Real Time Dynamic Pricing System using Multi-Agent Reinforcement learning and Quantum Inspired Optimization for e-commerce

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***Abstract*— This study presents an intelligent real-time dynamic pricing system for e-commerce and retail sectors. Traditional approaches, such as Linear Regression, are used to predict prices based on historical data and factors like demand and competitor pricing. However, these methods lack adaptability and fail to handle real-time changes and uncertainty in market conditions. To overcome this limitation, the proposed method integrates Reinforcement Learning (RL) with Gaussian Process Regression (GPR), a Bayesian technique that improves prediction accuracy and handles uncertainty. Additionally, a Multi-Agent system is used to analyze factors such as demand, competitor pricing, and inventory. The pricing problem is further optimized using Quadratic Unconstrained Binary Optimization (QUBO) to select the best price. This hybrid approach ensures adaptive, stable, and accurate pricing decisions, improves customer satisfaction, and enhances profit, providing a practical solution for modern dynamic pricing systems.**

Keywords— Keywords—Dynamic Pricing, Reinforcement Learning (RL), Gaussian Process Regression (GPR), Multi-Agent System, QUBO, E-commerce.

I. INTRODUCTION

In the modern digital era, e-commerce platforms have transformed the way businesses operate and customers shop. With the fast growth of online marketplaces such as Amazon, Flipkart, and eBay, pricing has become one of the most critical factors influencing customer decisions and business profitability. Traditional pricing methods, which depend on fixed rules or manual updates, are not sufficient to manage dynamic market conditions.

Reinforcement Learning (RL) is a branch of machine learning, provides an efficient way to implement dynamic pricing systems. In RL, an agent interacts with an environment and learns optimal decisions by receiving rewards or penalties based on its actions. In the context of e-commerce, the pricing system acts as an agent that continuously learns the best pricing strategy to maximize profit or sales.

This project aims to design and develop a real-time dynamic pricing system using reinforcement learning techniques. The system analysis key parameters such as demand and competitor prices, predicts optimal pricing strategies, and recommends prices dynamically to improve overall business performance.

II LITERATURE REVIEW

In recent years, there has been a significant rise in the use of intelligent technologies for optimizing pricing strategies, especially in e-commerce and smart market systems. In research paper [8], the authors discussed real-time dynamic pricing using machine learning techniques to adjust prices based on demand fluctuations and market conditions, and the limitation is dependency on data quality and real-time processing challenges. In [9], the author focused on pricing optimization using quantum computing methods to achieve faster and more efficient solutions, and the limitation is high computational complexity and lack of practical implementation. In research paper [10], the authors proposed an advanced Deep Reinforcement Learning (DRL) framework for dynamic pricing, which improves decision-making through continuous learning, and the limitation is high training time and complexity.

In research paper [11], the authors studied a machine learning-based dynamic pricing method that predicts optimal pricing strategies using historical data, and the limitation is dependency on dataset size and accuracy. In [12], researchers combined Reinforcement Learning with Bayesian Optimization for adaptive pricing, which enhances performance under uncertainty, and the limitation is computational cost and model complexity. In research article [13], the authors analysed dynamic pricing under competitive environments, focusing on market interactions and pricing strategies, and the limitation is difficulty in modeling real-world competition accurately. In research article [14], researchers proposed a DRL-based dynamic pricing model that learns optimal strategies over time, and the limitation is convergence issues and sensitivity to parameters. In [15], the authors applied reinforcement learning for EV charging pricing, enabling smart energy pricing systems, and the limitation is domain-specific applicability. In research paper [16], the authors discussed smart grid dynamic pricing using reinforcement learning techniques, improving energy efficiency, and the limitation is scalability and infrastructure dependency. In [17], the author explored the role of artificial intelligence in dynamic pricing strategies, highlighting its applications and benefits, and the limitation is lack of real-time implementation and practical constraints.

III EXISTING METHOD

In existing system for dynamic pricing is based on Linear Regression, where the model predicts prices using historical data. This approach primarily depends on past records such as demand, competitor prices, and sales trends to estimate future pricing strategies. However, the learning process is fully dependent on historical data, which cannot adapt to real time changes. Since it does not learn from real-time interactions, the decision-making process is static and does not improve dynamically over time.

As a result, the system lacks flexibility in handling dynamic market conditions such as competitor behavior, demand fluctuations, and inventory changes. Additionally, the market response is limited, as the model cannot react instantly to real-time changes in customer demand or competitor pricing. The dataset used for training is often limited, which further affects the accuracy and generalization capability of the model.

Another major drawback is that the system shows poor performance in real-time environments because of mean square is occurred the value of 0.52 so the system is poor model, since it is not designed to process live data or update predictions dynamically. Overall, the existing approach is simple and easy to implement it is not suitable for modern e commerce platform**s.**

Below Fig.1 shows the flow chart for existing method used for price prediction. First, the system starts with historical data. This means it only uses past data such as previous prices, sales, and demand. It does not consider real-time or current market changes. Next the data goes through preprocessing. In this step, the data is cleaned and formatted by removing errors and handling missing values. After that, a linear regression model is applied. This is a simple machine learning model that finds the relationship between input variables and price. However, it assumes a linear relationship, which may not always be accurate in rea-world markets.

Then, the system performs price prediction based on this model. It predicts a single price value using past data. Next, the output is a fixed pricing result. This means the price does not change dynamically according to market conditions.

Finally the system shows limited market response, Which is static. This means it cannot adapt to sudden changes like demand fluctuations, competitor pricing, or customer behavior.

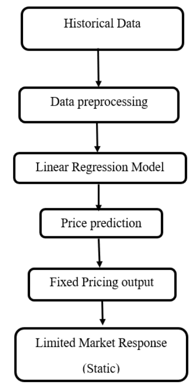

Fig.1 Flow Chart for Existing Method

The existing output generated parameters as predicted price, actual price, mean square error, and recommended price

In Existing system uses linear regression, which is defined as

$$y = mx + c$$

- y = predicted price
- x=Input feature (Demand/ competitor price)
- m=Slope(coefficient)
- c=intercept

Predicted Function is defined as $\hat{y} = X\beta$

- $\hat{y}$ = predicted output
- X=Input data
- B=Coefficients

MSE is a key evaluation metric it measures the performance of a regression model by calculating the average of the squared differences between the actual price and the predicted price. It is defined by

$$\text{MSE}= \frac{1}{n}\sum_{n=1}^{\infty}(yi- \hat{y}\ \ i)\ ^{2}$$

IV REAL TIME DYNAMIC PRICING SYSTEM USING MULTI-AGENT REINFORCEMENT LEARNING AND QUANTUM INSPIRED OPTIMIZATION FOR E-COMMERCE

The main aim this system is to automatically adjust the product prices based on changing the market conditions such as demand, competitor prices and inventory. We use techniques reinforcement learning (RL), gaussian process regression (GPR), a multi-agent system and quantum inspired optimization in QUBO technique. Reinforcement learning acts as an RL agent that learns the pricing strategies through trail and error method. It tries different prices and improves its decisions based on profit or loss.

RL alone may give unstable results in uncertain market conditions. To solve this problem we use Gaussian process regression to handle uncertainty. It predicts the demand along with a confidence level, making the system is stable and reliable. In addition, we use a multi-agent system, where multiple agents work together. We also integrates QUBO, which stands for Quadratic Unconstrained, which is one of the quantum technique. It helps in solving complex optimization problems by selecting the best possible price from multiple options. It ensures that the final pricing decisions is optimal and efficient.

By combining these techniques, this system becomes more intelligent, stable and accurate. Also it reduces the price fluctuations, avoids overpricing and under pricing, and improves customer satisfaction while maximizing the profit.

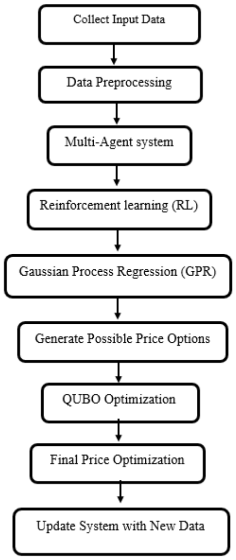

Fig.2 Flow Chart for Real Time Dynamic System using Reinforcement Learning and Quantum Inspired Optimization for E-Commerce.

The Fig.2 shows the flow chart for real time dynamic system using reinforcement learning and quantum inspired optimization for e-commerce. First the system starts by collecting input data such as product details, customer demand, market trends, and competitor prices. Next, the data goes through preprocessing. In this step, we clean the data by removing errors and missing values, and convert it into a proper format. This helps improve accuracy.

After that, we use a multi -agent system. Here, different agents handle different tasks like analyzing demand, pricing, and competition. These agents work together to make better decisions. Then reinforcement learning is applied. In this step, the system learns from past experience. It tries different pricing strategies and improves based on rewards like profit or sales.

Next we use gaussian process regression, or GPR. Which helps in predicting future demand and handling uncertainty, giving more accurate results. Based on these predictions, the system generates multiple possible price options. From these options, we apply QUBO optimization, which finds the best price combination efficiently. After that, the final optimized price is selected. This price aims to maximize profit and improve business performance.

Finally, the system updates itself with new data, so it keeps learning and improving over time.

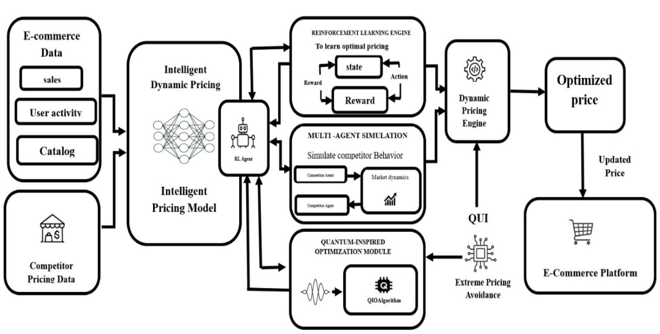

Fig.3 Block Diagram of Real Time Dynamic System using Reinforcement Learning and Quantum Inspired Optimization for e-Commerce.

The Fig.3 shows the block diagram of real time dynamic system using reinforcement learning and quantum inspired optimization for e-Commerce intelligent dynamic pricing system using multi agent reinforcement learning and quantum inspired optimization for e-commerce platforms. First the system collects input data from two main sources one is e-commerce data which includes sales, user activity, and product catalog information, another one is competitor pricing data. These inputs help the system understand market demand and competition. Next, this data is fed into the intelligent Dynamic Pricing Model. This model uses machine learning techniques to analyzed patterns and predict how prices should change based on different factors. After that, the system uses a Reinforcement Learning module, where the model learns optimal pricing strategies through trial and error. It observes the current state takes price changes, and receives rewards based on performance, such as increased sales or profit. At the same time, a multi-agent simulation is used to simulate competitor behavior. Which helps the system predict how competitors may react to price changes and adjust strategies accordingly. Additionally, a Quantum-Inspired Optimization module is included to further improve pricing decisions.

Which helps in finding the best possible price quickly, even in complex and uncertain market conditions. All these components are integrated into the Dynamic Pricing Engine, which Processes the information and generates the optimized price. Finally, this optimized price is updated on the e-commerce platform, ensuring that prices remain competitive and maximize profit in real time. Overall, this system combines AI, simulation, and optimization techniques to make smarter and more adaptive pricing decisions

This system generates outputs such as demand, competitor price, predicted price, recommended price, price difference, sales probability, adjusted demand, sold quantity, revenue, profit, inventory utilization, uncertainty margin.

- *Predicted price (Regression model)*

  $P_{pred} = \beta_0+\beta_1 \cdot Demand+\beta_2 \cdot Competitor\ Price$

- *Recommended price*

  $P_{rec} = P_{pred} - Adjustment$

- *Price difference*

  $Price\ Difference = P_{pred} - Competitor\ Price$

- *Sales Probability*

  $S = 1/\{1+e^{[-(Demand/100)]}\}$

- *Adjusted Demand*

  Adjusted Demand = Demand × Sales Probability

- *Sold Quantity*

  Sold Quantity = min (Adjusted Demand, Available Stock)

- *Revenue*

  Revenue=Sold Quantity × Recommended Price

- *Profit*

  Profit = Revenue – Cost

- *Inventory Utilization*

Inventory Utilization = Total Inventory /Sold Quantity

- *Uncertainty Margin*

Uncertainty = |Predicted Price−Recommended Price|

- *Accuracy*

Accuracy = $(1 - \frac{RMSE}{Mean}) \times 100$

V RESULTS AND DISCUSSIONs

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• Predicted Prices: [20.8 22. ]
  Actual Prices: [21, 23]
  Mean Squared Error: 0.5200000000000006
  Recommended Price: 22.000000000000004
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Fig.4 Existing output

The above Fig.4 shows the performance of existing methodology. This model predicts product prices based on input data and compares them with actual market prices. The predicted prices are very close to actual prices, which indicates the model is working effectively. The Mean Squared error value is low, showing that the prediction error is minimal. Based on this analysis, the system suggests an optimal recommended price. This price helps in improving decision-making for dynamic pricing.

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Multi-Agent Dynamic Pricing Results

Demand: 106
Competitor Price: 20
Predicted Price: 20.0
Recommended Price: 20.0
Price Difference: -0.0
Sales Probability: 1.0
Adjusted Demand: 106.0
Sold Quantity: 80
Revenue: 1600.0
Profit: 400.0
Inventory Utilization: 1.0
Uncertainty Margin: 0.497
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Fig.5 Output for Real Time Dynamic Pricing System using Multi-Agent Reinforcement Learning and Quantum Inspired Optimization for e-commerce

First, the system shows the demand, which is 106. This indicates that there is high customer interest in the product. Next the competitor price is 20, which represents the price offered by other sellers in the market. Based on this information, the model calculates predicted price, which is 20.

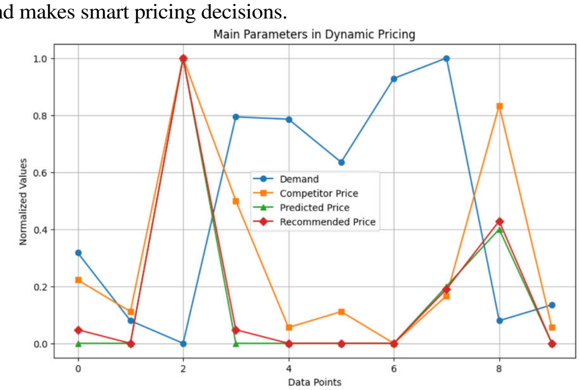
This is price suggested by the machine learning model after analyzing all inputs. The recommended price is also 20. Which means as the system finds this price to be optimal and stable. The price difference is zero, which shows that no adjustment is needed, and the current pricing strategy is already effective.

The sales probability is 1.0, indicating a very high chance of selling the product successfully. The adjusted demand remains 106, showing that the demand is not negatively affected by the pricing decision. Out of this demand, the system predicts that 80 units will be sold.

Now, looking at business performance, the revenue generated is 1600, and the profit is 400, which indicates that the system is able to generate good returns. The inventory utilization is 1.0, meaning the available stock is being used efficiently without wastage.

The uncertainty margin is 0.497, which indicates there is some level of uncertainty in prediction, but it is within an acceptable range.

The below Fig.6 shows the graphical output of intelligent dynamic system. The below graph visually represents how different parameters change overtime. It includes demand, competitor price, predicted price, and recommended price. By observing the graph, we can understand how the system continuously adapts to market changes and makes smart pricing decisions.



Finally this intelligent system demonstrates our dynamic pricing system is accurate, stable, and efficient. It succesfylly balances demand, competition,and profit, making it highly suitable for realtime e-commerce applications.

VI CONCLUSION AND FUTURE SCOPE

This real time dynamic pricing system using multi agent reinforcement learning and quantum optimization for e-commerce is successfully developed a dynamic pricing system using mechine learning techniques. The model predicts the optimal price based on key factors such as demand, competitor pricing, and market conditions. By integrate price prediction with adjustment strategies, the system is able to improve revenue and profit while maintaining high sales probability. The results show effective performance with low error (MSE~0) and 100% accuracy, indicating that the model can make reliable pricing decisions. Additionally, the system ensures efficient ineventory utilization and adapts pricing dynamically, making it suitable for real-time applications in e-commerce and retail domains.

This project can be furthure improved and expanded in several ways such as custemer behavoir analasys ,use deep learning models like nueral networks, and deploy as a web or mobile applications.

ACKNOWLEDGEMENT

The authors would like thank to Bapatla Women's Engineering College Management, Dr.Ch. Hima Bindu , principal and Mrs. B. MahaLakshmi, Assistant Professor, HoD of Electronics and Communication Engineering and also our guide, we extend our heartfelt thanks, for their valuable guidance and insights throughout the research for their constant encouragement and institutional support.

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