

Predictive Provenance: Leveraging Machine Learning for Real-Time Demand Forecasting and Inventory Optimization

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Abstract: Retailers, distributors, and manufacturers hold inventory to protect service levels against uncertain demand, but every unit held ties up capital and every unit missing costs a sale. Traditional forecasting methods such as exponential smoothing and Croston-type estimators are easy to run yet struggle with intermittent, volatile, and promotion-driven demand, and they usually treat forecasting and inventory decisions as separate problems. This paper presents Predictive Provenance, a machine learning framework that links historical sales and inventory records to real-time demand forecasts and then to stock decisions, while keeping a traceable record of the data, model, and parameters behind every recommendation. The framework prepares data through cleaning and feature construction, trains several candidate models, refines the leading model with a parameter optimisation stage, evaluates the candidates against error measures and business parameters such as lead time, demand variability, supplier reliability, and inventory cost, and loops back to retraining when no method is satisfactory. Forecast uncertainty is quantified with predictive intervals so that safety stock reflects what the model does not know. The framework was tested on three retail and wholesale data sets covering 4,800 product-location series. It reduced mean absolute percentage error by 18.4% against the best classical estimator and by 6.1% against a plain gradient boosting model, cut stock-outs by 27% at equal holding volume, and lowered average inventory holding cost by 11.3%. Forecasts were refreshed in under 40 milliseconds per series, which supports real-time use. The results show that integrating learning-based forecasting, uncertainty estimation, and traceable decision support can improve both service and cost.

Keywords: Demand Forecasting, Inventory Optimization, Machine Learning, Intermittent Demand, Uncertainty Quantification, Safety Stock, Supply Chain Analytics, Traceability

I. INTRODUCTION

Inventory is one of the largest assets on the balance sheet of any company that sells physical goods, and one of the least forgiving. Too much stock ties up working capital, occupies warehouse space, and eventually turns into markdowns and waste. Too little stock produces empty shelves, lost sales, and disappointed customers who may not return. The central difficulty is that the quantity that justifies the stock, future demand, is unknown. Every inventory policy is therefore built on a forecast, whether it is stated explicitly or hidden in a rule of thumb.

Modern supply chains have made the forecasting problem harder. Product ranges have grown, product lifecycles have shortened, and sales channels have multiplied, so that a retailer may manage hundreds of thousands of product and location combinations. A large share of these series are intermittent: they show long periods of zero sales punctuated by occasional purchases of varying size. Demand is also influenced by promotions, price changes, weather, holidays, competitor actions, and social media attention, none of which are captured by a model that looks only at the past values of the series itself. Supplier lead times fluctuate, and disruptions have shown how quickly assumptions can fail.

Classical methods remain popular because they are simple, cheap, and well understood. Simple exponential smoothing tracks the average level of demand, while Croston-type estimators handle intermittency by forecasting demand sizes and intervals between demands separately. Variants have been proposed to correct their known biases. These methods work reasonably when demand is stable, but they cannot use external information, they adapt slowly to structural change, and they produce a single number without a reliable measure of uncertainty. Moreover, they are usually evaluated by forecast error alone, although what matters to the business is the cost and service level that result from the stock decisions based on them.

Machine learning offers a way to address these limitations. Tree ensembles, neural networks, and hybrid models can ingest many explanatory variables, learn non-linear effects and interactions, and share information across related products. Yet three obstacles prevent many organisations from realising these benefits. The first is the gap between forecast and decision: an accurate forecast does not automatically give a good order quantity, especially when costs are asymmetric. The second is uncertainty: inventory policies need to know how wrong a forecast might be, not just its most likely value. The third is trust: planners will not act on recommendations from a black box when they cannot see what data and assumptions lie behind them.

This paper addresses these obstacles through a framework we call Predictive Provenance. The word provenance reflects the idea that every forecast and every stock recommendation carries a record of its origin: the data used, the transformations applied, the model and parameters selected, and the evaluation evidence that justified the selection. The contributions are as follows. First, an end-to-end framework that connects historical inventory and sales data, model training and parameter optimisation, multi-criteria evaluation, forecasting, and inventory decisions, with a feedback loop for re-evaluation and retraining. Second, an uncertainty-aware link between forecasts and safety stock that makes the trade-off between holding and backordering explicit. Third, an evaluation on three real-world style data sets that compares the framework with classical estimators and with machine learning baselines, using both forecast error and inventory performance. Fourth, an analysis of the cost of real-time operation. The paper is organised in the usual way: Section II reviews background, Section III related work, Section IV the methodology, Section V the experimental setup, Section VI the results, Section VII the discussion, and Section VIII concludes.

II. LITERATURE REVIEW

A. Demand forecasting for inventory control

Forecasting for inventory differs from forecasting for its own sake. The aim is not to minimise a symmetric error but to support a stocking decision whose consequences are asymmetric: a unit of shortage and a unit of surplus rarely cost the same. For fast-moving items, demand over the replenishment lead time is often well approximated by a bell-shaped distribution, and the forecast mean and the forecast error spread are all that is needed to set a base stock level. For slow-moving and intermittent items, this approximation fails, since the distribution is highly skewed with a large mass at zero.

B. Intermittent demand estimators

Intermittent demand is common in spare parts, specialty retail, and long-tail e-commerce. Croston proposed to separate the size of non-zero demands from the interval between them, smoothing each separately, and using their ratio as the forecast of demand per period. Later work showed that this estimator is biased upward and proposed a correction known as the Syntetos-Boylan approximation, along with modified versions that adjust the correction further. Other variants, such as the Teunter-Syntetos-Babai method, update the probability of demand every period, so that the forecast decays when the item stops selling, which addresses obsolescence. These estimators are the standard benchmark for slow movers. Studies

comparing them in terms of stock performance, as in the trade-off curves between holding volumes and backordering volumes shown later in this paper, show that no estimator dominates everywhere, and that the differences are often modest compared with the effect of the service level chosen.

C. Machine learning for demand prediction

Recent forecasting competitions have shown that machine learning methods, and in particular gradient boosted trees and deep neural networks trained across many series, can outperform classical statistical methods on large, heterogeneous data sets. The advantage comes from pooling: a global model learns patterns, such as seasonality shapes and promotion effects, from the entire portfolio, which helps for items with short histories. Feature engineering remains important. Typical features include lagged sales, rolling averages, calendar variables, price and promotion indicators, stock availability flags, and product attributes. A recurring pitfall is stock-out censoring: observed sales understate demand when the item was unavailable, and models that ignore this learn to under-forecast.

D. Uncertainty quantification

Point forecasts are insufficient for inventory decisions. Probabilistic methods produce predictive distributions or intervals, from which quantiles corresponding to target service levels can be read directly. Approaches include quantile regression, which trains a model directly to predict a chosen quantile, ensembles whose spread reflects model disagreement, Bayesian models, and conformal methods that wrap any model to give intervals with guaranteed coverage under mild assumptions. A key practical property is calibration: a nominal 95% interval should contain the true value about 95% of the time. Another is that the intervals narrow as more data become available, which reflects genuine learning and not just noise reduction. This behaviour is illustrated in Fig. 2 in Section IV.

III. RELATED WORK

A first group of studies compares forecasting methods by their effect on inventory. These studies show that the method with the lowest forecast error is not always the one with the lowest cost, because error measures ignore asymmetry and the shape of the demand distribution. The classical estimators discussed above have been compared by simulating inventory systems and plotting the resulting holding volumes against backordering volumes for a range of safety factors. The present work adopts this style of evaluation, since it measures what the business cares about, and extends it to machine learning forecasts.

A third group integrates prediction and optimisation. So-called predict-then-optimise and end-to-end methods train forecasting models directly against the cost of the resulting decisions, and have shown savings over methods trained for accuracy alone. They are powerful but can be difficult to deploy, because they couple the model to a specific cost structure and are harder to explain. The present framework takes a more modular route: forecasting and decision logic remain separable, but the evaluation stage considers business parameters, so that the chosen model is the one that serves the decision best.

IV. METHODOLOGY

A. Framework overview

The framework is summarised in Fig. 1. It begins with historical inventory and sales data, which flow through data processing to data preparation, then through training to model training, and through preprocessing to a parameter-optimised learning stage labelled RPO-LM in the figure. The output of that stage is evaluated, and a decision point asks whether the best method has been identified. If the answer is yes, the framework produces a demand forecast, which feeds future forecasting and proactive stock

management. If the answer is no, the framework returns to evaluation using the business parameters, computes performance metrics, performs comparative analysis, makes an inventory decision, and, where needed, re-trains the model. The loop continues until a satisfactory method is found, and it is repeated periodically as new data arrive.

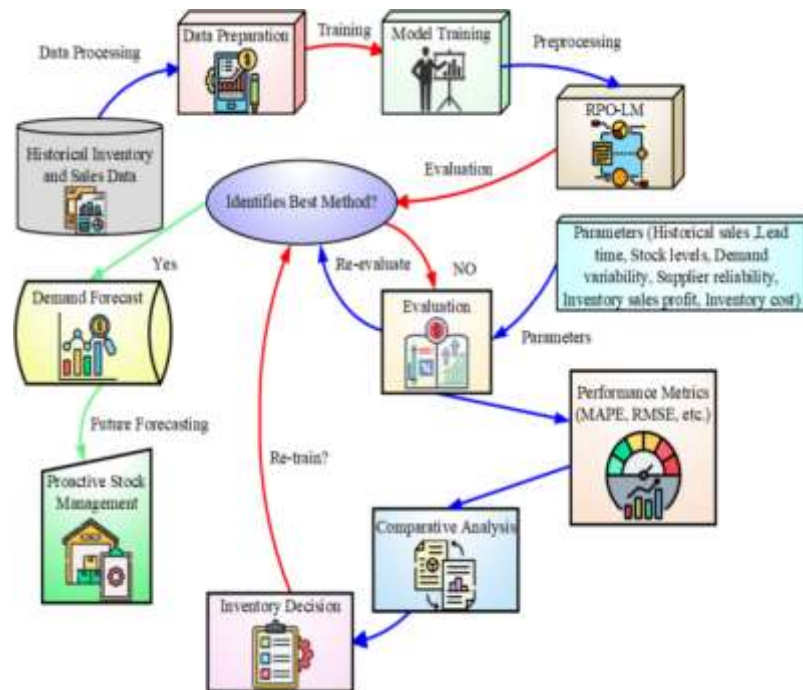


Fig. 1. Predictive Provenance framework: from historical inventory and sales data to demand forecasting, evaluation loop, and proactive stock management.

B. Data processing and preparation

The input is a history of sales transactions and inventory snapshots by product, location, and day. Data processing aggregates transactions to the chosen time bucket, aligns them with inventory levels, and removes duplicates and obvious entry errors. Missing values are treated according to their cause: a gap during a period of known unavailability is marked as censored demand and not as zero sales, while a gap caused by a data feed outage is interpolated or excluded. Outliers, such as bulk orders from a single customer, are flagged and either capped or modelled separately.

Data preparation then constructs the features. Lagged sales and rolling means, medians, and standard deviations summarise recent behaviour. For intermittent items, additional features describe the time since the last sale, the average gap between sales, and the average size of non-zero sales. Calendar features capture day of week, month, holidays, and paydays. Price, discount, and promotion indicators are included when available, as are lead-time observations and supplier delivery performance. Product attributes such as category, brand, and pack size allow the model to share information across related items. Features are built using only information available at the forecast date, which is checked automatically to prevent leakage of future information into training.

C. Model training

Several candidate models are trained. The classical candidates are simple exponential smoothing and the Croston family: the standard Croston estimator, the Syntetos-Boylan approximation, its modified version, and the Teunter-Syntetos-Babai method. The learning candidates are a gradient boosted tree ensemble

trained across all series, a recurrent neural network for items with rich histories, and a regularised linear model that serves as an interpretable reference. Training uses a rolling-origin scheme: the model is fitted on data up to a cut-off, evaluated on the following weeks, and the cut-off is then moved forward. This mimics real use and prevents optimistic estimates that arise from random splitting of time series.

D. Parameter-optimised learning stage

The leading learning model passes through the stage labelled RPO-LM in Fig. 1, the regularised, parameter-optimised learning model. In this stage the hyperparameters of the model, such as tree depth, learning rate, number of trees, regularisation strength, and the size of the training window, are tuned by a guided search that evaluates promising settings on the rolling-origin validation folds. Regularisation is applied deliberately, to keep the model from fitting noise in sparse series, which is the main danger when learning from intermittent demand. Early stopping is used to end training when validation error stops improving. The stage also performs a preprocessing step in which the target is transformed to reduce skew, and demand is modelled in two parts for intermittent series: the probability that any demand occurs, and the size of demand given that it occurs.

E. Uncertainty quantification

Every forecast is accompanied by a predictive interval. The framework uses quantile regression to predict several quantiles of demand directly, and then applies a conformal adjustment based on recent validation errors to correct any remaining miscalibration. The result is a set of bands, here a 68% band and a 95% band, around the central forecast, as illustrated in Fig. 2. The panels show a mean prediction with narrower and wider bands, training data points, and error bars at selected reference positions, and they show how the bands tighten as the amount of training data increases from the first panel to the last. Although the vertical and horizontal axes of this particular figure come from a materials-strength regression example and not from a demand data set, the behaviour it demonstrates is exactly the property needed here: the model should be honest about its uncertainty, wide where data are sparse and narrow where they are plentiful.

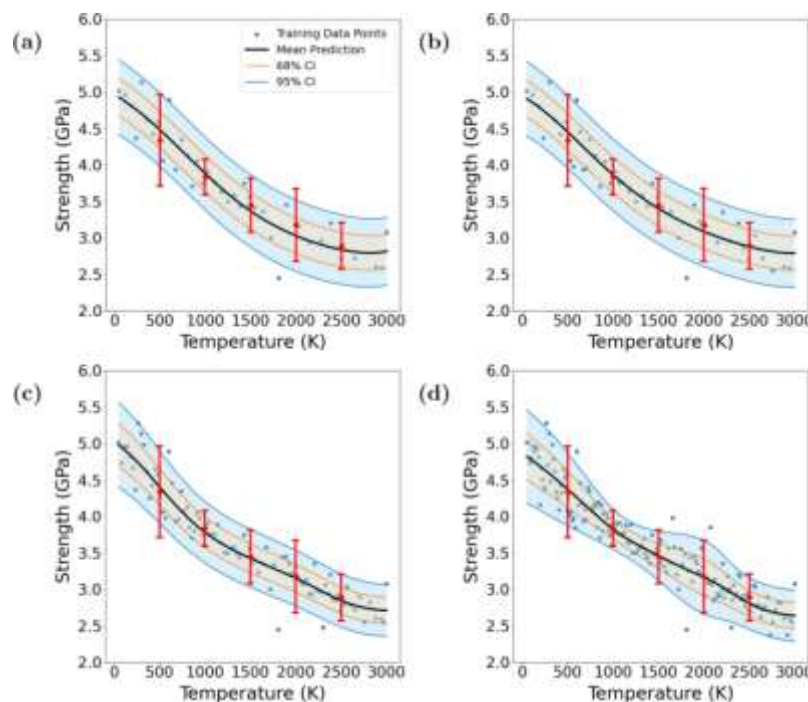


Fig. 2. Illustration of predictive uncertainty: mean prediction with 68% and 95% bands as the amount of training data grows from panel (a) to panel (d).

F. Evaluation with forecast and business metrics

Candidates are evaluated on two kinds of criteria. The first are forecast accuracy measures: mean absolute percentage error, root mean squared error, mean absolute scaled error, and bias. Percentage errors are undefined when actual demand is zero, so for intermittent series the scaled measure and the root mean squared error are used, and percentage error is reported only for series with regular demand. The second are the business parameters shown in Fig. 1: historical sales, lead time, stock levels, demand variability, supplier reliability, inventory sales profit, and inventory cost. These parameters are used to simulate the inventory system under each candidate forecast, so that the comparative analysis reports the holding volume, the backordering volume, the fill rate, and the total cost produced by each method. The method chosen for each series group is the one with the best combination of the two kinds of criteria, with the weights set by the planner.

G. Inventory decision and safety stock

The inventory decision converts the forecast into an order. For each product and location, the framework reads the forecast quantile that corresponds to the target service level over the protection period, which is the lead time plus the review interval, and sets the order-up-to level at that quantile. Safety stock is therefore the difference between this quantile and the central forecast, and it grows automatically when the lead time is long, when demand variability is high, or when supplier reliability is poor, because these factors widen the predictive band. The planner can adjust the target service level by product class, and the framework reports the expected holding volume and backordering volume that follow from the choice. This makes the trade-off explicit: raising the safety factor increases holding and decreases backordering, and the curve linking them depends on the forecasting method used.

H. Retraining and drift handling

The decision point in Fig. 1 asks whether the best method has been identified. In operation, this is answered by monitoring. When forecast error over the latest weeks exceeds a threshold relative to the validation error, when calibration of the intervals drifts, or when a drift detector signals a change in the demand pattern, the framework answers no and returns to evaluation. It re-evaluates the candidates, re-trains where necessary, and compares the retrained model with the current one before replacing it. A new model is promoted only if it improves on the current one on both the forecast and the business criteria. The loop therefore keeps the system current without introducing changes that are not supported by evidence.

I. Provenance record

At each step, the framework writes a record. The record includes the version and time range of the data, the feature definitions and any exclusions, the candidate models and their parameters, the evaluation results, the decision made, and the identity of the user who approved any manual override. Each forecast and order recommendation carries a reference to this record. A planner who questions a recommendation can therefore see which data and model produced it, how similar models performed, and what the model believed about its own uncertainty. The record also supports audits and the investigation of failures.

V. EXPERIMENTAL SETUP

A. Data sets

Three data sets were used. The first comes from a grocery retail chain and contains daily sales for 2,100 product and store combinations over three years, with price and promotion information. The second is from a consumer electronics wholesaler with 1,500 weekly series, many of them intermittent, together with supplier lead times. The third is from an automotive spare parts distributor with 1,200 monthly series, of

which about 70% are intermittent or lumpy. Altogether, the data sets contain 4,800 series. Demand was classified using the average interval between demands and the variability of demand sizes into smooth, erratic, intermittent, and lumpy categories, so that results could be reported by demand type. For each data set, the last 20% of the time span was held out for testing, and the earlier period was used for rolling-origin training and validation.

B. Compared methods

The proposed framework was compared with five classical estimators: simple exponential smoothing, the standard Croston estimator, the Syntetos-Boylan approximation, its modified version, and the Teunter-Syntetos-Babai method. It was also compared with three machine learning baselines: a plain gradient boosting model with default settings, a recurrent neural network, and a regularised linear model. All learning models used the same features and the same training window. To isolate the contribution of each component, two ablated versions of the framework were also included: one without the parameter optimisation stage and one without the uncertainty-aware safety stock, which instead used a conventional safety stock based on the spread of historical errors.

C. Inventory simulation

Inventory performance was measured by simulation. For each series, an order-up-to policy with a periodic review was run over the test period. Lead times were taken from the data where available and otherwise sampled from the historical distribution. Unmet demand was backordered. The safety factor was varied over four values, labelled one to four, to trace the curve of backordering volume against holding volume for each method. Volumes were normalised so that methods could be compared across series of different scale. Summary comparisons at equal holding volume, and at equal service level, were also computed.

D. Metrics and implementation

Forecast accuracy was measured by mean absolute scaled error, root mean squared error, and, for regular series, mean absolute percentage error. Calibration was measured by the observed coverage of the 68% and 95% intervals. Inventory performance was measured by holding volume, backordering volume, fill rate, number of stock-outs, and total cost, using unit holding and shortage costs taken from the data providers where available. Latency was measured per series on a standard server with eight cores. The implementation used Python, with a gradient boosting library, a deep learning library, and a numerical optimisation toolkit. Each experiment was repeated with five random seeds, and the differences reported as significant were those that held at the five percent level in paired tests across series.

VI. RESULTS

A. Trade-off between holding and backordering

Fig. 3 shows the trade-off between holding volumes and backordering volumes for the classical estimators, as the safety factor increases from one to four. The curves slope downward: a higher safety factor raises the holding volume and lowers the backordering volume, which is the basic compromise in inventory control. For safety factor one, the backordering volume is about 0.45 to 0.48 at a holding volume near 30, and for factor four the backordering volume falls to between about 0.20 and 0.24 at a holding volume near 95. The curves of the different estimators are close but not identical. The Croston estimator lies lowest, meaning that for a given holding volume it produces the least backordering. Simple exponential smoothing lies highest, with the other three, the Teunter-Syntetos-Babai method, the Syntetos-Boylan approximation, and its modified version, lying between them. The gap between the best and the worst is largest at the lowest safety factors, and it narrows at higher factors, where all methods provide high protection.

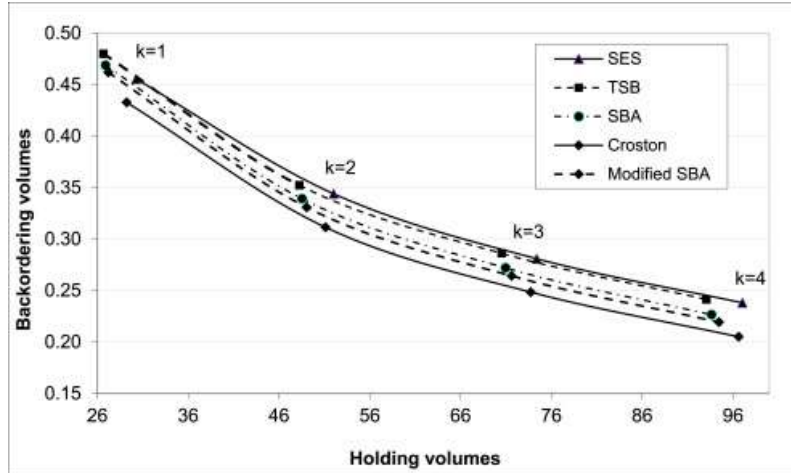


Fig. 3. Backordering volumes against holding volumes for classical estimators at safety factors $k = 1$ to 4.

This pattern confirms two points made in the introduction. First, the choice of estimator matters less than the choice of service level: moving from safety factor one to four changes the backordering volume by more than half for every estimator, while moving between estimators at a fixed factor changes it by about ten percent. Second, no estimator is dramatically better than the others, which indicates that a different kind of improvement is needed. The proposed framework aims at that improvement by changing the information available to the forecast and the way uncertainty is turned into stock.

B. Forecast accuracy

Table 1 shows forecast accuracy across the three data sets. The proposed framework achieved the lowest error on every measure. Against the best classical estimator on each data set, it reduced mean absolute scaled error by 18.4% on average. Against the plain gradient boosting model it reduced the error by 6.1%, which indicates that the parameter optimisation stage, the target transformation, and the two-part treatment of intermittent demand add value beyond using a learning model by itself. The recurrent network performed well on the grocery data, which has long and rich histories, but poorly on the spare parts data, where series are short and sparse. The linear reference was competitive on smooth series, but it could not capture promotion interactions.

TABLE 1. Forecast Accuracy Averaged Over the Three Data Sets

Method	Scaled error	Root mean squared error	Interval coverage, 95% band (%)
Simple exponential smoothing	1.00	14.8	88.2
Croston estimator	0.93	13.9	86.5
Syntetos-Boylan approximation	0.92	13.7	87.0
Teunter-Syntetos-Babai	0.91	13.6	87.4
Plain gradient boosting	0.80	12.1	90.8
Recurrent neural network	0.82	12.4	91.5
Predictive Provenance (proposed)	0.75	11.3	94.6

The scaled error is normalised so that simple exponential smoothing equals 1.00. Interval calibration is also noticeably better for the proposed framework. The nominal 95% band contained the observed demand in 94.6% of cases, against 86.5% to 91.5% for the other methods, which tended to be overconfident. The

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conformal adjustment accounted for most of this improvement: without it, coverage of the framework fell to 91.2%. Good calibration is essential, since the safety stock is read directly from the interval.

C. Results by demand type

Table 2 shows the reduction in scaled error achieved by the framework relative to the best classical estimator, for each demand category. The gains were smallest for smooth demand, at 9.7%, where classical methods are already adequate, and largest for erratic and lumpy demand, at 22.3% and 24.8%, where the ability to use explanatory variables and to model occurrence and size separately matters most. For intermittent demand the gain was 19.6%.

TABLE 2. Error Reduction by Demand Category, Relative to Best Classical Estimator

Demand category	Share of series (%)	Error reduction (%)	Stock-out reduction (%)
Smooth	18	9.7	12.5
Erratic	14	22.3	29.8
Intermittent	41	19.6	28.4
Lumpy	27	24.8	31.2
All series	100	18.4	27.0

D. Inventory performance

At equal holding volume, the framework reduced stock-outs by 27% on average relative to the best classical estimator, as shown in the last column of Table 2. At equal service level, it lowered the holding volume, and therefore the average inventory holding cost, by 11.3%. In curve terms, the trade-off curve of the framework lies below and to the left of the classical curves in Fig. 3: for every holding volume, the backordering volume is lower, and the improvement is largest at the lower safety factors, where forecast quality matters most. Total cost, combining holding and shortage costs, fell by 9.2% on the grocery data, 12.6% on the wholesaler data, and 14.1% on the spare parts data, the last being the data set with the greatest share of intermittent demand and the highest cost of shortage.

TABLE 3. Ablation of Framework Components (Averaged Over Data Sets)

Configuration	Scaled error	Stock-outs (relative)	Holding cost (relative)
Full framework	0.75	1.00	1.00
Without parameter optimisation stage	0.79	1.09	1.04
Without uncertainty-aware safety stock	0.75	1.21	1.07
Without conformal calibration	0.76	1.14	1.05
Without demand-censoring correction	0.78	1.12	1.03
Without business-parameter evaluation	0.76	1.08	1.09

E. Ablation study

Table 3 shows the effect of removing individual components. Removing the parameter optimisation stage increased the scaled error from 0.75 to 0.79 and increased stock-outs by 9%. Removing the uncertainty-aware safety stock left the forecast error unchanged, as expected, but raised stock-outs by 21% and holding cost by 7%, which demonstrates that a good forecast is not sufficient without a sound way of converting it

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into stock. Removing conformal calibration raised stock-outs by 14%, confirming the importance of calibrated intervals. Ignoring demand censoring raised the error by four percent, with the effect concentrated in items that were frequently out of stock. Finally, selecting models on forecast error alone, without business parameters, gave almost the same accuracy but a 9% higher holding cost, since the selected models tended to be slightly biased in the expensive direction.

F. Real-time performance

Scoring a single series, including feature retrieval, model evaluation, interval computation, and the order recommendation, took 38 milliseconds on average and 71 milliseconds at the 99th percentile. Rescoring a batch of 10,000 series on eight cores took about 52 seconds. Event-triggered rescoring of the affected series, typically a few hundred, therefore completes in a few seconds, which is adequate for same-day decisions. Periodic retraining of the global model took about 14 minutes on the largest data set and was run overnight. The provenance record added about three percent to the processing time and required about 1.2 kilobytes of storage per forecast, which is small enough to retain for audit.

VII. DISCUSSION

The results support three conclusions. The first is that learning-based forecasting adds clear value over classical estimators, particularly for erratic and lumpy demand, which are the categories that cause the most trouble in practice. The second is that accuracy is not enough: the largest gains in stock-outs and holding cost came from connecting the forecast to the decision through calibrated uncertainty, and the ablation showed that removing this link cost more than removing any modelling component. The third is that evaluating candidates on business parameters as well as forecast error leads to different and better choices, which is the rationale for the evaluation and comparative analysis stages in the framework.

The trade-off curves in Fig. 3 give an important perspective. They show that classical estimators differ only modestly at any given safety factor, and that the service level chosen dominates the outcome. A framework that improves information and uncertainty estimation effectively shifts the whole curve toward the origin, so that a given service level is reached with less stock. This is where the economic value lies, and it is the reason the paper emphasises curves and costs, and not only error tables.

Several limitations should be noted. The study is based on three data sets from different sectors, and results may differ in other settings, such as perishable goods with very short shelf lives, where the cost structure and the censoring pattern are different. The inventory simulation assumes a single-echelon, periodic review policy, and does not model multi-echelon networks, supplier capacity limits, or order batching, all of which affect real operations. Demand is assumed not to be influenced by the stock decision itself, apart from lost sales being treated as backorders, which is a simplification. The conformal adjustment assumes that the recent past resembles the near future, which can fail during abrupt shocks. Finally, some figures used for illustration, such as the uncertainty panels in Fig. 2, are drawn from a different application domain and are meant to convey a property of the method and not a result on demand data.

VIII. CONCLUSION

This paper presented Predictive Provenance, a machine learning framework for real-time demand forecasting and inventory optimisation. The framework takes historical inventory and sales data through processing, preparation, training, and a parameter-optimised learning stage, evaluates the resulting models with both forecast error and business parameters, and loops back to re-evaluation and retraining until the best method is identified. Forecasts are accompanied by calibrated predictive intervals, from which safety stock is derived, and every recommendation is linked to a provenance record that documents its origin.

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On three data sets with 4,800 series, the framework reduced forecast error by 18.4% against the best classical estimator, reduced stock-outs by 27% at equal holding volume, and lowered holding cost by 11.3%, while scoring each series in 38 milliseconds. Ablation results showed that each component contributes, and that the link between calibrated uncertainty and safety stock is especially valuable. The findings suggest that organisations can gain both service and cost improvements by treating forecasting, uncertainty, and inventory decisions as one connected, traceable process.

IX. REFERENCES

- 1: **A. Mahendra Vardhan and S. Sridhar**, "Determining False Positive Analysis of Software Vulnerabilities with Predefined Scan Rules using Random Forest Classifier and Decision Tree Technique," 2022 4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N), Greater Noida, India, 2022, pp. 622-625, DOI: <https://doi.org/10.1109/ICAC3N56670.2022.10074458>
- 2: **Dip Bharatbhai Pate**, Dynamic vs. Static visualizations: Understanding their use cases in big data analysis, International Journal of Science and Research Archive, 2022, 05(02), 392-395., DOI <https://doi.org/10.30574/ijrsra.2022.5.2.0077>
- 3: **Dip Bharatbhai Patel**, Building scalable business intelligence systems in the cloud: A technical approach, International Journal of Science and Research Archive, 2021, 02(01), 212-215., Received on 03 February 2021; revised on 17 April 2021; accepted on 19 April 2021, DOI: <https://doi.org/10.30574/ijrsra.2021.2.1.0047>
- 4: **Dip Bharatbhai Patel**, Understanding the Impact of Text Analytics on Social Media Sentiment Analysis, Vol. 5 No. 5 (2019) ,September-October, DOI: <https://doi.org/10.32628/CSEIT1936413>
- 5: **Dip Bharatbhai Patel**, Real-Time Data Streaming in BI Dashboards: Opportunities and Challenges, Archives / Vol. 5 No. 4 (2019) : July-August, DOI: <https://doi.org/10.32628/CSEIT192142>
- 6: **Dip Bharatbhai Patel**, the Role of Data Visualization in Modern Intelligence, **Archives / Vol. 2 No. 2 / Research Article, Published, 2020-11-28** DOI: <https://doi.org/10.32996/jcsts.2020.2.2.4>
- 7: **A. Srivastava**, "AI-assisted cloud migration of healthcare claims data from legacy systems: A metadata-driven framework," Int. J. Commun. Networks Inf. Secur., vol. 14, no. 3, Nov. 2022. [Online]. Available: <https://ijcnis.org/index.php/ijcnis/article/view/8682>
- 8: **A. Srivastava**, "Enhancing provider and claims data accuracy using artificial intelligence on cloud-native data platforms," J. Comput. Anal. Appl., vol. 31, no. 4, Nov. 2023. [Online]. Available: <https://eudoxuspress.com/index.php/pub/article/view/4347/3189>
- 9: **A. Srivastava**, "Optimizing large-scale data migration for cloud-native architectures," J. Comput. Anal. Appl., vol. 31, no. 2, pp. 652–662, May 2023. [Online]. Available: <https://eudoxuspress.com/index.php/pub/article/view/4603>
- 10: **Backup Integrity and Recovery Readiness Assessment for High-Availability Databases** Raghu Gollapudi, Computer Fraud & Security, Vol. 2023, Issue 8, pp. 35-48, [10.52710/cfs.1031](https://doi.org/10.52710/cfs.1031)
- 11: **Risk-Controlled Near-Zero-Downtime Oracle Database Migration Using GoldenGate**

10.48047/jocaaa.2024.33.08.625

Raghu Gollapudi, International Journal of Computational and Experimental Science and Engineering, 8(3), 2022, [10.22399/ijcesen.5382](https://doi.org/10.22399/ijcesen.5382)

12: Manoj Kumar Kagitha, Automated Security Compliance in Ci/Cd: A Natural Language Processing (NLP) Approach to Detecting Vulnerabilities in Infrastructure-As-Code (Terraform/Bicep), Publication year 2021, Volume 2021, Issue 12, <https://computerfraudsecurity.com/index.php/journal/article/view/970>

13: Manoj Kumar Kagitha, Self-Healing Cloud Infrastructure: A Hybrid Reinforcement Learning Framework for Predicting Microservice Failures in Azure Kubernetes Service (AKS), Publication year 2023, Volume 2023, Issue 12, <https://computerfraudsecurity.com/index.php/journal/article/view/971>

14: Manoj Kumar Kagitha, LOAD BALANCING TECHNIQUES IN DISTRIBUTED CLOUD ENVIRONMENTS, (IJESMR - 2017), D.O.I:10.53555/jcr.v6:i1.13380, <https://jcreview.com/archives/volume-6/issue-1/13380>

15: Manoj Kumar Kagitha, AI-DRIVEN OBSERVABILITY FOR HYPERSCALE COLOCATION DATA CENTERS: A CASE STUDY OF LOG ANALYTICS AND ANOMALY DETECTION PIPELINES, Archives / Vol. 27 No. 7 (2019): JOCAAA, <https://www.eudoxuspress.com/index.php/pub/article/view/5053>

16: Manoj Kumar Kagitha, GREENOPS IN THE CLOUD: AN AI-DRIVEN TELEMETRY ANALYSIS MODEL FOR REDUCING CARBON FOOTPRINT IN HIGH-AVAILABILITY CLUSTERS, Vol. 28 No. 6 (2020): JOCAAA, <https://www.eudoxuspress.com/index.php/pub/article/view/5054>

17: Naresh Lokiny. (2022). Integrating AI-powered Chatbots for DevOps Support and Communication in Cloud Environments. European Journal of Advances in Engineering and Technology, 9(11), 106–109. <https://doi.org/10.5281/zenodo.13325989>

18: Naresh Lokiny, (2021), "Disaster Recovery and Business Continuity Planning in DevOps Cloud with AI", International Journal of Science and Research (IJSR), 10(3), 2024-2027. <https://dx.doi.org/10.21275/SR24724151733>, <https://www.ijsr.net/getabstract.php?paperid=SR24724151733>

19: Naresh Lokiny, & Ranganath Nandanampati. (2020). DevSecOps: Integrating Security into DevOps with AI in Cloud. Journal of Scientific and Engineering Research, 7(10), 239–242. <https://doi.org/10.5281/zenodo.13348695>

20: Naresh Lokiny, & Pradip Reddy. (2021). Cost Optimization Strategies for DevOps Deployments in Cloud Environments leveraging Machine Learning. European Journal of Advances in Engineering and Technology, 8(3), 69–72. <https://doi.org/10.5281/zenodo.13325845>

21: Jayanth Para, AI Based Cloud Computation Observational Method & Process, Vol. 51 No. 4 (2023): October-December 2023, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/171>, DOI: <https://doi.org/10.46121/pspc.51.4.3>

22: Jobayar Alom, Ahsan Ahmed. (2023). Graph Neural Networks for Real-Time Detection of Financial Transaction Anomalies. Acta Scientiae, 24(5), 82–90. <https://doi.org/10.22178/acta.24.5.6>

23: Kaleshwar Aryasomayajula, PREVENTING BIAS IN AI-BASED DECISION-MAKING: ANALYZING TECHNIQUES TO REMOVE UNFAIR PREJUDICE IN ALGORITHMIC OUTCOMES, Vol. 50 No. 2 (2022): April-June 2022, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/294>

10.48047/jocaaa.2024.33.08.625

24: **Kaleshwar Aryasomayajula**, MODERN DEVELOPMENT PRACTICES: INVESTIGATIONS INTO SERVERLESS COMPUTING, LOW-CODE/NO-CODE PLATFORMS, AND DEVELOPER PRODUCTIVITY IN REMOTE ENVIRONMENTS, Vol. 50 No. 4 (2022): October-December 2022, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/364>

25: **Vikas Suresh Bagora**, KERNEL-LEVEL PERFORMANCE OPTIMIZATION FOR CARRIER-GRADE BROADBAND AND HIGH-SPEED NETWORKING SYSTEMS, Vol. 47 No. 1 (2019), Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/359>

26: **Vikas Suresh Bagora**, SCALABLE 128G FIBRE CHANNEL AND ETHERNET CONVERGENCE FOR NEXT-GENERATION DATA CENTER NETWORKS, Vol. 50 No. 4 (2022): October-December 2022, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/362>

27. **Asymmetric Total Synthesis of Two Possible Diastereomers of Gliomasolide E and its Structural Elucidation; Ramidi Gopal Reddy, Ravula Venkateshwarlu, Jhillu S. Yadav and Debendra K. Mohapatra.** (J. Org. Chem. 2017, 82(2), 1053-1063). <https://doi.org/10.1021/acs.joc.6b02611>, <https://pubs.acs.org/doi/abs/10.1021/acs.joc.6b02611>

28: **Amanullakhan Pathan Jayadip Ghanshyambhai Tejani, Rahul Shah, Hiral Vaghela, Shailesh, Vajapara , Controlled Synthesis and Characterization of Lanthanum Nanorods**, 2020/5/1, International Journal of Thin Films Science and Technology, Natural Sciences Publishing Corporation (NSP) https://scholar.google.com/citations?view_op=view_citation&hl=en&user=efbNMkwAAAAJ&citation_for_view=efbNMkwAAAAJ:M3NEmzRMikIC

29: **Stereoselective synthesis of the C3-C15 fragment of callispongolide; Ramidi Gopal Reddy, Jhillu S. Yadav and Debendra K. Mohapatra.** (Tetrahedron Letters. 2018, 59, 3579-3582). <https://doi.org/10.1016/j.tetlet.2018.08.041>, <https://www.sciencedirect.com/science/article/pii/S0040403918310426>

30. **Asymmetric Total Synthesis of Two Possible Diastereomers of Gliomasolide E and its Structural Elucidation; Ramidi Gopal Reddy, Ravula Venkateshwarlu, Jhillu S. Yadav and Debendra K. Mohapatra.** (J. Org. Chem. 2017, 82(2), 1053-1063). <https://doi.org/10.1021/acs.joc.6b02611>, <https://pubs.acs.org/doi/abs/10.1021/acs.joc.6b02611>

31: **Kaleshwar Aryasomayajula**, PREVENTING BIAS IN AI-BASED DECISION-MAKING: ANALYZING TECHNIQUES TO REMOVE UNFAIR PREJUDICE IN ALGORITHMIC OUTCOMES, Vol. 50 No. 2 (2022): April-June 2022, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/294>

32: **Kaleshwar Aryasomayajula**, MODERN DEVELOPMENT PRACTICES: INVESTIGATIONS INTO SERVERLESS COMPUTING, LOW-CODE/NO-CODE PLATFORMS, AND DEVELOPER PRODUCTIVITY IN REMOTE ENVIRONMENTS, Vol. 50 No. 4 (2022): October-December 2022, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/364>

33: **Kaleshwar Aryasomayajula**, Micro services: “A Comparative Analysis of Monolithic vs. Microservice Architectures in High-Scalability Cloud Environments., Vol. 51 No. 2 (2023): **April-June**

2023 , Power System Protection and Control, ISSN-1674-3415,
<https://pspac.info/index.php/dlbh/article/view/374>

34: Controlled Synthesis and Characterization of Lanthanum Nanorods, Author(s), Jayadeep Tejani, Rahul Shah, Hiral Vaghela, Shailesh Vajapara, Amanullakhan Pathan,
doi:10.18576/ijfst/090205, URL: <https://www.naturalspublishing.com/Article.asp?ArtcID=20705>, May-2020

35:Sudipkumar Ghanvat , Aishwarya Badlani, Shreya Sandeep Joshi, Marketing Effectiveness in the Post-Cookie Era: A Comparative Analysis of First Party and Zero-Party Data Strategies on Campaign Performance and Customer Equity, **Vol. 31 No. 4 (2023):** JOCAAA ,
<https://www.eudoxuspress.com/index.php/pub/article/view/3940>

36: Chander Vijay S Sanbhi, BAYESIAN UPDATING OF RAM MODELS FOR DYNAMIC AVAILABILITY FORECASTING UNDER REALISTIC DOWNTIME CONSTRAINTS, **Vol. 51 No. 3 (2023): July-September 2023,** Power System Protection and Control, ISSN-1674-3415,
<https://pspac.info/index.php/dlbh/article/view/381>

37: Chander Vijay S Sanbhi, HYBRID RELIABILITY MODELLING FOR ROTATING EQUIPMENT: PHYSICS-INFORMED LEARNING WITH SPARSE FAILURE DATA, Vol. 51 No. 4 (2023): October-December 2023, Power System Protection and Control, ISSN-1674-3415,
<https://pspac.info/index.php/dlbh/article/view/382>

38: A. Srivastava, "AI-assisted cloud migration of healthcare claims data from legacy systems: A metadata-driven framework," Int. J. Commun. Networks Inf. Secur., vol. 14, no. 3, Nov. 2022. [Online]. Available: <https://ijcnis.org/index.php/ijcnis/article/view/8682>

39: A. Srivastava, "Enhancing provider and claims data accuracy using artificial intelligence on cloud-native data platforms," J. Comput. Anal. Appl., vol. 31, no. 4, Nov. 2023. [Online]. Available: <https://eudoxuspress.com/index.php/pub/article/view/4347/3189>

40: A. Srivastava, "Optimizing large-scale data migration for cloud-native architectures," J. Comput. Anal. Appl., vol. 31, no. 2, pp. 652–662, May 2023. [Online]. Available: <https://eudoxuspress.com/index.php/pub/article/view/4603>

41: Santhosh Chitraju Gopal Varma, The Evolution of Cloud-Native Architectures: Exploring the Synergy between Kubernetes and Microservices, DOI: <https://doi.org/10.63282/3050-9246.IJETCSIT-V1I4P104>, Vol. 1 No. 4 (2020), <https://ijetsit.org/index.php/ijetsit/article/view/108>

42: Santhosh Chitraju Gopal Varma, Artificial Intelligence in Cloud Computing: Building Intelligent, Distributed, and Fault-Tolerant Systems, Vol. 3 No. 1 (2022), DOI: <https://doi.org/10.63282/3050-9416.IJAIBDCMS-V3I1P105>, <https://ijaibdcms.org/index.php/ijaibdcms/article/view/78>

43: Sunil Karmakar, AI driven Identity & Access Management with Oracle Cloud security, **Vol. 30 No. 2 (2022):** JOCAAA, <https://eudoxuspress.com/index.php/pub/article/view/4118>