Dynamic Parking Pricing Simulation Report

1. Introduction

This report outlines the implementation and analysis of dynamic pricing models for parking lots. The goal is to optimize parking revenue while maintaining customer satisfaction by adjusting prices based on demand, competition, and other external factors.

Key Objectives:

- Develop three pricing models:
  - **Basic Linear Pricing** (Model 1)
  - **Demand-Based Pricing** (Model 2)
  - **Competitive Pricing** (Model 3)
- Compare pricing strategies under different demand scenarios.
- Visualize price fluctuations and occupancy relationships.

2. Methodology

2.1 Data Preprocessing

- **Dataset:** Parking occupancy data with timestamps, capacity, vehicle types, and traffic conditions.
- **Processing Steps:**
  - Convert timestamps to datetime format.
  - Map traffic conditions to numerical values (low=0.3, medium=0.6, high=0.9).
  - Handle missing values in QueueLength.
  - Sort data chronologically for time-series analysis.

2.2 Pricing Models

Model 1: Basic Linear Pricing

- **Formula:**

$$\text{New Price} = \text{Previous Price} + \alpha \times \text{Occupancy Rate}$$

    - Bounded between **50%–200%** of base price ($10).

- **Justification:**
    - Simple and interpretable.
    - Directly ties price to occupancy.

Model 2: Demand-Based Pricing

- **Factors Considered:**
    - Occupancy rate
    - Queue length
    - Traffic congestion
    - Special events (holidays, concerts)
    - Vehicle type (car, truck, bike)
- **Formula:**

$$\text{Demand Score} = \alpha \times \text{Occupancy} + \beta \times \text{Queue} - \gamma \times \text{Traffic} + \delta \times \text{Special Day} + \epsilon \times \text{Vehicle Weight}$$

Model 3: Competitive Pricing

- **Key Features:**
    - Considers nearby parking lots (within **1km**).
    - Adjusts prices based on competitors' availability and pricing.
- **Logic:**
    - If **high occupancy (>90%)**, match or slightly undercut competitors.
    - If **low occupancy**, price within market range (90%–110% of competitors).

3. Demand Function & Assumptions

3.1 Demand Function

The demand function in **Model 2** combines:

Demand=Occupancy+Queue Effect−Traffic Deterrent+Special Events+Vehicle Type AdjustmentDemand=Occupancy+Queue Effect−Traffic Deterrent+Special Events+Vehicle Type Adjustment

- **Occupancy (α):** Primary driver (weight = 0.6).
- **Queue (β):** Indicates pent-up demand (weight = 0.4).
- **Traffic (γ):** Reduces demand (weight = 0.3).
- **Special Events (δ):** Increases demand (weight = 0.5).
- **Vehicle Type (ε):** Trucks pay more (1.5x), bikes less (0.7x).

3.2 Assumptions

1. **Competitor Data:** Simulated (randomized prices and occupancy).
2. **Traffic Impact:** High traffic reduces demand (drivers avoid congestion).
3. **Price Bounds:** Minimum **$5**, maximum **$20**.
4. **Time Intervals:** Data sampled every **30 minutes**.

4. Price Dynamics

4.1 How Price Changes with Demand

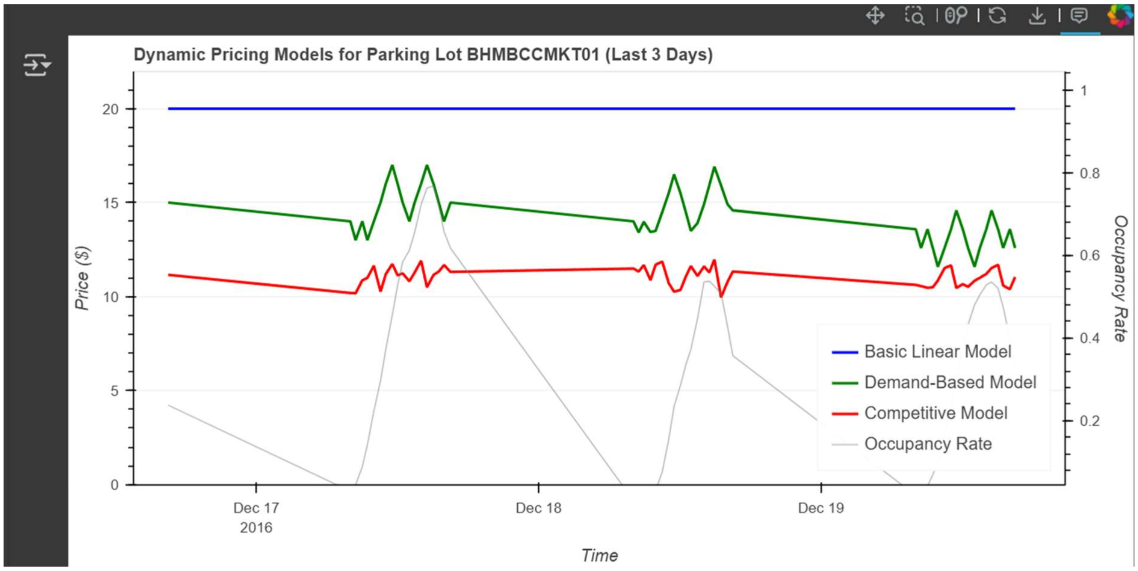
- **Model 1:** Linear increase with occupancy.
- **Model 2:** Non-linear, accounts for multiple demand factors.
- **Model 3:** Adjusts based on competitors (avoids underpricing).

4.2 Competitive Effects

- **High Demand:** If competitors are full, prices rise.
- **Low Demand:** If competitors have space, prices stay competitive.

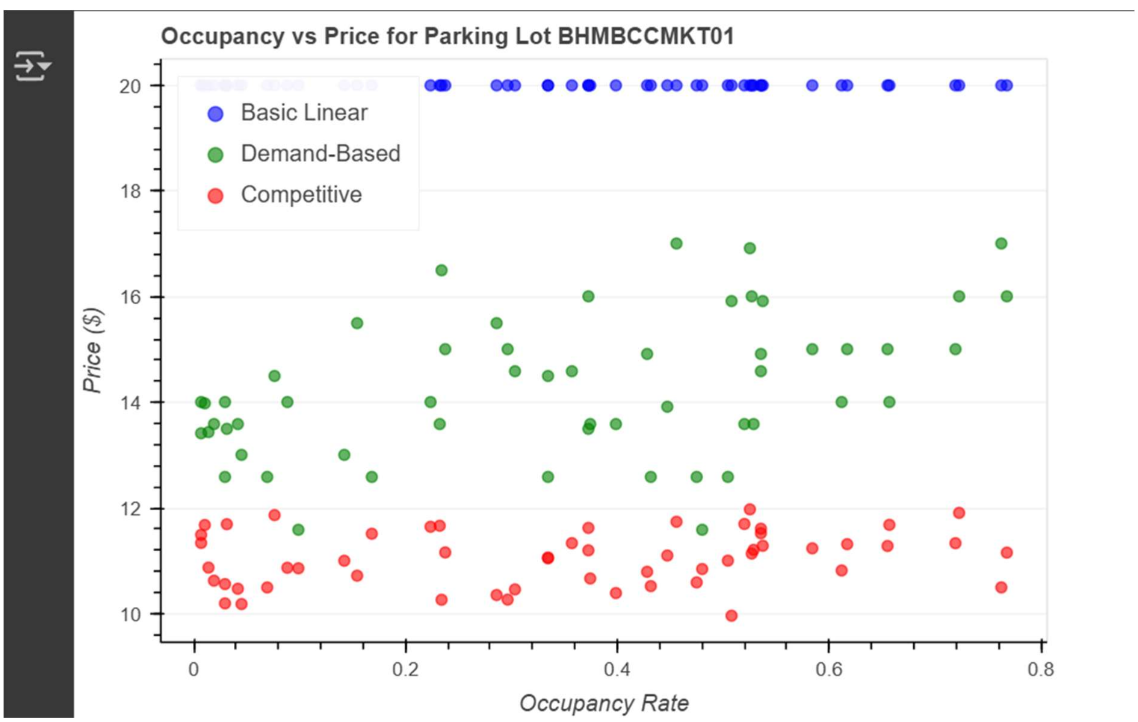
5. Visualizations

5.1 Time-Series Price Comparison



- **Blue:** Model 1 (Basic Linear)
- **Green:** Model 2 (Demand-Based)
- **Red:** Model 3 (Competitive)
- **Gray:** Occupancy Rate (secondary axis)

5.2 Price vs. Occupancy Rate



- Shows how each model responds to occupancy changes.

6. Conclusion

- **Model 1** is simple but lacks responsiveness.
- **Model 2** adapts better to demand fluctuations.
- **Model 3** provides the most balanced approach by considering competition.

Future Improvements

- Incorporate real-time competitor API data.
- Machine learning for dynamic parameter tuning.