Real-Time Dynamic Pricing Under Demand Uncertainty: A Hybrid Predictive-Optimization Approach

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***Abstract*—This study presents a dynamic pricing and inventory framework designed to adjust in real time to shifting demand signals. By combining stochastic modeling with advanced machine learning techniques, our approach enhances demand forecasting accuracy while supporting data-informed pricing decisions. The proposed method integrates a hybrid ensemble model including LSTM, XGBoost, and a Random Forest meta-learner,within a probabilistic demand environment shaped by Poisson processes and Markov transitions. Demand forecasts inform adaptive price recommendations, helping align inventory levels with customer behavior and maximizing revenue opportunities. The framework's flexibility and accuracy demonstrate its practical value across diverse retail settings, particularly where traditional models underperform in the face of uncertain or non-stationary demand**

Keywords—-Time Dynamic Pricing, Stochastic Demand Forecasting, Inventory Optimization, Machine Learning, LSTM, XGBoost, Random Forest, Stacked Ensemble Model, Feature Engineering, Poisson Process, Markov Chain, Profit Maximization, Contextual Pricing, Time Series Prediction

I. Introduction

Accurately predicting customer demand remains a pressing challenge in today's rapidly changing retail environments. Businesses often struggle to balance inventory levels and pricing decisions when customer behavior becomes unpredictable. Traditional forecasting tools, though useful in stable markets, tend to underperform when exposed to fluctuating patterns caused by seasonal trends, shifting preferences, and unforeseen events. Recent advances in data availability and machine learning have enabled more nuanced demand models, yet many approaches still fall short. Some ignore the randomness present in actual purchase data, while others rely on a single forecasting technique that may not generalize across products or timeframes. In real-world scenarios, demand is influenced by a complex mix of repeatable trends and random shocks, calling for more resilient and adaptable forecasting methods. This paper addresses this gap by developing a hybrid approach that integrates stochastic elements with machine learning to better represent demand variability. The model combines Poisson-based demand simulation, Markov chains for behavioral transitions, and an ensemble forecasting structure involving LSTM and XGBoost. By unifying these methods, we aim to improve prediction accuracy and offer retailers a tool that not only anticipates demand but also suggests optimal pricing strategies in response to evolving market signals.

II. Related Work

Numerous studies have explored the intersection of dynamic pricing, demand forecasting, and inventory control under uncertainty. Foundational contributions in this space, such as those by Kumar et al. [1], leveraged classical exponential smoothing techniques, demonstrating that careful tuning of smoothing parameters can improve forecast responsiveness in volatile environments. However, their approach remained limited by its deterministic nature, which does not sufficiently capture demand stochasticity. Zhao et al. [2] addressed the joint challenge of pricing and inventory by designing a two-phase optimization framework, specifically targeting manufacturing contexts under demand uncertainty.While their work contributes significantly by exploring different demand regimes and replenishment frequencies, its focus is largely theoretical, lacking model generalizability across diverse retail domains. Stochastic dynamics within production environments have also been investigated through more probabilistic lenses. Covei et al. [3] applied regime-switching models using Markov chains to simulate economic fluctuations and their impact on operational costs. Although their formulation enriches production planning frameworks, it primarily addresses macroeconomic transitions rather than granular consumer behavior. Monte Carlo-based simulation techniques have been explored by Maitra [4] for optimizing inventory policies under uncertainty. Their combination of simulation and Bayesian optimization is methodologically sound but lacks scalability when extended to multivariate demand contexts involving both price sensitivity and customer behavior dynamics. Contemporary efforts have increasingly shifted toward integrating machine learning into these domains. Liu et al. [5], for example, utilized deep reinforcement learning for pricing decisions in e-commerce, modeling the problem as a Markov Decision Process. This formulation is notably adaptive and capable of real-time policy refinement, though its dependence on large, high-frequency datasets can limit its applicability in settings with sparse or irregular data. Yao [6] introduced Brownian motion into stochastic inventory-pricing models to account for continuous uncertainty. While mathematically elegant, this framework assumes smooth demand volatility, which may not align with the abrupt fluctuations common in many retail environments. Other scholars, such as Surti et al. [7], have emphasized the role of supply-side uncertainty by developing unified frameworks that couple pricing flexibility with inventory resilience. Their insights are valuable in industries with constrained or variable supply chains but may not directly address consumer-driven demand variability. Metaheuristic algorithms have also been adopted in recent work. Tan et al. [8] employed grey wolf optimization to manage inventory under stochastic conditions, seeking trade-offs between profitability and spatial constraints. While promising in performance, such algorithms often lack transparency and theoretical convergence guarantees. In the realm of stochastic control, Oladejo et al. [9] highlighted how variable demand rates can be accommodated through optimal production-inventory policies. Their work reinforces the importance of embedding stochasticity at the system design level but stops short of integrating learning-based approaches.Suthar and Soni [10] examined joint decisions involving pricing, promotions, and deteriorating inventory. Their model addresses practical complexities such as partial backlogging and non-instantaneous replenishment, underscoring the importance of modeling item perishability—though it does not incorporate predictive modeling or dynamic price adaptation.

TABLE I. LITERATURE REVIEW TABLE

Author(s)	Stochastic Demand	Dynamic Pricing	Demand Forecasting	Hybrid Ensemble Method
Alawneh & Zhang et al. [11]	✓	✗	✗	✗
Boukas et al. [12]	✓	✗	✗	✗
Boer & Zwart [13]	✗	✓	✗	✗
Chen et al. [14]	✓	✗	✗	✗
Gallego & Van Ryzin [15]	✓	✓	✗	✗
Garai & Paul [16]	✓	✗	✗	✗
Hsieh & Dye [17]	✗	✓	✗	✗
Jauhari et al. [18]	✓	✗	✗	✗
Willemain et al. [19]	✗	✗	✓	✗
You [20]	✗	✓	✗	✗
Kumar et al. [1]	✓	✓	✓	✗
Proposed Paper (2025)	✓	✓	✓	✓

III. OBJECTIVES

This study aims to develop an integrated framework that links demand forecasting with real-time pricing and inventory strategies, tailored to the practical complexities of modern retail operations. By adopting a hybrid ensemble approach—merging Long Short-Term Memory (LSTM) networks and XGBoost regressors—the model is designed to uncover both temporal sales trends and intricate feature-level interactions. This dual capability allows for more accurate demand estimation and supports data-driven pricing decisions that adapt to changing market dynamics. To address the inherent randomness in consumer demand, stochastic elements such as Poisson process simulation and Markov chain modeling are incorporated to reflect real-world uncertainty and behavioral transitions. A key goal is to translate these insights into an adaptive pricing strategy that optimizes revenue through real-time price recommendations based on forecasted demand. The proposed approach is rigorously evaluated against traditional models like ARIMA, SVR, and Random Forest, LSTM, Gradient Boosting, and XGBoost using metrics such as MAE, RMSE, and accuracy. Ultimately, this research seeks to contribute a data-driven model that provides actionable forecasting and pricing recommendations, suitable for operational deployment in dynamic retail settings.to make more informed pricing and inventory decisions in today's fast-evolving, data-centric retail environments.

IV. METHODOLOGY

We design a composite multi-phase approach(Fig. 1) for demand forecasting that integrates classical stochastic modeling with modern deep learning and ensemble machine learning.

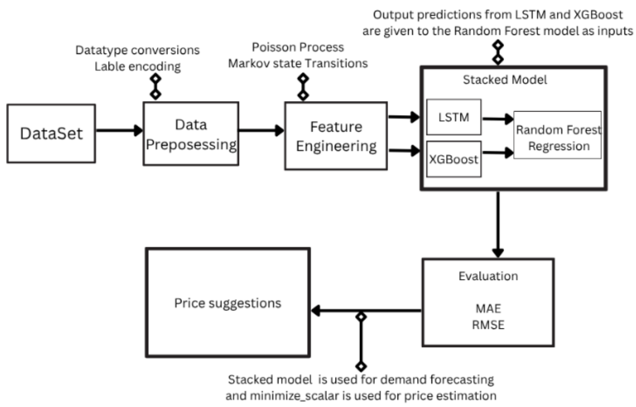

Fig. 1. Architecture of the proposed process

A. Dataset Description

The original dataset contains 25 attributes covering various aspects of sales transactions, including order identifiers, product details, customer contact information, geographic location, and sales figures. Some of the notable fields are OrderNumber, QuantityOrdered, PriceEach, Sales, OrderDate, CustomerName, and DealSize. But there are many features here that are unnecessary, so we remove them and considered only 6 features for our proposed model they are Quantityordered, Priceeach, Sales, Orderdate, Msrp, Dealsize. Dataset will be made available on request.

B. Markov Chain Modeling for Deal Size Transition

To understand temporal patterns in customer purchasing behavior, we model the transitions between DEALSIZE (e.g., Small → Medium, Medium → Large) using a first-order discrete-time Markov chain. The Markov assumption simplifies sequential dependencies by assuming that the next state depends only on the current state. Let the set of possible deal sizes be $S = \{s1, s2, \dots, sn\}$, and the transition probability from state s_i to s_j be P_{ij}.

$$P_{ij} = P\left(X_{t+1} = s_j \,\middle|\, X_t = s_i\right)$$

For instance, suppose historical data shows the following transitions over time:

Small → Small → Medium → Large → Medium → Small. From this, we construct a transition matrix P where P_{ij} represents the empirical probability of transitioning from state i to j.

$$P = \begin{bmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{bmatrix}$$

The Markov features—probabilities of staying, growing, or shrinking—are used as input to downstream forecasting models. So the features we add to the dataset are P_Stay, P_Grow, And P_Shrink. Where they are only with values 0 or 1. This helps the model to understand how the future instance is going to get transformed.

C. Poisson Processor for Demand Simulation

To capture the random nature of demand, we model the count of orders over time as a Poisson process. Poisson models help quantify how frequently demand events (orders) occur within fixed time spans, under the assumption of independence occurring within fixed intervals.

If the mean demand rate is λ, the probability of observing k orders is:

$$\mathrm{P(D = k)} = \frac{\left(\mathrm{e}^{\lambda}\, \lambda^{\mathrm{k}}\right)}{k!}$$

Where:

- λ is the average demand rate estimated from historical data
- $k \in \mathrm{N}$ is the simulated quantity ordered.

For example, $\lambda = 20$, the simulated demand might vary as $\{18,21,19,22,20\}$ per time interval. These values are used as features in the supervised learning models to encode the stochastic aspect of demand.

We obtained two features from this technique, Poisson_Lambda and Poisson_Sim. The former is the mean of the orders and the latter is the simulated orders value according to the Poisson process.

D. LSTM – Based Temporal Forecasting

Unlike standard RNNs, LSTM models are equipped with gated structures that enable them to selectively retain or discard information over multiple time steps. This makes them particularly suitable for demand forecasting tasks, where understanding long-term purchasing behavior is essential. Our implementation feeds past sales quantities through a rolling window to generate short-term forecasts. Here, the LSTM model predicts future demand based on a sliding window of past quantities ordered. Its gated architecture makes it suitable for capturing long-term temporal dependencies., so this model can help us to get the long-term dependencies. In our implementation, we define the input sequence as $\mathrm{x}_{\mathrm{t-n}}, \dots, \mathrm{x}_{\mathrm{t}}$ where x_i denotes the observed demand at time t. The model is tasked with predicting the subsequent value y_{t+1}, forming a one-step-ahead forecast based on the recent demand history. The LSTM network processes this sequence through gated mechanisms that regulate information flow across time steps. Its internal operations can be summarized as:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$\widetilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$
$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t * \tanh(C_t)$$

Here, f_t, i_t, o_t represent the forget, input, and output gates, respectively. The cell state C_t maintains long-term memory, while the hidden state h_t acts as the output at each time step. The sigmoid activation σ and tanh functions are used to scale the gate activations and internal cell updates.

A critical hyperparameter in LSTM design is the lookback period used to generate input sequences to consider for the LSTM. To answer this, we considered some values and then iterated the model on these values and selected the value that yields the least error while predicting. And the architecture of the model is not very complex; rather, it is very simple.

TABLE II. ARCHITECTURE OF LSTM MODEL USED

Layer	Type	Details	Output Shape
1	Input	Sequence of past demand values	(lookback, 1)
2	LSTM	64 memory units, return sequences = False	(64,)
3	Dense (Fully Connected)	1 neuron (linear activation)	(1,)
4 (Final Output)	Prediction Output	Forecasted demand value	Scalar (next timestep)

E. XGBoost Regressor for Feature-Based Learning

Extreme Gradient Boosting (XGBoost) is a scalable, regularized, tree-based ensemble algorithm known for its performance on structured tabular data. In this study, we use this model to learn complex relationships between engineered features and demand patterns, complementing the temporal modeling capabilities of the LSTM model with robustness to accommodate the sudden dips in the sales of the products.

The features we input to this model are the processed features in the previous processes.

F. Random Forest as Meta-Model

To enhance robustness, a Random Forest Regressor is used as a meta-model that stacks the outputs from LSTM and XGBoost. The stacked ensemble integrates sequential pattern extraction from LSTM with XGBoost's strength in modeling complex feature interactions, resulting in a more comprehensive representation of demand behavior.

Let:

y_{LSTM} = Prediction from LSTM

y_{XGB} = Prediction from XGBoost

Then meta-model learns:

$$y_{final} = RF([y_{LSTM}, y_{XGB}])$$

Where RF denotes the Random Forest regressor trained on the predictions of base model.

Although several algorithms are suitable for stacking predictions from base models, Random Forest was selected as the meta-regressor due to its ability to handle nonlinearity, resist overfitting, and integrate predictions without requiring feature scaling. Its balance of interpretability and performance makes it ideal for capturing residual interactions between the LSTM and XGBoost outputs.

G. Price Optimization

This work identifies revenue-maximizing price points through numerical optimization, grounded in demand forecasts generated by the ensemble model applies a numerical optimization approach using the minimize_scalar function from the scipy.optimize library. This technique is particularly useful when working with machine through models such as LSTM and XGBoost, where the functional form of the demand-price relationship is non-transparent and data-driven, making analytical derivation impracticalbetween price and predicted demand is complex and cannot be expressed with a simple mathematical formula. After forecasting demand using the stacked model, the predicted values are used to simulate how revenue changes at different price levels. The minimize_scalar function evaluates revenue across a defined price range—such as a to b—and identifies the price that yields the highest expected revenue. In contrast to gradient-based optimizers, minimize_scalar can operate without requiring derivative information, making it suitable for optimizing non-differentiable or black-box functions to be differentiable, making it well-suited for black-box models. This approach effectively translates demand forecasts into real-time pricing recommendations, allowing businesses to make informed decisions grounded in data-driven insights.

V. Evaluation and Results

The proposed forecasting framework was evaluated using real-world sales data spanning Classic Cars. Data was preprocessed to address missing values, encode categorical features such as DealSize, and create time series grouped by product lines and months.To evaluate the model's predictive ability, the dataset was divided into two subsets: 80% for training and 20% for testing. This separation allows us to assess how well the model generalizes to unseen data. Forecast accuracy was assessed using three standard metrics. First, Mean Absolute Error (MAE), which captures the average size of forecast errors, regardless of their direction. Second, Root Mean Squared Error (RMSE), which assigns higher penalties to larger deviations, offering insight into model stability and sensitivity to outliers. Lastly, Accuracy was used as a contextual metric to reflect the proportion of closely matched predictions, computed as $1 - \frac{RMSE}{Range\ of\ actual\ values}$, this contextual metric helps interpret performance across varying product demand scales. The hybrid stacked model—composed of an LSTM network, an XGBoost regressor, and a Random Forest meta-learner—consistently outperformed standalone models. Table II summarizes the results across forecasting techniques on a representative product line (*Classic Cars*), where the proposed ensemble model achieved the lowest MAE and RMSE, and the highest accuracy.

TABLE III. FORECATING PERFORMANCE COMPARISON

Model	**MAE**	**RMSE**	**Accuracy**
Support Vector Regression	9.35	12.65	85.45
LSTM	9.15	12.43	85.8
XGBoost	9.46	12.55	85.57
Gradiant Boosting	11.49	15.35	82.36
Random Forest	10.07	13.78	84.15
Proposed Model	3.05	4.49	93.20

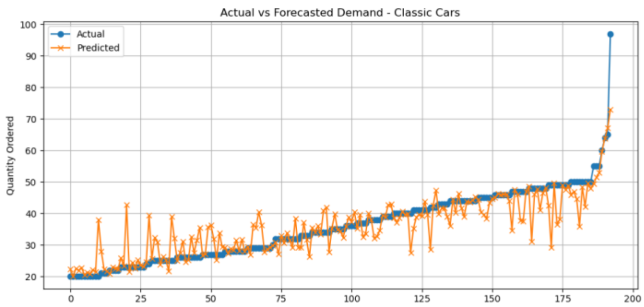

Fig. 2. Line Plot of Actual vs Forecasted demand

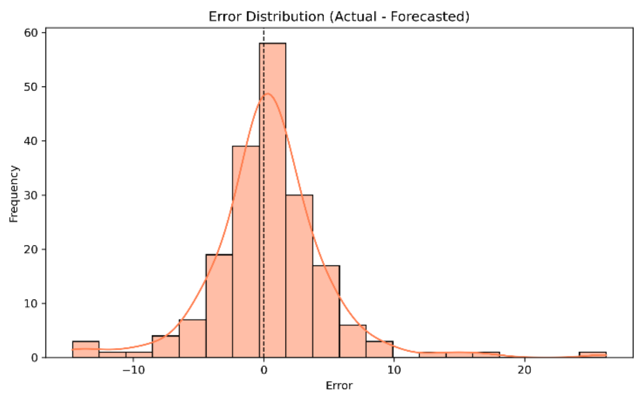

Fig. 3 Error Distribution over the data instances

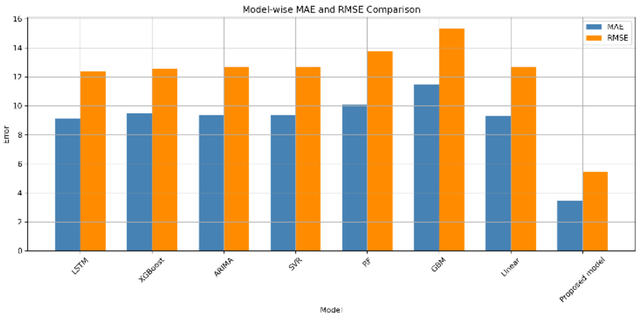

Fig. 4. Comparison of the MAE, RMSE over some ML and Timeseries models

To better understand the effectiveness of the proposed forecasting model, several diagnostic visualizations were used to evaluate prediction performance both quantitatively and qualitatively. Fig. 2. presents a line plot comparing actual and forecasted demand over time. This visualization helps assess the model's ability to follow the real-world demand trajectory and capture fluctuations accurately across the forecast horizon. A close alignment between the two curves reflects high temporal accuracy, particularly in dynamic retail scenarios. Fig. 3 illustrates the distribution of forecasting errors (actual minus predicted demand). A narrow and symmetric error distribution centered around zero indicates that the model is both unbiased and stable. This histogram or kernel density estimation (KDE) plot provides valuable insights into systematic overestimation or underestimation by the model. Fig. 4 provides a bar chart comparison of MAE and RMSE across multiple models. This visualization enables a straightforward, interpretable performance benchmark, highlighting how the proposed stacked ensemble model outperforms classical models such as ARIMA, SVR, and standalone LSTM or XGBoost in both average and worst-case error magnitudes. Together, these figures support a comprehensive evaluation of forecasting accuracy and robustness, reinforcing the quantitative improvements observed in the performance metrics.

VI. Conclusion

This research proposes a unified forecasting and pricing system that blends probabilistic modeling with machine learning to better address real-world demand uncertainty. By incorporating both Poisson and Markov structures, the proposed approach captures not only the inherent randomness of customer demand but also its sequential behavioral patterns. The forecasting pipeline combines temporal learning from LSTM with feature-based prediction from XGBoost, and consolidates these outputs through a Random Forest meta-regressor. Experimental results show that this ensemble consistently outperforms standalone models in terms of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), underscoring its practical relevance for dynamic pricing in retail environments where demand is highly variable. Moreover, the pricing layer—powered by numerical optimization—translates demand forecasts into actionable revenue strategies. The results confirm that integrating stochastic theory with machine learning produces not just accurate forecasts, but practical business value. Overall, this approach contributes a scalable and adaptable system suited for environments where demand is both volatile and competitive, offering retailers a more intelligent pathway to profitability through informed pricing and inventory control.

VII. Future Work

While the current framework effectively integrates machine learning and optimization under uncertainty, several promising directions exist for further enhancement and exploration. One such direction is the integration of Reinforcement Learning (RL) techniques, which would enable the pricing model to adapt in real time based on market feedback and continuously evolving demand, moving beyond fixed interval-based strategies. Another potential advancement involves multi-product and cross-elasticity modeling, wherein pricing decisions are optimized across a portfolio of products while accounting for inter-product relationships such as substitution or complementarity effects, thereby increasing overall profitability. The incorporation of external macroeconomic indicators—such as inflation trends, consumer sentiment indices, and competitor promotional activity—could further improve the model's forecasting accuracy, particularly during periods of economic volatility or external shocks. Additionally, the use of advanced probabilistic forecasting techniques, including Bayesian models or quantile-based LSTM architectures, may provide prediction intervals rather than point estimates, allowing for risk-adjusted pricing decisions that are better suited for environments with high uncertainty. To enhance practical deployment, future work may focus on transitioning the current architecture into a real-time API-enabled system**,** integrated with cloud infrastructure to interface with point-of-sale terminals, ERP systems, or e-commerce platforms. This would enable dynamic pricing decisions to be made and executed instantly in production settings. Finally, incorporating sustainability-driven constraints**,** such as minimizing carbon footprint, controlling inventory waste, and considering overproduction penalties, would align the pricing strategy with broader ESG (Environmental, Social, and Governance) objectives, ensuring that profitability is achieved responsibly and sustainably.

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