

Machine Learning-Based Decision Support System for Optimizing Business Operations and Resource Allocation

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Abstract

Traditional managerial heuristics like moving averages are widely used in operational decision-making subject to uncertainty, and they are slow to respond to volatility, which results in misallocation of resources, surplus of inventory, and capital wastage. While digital transaction data can help inform evidence-based planning, research in organizations has shown that there is a continuing lack of predictive analytics to produce better, cost-effective decision results. To overcome this challenge, this research introduces and tests a machine learning-enabled decision support system (DSS) which successfully transforms the demand forecasts into an optimized and budget-constrained resource allocation. The methodology is a controlled, repeatable one where a naive baseline rule and a moving average baseline rule are compared to a linear regression, a random forest and a gradient boosting learner, and this comparison holds the allocation rule constant to isolate the effect of the demand signal, while varying the level of resource scarcity. The empirical results show that the random forest-based DSS can significantly improve the accuracy of the forecast, and the mean absolute error and weighted absolute percentage error are lower than the heuristic methods used as a baseline. The system reduces excess stock by 10% to 19% in every budget scenario and achieves reduced stockout rates in balanced and generous situations in resource allocation outcomes. Moreover, the results demonstrate that the value of the ML-based decision support depends significantly on resource scarcity, so that, when budgets are limited, the added value of the ML-based decision support is at its maximum. This study offers helpful benchmarks and strategic direction on how to enhance operational efficiency by treating the DSS as augmentation for the normal replenishment process instead of a complete automation solution.

Keywords: Decision Support System; Machine Learning; Resource Allocation; Demand Forecasting; Operations Management; Managerial Decision-Making.

I. INTRODUCTION

With uncertain demand, limited budgets, inventory, and capacity, organizations continually have to consider how to allocate the available resources to meet competing demands. This is because managers are faced with more information than they can process and will therefore use

simple decision rules which are satisfactory, rather than optimal, (Giarlotta & Petralia, 2024). In operations, a rule of thumb is to do the same as the previous period or use a short moving average. While these rules are simple and clear, they are very slow to respond to trends or seasonal variations, leading to inefficiencies such as stockouts, excess inventory, and blocked cash.

While today digital transaction data and tools for machine learning are available to replace some of this judgment with data, many companies have data but have not turned it into "good" allocations. Decision support research shows that many systems are designed and implemented without being tested against their capacity to support actual decision-making processes; and the effectiveness of an ML system in producing outcomes is strongly dependent on the embedding of the system in organizational structures and whether the system deploys technology to enhance or supplant human managers (Arnott & Pervan, 2005; Shrestha et al., 2019; Raisch & Krakowski, 2021).

Research gap

There are three gaps that drive this study. First, although a lot of operations research measures predictive accuracy alone, management research requires predictions to be measured on the basis of their real-life performance on decision quality. Second, empirical knowledge of the impact of the benefits of prediction on the scarcity of the resource is still limited, though the scarcity of the resource is the main factor that contributes to misallocation costs. Third, many studies use proprietary data or are too complex to be reproduced and easily understood by general management readers and small companies.

Objective and research questions

This paper aims to design and empirically test a straightforward, machine-learning-based decision support system (DSS) for budget-constrained resource allocation and to investigate whether and under which conditions it is superior to traditional managerial heuristics, based on open data. The study attempts to answer the following research questions:

- RQ1. Does the use of ML improve the forecast error over managerial heuristics?
- RQ2. Does allocation based on the DSS lead to a better matching of demand and reduce stockouts or overstocking for the given budget?
- RQ3. Does the tightness of the budget affect the benefit of the DSS?

Contributions

This paper employs a controlled, repeatable setup where the effectiveness of the demand signal is tested under different resource limitations, using standard baseline heuristics and advanced models based on trees. There are three types of contributions:

- Conceptual: It suggests a five-step model that includes data, prediction, constrained allocation, manager review, and outcomes, to provide a structure that connects predictive analytics to decision outcomes.
- Empirical: It offers a controlled evaluation with allocation rules and budgets being the same for all methods, with testing conducted in three different budget scenarios and several robustness checks.

- Practical: It defines exactly where machine learning is adding value to the operations – where is the waste being cut and where are the stock-outs (or no-stock) situations? It provides direct guidance on managing the operation to augment the role of machine learning.

The remainder of this paper is organized as follows: Section 2 reviews the literature, Section 3 outlines the methodology, Section 4 presents the results and discussion, and Section 5 concludes.

II. LITERATURE REVIEW

Managerial decision-making and heuristics

Bounded rationality is defined as a tendency to use "rules of thumb" on the part of decision makers that reduce the amount of thought required in decision making (Giarlotta & Petralia, 2024). These rules are typically adopted in replenishment and budgeting in reference to the past. They trade reasonably well in a non-trending environment and are oblivious to trends, volatility, and the calendar. The nature of decision-making shifts as AI systems take over some of the information processing, changing who makes decisions, who they make them on, and how they are accountable for the decisions made (Shrestha et al., 2019).

Resources, capabilities and analytics

The resource-based view regards valuable and difficult-to-imitate resources as the sources of sustained advantage, while the dynamic capabilities focus on a company's ability to sense change and reconfigure its resources (Barney, 1991; Teece et al., 1997). As seen from this perspective, analytics is a capability within the organization, and the usefulness of data is how it helps to optimally allocate resources. That is the message in the popular management literature, which characterizes data-driven decision making as a management revolution (Hu & Kaabouch, 2014) and documents the performance of firms competing on analytics (Davenport & Harris, 2007).

Decision support systems

This DSS research has progressed from model-driven to data-driven and AI. A common result is that the field is on the strong side of design and the weak side of the decisions that lead to improved design (Arnott & Pervan, 2005). Successful systems include a reliable predictive element, clear logic, and a clear and unambiguous role for the user that encourages layered design, as described in this paper.

Forecasting and prescriptive analytics

Most operational DSS are based on a predictive core, namely demand forecasting. It has been demonstrated that ML techniques, such as tree ensembles and gradient boosting based on lagged demand, price, and calendar data, can be as accurate as or more accurate than traditional statistical methods in large public forecasting competitions on retail sales (Makridakis et al., 2022). But prediction does not imply allocation of resources. Prescriptive analytics informs predictions with optimizations, while taking budget constraints, etc., into account; it also assesses the accuracy of the approach based on the quality of the decision (Bertsimas & Kallus, 2020). The line between those two is very important here, as a small accuracy improvement could or could not improve allocation.

Augmentation versus automation

AI research in management suggests there is a paradox between the efficiency that automation brings and the lack of human decision-making, versus the human decision-making and responsibility that augmentation keeps, but at the expense of fewer efficiency gains (Raisch & Krakowski, 2021). Managers have contextual knowledge, for example, promotions or supply disruption, that is not in the historical data. For this reason, this study assumes that the DSS is a recommender which is then checked by a manager.

Synthesis and hypotheses

The literature indicates that bounded heuristics are used, the value of analytics is related to the outcomes of the decisions, and augmented, prescriptive systems are the most promising configuration. Empirically, it hasn't been tested yet how much better a forecast-driven allocation is at different levels of scarcity than heuristics. We therefore test:

- H1. The forecast error of ML-based demand prediction is lower than that of the heuristic baselines.
- H2. When allocated using the same budget, the allocation of fulfilled demand based on DSS is higher than that of the allocation using the heuristic approach.
- H3. DSS allocation leads to fewer stock-outs and less excess stock than when the same budget is used for heuristic allocation.
- H4 (exploratory). The relative benefit of the DSS is larger when the budget is tight.

III. METHODOLOGY

Research design and workflow

The study is a controlled, quantitative study using secondary data. The workflow is summarized in figure 1. Operational data is prepared and transformed into features; forecasting models are trained on early data and tested on the corresponding later data; forecasts are implemented in the data with budget constraints and outcomes are compared to heuristic implementations with the same rule and budget.

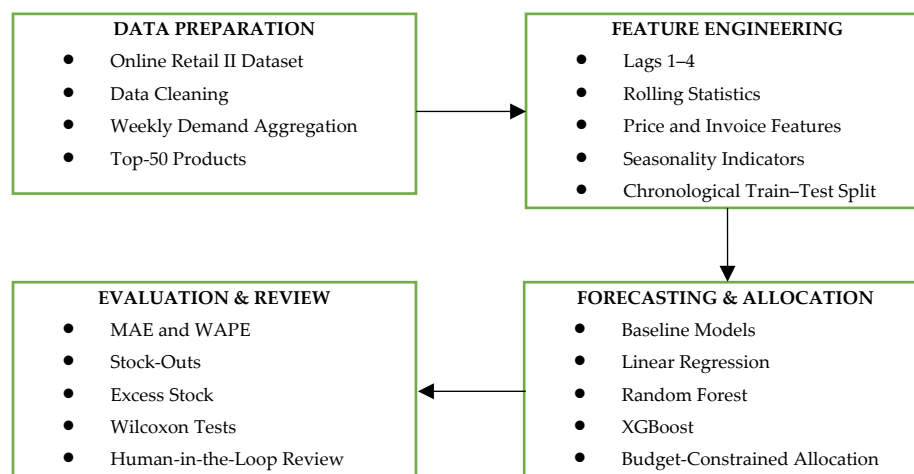


Figure 1: Proposed Methodology of ML-based DSS

Data and preparation

The data used is the Online Retail II dataset, which covers the period from December 2009 to December 2011 from an online retailer based in the United Kingdom (Chen, 2012). After applying the usual data cleaning (cancellations, non-positive quantities or prices, and non-product codes), the transactions were totaled into weekly demand volumes. The top 50 high-volume products are analyzed to reduce high intermittency. The data are characterized by some very large wholesale orders, making it better suited to use robust error measures and showing strong right-skewness. Table 1 shows the key data set parameters.

Table 1: Dataset Summary

Item	Value
Raw transaction records	1,067,371
Records after cleaning	1,036,877
Products retained (top by volume)	50
Weekly observations per product (after lag construction)	102
Training weeks/test weeks	81 / 21
Test period	18 Jul – 5 Dec 2011
Test product-week observations	1,050

Features and forecasting models

Each product i has a set of predictors based on all information prior to week t . This includes lagged demand, rolling window statistics, pricing, invoice counts and seasonality indicators. Naive and moving-average rules are used as managerial baselines that are compared against linear regression, random forest and gradient boosting (XGBoost) learners. Tree based models use a log transformation to deal with the skewness in the data, and raw-target versions are stored for ablation. Strict time-ordered expanding-window cross-validation is used to fine-tune the hyperparameters from the training data only.

Allocation model

Each week a budget B is distributed over the products. Let d_i be actual demand, q_i the demand signal, c_i the unit cost and x_i the units allocated. Because the data contain no costs, c_i is set to 60% of the unit price. The budget constraint and proportional allocation rule are formulated as given in equation 1 and equation 2

$$c_i \cdot x_i \leq B \quad (1)$$

$$x_i = \lambda \cdot q_i, \text{ where } \lambda = \frac{B}{\sum_j c_j \cdot q_j} \quad (2)$$

The demand signal q_i corresponds to the naive baseline, moving average, or DSS forecast. The weekly budget is computed as $B = \theta \cdot c_i \cdot d_i$, where parameter θ dictates the scarcity scenario: tight ($\theta = 0.8$), balanced ($\theta = 1.0$), and generous ($\theta = 1.2$). Furthermore, as a robustness check, allocation can also be modeled as a linear program that maximizes margin subject to Eqn 1.

Evaluation metrics and testing

Forecast accuracy is evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Weighted Absolute Percentage Error (WAPE) as formulated in equation 3:

$$WAPE = \frac{d_i - d'_i}{d_i} \quad (3)$$

Allocation outcomes are calculated weekly and averaged across the test period. The fulfilled demand rate and its cost-weighted counterpart (fulfilled value) are defined as shown in equation 4:

$$\text{Fulfilled Demand Rate} = \frac{\min(x_i, d_i)}{d_i} \quad (4)$$

Operational risks are measured via the stock-out rate (the share of product-weeks where $x_i < d_i$) and the excess stock rate as given in equation 5:

$$\text{Excess Stock Rate} = \frac{\min(x_i - d_i, 0)}{d_i} \quad (5)$$

Paired Wilcoxon signed-rank tests with a 5% significance level are used to determine if there is a statistical difference between the decision support system and the most successful heuristic. The computational experiments are performed with Python, scikit-learn, XGBoost and SciPy with a fixed random seed.

IV. RESULTS AND DISCUSSION

Forecasting performance (H1)

The forecasting results on the test set are given in table 2. After training-only cross validation, the log-target random forest model was selected as the best DSS model as it achieved a cross validated MAE of 235.6, lower than XGBoost with a cross validated MAE of 238.0. The model resulted in an MAE of 304.4 and a WAPE of 60.0% (Table 2). The raw-target variants did not improve over the moving-average baseline, further reiterating the importance of the log transformation to deal with the skewness of the data. At the same time, RMSE was similar among all models due to the significant effect that was had by exceptionally large wholesale demand surges, which were hard to predict. Thus, the use of H1 is recommended for MAE and WAPE, but not recommended for RMSE.

Table 2: Test-Set Forecast Accuracy

Model	MAE	RMSE	WAPE (%)	MAE vs best baseline
Naive (baseline)	363.8	2,562.6	71.7	–
Moving average (baseline)	319.2	2,541.5	62.9	–
Linear regression (raw target)	326.4	2,537.3	64.4	+2.3%
Random forest (log target)	304.4	2,545.7	60.0	–4.6%
XGBoost (log target)	313.2	2,546.0	61.8	–1.9%
Random forest (raw target)	335.9	2,544.3	66.2	+5.2%
XGBoost (raw target)	344.8	2,544.4	68.0	+8.0%

Note: Units are per product-week; lower values indicate better accuracy. Best values correspond to the log-target random forest.

Allocation performance (H2, H3 and H4)

The results of the allocation are shown in table 3 for the different budget scarcity levels. The DSS always reduced excess stocks in all scenarios as compared to the moving-average heuristic,

which confirms H3. Under balanced and generous budget conditions, stock-out rates also saw substantial decreases while under tight budgets the changes were not statistically significant. Demand for fulfilled items is mixed. The total fulfillments ratio of the DSS was marginally lower than the moving average, which means the DSS is not supported on a unit basis in H2. However, the DSS worked significantly better in cost weighted terms (fulfilled value), and was statistically similar in both balanced and generous budgets under an "unbalanced" budget. This shows the system working and is a way to get resources to the more valuable items and to reduce waste. Furthermore, supporting the exploratory hypothesis H4, the relative benefits of the DSS—such as waste reduction and financial fulfillment efficiency—were most pronounced under tight resource constraints.

Table 3: Allocation Outcomes by Budget Scenario (Weekly Averages Over the Test Period, %)

Budget (θ)	Method	Fulfilled units	Fulfilled value	Stock-out	Excess stock
0.8 (tight)	Naive	58.0	61.0	55.0	29.6
	Moving average	61.9	63.6	48.9	24.6
	DSS (random forest)	60.1	64.6	47.5	19.8
1.0 (balanced)	Naive	65.3	69.0	44.6	36.6
	Moving average	70.0	72.3	37.8	31.8
	DSS (random forest)	68.0	72.7	33.6	27.5
1.2 (generous)	Naive	70.6	74.6	36.6	42.9
	Moving average	75.6	78.2	27.7	38.5
	DSS (random forest)	73.5	78.0	25.0	34.6

Note: Lower values are preferred for stock-out and excess stock; higher values are preferred for fulfillment metrics.

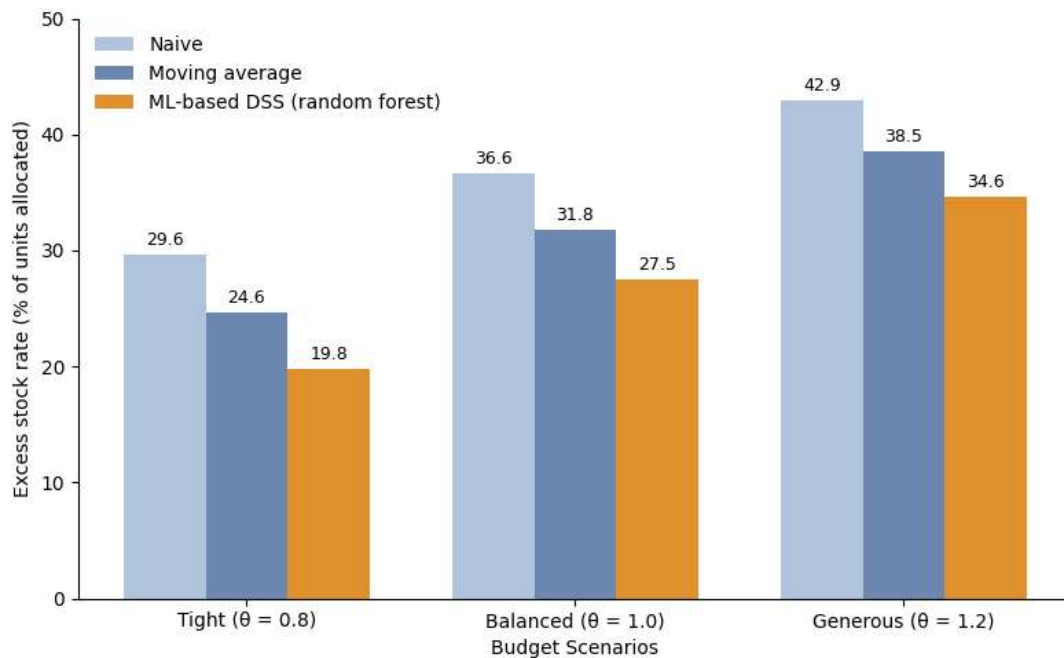


Figure 2: Excess Stock Rate by Budget Scenario

Figure 2 shows a comparative bar chart of the excess stock rate percentages across three

different budget scenarios, which shows that the ML-based DSS has the lowest waste in all scenarios. In the case of H4, the relative benefit is in fact greater when the product is scarce. The excess stock reduction compared to the moving average becomes less at 19% ($\theta = 0.8$), 13% ($\theta = 1.0$) and 10% ($\theta = 1.2$) and the cost-weighted fulfillment gain is only observed at $\theta = 0.8$. This is in line with the argument that it is least expensive to allocate resources when they are scarce.

Robustness

The main conclusions are robust, as evidenced by the results of the robustness checks presented in table 4. The random forest was consistently able to lower WAPE and excess stock for any scale of product ($N = 30$ or $N = 100$) while still providing a similar cost-weighted fulfillment. Marginally reallocating stock to maximise the margin (replacing proportional allocation) resulted in a greater reduction in excess stock (to 18.4%) but reduced the filled value and did not reduce stock-outs. Therefore, the advantage of the DSS in terms of reducing waste is significant in all allocation structures, while the fulfillment effects depend on the rule. A cost-ratio check was found to be cost-scaling evenly and therefore was invariant.

Table 4: Robustness Checks at Balanced Budget ($\theta = 1.0$); DSS = Random Forest Vs Moving Average

Specification	WAPE change	Fulfilled value MA	Fulfilled value DSS	Excess MA	Excess DSS
Main ($N = 50$)	-4.6%	72.3	72.7	31.8	27.5
$N = 30$ products	-4.3%	72.1	73.4	31.8	27.7
$N = 100$ products	-5.2%	71.4	72.1	31.3	28.4
LP allocation ($N = 50$)	-4.6%	65.1	63.6	26.8	18.4

Note: Values are in percentages; WAPE change represents the DSS forecast relative to the moving average; MA = moving average.

Validation of the contributions

The practical results confirm the very basis of the model, that is, that tied to a limited allocation of resources, fewer waste and stock-outs are observed than a uniform increase in raw fulfillment. These hypothesis tests and contributions are summarized in table 5.

Table 5: Summary of Hypothesis Tests and Contributions

Item	Evidence	Verdict	Contribution supported
H1	MAE -4.6%, WAPE 62.9→60.0% ($p = 0.024$); RMSE unchanged	Supported (MAE, WAPE)	Empirical (i)
H2	Units -2 pts ($p \leq 0.006$); value +1.0 pt only at $\theta = 0.8$	Not supported / partial	Practical (iii)
H3	Excess stock -10 to -19% ($p \leq 0.0004$); stock-outs lower at $\theta \geq 1.0$	Supported	Empirical, practical
H4	Excess reduction 19% → 13% → 10% as budget loosens	Supported (exploratory)	Empirical (ii)

Log transformed models better predict typical demand as moving averages are subject to chasing historical peaks/clamouring for one-off wholesale orders which directly impacts on

excess stock. The lower unit fill rate is due to log models sometimes under-predicting extreme peaks. The importance of this is that the DSS performs well in routine replenishment, while managers deal with qualitative adjustments, which are based upon human-AI augmentation principles (such as promotions or unrecorded bulk orders).

V. CONCLUSION AND IMPLICATIONS

Conclusion

This paper aimed to develop and evaluate an ML-based decision support system to convert demand forecasts into a budget-constrained allocation, identifying where it is superior to traditional managerial heuristics. The random forest-based DSS minimized forecast error by 4.6% (from 62.9% to 60.0% for the same allocation rules and budget) and, with the same allocation rules and budget, decreased excess stock by 10% to 19% compared to the moving average heuristic and 19% to 33% compared to the naive baseline. Moreover, it mitigated stock-outs under balanced and generous budgets and enhanced the cost-weighted fulfillment under constrained budgets. It did not increase raw unit fill rates and the benefit on RMSE was minimal because of spiky wholesale orders. Overall, the most significant system benefits occurred under resource scarcity.

Managerial Implications

The results have three main implications for practice. There are two points to consider here: 1) the decision support systems should be assessed by operational allocation outcomes rather than on predictive accuracy metrics only, and 2) the assessment should be done on the basis of the operational allocation outcomes. Second, the top financial and operational return on analytics investments occurs when budgets, inventory, or operational capacity is limited. Third, systems should automate repetitive replenishment processes and leave human managers free to handle special situations where promotions or bulk orders are placed, with the proper data governance and open-source software available to small businesses.

Limitations and Future Research

Some of the limitations of this study are that the data are only from one retailer and at one point in time, the cost ratio is assumed, the model used for allocating costs is simplified proportional and no manager behavior is observed. In future work, this framework should be extended to other industry sectors, extended optimization constraints to include more complex constraints, and empirical studies should be conducted to investigate how managers adapt algorithmic recommendations in practice.

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