Dynamic Pricing for Parking Systems — Project Report

🧩 1. Overview

This project focuses on simulating and evaluating dynamic pricing strategies for a network of parking lots. The aim is to model real-world economic behavior—such as demand fluctuations, environmental conditions, and market competition—and translate it into intelligent price recommendations. The process consists of three progressively smarter pricing models, each building upon the logic of the previous one.

🧼 2. Data Preprocessing

The raw dataset was cleaned and transformed to prepare it for modeling. This involved combining date and time columns into a unified datetime format for proper time-series handling. The data was sorted chronologically by parking system to preserve the temporal structure needed for dynamic pricing.

Occupancy rates were calculated by dividing the number of occupied spots by the total capacity. Categorical features like vehicle type and nearby traffic conditions were encoded using one-hot encoding, allowing them to be included as numerical features in the models.

🧠 3. Model 1 — Linear Baseline Pricing

The first model serves as a simple baseline, where prices increase incrementally based solely on the occupancy rate of each parking lot. All systems begin with the same fixed base price. As demand (measured via occupancy) increases, the price rises linearly at a fixed rate per time interval.

This model reflects a basic supply-demand principle: higher utilization leads to higher prices. It is intentionally naive but provides a foundational comparison for more complex strategies.

📊 4. Model 2 — Demand-Based Pricing

The second model incorporates a broader set of features to estimate demand more realistically. It considers occupancy rates, queue lengths, and whether the day is marked as special (e.g., a holiday or event). Additionally, it factors in the type of vehicles present (e.g., bikes, trucks, cycles) and surrounding traffic conditions (e.g., high or low congestion).

These variables are each assigned specific weights to calculate a raw demand score. This score is normalized across the dataset to ensure consistency. The final price is then adjusted based on the normalized demand value, allowing for more responsive and nuanced pricing. Safeguards are built in to prevent the price from becoming too low or excessively high, maintaining a fair and sustainable range.

🧮 5. Model 3 — Competitive Pricing

The third model adds a market-oriented layer by analyzing how nearby parking lots are priced. It uses geographical coordinates to measure the distance between systems and identifies those within a close radius (e.g., 1.5 km) as competitors.

For each timestamp, if a system is nearly full and its competitors are charging lower prices, its own price is reduced slightly to remain competitive. Conversely, if nearby competitors are charging significantly more, the system raises its price moderately. This introduces competitive pressure, encouraging price sensitivity to both demand and external market dynamics.

🔁 6. Data Streaming Simulation

To simulate a real-time data environment, a generator-based approach was conceptually implemented. This mimics data arriving row by row, as it would in a live IoT setting where parking data updates continuously. While this project used pre-loaded data, the simulation lays the groundwork for future real-time integration with platforms like Pathway or Kafka.

📊 7. Visualization

Interactive plots were generated using Bokeh to visually compare pricing behavior across the three models. A selection of parking lots was chosen to maintain readability. The time-series plots clearly illustrate how pricing evolves under different models. Model 1 shows a steady upward trend, Model 2 reflects variable sensitivity to multiple factors, and Model 3 demonstrates adaptive behavior in response to competitor activity.

Color palettes were chosen carefully to distinguish each model visually, and legends were configured to allow toggling for clarity.

🧠 8. Demand Function Explained

The demand function combines multiple weighted factors: occupancy rate (to reflect current usage), queue length (as a proxy for unmet demand), and special days (which often increase demand). Vehicle types and traffic conditions further modify this score to account for real-world behavioral differences.

Each factor contributes differently to the overall demand. For example, heavy vehicles and high traffic increase demand more than cycles or low traffic. After combining all components, the result is normalized and used to influence pricing proportionally.

📌 9. Assumptions Made

- All parking systems begin with the same base price.
- Data is structured such that only one observation exists per parking lot per timestamp.
- Dummy variables may not exist in all datasets, so flexible access methods are used to prevent failure.

- The comparison between competitors is done at the exact same timestamp, assuming real-time synchronicity.
- A fixed proximity radius is used to define competitive zones (e.g., 1.5 km).

📈 10. Price Behavior Summary

Scenario	Model 1	Model 2	Model 3
High Occupancy	Gradual Increase	Rapid Increase	Possible Discount (if undercut)
Low Occupancy	Slow or No Rise	May Decrease	No Change
Special Event	No Effect	Significant Price Boost	Indirect Influence
Nearby Expensive Competitors	No Effect	No Effect	Slight Price Increase
Nearby Cheaper Competitors + High Load	No Effect	No Effect	Slight Price Drop

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✅ 11. Conclusion

This project developed and compared three dynamic pricing models, progressively integrating more complexity and real-world relevance. It transitioned from a simple linear strategy to a demand-aware system, and finally, to a market-aware competitive pricing approach.

Each model brings unique advantages, and the visual analysis highlights their differences clearly. The framework is scalable, adaptable to live environments, and can support integration with real-time data streams or advanced machine learning models in future expansions.