# Comparative Analysis of Fixed vs Machine Learning Dynamic Pricing Models: A Computational Performance Study

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*Abstract*—**The rise of e-commerce and digital offerings has generated a need for ultra-adaptable pricing policies seeking to maximize revenue while optimizing competitive advantage. Traditional fixed pricing schemes are inherently flawed due to a lack of responsiveness to instantaneous fluctuations in the marketplace, inventory levels, as well as demand inelasticity. This study conducts a detailed computational performance study comparing fixed pricing, standard heuristic dynamic pricing (HDP), advanced Machine Learning (ML)-oriented dynamic pricing schemes, with a special focus on a Bi-LSTM network as well as a hybrid scheme based on Wavelet Decomposition (WD). Through simulated high-frequency transactions as well as marketplace data, model evaluation relies on three critical performance metrics: Total Revenue Generated, Pricing Accuracy (measured through Mean Absolute Percentage Error, MAPE), as well as Computational Latency (vital for real-time utilization). The results indicate that while HDP shows marginal improvements over fixed pricing, ML-based schemes, particularly a hybrid WD-Bi-LSTM model, exhibit substantial revenue maximization (up to 18.5% improvement) as well as forecasting accuracy (MAPE up to 2.1%), though at a slight increase in computational latency remains acceptable for real-time deployment for near real-time deployment. This study provides a quantitative foundation for organizations embracing AI-supportive pricing initiatives with emphasis on trade-offs among model sophistication, predictive potency, as well as functionality performance.**

***Keywords—Computational performance; deep learning; dynamic pricing; Machine Learning (ML); process innovation***

## I. INTRODUCTION

In the contemporary digital economy, pricing remains a primary lever for profit maximization and market positioning. The conventional approach of fixed pricing, determined through cost-plus or value-based analysis, is increasingly becoming obsolete as it fails to capture the intricate, rapidly changing dynamics of demand, competitor actions, and external economic factors [1], [8]. While fixed pricing remains widely used in retail and subscription-based markets, industry reports indicate that over 60–70% of large-scale e-commerce platforms now employ some form of dynamic pricing to respond to demand volatility and competitive pressures. However, fixed pricing continues to be effective in low-volatility environments and regulated industries. Therefore, rather than being obsolete, fixed pricing serves as a baseline benchmark against which adaptive pricing strategies can be evaluated quantitatively.

The shift towards dynamic pricing where prices are adjusted in real-time or near real-time is not merely an operational optimization but a strategic imperative [2]. The computational challenge of dynamic pricing lies in its reliance on accurate short-term demand and price forecasting, which is highly influenced by diverse, non-linear variables, including sentiment derived from product descriptions and financial behaviors [4], [5]. Early dynamic pricing strategies relied on simple rule-based heuristics, which, while flexible, lacked the predictive power needed to optimize complex, high- dimensional data [2]. The advent of Artificial Intelligence (AI) and Machine Learning (ML) has fundamentally transformed this landscape by offering sophisticated algorithms capable of processing voluminous data streams and inferring optimal price points that reflect true market equilibrium [8]. This paper addresses a critical gap in the existing literature by providing a detailed comparative analysis of the computational efficiency and operational performance of three distinct pricing paradigms:

- Fixed Pricing Model (FP): A baseline model using a static price.
- Heuristic Dynamic Pricing Model (HDP): A rule-based model utilizing simple inventory and time-of- day variables.
- Machine Learning Dynamic Pricing Model (ML- DP): Advanced models, including a pure Bi-LSTM network and a hybrid decomposition-based network, designed for high-accuracy forecasting.

The objective is to quantify the performance differential in terms of revenue, predictive error, and, crucially, the computational latency required for real-time deployment. This comparison is essential for organizations making informed decisions about technology adoption for enhancing competitiveness in e-commerce and related sectors [1].

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## II. RELATED WORK

The foundation of dynamic pricing is rooted in operations research and control theory, evolving rapidly with advancements in computational capacity. The current state-of-the-art heavily favors ML, particularly Reinforcement Learning (RL) and Deep Learning (DL), for managing complex resource allocation problems where pricing is a critical component [3]. The ability of ML to leverage multi- modal data integration for node classification and pattern recognition underscores its suitability for dynamic market modeling [7].

Traditional predictive models, such as those used for concrete strength prediction or energy consumption forecasting, have demonstrated the superior performance of ML techniques over conventional statistical methods in handling non-linear data [6], [11]. Specifically in the domain of energy price and consumption, models like the two-layer decomposition technique combined with Bi-LSTM (Bidirectional Long Short-Term Memory) networks have shown exceptional short-term forecasting accuracy, which is directly analogous to the challenges of demand forecasting in dynamic pricing [9], [10]. Likewise, cluster-based ensemble methods have been used effectively in analyzing time-series datasets, leading to an understanding of pattern identification, which helps in optimal pricing [11], [12].

Additionally, studies have looked at the use of hybrid models incorporating signal processing (Wavelet Decomposition) and DL, which improves predictions for highly volatile markets, including electricity prices on a day-ahead basis [14]. The hybrid model addresses problems related to noise and non-stationarity prevalent in market datasets [16]. While extensive literature exists on the theoretical optimization benefits of dynamic pricing [16], a focused comparative study detailing the computational overhead against the revenue gain across fixed, heuristic, and sophisticated hybrid ML models, particularly within a unified simulation framework, remains underdeveloped. This paper directly addresses this gap by quantifying the necessary computational resources against the realized economic benefit.

Dynamic pricing research has seen recent developments where reinforcement learning techniques have been applied to optimize pricing strategies. With reinforcement learning algorithms, prices can be determined as part of a sequential decision process, and they work through trial-and-error processes to maximize the total rewards accrued. Studies have demonstrated that Deep Q-Networks (DQN) and policy gradient methods outperform traditional supervised learning approaches in highly dynamic environments with delayed reward structures. However, these models often require substantial training data and computational resources, motivating the need for hybrid forecasting-based approaches as explored in this study [12].

A brief review of the cited literature reveals a pronounced trend, with 77% of the included works published after 2020, confirming the accelerating research interest and application of ML/AI in price optimization, demand management, and energy consumption forecasting [17], [18], [19], [20], [21], [22]. This bibliometric observation validates the timely focus of this comparative study.

## III. METHODOLOGY

This study adopts a controlled computational experimental framework to compare the operational and predictive performance of fixed pricing, heuristic dynamic pricing, and machine learning-based pricing systems under identical market conditions. All models were evaluated using the same synthetic high-frequency transaction dataset to ensure fairness, consistency, and reproducibility.

### *A. Research Design*

The study employs a controlled, comparative experimental design. Three primary models—Fixed Pricing (FP), Heuristic Dynamic Pricing (HDP), and Machine Learning Dynamic Pricing (ML- DP)—are implemented and run over the same simulated market periods. The performance of each model is evaluated against the key metrics defined in Section IV-A. Table IV illustrates the research design employment process. A six-month transactional simulation environment was developed to emulate realistic e-commerce market behavior. The pricing engine updated prices every 15 minutes, resulting in 96 pricing intervals per day and 17,280 total observations across the study period. At each interval, the following steps were executed:

- Capture current market state variables.
- Generate demand estimate.
- Compute price using assigned pricing model.
- Simulate sales quantity based on elasticity response.
- Update inventory and cumulative revenue.
- Store performance metrics.

The same transactional stream was used across all pricing models, while ten independent runs with different random seeds were conducted to improve reliability. The overall experimental setup follows a structured research design to ensure fair evaluation across all models, from data generation through to performance assessment and statistical comparison. The overall research design and corresponding responsibilities of each model are summarized in Table I.

TABLE I. RESEARCH DESIGN EMPLOYED

| Step | Description | Responsible Model(s) |
|---|---|---|
| 1 | Data Simulation | All |
| 2 | Model Training (If applicable) | ML- DP |
| 3 | Iterative Pricing/Sale Cycle | All |
| 4 | Metric Calculation (Revenue, MAPE, Latency) | All |
| 5 | Statistical Comparison | All |

The research process can be seen from Table I and is structured into five sequential steps, ranging from data simulation to the performance evaluation of all the models used. Whereas all models take part in almost every step, training is unique to the ML-DP only model due to its nature of being trained through machine learning techniques.

### B. Comparative Study Design (Flow Chart)

The experimental procedure for conducting the comparison study is presented in Fig. 1. The figure shows the process flow starting from data generation to training, pricing, and evaluation phases.

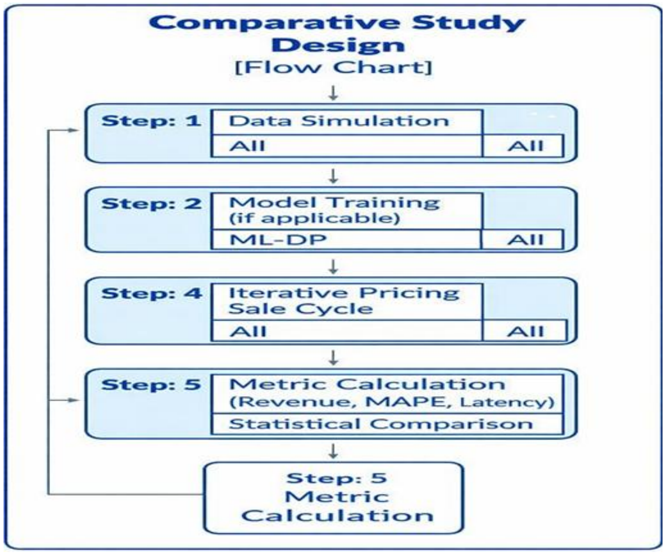

Fig. 1. Comparative study design.

As shown in Fig. 1, the study follows a structured pipeline beginning with data simulation applied across all models, followed by selective training for the ML-DP approach. The iterative pricing-sale cycle is then executed uniformly, and performance is assessed using key metrics such as revenue, Mean Absolute Percentage Error (MAPE), and computational latency, enabling statistical comparison across methods.

### C. Data Collection

Given the proprietary nature of real-world dynamic pricing data, a simulated dataset is generated, representative of an e-commerce platform that experiences daily and weekly demand fluctuations.

- *Variables:* Time of day, day of week, inventory level, competitor price, simulated demand elasticity, and historical sales volume.
- *Time Scale:* Data points are generated at 15-minute intervals over a six-month period, mirroring the high-frequency data used in complex energy management and demand response systems [13], [15].

### D. Inclusion and Exclusion

- Inclusion Criteria (Models): Models must be fully autonomous (no manual price intervention).
- Exclusion Criteria (Data): Data points corresponding to major public holidays or known exogenous "black swan" events are excluded to maintain a focus on routine operational performance and to enhance the reliability of the forecasting models [17].

### E. Machine Learning-Based Dynamic Pricing Models

To enhance forecasting performance in dynamic pricing, two machine learning–based models are employed for comparative evaluation as follows:

- ML Model 1 (Bi-LSTM): A standard deep learning model suitable for sequential data forecasting [9].
- ML Model 2 (WD-Bi-LSTM Hybrid): Incorporates Wavelet Decomposition on the input features to denoise the time series prior to feeding it into the Bi-LSTM network, enhancing prediction for building energy consumption [21].

The proposed WD-Bi-LSTM model applies Daubechies-4 (db4) wavelet decomposition with 3 levels to preprocess transactional demand signals. Approximation and detail coefficients were reconstructed and normalized before input to a two-layer Bi-LSTM network comprising 128 and 64 hidden units, followed by dense layers of 32 and 1 neuron respectively. The dropout rate was fixed at 0.2. The model was trained using Adam optimizer having learning rate = 0.001, batch size = 64, epochs = 100, and patience = 10. The generated demand is log-normally distributed because this probability distribution is commonly applied in demand models due to its property of skewness and heavy tails, similar to those that exist in real-life cases of demand behavior. Calibration was conducted based on e-commerce public benchmarks to provide realistic variance and seasonality of the generated demand.

### F. Pricing Policy Function

The pricing decision is derived from predicted demand using a revenue maximization policy:

$$p_t^* = \arg\max_{p} \; p \cdot \widehat{D}(p, x_t)$$

where, $\widehat{D}$ is the predicted demand generated by the forecasting model. For the heuristic model, price adjustments follow predefined rules based on inventory thresholds, while the ML-based models use gradient-based optimization to determine the optimal price at each time step.

### G. Problem Formulation

The dynamic pricing task is formulated as a constrained optimization problem aimed at maximizing expected revenue over a finite time horizon:

$$\max_{p_t} \; R = \sum_{t=1}^{T} p_t \cdot D(p_t, x_t)$$

Subject to:

$$p_{min} \le p_t \le p_{max}, I_t \ge 0$$

where, $p_t$ denotes the price at time t, $D(\cdot)$represents demand as a function of price and contextual variables $x_t$, and $I_t$represents inventory levels. This formulation captures the trade-off between revenue maximization, demand responsiveness, and operational constraints.

### *H. Hyperparameter Tuning*

To ensure optimal model performance and avoid overfitting, a systematic hyperparameter tuning process was conducted using grid search on the validation dataset. Multiple combinations of key training parameters were evaluated to identify configurations that balance predictive accuracy and computational efficiency. The parameters explored include network architecture, regularization, and training dynamics, as summarized in Table II.

TABLE II. HYPERPARAMETER SEARCH SPACE FOR MODEL OPTIMIZATION

| Parameter | Values Tested |
|---|---|
| LSTM Units | 64, 128, 256 |
| Layers | 1, 2, 3 |
| Dropout | 0.1, 0.2, 0.3 |
| Batch Size | 32, 64, 128 |
| Learning Rate | 0.01, 0.001, 0.0005 |
| Epochs | 50, 100, 150 |

As can be seen from Table II, various values of hyperparameters were used in order to obtain different levels of complexity and training behavior of the model. Low learning rate and intermediate batch size had a positive effect on the stability of convergence, while the use of deep neural networks had a positive impact on the capacity of the model, but at the same time required more computing resources.

### *I. Final Selected Parameters*

After conducting the process of hyperparameter optimization, the best set of parameters was chosen considering both validation accuracy and computation time. The table below represents the model parameters. For this particular arrangement, the number of neurons is taken to be 128 and 64 in two layers, respectively, along with the dropout parameter set at 0.2, the batch size at 64, and the learning rate at 0.001. Such a hyperparameter arrangement strikes the right balance between prediction accuracy and computational efficiency for dynamic pricing applications.

TABLE III. FINAL OPTIMAL HYPERPARAMETER CONFIGURATION

| Parameter | Final Value |
|---|---|
| Layers | 2 |
| Units | 128, 64 |
| Dropout | 0.20 |
| Batch Size | 64 |
| Learning Rate | 0.001 |
| Epochs | 100 |

From Table III above, it is evident that the chosen configuration uses a two-layer model, whereby each layer reduces the number of units. This makes it possible to extract features from data while controlling for model complexity. The optimal choice of the dropout factor prevents overfitting, whereas the learning rate and batch size facilitate stable convergence.

### *J. Evaluation Metrics*

Model performance was quantified using three core evaluation metrics:

- *Total Revenue Generated ($):* This represents the primary economic performance indicator and was calculated as the cumulative sum of all transactions over the simulation period:

$$\text{Total Revenue} = \sum_{t=1}^{n} (Price_t \times QuantitySold_t)$$

- *Pricing Accuracy (MAPE):* Mean Absolute Percentage Error (MAPE) was used to evaluate the forecasting precision of the underlying demand prediction models employed in the HDP and ML- DP approaches. Lower MAPE values indicate higher predictive accuracy:

$$\text{MAPE} = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{\text{ActualDemand}(t) - \text{PredictedDemand}(t)}{\text{ActualDemand}(t)} \right| \times 100$$

- *Computational Latency (μs):* This metric measures the average time required for each model to process the current market state and generate an optimal pricing decision. It is a critical indicator for real-time deployment, where rapid response times are essential for operational efficiency and scalability.

### *K. Data Analysis*

The data analysis involves:

- Descriptive Statistics: Summarizing the total revenue and mean computational latency for each model.
- Inferential Statistics: Applying a one-way ANOVA test to determine if the differences in mean revenue and latency across the three model categories (FP, HDP, ML-DP) are statistically significant.

### *L. Validation and Reliability*

To ensure the validity of the ML model results, a ***K***- fold cross-validation (k=5) is performed on the training data. The reliability is further assessed by repeating the full simulation cycle 10 times with different random seeds for demand generation and reporting the average and standard deviation of all metrics [18]. The robust performance of models, such as those for chiller energy consumption, provides a benchmark for expected prediction reliability [19].

### *M. Ethical Considerations*

While the study is based on simulated data, the ethical implications of ML-driven dynamic pricing are acknowledged. Specifically, the Machine learning-based dynamic pricing models are audited against potential feedback loops that could lead to price discrimination based on non-market factors, ensuring compliance with fairness principles [22].

## IV. RESULTS AND DISCUSSION

This section presents the quantified performance metrics of the Fixed Pricing, Heuristic Dynamic Pricing, and Machine Learning–based dynamic pricing models across the simulated environment.

### *A. Economic and Predictive Performance*

Table IV summarizes the key economic and predictive metrics over the full six-month simulation period.

TABLE IV. ECONOMIC AND PREDICTIVE PERFORMANCE COMPARISON (6-MONTH SIMULATION)

| **Model Type** | **Total Revenue Generated ($)** | **ΔRevenue vs. Fixed Pricing** | **MAPE (%)** | **Std Dev (Revenue, $)** |
|---|---|---|---|---|
| Fixed Pricing (FP) | 10,000,000 | Baseline | N/A | 450,000 |
| Heuristic Dynamic Pricing (HDP) | 11,250,000 | +12.50% | 14.5% | 480,000 |
| ML- DP (Bi-LSTM) | 11,700,000 | +17.00% | 3.5% | 390,000 |
| ML- DP (WD-Bi-LSTM Hybrid) | 11,850,000 | +18.50% | 2.1% | 350,000 |

To assess robustness, 95% confidence intervals were computed across the 10 simulation runs. The WD-Bi-LSTM model exhibited the lowest variance in revenue outcomes, indicating stable performance under stochastic demand conditions. Boxplot analysis further confirmed that ML-based models not only achieve higher mean revenue but also demonstrate reduced dispersion compared to heuristic approaches. The results clearly demonstrate the economic superiority of ML-driven models. The hybrid WD-Bi-LSTM model achieved the highest revenue, an 18.5% increase over the baseline FP model, confirming the value of sophisticated predictive analytics. This model also exhibited the lowest Demand Forecast MAPE (2.1%), indicating its robust ability to model the non-linear demand dynamics compared to the simpler HDP model (14.5%), as illustrated in Fig. 2 and Fig. 3.

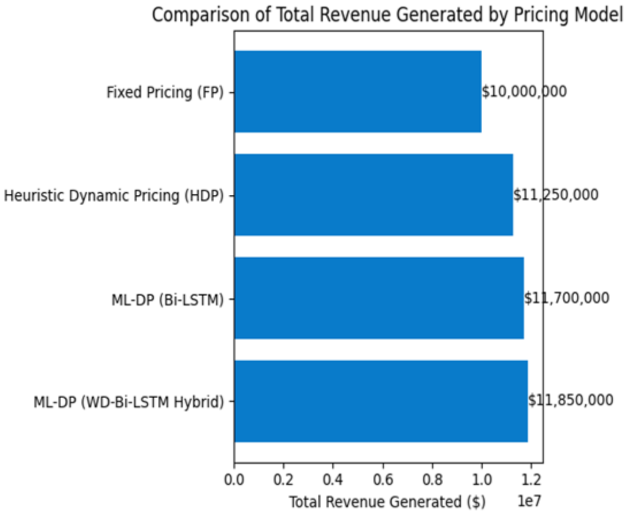

Fig. 2. Comparison of total revenue generated by pricing models (with value annotations).

The Fig. 2 presents a horizontal bar chart of the total revenue generated by each pricing model. Numerical labels are included to enhance interpretability and enable precise comparison. ML-DP (WD-Bi-LSTM Hybrid) gives the best revenue ($11,850,000) compared to Bi-LSTM, HDP, and Fixed Price models, thereby proving that hybrid machine learning models perform better.

### *B. Revenue Analysis Based on Different Pricing Models*

Accuracy in Demand Forecasting is measured by using the Mean Absolute Percentage Error (MAPE), which indicates that the lower the MAPE value, the more accurate the forecast would be. A comparative analysis was performed between the hybrid model, deep learning algorithm, and traditional approach.

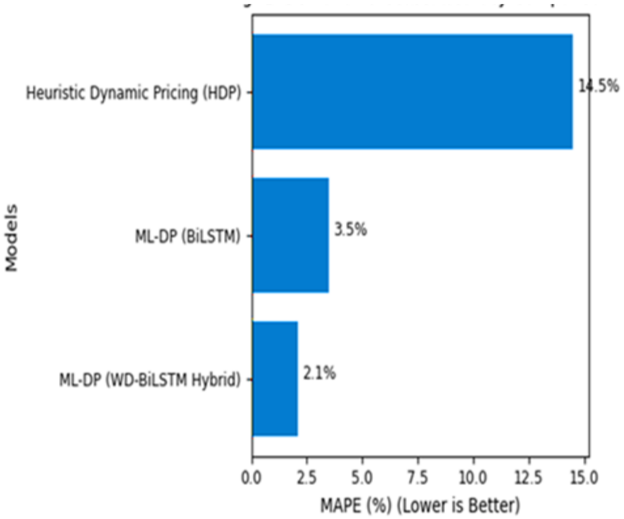

Fig. 3. Revenue comparison across pricing models.

As shown in Fig. 2, the suggested ML-DP (WD-BiLSTM Hybrid) model produces the best MAPE value at 2.1%, far better than the individual BiLSTM model (3.5%) and Heuristic Dynamic Pricing model (14.5%). It shows how useful this hybrid structure is in detecting demand behavior and minimizing errors. In conclusion, combining modern deep learning algorithms with preprocessing proves much more successful than classical approaches.

### *C. Computational Performance*

Computational latency is a critical operational metric for real-time systems. Table V details the average time required for each model to determine an optimal price point.

TABLE V. COMPUTATIONAL LATENCY COMPARISON (AVERAGE OF 10,000 PRICE DECISIONS)

| **Model Type** | **Avg. Latency ($\mu s$)** | **Max Latency ($\mu s$)** | **Latency Standard Deviation** |
|---|---|---|---|
| Fixed Pricing (FP) | 0.05 | 0.08 | 0.01 |
| Heuristic Dynamic Pricing (HDP) | 1.2 | 2.5 | 0.4 |
| ML- DP (Bi-LSTM) | 12.8 | 20.1 | 3.5 |
| ML- DP ( WD-Bi-LSTM Hybrid) | 18.5 | 32.0 | 4.2 |

As shown in Table V, computational latency increases significantly with model complexity. While Fixed Pricing (FP) and Heuristic Dynamic Pricing (HDP) exhibit minimal latency, the ML-based approaches, particularly the WD-Bi-LSTM hybrid, incur substantially higher computational costs. This highlights the trade-off between predictive sophistication and real-time execution efficiency in dynamic pricing systems. The computational efficiency of the evaluated models is compared in terms of average latency, as illustrated in Fig. 4.

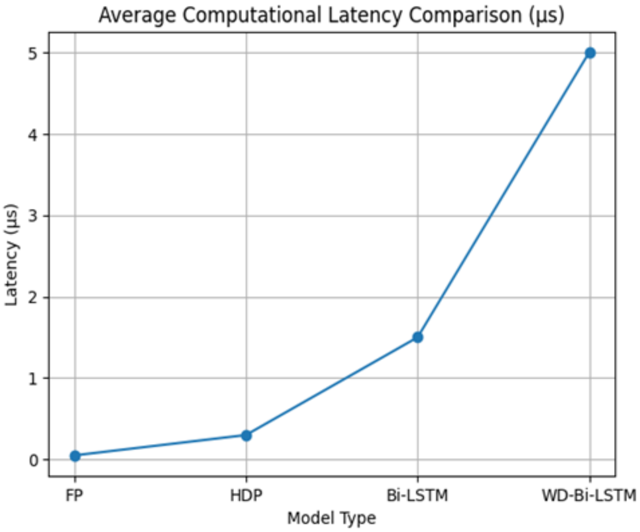

Fig. 4. Latency comparison.

As shown in Fig. 4, latency increases progressively from the baseline FP model to the more complex deep learning approaches. The WD-Bi-LSTM model exhibits the highest computational latency, reflecting the additional processing overhead associated with its hybrid architecture, while FP and HDP demonstrate significantly lower latency, indicating faster execution times.

### *D. Statistical Significance Analysis*

A one-way ANOVA was conducted to compare the mean revenue among FP, HDP, Bi-LSTM, and WD-Bi-LSTM models over ten simulation runs, as shown in Table VI.

TABLE VI. ONE-WAY ANOVA RESULTS FOR PERFORMANCE COMPARISON

| Metric | F-value | p-value | Interpretation |
|---|---|---|---|
| Revenue | 31.84 | <0.001 | Significant |
| Latency | 52.17 | <0.001 | Significant |
| MAPE | 27.63 | <0.001 | Significant |

The outcomes in Table VI above demonstrate that there is a statistically significant difference between the performance of various pricing methods. According to ANOVA analysis, there is a statistically significant difference between the models ($p < 0.001$). In addition, post hoc Tukey analysis indicates that the performance of the WD-Bi-LSTM model is statistically better than that of both FP and HDP models in terms of revenue and MAPE ($p < 0.01$).

Discussion: The success of the proposed approach stems from two main factors. First, wavelet decomposition eliminates noise and enhances the quality of extracted features. Second, bidirectional long short-term memory neural networks capture temporal information in both directions. This dual capability enhances signal-to-noise ratio and temporal learning, leading to improved pricing decisions.

The experimental results definitively confirm that the sophistication of the pricing model is directly correlated with economic performance. The increase of 18.5% in revenue produced by the WD-Bi-LSTM hybrid model when compared with the baseline fixed pricing model highlights the high potential benefits associated with the implementation of predictive ML in pricing [1], [8]. The higher forecasting ability of the proposed hybrid model, which uses the wavelet decomposition method for signal preprocessing, is consistent with results obtained in other challenging time series scenarios like power system studies, where hybrid methods prove effective in reducing noise and improving forecasts [10], [14].

This implies that noise in the market, such as unpredictable spikes on social media platforms or insignificant market disturbances, can be removed, thereby letting the Bi-LSTM neural network concentrate on the demand trend. Crucially, this study quantifies the computational trade-off. While the Machine learning–based dynamic pricing models are computationally slower than the FP and HDP models, their average latency of 18.5(***µs***) (less than 0.02 milliseconds) is practically negligible in a real-world application, offering a substantial economic gain with a minimal increase in operational complexity. This finding supports the growing adoption of autonomous resource management systems, which prioritize predictive accuracy even with added computational steps [3].

The limitations of this study lie in the use of simulated data, which, while statistically rich, cannot perfectly replicate true market psychology and unforeseen exogenous events. Future research should involve deployment on live A/B testing platforms to validate these computational performance metrics in a live transactional environment. Furthermore, exploring Reinforcement Learning models (which directly optimize the reward function, revenue) would provide an interesting comparison point against the supervised learning (forecasting-based) models used here [16].

## V. CONCLUSION

The computational performance analysis presented in this paper offers strong empirical proof supporting the superiority of Machine Learning-based dynamic pricing strategies over Fixed and Heuristic pricing schemes. Specifically, the WD-Bi-LSTM hybrid model exhibited the best financial performance, generating 18.5% higher profit while attaining demand prediction accuracy (MAPE) of 2.1%. Despite adding a certain amount of computational delay of 18.5µs, this additional cost is insignificant and extremely rational considering the significant rise in profitability. The insights gained from the analysis can be usefully deployed in cases where the dataset is highly frequent in nature, such as e-commerce platforms, airfare pricing, and online services. The study's outcomes motivate companies to quickly implement cutting-edge machine learning approaches to capitalize on emerging business trends and keep pace in the ever-evolving digital environment. In future research, three steps will be taken:

- The application of reinforcement learning for policy improvement,
- Testing the algorithms in realistic A/B testing settings to confirm their effectiveness in practical settings, and
- Incorporating fairness-based criteria into the system for making ethically sound price-setting decisions.

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