Artificial Intelligence and Dynamic Pricing Strategies: Enhancing Competitiveness in E-Commerce

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Abstract*—Dynamic pricing is vital for e-commerce companies to adapt to the dynamic pricing techniques if they have to maximize their revenues without having too much stock. To efficiently respond to changes in demand, accurate demand forecasting is central to the process of making changes in pricing. The main problem with conventional approaches to price determination is that usually there is no way the price can be changed in response to changes in the market. New developments in Fourier Analysis Networks (FANs) and Reinforcement Learning (RL) present the potential for improving demand forecasts and price optimization. The objective of this work is to implement FANs for demand forecasting in parallel to an RL agent for dynamic pricing and fine-tune the RL agent via Hyperband as the hyperparameter tuning method to create an efficient and adaptive pricing model. Thus, the integration of time series demand forecast with dynamic pricing mechanism allows for daily business to change their prices according to the forecasted demands, market status, and competitive prices. The hybrid system takes the demand forecast from the FANs to facilitate the RL agent's decision to set appropriate prices. RL agent acts with the environment, changing prices based on the forecasts of demand and stock, as well as the prices of competitors. Hyperband optimization, therefore, refines the hyperparameters of the agent to increase efficiency. The findings show how the implementation of the proposed hybrid system exceeds conventional pricing models. The demand forecast accuracy of the model stood at 95.65 % to achieve better revenues uplifts. The presented framework provides the e-commerce companies with the opportunity for better adjustment and implementation of different pricing strategies to increase profitability and minimize the time spent on identification of different conditions on the market.

Keywords: Dynamic Pricing, E-commerce, Demand Forecasting, Fourier Analysis Networks (FANs), Reinforcement Learning (RL), Hyperband Optimization, Real-time Pricing.

I. INTRODUCTION

Implementing dynamic pricing has become a vital necessity in e-commerce organizations with the desire to enhance the firm's revenue, stock control, and market stake [1]. In price information age the price is not fixed and is adjusted according to various factors including; demand swings, market trends, customer and competitor's behaviour, and seasonality [2]. Today and adaptive pricing strategies have been popularised by the giants in the e-commerce business such as Amazon and eBay. This strategy helps businesses to make much higher profits during event's high demand and fare better in periods of low output demand [3]. It is therefore clear that successful dynamic pricing rests on the robust demand forecast whose output feeds into the right price [4]. Thus, Artificial Intelligence (AI) has emerged as a potent tool to improve the aspect of pricing by providing unprecedented access to large datasets and knowledge. Independent on the type of good or service, there is evidence that the utilization of machine learning (ML) algorithms is rising sharply for enhancing dynamic pricing models, which goes through historical data, market trend, and consumer's behaviour analysis in consolidating its strategies for the future demand [5]. As Remember, AI algorithms in pricing have the capabilities to acquire an understanding of customer behaviour; respond to consumers' views dynamically and improve their algorithms through learning processes [6]. Meanwhile, by utilizing AI and especially such methods as Reinforcement Learning (RL) and Fourier Analysis Networks (FANs) businesses can optimize the price making process and increase the resulting revenues and satisfy the customers at the same time [7] [8].

The impact of this research is that it facilitates proper evaluation of current and future prices for e-commerce companies so that they may adapt to the ever-changing market conditions. Using Fourier Analysis Networks (FANs) for demand forecasting and Reinforcement Learning (RL) for dynamic pricing, this work offers a novel framework that presents the state-of-the-art solution for companies to make the right pricing decision in real time. This study improves the current knowledge regarding the use of AI in dynamic pricing by presenting a compound model, which is effective in dynamically responding to the fluctuations in the market environment.

- The current framework presents a dual model consisting of FANs for demand forecasting and RL for pricing adaptations with better flexibility and precision.
- Hyperband optimization is used to improve the hyperparameters of the RL agent, which involves less time to train and more precise price to make instant changes.
- An analysis of the hybrid system shows that it is better than conventional pricing models when it comes to overall revenue estimates as well as the errors in the estimates.
- Real time price changes can assist an organization in reversing quickly and help in enhancing business competitiveness and profitability.

The rest of the sections of this research have been organised as follows: Review of the existing literature of AI-driven dynamic pricing models in Section II. In Section III, proposed hybrid technique is explained. The presents the experimental results in Section IV. In Section V, Conclusion and further work is mentioned and the study is concluded.

II. LITERATURE REVIEW

Dynamic pricing, which is a rather dry-sounding word to describe a very colourful practice, refers to the practice of modifying prices continuously within the e-commerce realm, based on real-time demand, competition, inventory, and other market conditions [9]. It is the presence of AI that makes dynamic pricing so much better than anything we've ever had before: it allows the system to forecast demand and adjust prices as indicated by real estate analytics that take in a wealth of data and complex algorithms. Personalized pricing according to individual customer profiles, historical data, and purchasing behaviours is really what's at heart of these models, which AI powers into real-time adjustments in prices [10]. Dynamic pricing has evolved over time such that, while it started from being relatively simple supply-and-demand models, it has gone on to realize far more sophisticated algorithms adjusting prices due to a wider range of factors, including competitors' price fluctuations and customer behavior changes [11]. This early system depended on rule-based form of price adjustment; but, plans have changed since a huge influx of more and more complicated data comes with breakthrough advancements in machine learning (ML) [12]. Driven by the need to improve revenue optimization, inventory management, and personalization of consumer experience, dynamic pricing systems powered by AI have been on the rise lately among e-commerce [13]. Some of the ML models in use across industries for dynamic pricing and demand forecasting include; Machine Learning [14], Deep Learning, and Reinforcement Learning in retail, hospitality, and transportation [15]. With the use of AI, the pricing strategy results from past experiences as well as capturing relationships within the market, gaps are still present as to addressing functional issues [16]. Further, limited literature has been published to understand the long-term effects of dynamic pricing on customer base, the ethical, transparency and regulatory issues that businesses may encounter while rolling out AI based pricing strategies [15]. More research needs to be dedicated to ensure that alongside our profit chase we are fair to our customers while addressing issues of transparency in pricing of AI solutions.

III. RESEARCH MECHANISM

The proposed methodology involves the use of Fourier Analysis Networks (FANs) for demand forecasts with a decision-making Reinforcement Learning (RL) agent bounding Hyperband optimization for dynamic e-commerce prices. FANs are used to decompose the historical sales data, in terms of frequency, to obtain information on cycles and seasonality effects. These predictions act as the input for the RL agent who then modifies the price in response to markets conditions, stock availability and competitors.

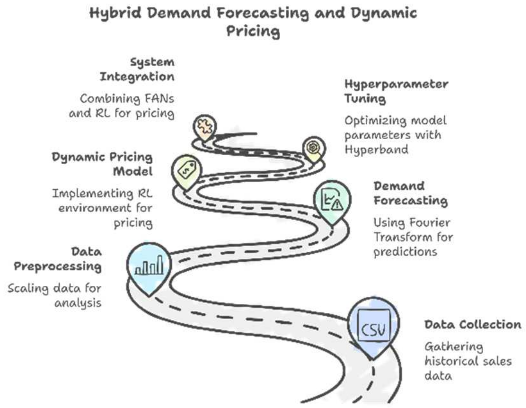

Fig. 1. Architecture of the Suggested approach

The RL agent learns over cases and thus optimizes the price model for revenue, customers' retention as well as competitiveness in real-time. Hyperparameters of the RL agents are adjusted using hyperband optimization to guarantee the efficiency of the training phase working. The policy structure is a real-time pricing adjustment loop that constitutes responding to the new anticipated demand and changing in the market. The system is learned from past data and is assessed from the performance of the expected forecasts, revenues, and the effectiveness of the pricing strategies adjustment. Thus, the proposed solution based on the FANs for demand forecasting in combination with RL for adaptive pricing, hyperparameters optimization through Hyperband provides the e-commerce businesses with a reliable, scalable solution improving the pricing strategies, increasing the profitability, and decreasing the time for operations.

A. Data Collection

The Online Retail II dataset in which the data retrieved from Kaggle involves the transaction information of a UK based non-store retailing company which mainly deals in all-occasion gift-ware rides. This data set is from December 1, 2009, to December 9, 2011 and have various types of transactions involved most of the customers being wholesalers. The dataset includes several key attributes: Option Invoice No; Stock Code; Description, Quantity; Invoice Date; Unit Price: The price per unit in British pound (£); Customer ID; Country. This data can be accessed on Kaggle, and is commonly employed in e-commerce research to examine trends in sales, why customers behave the manner they do and its access to areas like demand forecasting and dynamic pricing [17].

B. Data Pre-processing

The initial steps in data pre-processing for this Online Retail II dataset includes the following important steps. First, there are gaps which contain missing values: it is possible to drop such rows or impute values, for example, in the CustomerID column depending on the purpose of analysis. The Description field can also have missing values which can be changed to "Unknown Product" or, if not significant, can be deleted. For improves data cleanliness, only the transaction where the Invoice No starts with 'C' are omitted for they indicate cancellations. Second, data types are guaranteed to be correct; for instance, in the dataset, Invoice No is converted into a string form of data, while Invoice Date is changed to time series format for time analysis. Quantity and Unit Price are identified for Outliers where minimum and maximum values are placed at appropriate limits and/or negative entries are eliminated by applying Outlier detection using Z-Score. Also, the Country field has redundancy because country names are normalized because they sometimes differ from each other, for instance UK and United Kingdom.

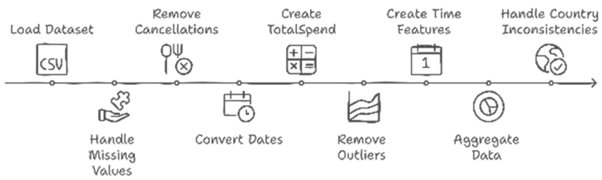

Fig. 2. Data Cleaning and Transformation Process

C. Fourier Analysis Networks (FANs) for Enhanced E-Commerce Sales Forecasting

Fourier Analysis Networks (FANs) introduce Fourier transforms in conjunction with deep learning to discover and forecast cyclic reoccurrence present in time series data. Discrete Fourier transforms decompose time varying signals into their frequencies so as to identify repetitive cycles within them. This method is particularly appropriate in environments such as the sale of clothes and other products through the Internet since sales records often display cycles within the year, the week or the month due to things such as seasons, holidays, and promotional events. FANs employ the Fourier transforms to search for the frequency contents of the sales data that can be imported to a neural network for further trend forecasting and the best pricing policy determination. This can be observed through periodic trends in the features InvoiceDate and Quantity on the Online Retail II dataset containing transaction data. Through the use of FANs on this kind of data, e-commerce firms will be able to capture nonlinear patterns such as cyclic features such as increase in demand during certain times of the year or during promotions, thus improving sales forecast and pricing strategy.

$$F(w) = \int_{-\infty}^{\infty} x(t)e^{-iwt}dt \tag{1}$$

Here, $F(\omega)$ represents the Fourier coefficients (frequency components), ω is the angular frequency, and $x(t)$ is the time-domain signal (sales data).

D. Design of the RL Agent for Dynamic Pricing

Dynamic pricing is the very timely phenomena of pricing products based on changing demand, competitors' prices, customers' behaviour, and other market conditions. Reinforcement Learning (RL) is actually a paradigm that fits best for this real-time dynamic adjustment of prices on the agent learning from his/her own experience as a result of all previous possible pricing decisions and the feedback from them. This will be further enhanced if integrated with particular advanced techniques like Fourier Analysis Networks (FANs) for predicting demand. This study describes the design of the RL agent, the optimization method Hyperband optimization, and how FANs combine with RL for a better dynamic pricing policy.

1) Hyperband for RL Hyperparameter Tuning

Hyperband is an important efficient optimizer to tune hyperparameters for reinforcement learning models, which cost time in training. It dynamically allocates resources over different hyperparameter configurations, early-stopping underperformers, and it can balance exploration of novel configurations against exploitation of promising ones. Acceleration has thus been achieved in finding optimal settings like learning rate, discount factor, and exploration-exploitation trade-offs, thereby significantly improving the performance of RL agents.

E. Dynamic Pricing Optimization with FANs and Enhanced Hyperband-Optimized RL

The combination of Fourier Analysis Networks (FANs) with a Reinforcement Learning (RL) system improved by an improved Hyperband brings synergistic learning to the area of dynamic pricing. The periodic characteristics such as seasonal, weekly and daily sales patterns can be observed after time-series sales data is decomposed by FAN into frequency components. This lets one expect demand of a certain product to very high degree depending on simple factors such as holidays, promotions and cyclical trends. These specific predictions can, therefore, be employed by the RL agent to update prices to achieve business goals. An improved version is applied to Hyperband as the novel way of fine-tuning the RL system's hyperparameters with significant efficiency. In traditional Hyperband HRB splits up the fixed CPU cycles and pushes the configurations which have a higher potential for better results to go ahead with early stopping. Some improvements could be the inclusion of a Bayesian optimization within the Hyperband paradigm in order to better steer the resource decisions. The method proposed herein merges the randomness of Hyperband with the probabilistic approach of Bayesian methods, aiming at a more efficient and efficient exploration of large hyperparameter search spaces. The improved Hyperband acts as a control algorithm which increases learning convergence rates through adjusting exploration–exploitation trade off according to performance trends.

This real-time workflow action begins with data collection such that it gathers transaction data along with inventory levels, customer behaviour, and even competitor prices. After collecting, FANs process historical sales records and use them to forecast demand using update in state for the RL agent and also a context. The RL agent is, therefore, empowered with optimally fine-tuned hyperparameters to autonomously decide from among pricing actions, such as increase or decrease or maintain prices, in order to maximize rewards like revenue or customer loyalty or inventory turnover. Reward feedback is used to iteratively update the agent's strategy with improved adaptations Hyperband ensures continuous hyperparameter refinement along with more robust learning outcomes. The RL agent's puissant ability allows this advanced system to adapt its modeling with agility to market changes using still the fine prediction made by FANs of demand and the efficient hyperparameter tuning of the Hyperband. Subsequently, such techniques are useful in achieving dynamic and really flexible pricing strategies, collecting short-term revenue advantage with long-term strategic objectives such as customer retention and competitiveness in the market for sustainable growth under the e-commerce landscape.

IV. Results and Discussion

This section discusses the findings of incorporating Fourier Analysis Networks (FANs) into Reinforcement Learning (RL) for dynamic pricing for e-business. The findings show the system is beneficial for demand forecasting, price changes, and saves time more than traditional approaches. The system was programmed in Python and utilized TensorFlow, Pandas, and Matplotlib; the RL agent used Hyperband optimization to achieve target hyperparameters. The subsequent sub-sections present an elaborate, analysis of the performance metrics and the finding as illustrated below.

A. *Pricing Adjustment Decisions by the RL Agent*

Table 1 shows the RL model alignments of product prices relative to demand, competitor's prices, and customer behaviours. Subsequently, based on Fourier Analysis Networks (FANs) demand forecasts, the RL agent adjusts the prices for the product to maximize revenue while remaining affordable. To increase sales volume of products such as Product IDs 10001 and 10004, the agent raises their prices while lowering prices of products with low sales volume, such as Product ID 10003. In the case of stable demand products such as Product ID 10002, the company's agent does not change prices. These adjustments also factor in a competitor's strategies and this makes for a more strategic approach to pricing.

TABLE I. Pricing Adjustment Decision

Product ID	Predicted Demand (Units)	Current Price (£)	Competitor Price (£)	Price Adjustment Action	New Price (£)
10001	1200	15.00	14.50	Increase	16.00
10002	850	20.00	21.00	Maintain	20.00
10003	450	10.00	10.50	Decrease	9.50
10004	2300	30.00	29.50	Increase	32.00
10005	1500	25.00	24.00	Decrease	23.00

B. *Evaluation of FANs Model Demand Prediction Accuracy*

Figure 3 analyses the degree of fit of the actual and the predicted values of demand made using the Fourier Analysis Networks (FANs) model for different products. Taken altogether, the FANs model was highly accurate, exhibiting variations in error between 2.13% and 12.5%. For instance, Product ID 10004: the Demand predicted - 2,300, the actual demand recorded - 2,350, the error percentage - 2.13% and accuracy level down to 97.87%. Nevertheless, the analysis for Product ID 10003 yielded only a relatively low accuracy of only 87.5 percent and error rate of 12.5 percent only. In general, FANs model allowed for accurate demand forecasts which are essential for price changing in the hybrid FANs-RL system.

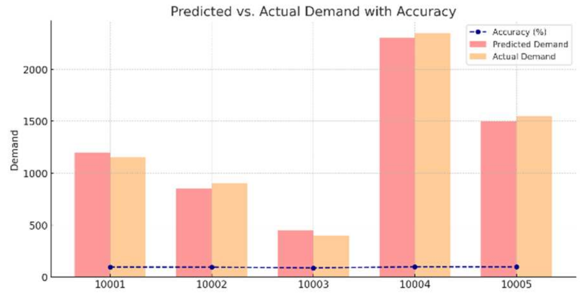

Fig. 3. Demand forecasting Assessment

C. *Comparison of Forecasted and Actual Revenue in FANs-RL System*

Figure 4 evaluates the performance of the hybrid FANs-RL system based on the actual and the forecasted revenues based on the dynamically adjusted price. In the case of most commoditized products, the RL agent's price action provided actual revenues that were at par or even better than the revenue estimates, for example Product ID 10001 had increased its revenue by 6.67%. Product ID 10004 was also over forecast by an average of 6.57% . Yet, although there are minor revenue shortfalls in the products 10002, 10003, and 10005, the forecast errors are only between - 1.43% and - 5%. As shown by the given table, the system is efficient in using demand forecast for flexible pricing and in generating maximum revenue.

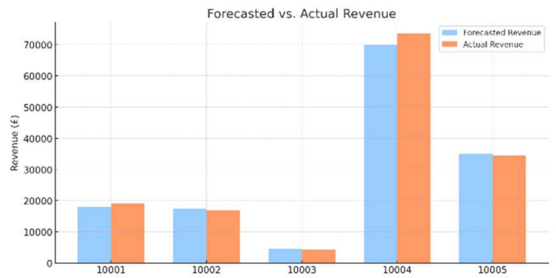

Fig. 4. Forecasted and Actual Revenue in FANs-RL System

D. *Analysis of Time Efficiency in the Hybrid FANs-RL System*

Figure 5 brings illustrations of how the proposed hybrid system which is the FANs-RL system incorporating Fourier Analysis Networks (FANs) with a RL algorithm optimized by Hyperband works with improved time efficiency. The hybrid system halves the training time to six hours because of Hyperband's ability in hyperparameter tuning in comparison to the ten hours of traditional techniques. Also, the real-time pricing adaptation time is improved to 18 seconds, while it takes at least 30 seconds in previous systems. The total consolidation time of the hybrid system is approximately 6.3 hours, which is faster when compared to 10.5 hours of conventional methods indicating the effectiveness of the system in training as well as implementation. This improvement helps organizations to have more opportunities to make better and quicker data-based decisions about their prices in the market.

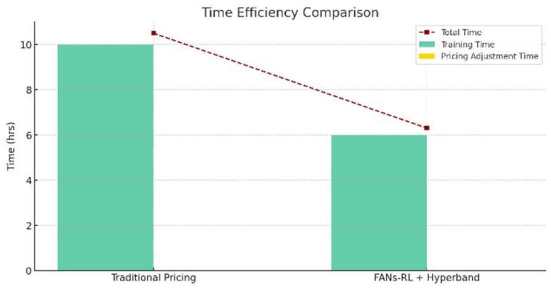

Fig. 5. Time Efficiency Analysis

V. CONCLUSION AND FUTURESCOPE

This research proves how the proposed approach of augmenting Fourier Analysis Networks (FANs) for precise demand prediction with an efficient RL agent for real-time price modelling in e-commerce is useful. With Hyperband for hyperparameter tuning in the hybrid system, the pricing can be made significantly more accurate and efficient compared to traditional pricing models while also maximizing the revenue. These findings reveals better enhancements, with forecasted revenue enhancements of up to 6.67%, the least forecasted error of 5.56%, and high model precision of 95.65 % in demand estimations. As it stands the proposed framework presents e-commerce businesses with a scalable and responsive model where dynamic pricing can be done in real-time depending on forecast demand, competitor's price, stock availabilities and the like. This adaptive pricing system not only improves the manipulative capability and increases profitability but also decreases the operation time thus offering a good mechanism due to the high variations and intense competition in the online market. In aggregate, FANs, RL, and Hyperband afford an exciting prospect for fine-tuning price policies and optimising choices in the context of continuously shifting e-commerce environment dynamics.

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