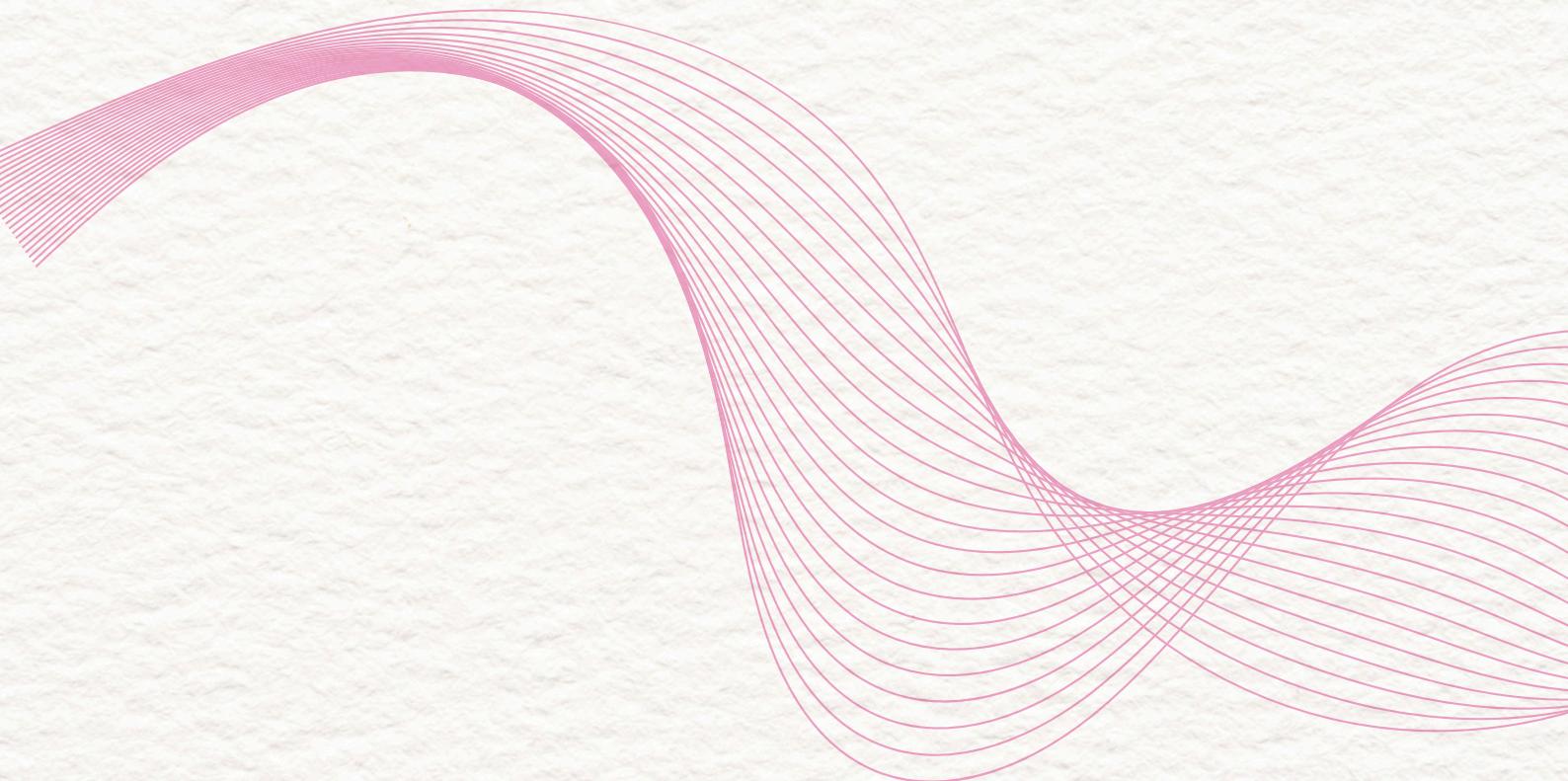


Dynamic Pricing for Urban Parking

CAPSTONE PROJECT REPORT

SUMMER ANALYTICS 2025



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Executive Summary

Urban parking is a limited and in-demand resource. Static pricing leads to either overcrowding in prime locations or underutilization in distant lots. This project aims to build a real-time, data-driven pricing engine for 14 parking lots using occupancy, traffic, queue length, vehicle type, and proximity to competitors.

Three progressively intelligent models were designed:

- **Model 1: Linear pricing based on occupancy rate**
- **Model 2: Demand-based pricing using multiple real-world factors**
- **Model 3: Competitive pricing that accounts for nearby lots and rerouting logic**

We used Python, Pandas, Numpy, and Bokeh to simulate real-time pricing and visualize trends, ensuring decisions are smooth, bounded, and explainable.

Problem Statement

Parking spots are a scarce urban asset. Cities often use fixed rates regardless of demand spikes during peak hours or empty lots during slow periods.

This leads to:

- **Overcrowding at central lots**
- **Wasted capacity in outer zones**
- **Long queues and frustrated users**
- **Missed revenue opportunities**

To combat this, we developed a dynamic pricing engine that:

- **Adjusts price in real-time**
- **Considers demand indicators**
- **Simulates intelligent decision-making**
- **Visualizes the impact live**

Dataset Overview

The dataset covers:

- **14 urban parking lots**
- **73 days**
- **18 time samples per day (from 8:00 AM to 4:30 PM)**

We cleaned, merged, and sorted data chronologically for each lot.

Feature	Description
SystemCodeNumber	Unique lot ID
Latitude / Longitude	Used to calculate proximity
Occupancy / Capacity	Used to compute OccupancyRate
QueueLength	Vehicles waiting
TrafficConditionNearby	Categorical: low/average/high
VehicleType	car, bike, truck, cycle
IsSpecialDay	0 or 1
LastUpdatedDate + Time	Merged into Timestamp

Assumptions

List all design assumptions:

Aspect	Value
Base Price	\$10
Price Range	\$5 to \$20
Traffic Map	low=0.2, average=0.5, high=0.8
Vehicle Weights	cycle=0.3, bike=0.6, car=1.0, truck=1.5
Rerouting Radius	0.5 km
Model Updates	Every 30 mins

Pricing Models Explained

Break it down clearly:

Model 1: Linear Based on Occupancy

Formula:

$$\text{Price}_{t+1} = \text{Price}_t + \alpha \times (\text{Occupancy} / \text{Capacity})$$

Base = 10, $\alpha = 2$

Increases as space fills

Visual: Include Bokeh chart of price curve over time

Model 2: Demand-Based

Demand function:

$$D = \alpha \cdot \text{OccupancyRate} + \beta \cdot \text{QueueLength} - \gamma \cdot \text{Traffic} + \delta \cdot \text{SpecialDay} + \varepsilon \cdot \text{VehicleWeight}$$

Price:

$$\text{Price} = \text{Base} \times (1 + \lambda \times \text{NormalizedDemand})$$

Parameters used:

$$\alpha = 0.6, \beta = 0.4, \gamma = 0.3, \delta = 1.0, \varepsilon = 0.7, \lambda = 0.5$$

Include:

Formula

Demand histogram

Price vs Occupancy chart

Model 3: Competitive Pricing

Adds spatial intelligence (haversine distance)

Logic:

- If my lot is nearly full and others nearby are cheaper → reduce price or reroute

If competitors are more expensive → slight price bump

Visuals:

Show pricing curves for 4 lots side-by-side

Include a map or table of lot coordinates (optional)

Pricing Models Explained

Let us break it down clearly:

Model 1: Linear Based on Occupancy

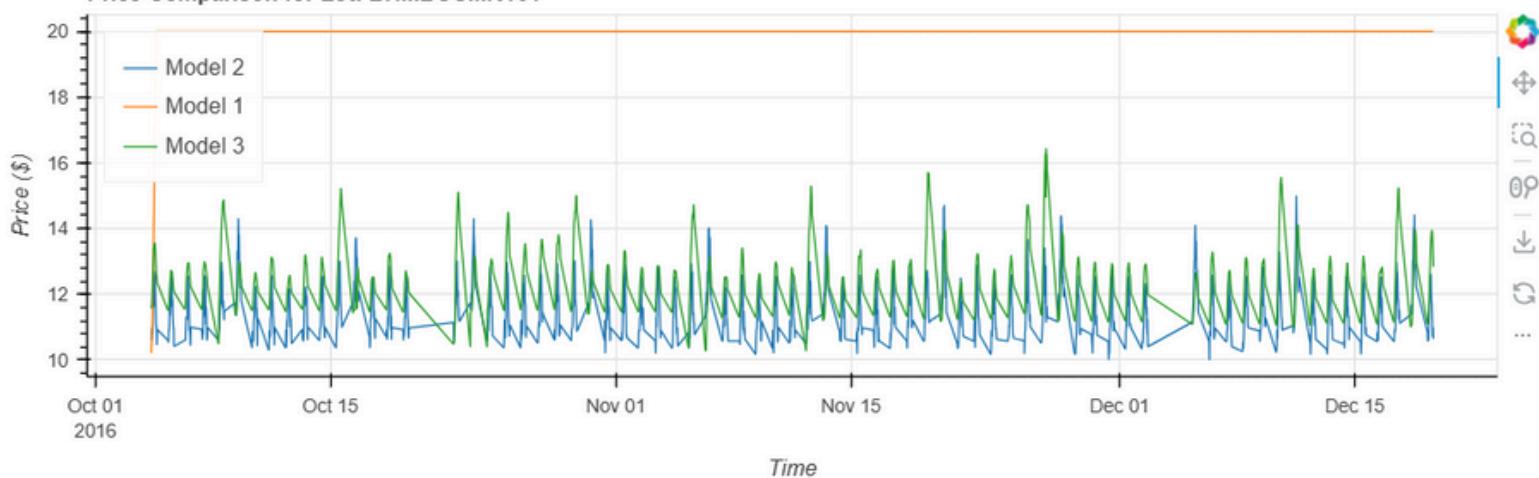
Formula:

$$\text{Price}_{t+1} = \text{Price}_t + \alpha \times (\text{Occupancy} / \text{Capacity})$$

Base = 10, $\alpha = 2$

Increases as space fills

Price Comparison for Lot: BHMBCCMKT01

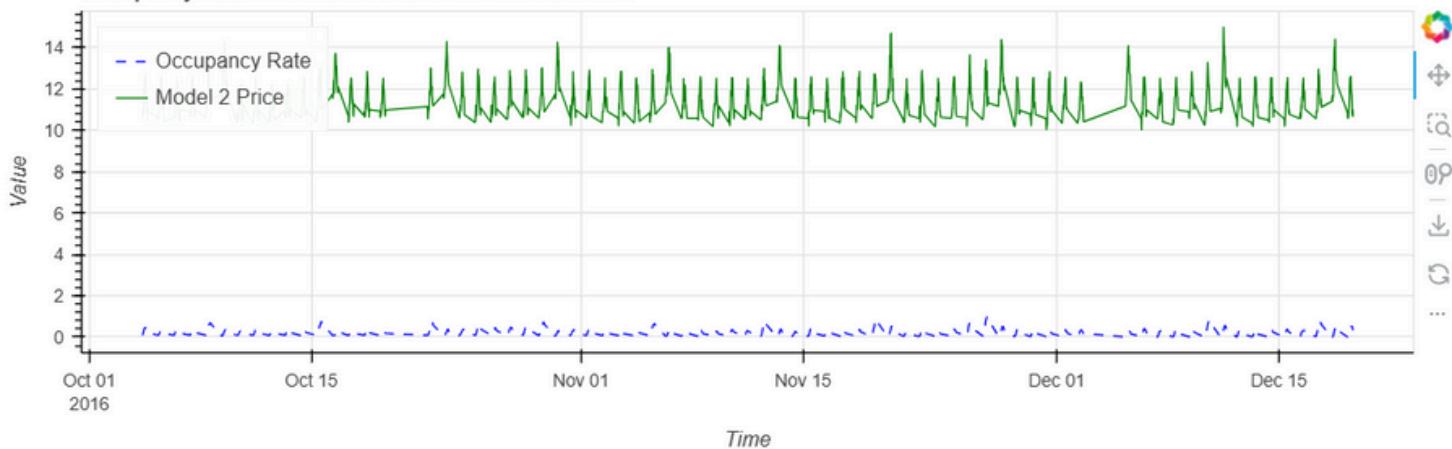


Pricing Models Explained

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$$D = \alpha \cdot \text{OccupancyRate} + \beta \cdot \text{QueueLength} - \gamma \cdot \text{Traffic} + \delta \cdot \text{SpecialDay} + \varepsilon \cdot \text{VehicleWeight}$$
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$$\text{Price} = \text{Base} \times (1 + \lambda \times \text{NormalizedDemand})$$
- **Parameters used:**
○ $\alpha = 0.6, \beta = 0.4, \gamma = 0.3, \delta = 1.0, \varepsilon = 0.7, \lambda = 0.5$

Occupancy Rate vs Model 2 Price: Lot BHMBCCMKT01



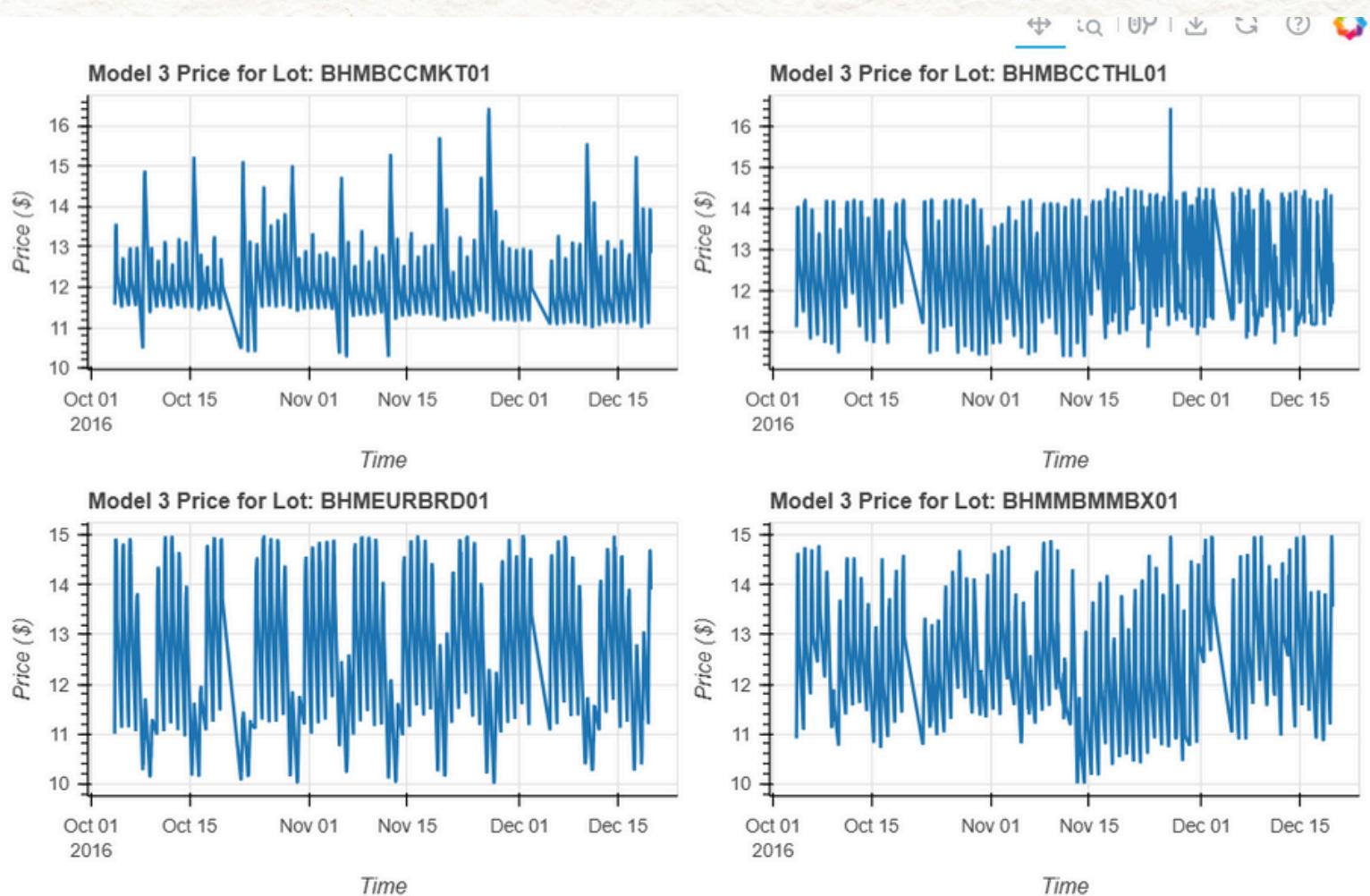
Pricing Models Explained

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- Adds spatial intelligence (haversine distance)

Logic:

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Observations & Insights

Key Observations:

- **Occupancy Drives Price, but Not Alone**
High occupancy increases price in all models, but Model 2 adjusts based on real context (queue, vehicle type).
- **Special Days Create Price Surges**
Price jumps are more aggressive on flagged holidays (`IsSpecialDay=1`), validating the impact of δ in Model 2.
- **Model 3 Prevents Overpricing**
Competitive logic causes price to drop if neighboring lots are cheaper, making the system more fair and efficient.
- **Rerouting is Effective**
Model 3 price dips during over-occupancy show that rerouting logic kicked in – encouraging flow to cheaper lots nearby.
- **Vehicle Type Bias is Useful**
Trucks are priced higher due to higher weights, subtly prioritizing smaller vehicles in congested areas.

Appendix

Include:

-  **dataset.csv (used for simulation)**
-  **Dynamic_Pricing.ipynb (notebook)**
-  **library list: pandas, numpy, bokeh**
-  **full-resolution screenshots of plots**