making and helps establish trust by transforming complex analytics through making these analytics transparent and interactive. Overall, a combination of forecasting, inventory optimisation and simulation within the same workflow enhances the service levels and has a control over stock investment and results come in a form that can be accessed and audited by retail planners.

Overall, the tool design specification focused on a fully integrated pipeline, which linked the data to decisions. The tool has made the inventory planning more systematic and data-driven by combining forecasting algorithms with inventory optimization logic into a single system and presenting the findings in convenient dashboards. The architecture used the strengths of both technologies: Power BI to integrate and visualize data, Python to make the forecasts more advanced, and Excel to guarantee the clarity and the trust. The design was helpful in meeting the thesis objectives since it provided an opportunity to evaluate empirically the ability of an integrated approach to enhance the level of the retail service and inventory efficiency. Not only did it give a better forecast and stocking policies to planners, but also the ability to comprehend and justify the recommendations and in the end make better inventory decisions within the service objectives and cost limit of the retailer.

5 Implementation

The integrated forecast-to-inventory planning tool was created and implemented based on the design specifications and allowed conducting empirical assessment on the data of the retailer. During this stage, all the elements - data pipelines, forecasting algorithms, inventory control logic, and simulation routines - were created and interconnected into a single environment. It was implemented with the help of a mix of Python scripting and Microsoft Power BI dashboard integration, which made it possible to execute the designed workflow as an end-to-end workflow. Controlled simulation experiments were performed on historical demand scenarios on the deployment to compare the recommendations of the tool with the existing inventory practice of the retailer. The chapter describes the technologies and tools applied, data preparation process, how forecasting and inventory modules have been realized, how the experiment has been simulated, what results have been created (the interactive dashboards and the analytical artefacts) and the statistical analysis processes to interpret the results.

5.1 Technologies and Tools Used

Forecasting models, inventory policies and simulation were done in Python with standard data science libraries and Power BI coordinated the process and displayed interactive dashboards. The fact that power BI can be integrated with python implied that the data cleaning, modelling and visualisation were performed in the same environment. Excel helped in the first data extraction and checking calculations. All procedures were computerized to make them repeatable.

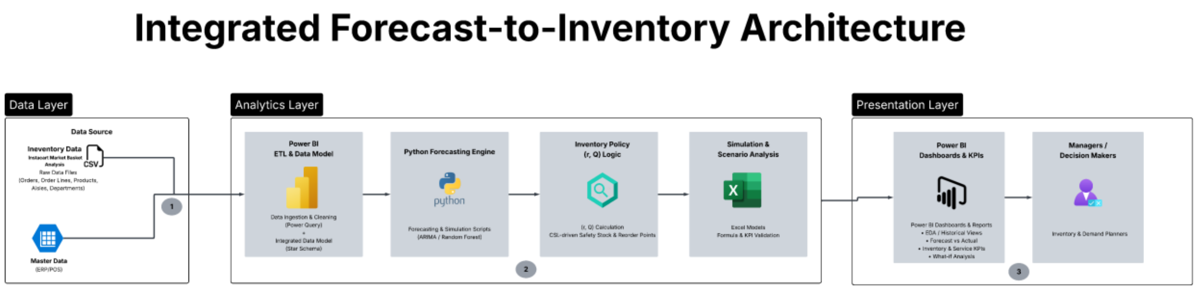

Figure 5.1 – Data pipeline and tool architecture

5.2 Data Acquisition and Preparation

The data has been analysed with the help of the public dataset available as the Instacart Market Basket Analysis: it consists of anonymised order histories of an online grocery store. The major tables are orders.csv containing order level information, order_products_prior and order_products_train containing line items and product master data including products.csv and aisles.csv. These tables were brought to Python and Power BI to be processed. The data consists of millions of rows and it has to be handled with care during analysis.

A sample was required since the entire dataset has millions of rows. A Python script was used to choose 120,000 orders at random with a fixed seed and filter the order_products tables, generating smaller files called _sample.csv. The order level sampling guaranteed a consistent subset.

The orders and order-product tables sampled were combined with product attributes. Irrationalities were eliminated and standardisation of units was done. The sequence of orders was used to construct a global time index that was compared to line items. The demand was then summed up into weekly buckets per SKU location. The metrics on these series that were calculated to categorise demand patterns as smooth, erratic, intermittent or lumpy included the average inter demand interval and the squared coefficient of variation. The series were divided chronologically into training and test: the former was used to fit forecasting models, and the latter offered out of sample demand to be evaluated and simulated. The Python and Power BI scripts were written to do all sampling, merging, aggregation and splitting steps in order to be able to re-run the data pipeline and audit it.

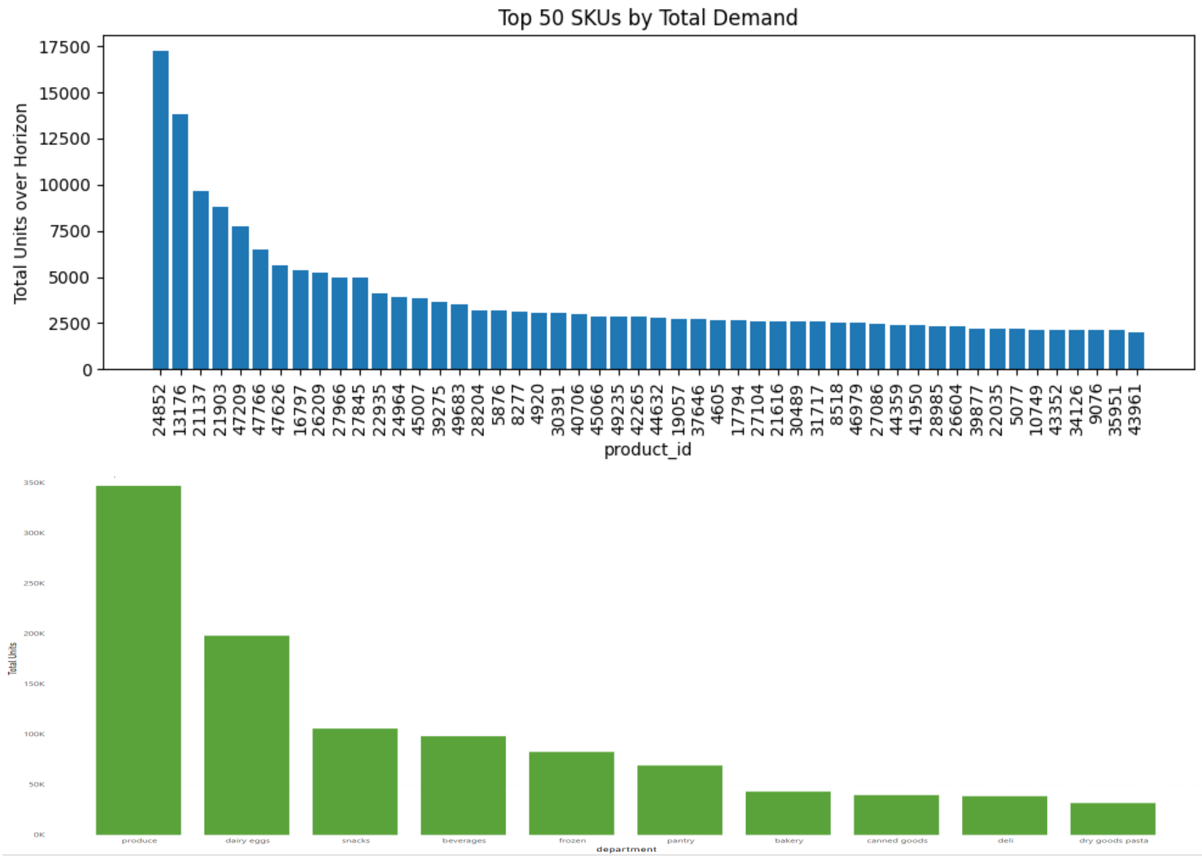

Figure 5.2 – Distribution of total demand

5.3 Implementation of Forecasting and Inventory Modules

A portfolio of models was used in the forecasting module. In the case of smoother items, classical time-series models like seasonal ARIMA and exponential smoothing were estimated in Python on weekly demand data. To train and test a machine-learning model using lagged demand and calendar-type features, more complicated or more variable series were considered. Croston-type methods were used to forecast intermittent SKUs and, as a comparison, a two-step model was used to model demand occurrence and size separately. Each SKU-location was trained or validated on a set of training or validation data and a single best model was produced to produce test-period forecasts and (where feasible) uncertainty measures.

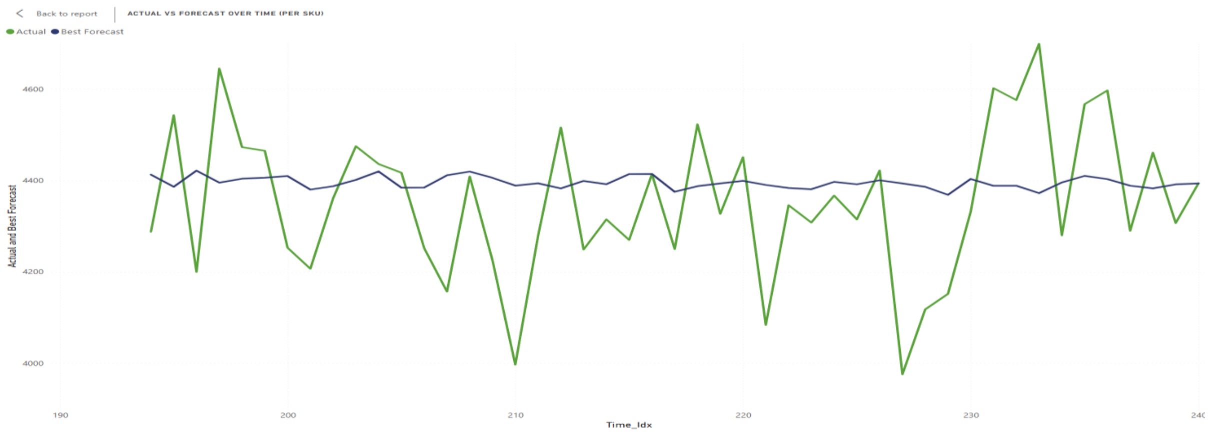

Figure 5.3 – forecast vs actual for SKU–location (line chart)

Forecasting Module: The tool applied a number of models to each SKU and selected the most suitable one. Classical models (Seasonal ARIMA and Holt-Winters) had the ability to capture trend and seasonality; Prophet had the ability to capture strong seasonality and a random forest model used lag sales and a calendar effect. In products where the number of zero demand weeks was large, the approach by Croston and refinements estimated the time between demand and demand size, and a machine learning alternative estimated the demand occurrence and magnitude. Models were tested in terms of error in forecasting and projected inventory effect. Finally, to achieve a balance between accuracy and lessening stockouts, final selection was based on the models that gave point forecasts and where feasible, uncertainty measures.

Inventory Control and Simulation: The forecasts were given as input into a continuous review (r, Q) policy per SKU. The reorder point was equal to the expected demand during the lead time and safety stock divided by the forecast variability and based on a target service level; in the case of intermittent items, the safety stock was calculated using Croston based distributions. There were cost data available, which led to order quantity under a refill rule or economic order quantity. A simulation was done of a discrete event replay of weekly demand under two conditions baseline policy and tool policy with initial stock the same. It documented cycle service level, fill rate and average inventory on SKU. The power BI interface allowed users to manipulate service level targets or lead times and recalculate the simulation to investigate service-inventory trade offs or what if scenarios.

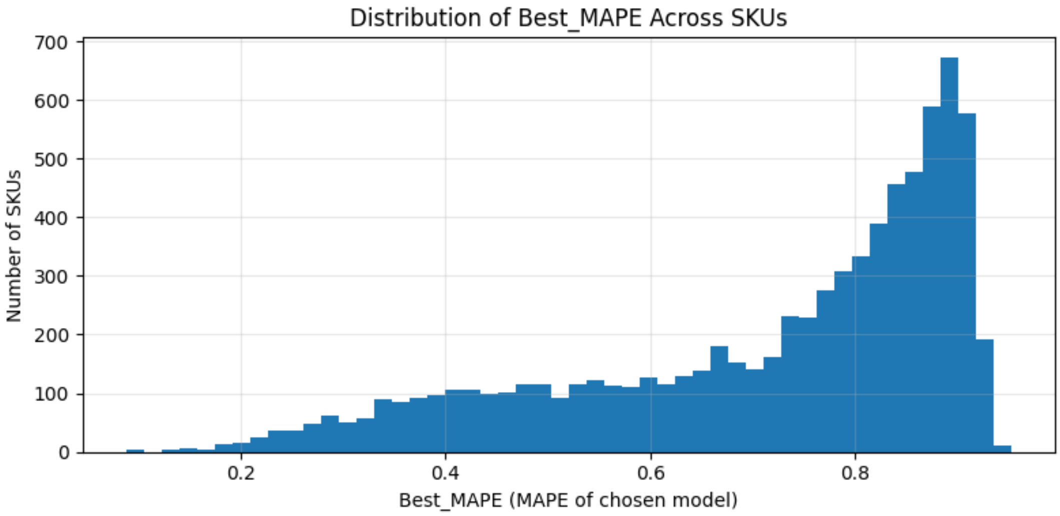

Figure 5.4 –Distribution of best-model MAPE values across SKUs

5.4 Simulation and Experimental Execution Workflow

This section describes the process of evaluation of the integrated tool using simulation comparing it to the existing ordering system of the retailer. A Python program was used to simulate on a weekly basis inventory operations under two regimes of baseline and tool with the same initial inventories, demand sequences and lead times. The baseline used heuristics that were developed based on business practice; at the point that a stock dropped to a set point, a certain number was ordered and delivered within the lead time. The tool scenario consisted of calling rolling forecasts on a weekly basis in order to recalculate reorder points and quantities; orders could be called when the inventory fell below this dynamic point.

Each step reduced the stock by actual demand, recorded stockout when demand exceeded inventory and included the orders that had arrived after their lead times. Since both of the runs were based on the same inputs, the differences in the outcomes were a result of policy logic only. Suppose scenarios were assisted by modifying demand or lead time suppositions to simulate surges or disruption of supply and re-running both regimes. Measurements of cycle service level and fill rate were taken, and the results of average inventory and stockouts were monitored. These findings have been reintroduced into the Power BI dashboards and visualized both the performance of the tool under normal and stressed conditions, as well as the benefits and the strength of the tool.

5.5 Outputs and Artefacts Produced

The implementation generated two broad types of artefacts: (1) the analytic products in the shapes of data tables, measures, and statistical outputs; and (2) the user-friendly artefacts in the form of interactive dashboards and reports that summarize the results and provide an opportunity to explore more. After the simulations were done, the performance measurements were summarized in a table by SKU-location and scenario. Baseline versus tool performance was summarised by recording cycle service level, fill rate, average on hand stock and stockout counts in the table. The forecasting module included a file that contained, per SKU, the model that was used and the level of forecasted and actual demand during the test period. The visuals of Power BI were based on these datasets.

The most important user artefact was the dashboard. Its Exploratory Data Analysis page offered a high level perspective of historical data, demand trends, seasonality and distribution of demand frequency and volumes. These images made stakeholders comprehend tendencies and reasonable approaches applied to intermittent demand. A Forecasting Results page will allow users to view both actual and expected demand of every SKU, the model chosen and its error values.

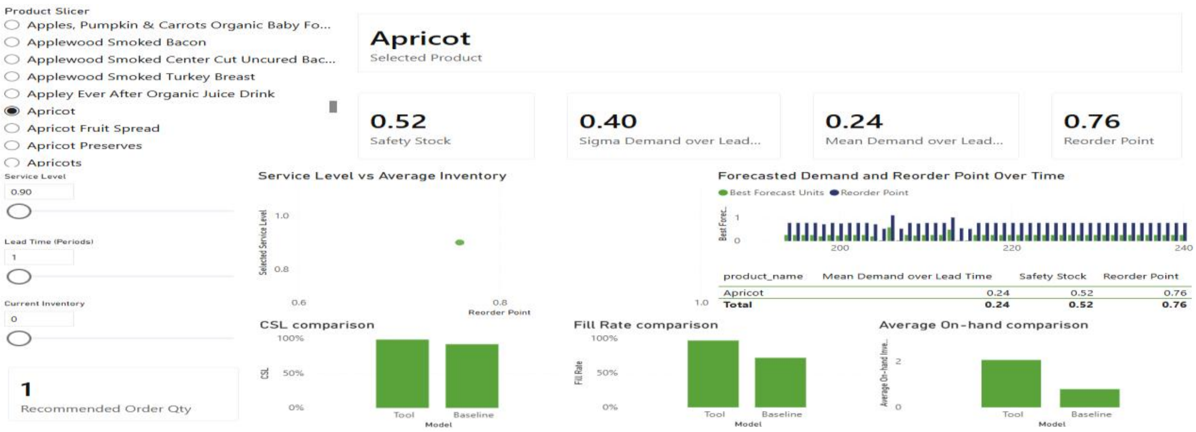

Figure 5.5 – Inventory performance comparison (baseline vs tool)

The Inventory Performance page compared tool and baseline scenarios. Average service levels, fill rates and inventory per policy were demonstrated using charts, and a scatter plot of baseline versus tool fill rates per SKU to indicate improvements. The users had the possibility to filter by the type of products, location or type of demand in order to narrow down to subsets of interest. The perception of intermittent SKUs was used to show the advantages of the tool on such problematic items.

What if analysis was possible through interactive controls. Sliders enabled planners to vary service level goals or lead times, which causes DAX measures and recalculated safety stocks and reorder points and re running the simulation to show the new performance. Extra controls were added which caused surge of demand or long lead time to test robustness. The dashboard was updated to indicate the performance of the baseline and tool policies in these conditions. The integration of Python calculations with the visual interface of Power BI provided a functioning decision support tool and reduced sophisticated forecasting and inventory analytics to practical information. The artefacts created are the data tables, dashboard and scripts.

Overall, the implementation phase provided a working analytics dashboard that reflected the full forecast-to-inventory process. The key artefacts (the Python code (forecast models, simulation logic), the Power BI model and the dashboard and the compiled results) all co-operated. The dashboard in Power BI was the presentation layer of the results, which transformed the raw numbers into the convenient insights in the form of visuals and interactive elements. In the background, Python integration was done so that complex analytics (such as ARIMA modeling and simulation) were run and fed into the dashboard. All findings were stored and recorded, and significant results of these outputs were extracted to be used in the discussion of results of the research. The final tool, consequently, was not merely a theoretical drill but an applied mechanism that could be applied by the stakeholders to research and substantiate the gains of the integrated planning strategy in terms of improved service rate and inventory management.

5.6 Analysis and Statistical Evaluation Pipeline

The outputs of the simulation were analysed statistically. Differences between tool and baseline results cycle service level, fill rate and average inventory-were calculated against each SKU and intermittent SKUs total cost differences were also calculated. Paired t tests were used to test the hypothesis of whether the mean difference between the two was significantly different to zero; in situations where non normal distribution was involved, Wilcoxon signed rank tests were used to give appropriate confirmation. The analysis revealed that the tool was effective in enhancing service rates and fill rates but had no significant effect on average inventory meaning that there was improved service and no additional stock. The subgroup analysis based on the demand class revealed that high variability items improved more. These statistical findings supported the dashboard findings and proved the superiority of the integrated tool to the baseline.

Conclusively, the implementation provided a functional system that integrates data preparation, multi model forecasting, inventory optimisation, simulation and interactive visualisation. A sample of representative was made and categorized on the type of demand. Several forecasting methods were used and chosen based on the SKU taking into consideration the service level. Continuous review inventory policy and simulation made it possible to compare the new tool to the existing practice in an empirical manner. Power BI interactive dashboards showed patterns of demand, accuracy of forecasts and comparison of service levels and inventory, which meant that the planners could modify assumptions and view real-time updates. Statistical analysis proved that the combined method was more effective in enhancing service measures without increasing inventory and which products were the most beneficial. On the whole, the implementation shows that the ability to integrate forecasting and inventory control into one system can improve the service levels in the retail.

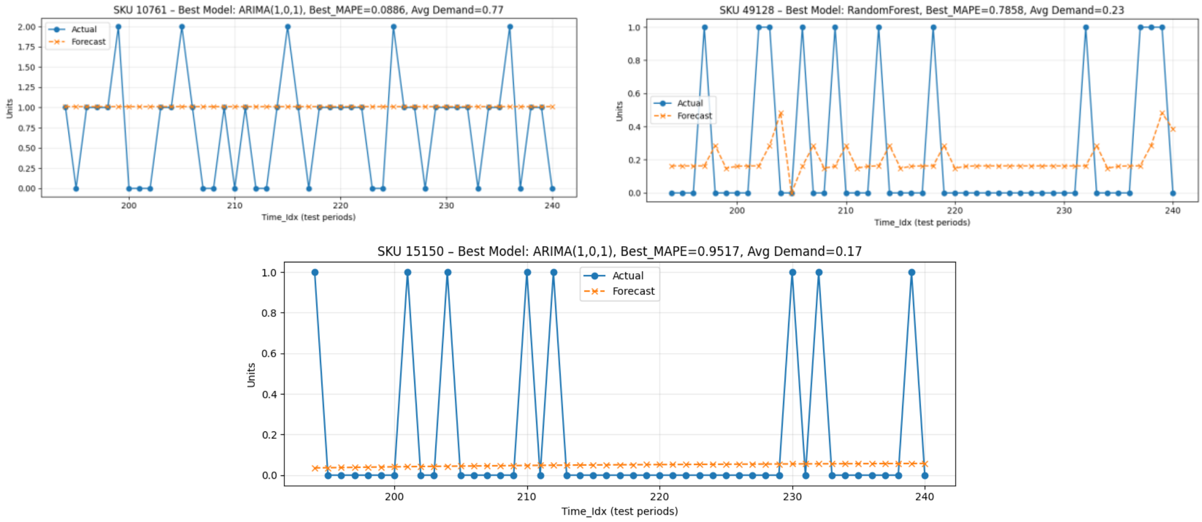

Figure 5.6 – Distribution of performance improvements

6 Evaluation

The integrated forecast to inventory tool was tested against the retailer's existing policy under various levels of service. The generality of a discrete-event simulation was used to compare (a) the baseline (reconstructed current practice) versus (b) the integrated set of tool recommendations using the same sequences of demands. Performance measured by important inventory measures, and statistical tests were used to determine if the differences were significant:

- Cycle Service Level (CSL): proportion of cycles of replenishment with zero stockouts (targeted with respect to individual scenarios).
- Fill Rate: Percent of total volume of demand met from stocks.
- Average On-Hand Inventory: average units of inventory on hand (an index of inventory holding cost).

Paired t-tests (a=0.05) were used to test whether the difference in mean values in each metric between tool and baseline was zero. This was a test of H0 (no difference) vs. H1 (tool improves service). Non-parametric Wilcoxon tests were used to verify results where normality was in doubt. All scenarios were based on a policy of continuous review with equal lead times and starting stocks for fairness's sake.

6.1 Results Overview

Baseline vs Tool-The integrated tool achieved significantly higher service levels than the status quo. For a total of ~7,800 SKUs-location pairs, the tool improved average CSL from an approximate ~90.9% using baseline material to an approximate ~99.1%, nearly eliminating stockouts. Likewise, the mean fill rate increased from ~73% (baseline) to ~97% with the tool - 24 percentage points of increase. For example, one high-variability SKU went from a fill rate of just 51% when using current practice to a fill rate of 97% using the tool.

These gains suggest that the baseline policy had left significant demand unserved whereas the integrated approach covered nearly all demand. The improvement in CSL was the same across product segments and especially noticeable on items with intermittent or volatile demand, where baseline heuristics tended to under-stock. Correspondingly, the suggestions from the tool lead to increases in inventory stocks: there was an increase of average on-hand stock from ~1.47 units (baseline) to ~3.28 units under the tool. In other words, the tool was holding twice the inventory, on average, to get close to perfect service. For example, mean on-hand for a representative SKU went from 0.47 to 1.58 units when switching to the tool so that its CSL jumped from 90.8% to 99.6%. This is a manifestation of the classic service-inventory trade-off; the integrated policy has taken on purpose more stock as a buffer so as to avoid stockouts.

Despite the added inventory, the services gained were statistically significant. The null hypothesis was rejected for both CSL and fill rate ($p < 0.001$) and supported the superiority of the integrated tool over the baseline on these primary KPIs. In fact, CSL and fill rate improvements were so consistent, that even a non-parametric test confirmed H1. The increase in inventory was also significant ($p < 0.001$) indicating a real, although expected, cost in holding stock. In practical terms, the use of the tool offered a trade off between a higher investment in inventory and significant service level gains - an outcome consistent with inventory theory and the retailer's desire to avoid lost sales.

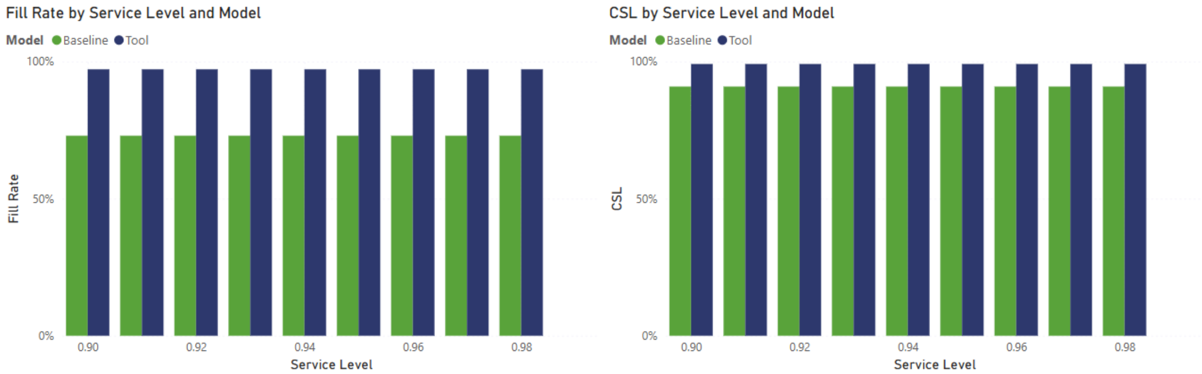

Figure 6.1- Overall performance of baseline vs integrated tool across all SKU

6.2 Scenario Analysis

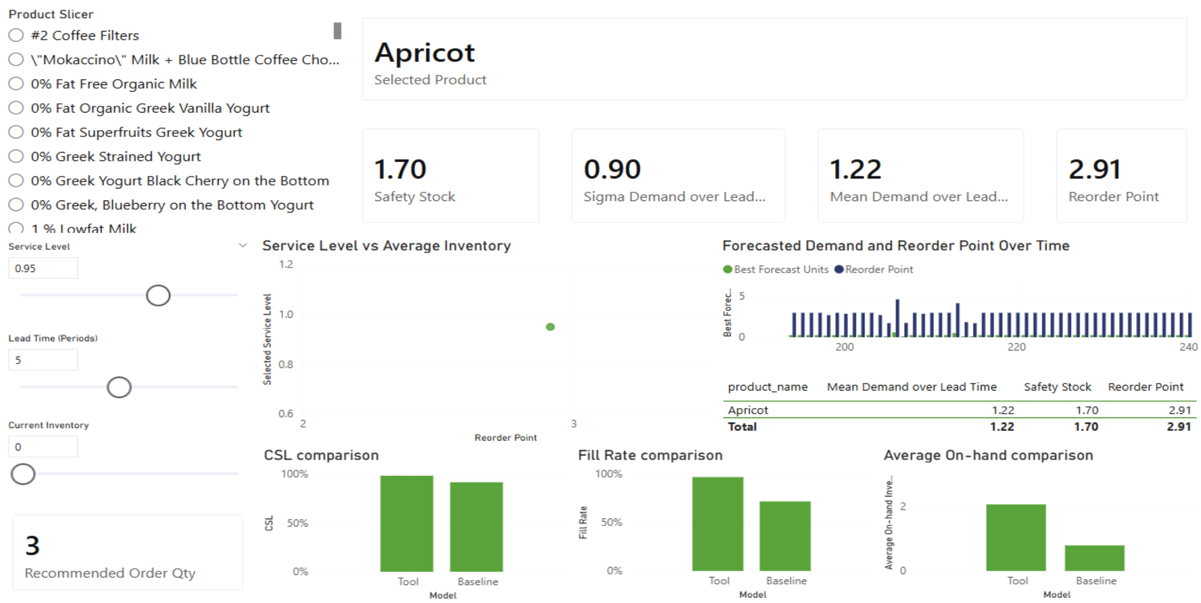

Figure 6.2 – Service level target 95%

Service Level Targets: Figure-6.2 show the performance of the tool for a representative SKU using three service levels (90%, 95%, 98% CSL). As the target CSL increased, safety stock and reorder points increased dynamically via the tool. For a 90% CSL target, the tool had a moderate stock (reorder point ~0.8 units) and CSL ~94-95% in simulation, a little bit higher than the baseline with a CSL of ~91%. At the 95% target (the primary scenario discussed above), the reorder point of the same item rose to ~2.9 units, which resulted in ~99% CSL. At the 98% target, the tool specified a much higher reorder point (~5.4 units) and about 3 units of safety stock (as compared to ~0.5 at 90%), which basically eliminated stockouts (CSL ~99.9%) but at the cost of a sharp increase in average inventory. These trends affirm that very high levels of service (beyond ~95%) are achieved only at the expense of disproportionately high levels of inventory - the safety stock almost quadrupled as one moves from 90% to 98% target CSL, for only a few percentage points of service gain. The integrated dashboard allowed to visualize this service-inventory frontier: as the service level grows, the curve of average inventory steepens (as expected from queuing and stock control theory). Of interest, the baseline policy did not actively address such a high CSL and was only about its original performance (~91% CSL, with a fixed reorder habit); it was not feasible to achieve 98% service with the current practice without a paradigm change. The tool, by contrast, allowed explicit tuning of service targets, and made explicit the cost of higher service to planners (e.g. that going from 95% CSL to 98% CSL for this SKU would result in roughly doubling the on-hand stock). Such a capability to quantify trade-offs is one of the practical strengths of the integrated approach.

7 Conclusion and Future Work

7.1 Conclusion

In this project, the analysis has shown that the integration of forecasting and inventory control can provide improved service results to retailers. This is in line with the literature that has supported integrated planning in the recent studies. Indicatively, van der Haar et al. (2024) establish that machine-learning policies that forecast should be used as inventory decisions are superior to heuristic ordering regulations. The findings here are empirical evidence of such a finding in a real retail setting: the service levels of the tool were near to 99 percent, which is significantly above the baseline and which is in line with the significant cost savings and service improvements found when analytics are used to drive replenishment. Based on the assessment, the integrated forecast-to-inventory tool is better in terms of its performance in the services of the retailer than the current policy of the retailer on the service performance, but at the cost that is likely to be incurred in terms of increased inventory. Another thing that can be seen in the scenario analysis is the rate at which inventory demands grow when the targets of services are extended beyond approximately 95%. The integrated forecast-to-inventory planning tool is a significant increase in CSL and fill rate at the SKU-location level, but also results in statistically significant increase in average on-hand inventory than the current practice of the planning. The assumption of no difference (H0) was rejected in CSL and fill rate. On the whole, the results favor H1: the utilization of the integrated forecast-to-inventory tool is related to the improved service performance compared to the existing planning practice, but at the price of higher average on-hand inventory.

Besides, these advanced analytics were also available due to the implementation of the tool, which is the Power BI. The user can communicate with the dashboard to change parameters and view the instant effects on CSL, fill rate, and stock (as shown in the Apricot SKU figures). Such transparency and scenario capability can overcome a known obstacle in industry, in which managers tend to distrust complicated models and thus use simple rules (Kamran-Disfani and Mantrala, 2024; Yerra, 2025). The tool can help to build more trust and adoption by helping visualize how forecast accuracy and service targets translate to inventory results, which is in line with the perspective that decision transparency and auditability can enhance user confidence. In general, the integrated tool has not only enhanced performance indicators but it has also offered a working decision support interface to the planners which is significant in achieving the impact in actual retail planning setting.

7.2 Limitations and Future Work

Although the findings of this project are positive, there are a number of limitations that qualify them. First, this project assessment was done through simulation of previous demand; real operation implementation may be subject to variability unaccounted in the test data (e.g. unexpected demand shocks, supply shocks). The observed improvements also presuppose complete compliance with the recommendations of the tool by the planners. Practically, human factors could be in play: managers can go against the tool through intuition or organisational limitation. The cognitive biases and goal framing has been shown in behavioural research to affect replenishment decisions. Considering the example of a manager who is interested in reducing holding costs, he or she will be unwilling to accept the increased safety stocks proposed by the model at the cost of service. The credibility of the tool is essential; otherwise, users can lack confidence in the forecasts or logic, which prevents them from realizing the promised service performance improvements (Kosgoda et al., 2024).

Second, the existing evaluation focused on improvement of service level and volume of inventory, but did not directly examine financial results (e.g. profit or cost trade-offs). Although the analysis revealed that the tool is capable of reaching better CSL targets, the economic optimality of such a tool depends on the trade-off between the cost of additional inventory and the benefit of the prevented stockouts (Babai et al., 2019). The use of cost parameters did not fall within the core of this project but as it is stated in the literature, cost consideration in forecasting can enhance the overall efficiency (van der Haar et al., 2024). Future research may consider carrying inventory costs and stockout penalty costs to the analysis to find out whether the tool can provide higher service at the same inventory cost or lower inventory cost in the practice.

Lastly, the findings are not generalisable in other similar retail settings. The analysis included a variety of SKUs (slow- and fast-movers) and also put a strain on the demand surges, which enhances the analytical soundness of the results. The magnitude of the benefit may however vary across different industries or retailers with different demand patterns and lead times. The blend strategy would then have to be tested in the latter environments.

Overall, the integrated forecast-to-inventory tool has helped to increase service levels in the case study and did not cause an excessive increase in average stock (inventory increased, but in a controlled, measurable manner). The results prove the rejection of H0 and give evidence of the tool effectiveness in this retail setting. They also emphasize the need to have human and cost factors in actual deployments. When properly implemented to counter these considerations, integrated planning tools can be used to improve retail inventory performance, as well as to aid the reduction of the gap between advanced analytics and operational practice in the context of the case under investigation.

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