Dynamic Pricing for Urban Parking Lots

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Abstract

Urban mobility presents an evolving challenge, especially in densely populated areas where static parking fees do not account for dynamic supply-demand shifts. This report proposes a real-time pricing mechanism for urban parking lots, designed and implemented using Pathway's stream processing platform. Two models were developed: a rule-based incremental model and a more sophisticated continuous demand model. Visualizations were implemented using Bokeh and Panel. The system demonstrates potential for scalability, adaptability, and intelligent urban planning.

Introduction

Urban areas suffer from inefficient parking systems driven by fixed pricing strategies. Drivers either overpay during low-demand periods or congest prime locations during peak hours. The motivation for this project is to build a dynamic, demand-aware pricing model that updates in real time based on key influencing factors such as occupancy, traffic, and events.

Dataset Overview

The dataset used includes records for multiple parking lots over time with the following columns:

- **Occupancy, Capacity** — Current lot usage and size
- **QueueLength** — Vehicles waiting to park
- **TrafficConditionNearby** — Traffic density (low, medium, high)
- **IsSpecialDay** — Boolean indicator for special event days
- **Timestamp** — Combined from date and time fields
- **Latitude, Longitude** — Given Lat-Long of parking lots

The dataset was cleaned to remove duplicate timestamps and sorted by SystemCodeNumber and Timestamp for proper stream replay.

Model 1: Rule-Based Incremental Pricing

Objective

Model 1 incrementally adjusts price daily based on lot occupancy, where the next price is a function of the previous price and current occupancy

Pricing Formula

$$\text{Price}_t = \begin{cases} \text{BasePrice} + \alpha \cdot \left(\frac{\text{Occupancy}}{\text{Capacity}}\right), & \text{if first day} \\ \text{Price}_{t-1} + \alpha \cdot \left(\frac{\text{Occupancy}}{\text{Capacity}}\right), & \text{otherwise} \end{cases} \tag{1}$$

Assumptions

- Pricing updates once per day per parking lot
- Base price and scaling factor are fixed (Base = 10, $\alpha = 2$)
- No influence from external conditions

Model 2: Continuous Demand-Based Pricing

Overview

Model 2 builds a real-valued demand score from scaled real-time features. Pricing adjusts smoothly and continuously.

Feature Transformations

- **Occupancy Ratio:** $\text{Occ\%} = \frac{\text{Occupancy}}{\text{Capacity}}$
- **QueueLength Scaled:** $\text{QueueScaled} = \min\left(\frac{\text{QueueLength}}{10}, 1\right)$
- **Traffic:** {low: 0, medium: 0.5, high: 1.0}
- **Special Day:** Binary (0 or 1)

Demand Function

$$\text{Price} = \text{BasePrice} + \beta_1 \cdot \text{Occ\%} + \beta_2 \cdot \text{QueueScaled} + \beta_3 \cdot \text{TrafficVal} + \beta_4 \cdot \text{IsSpecialDay} \tag{2}$$

Parameter Selection

- **BasePrice** = 10
- $\beta_1 = 6$, $\beta_2 = 2$, $\beta_3 = 3$, $\beta_4 = 1.5$
- Final price is rounded to one decimal place

Implementation

- **Streaming Framework:** Pathway
- **Windowing:** Tumbling window (1-day) per parking lot
- **Visualization:** Bokeh for plotting, Panel for dashboards
- **Environment:** Python (Google Colab)

Lot-wise Price Visualizations (Model 1)

This section presents daily dynamic pricing plots for each parking lot (Lot 1 through Lot 14) under Model 1. These follow the rule-based incremental logic described earlier.

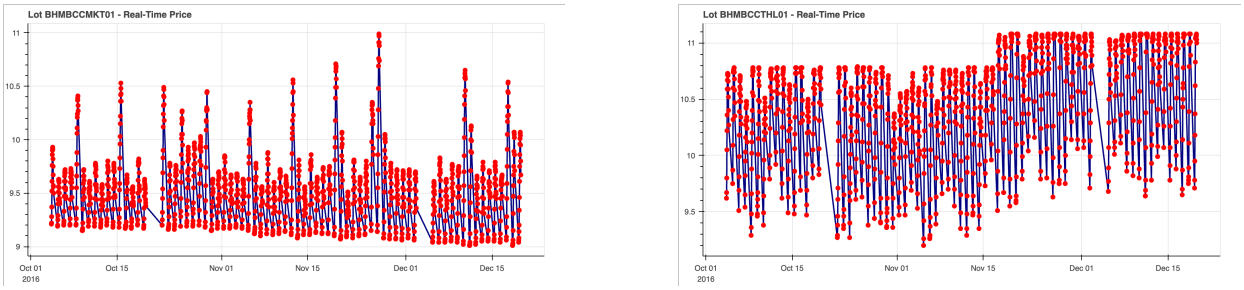


Figure 1: Lot 1 and Lot 2

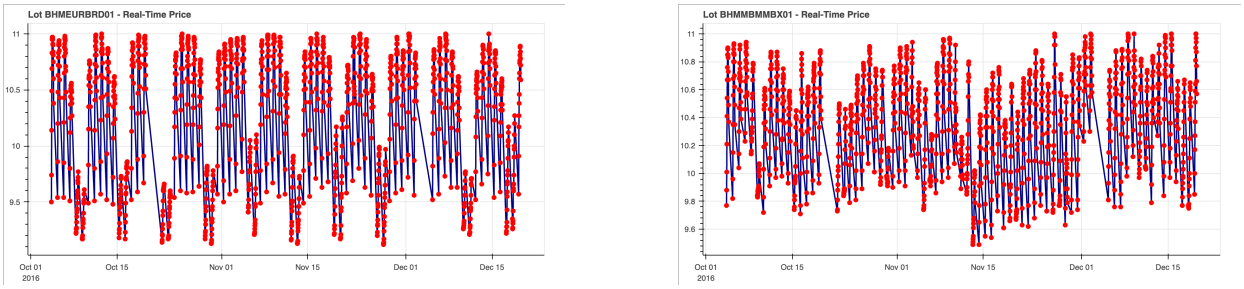


Figure 2: Lot 3 and Lot 4

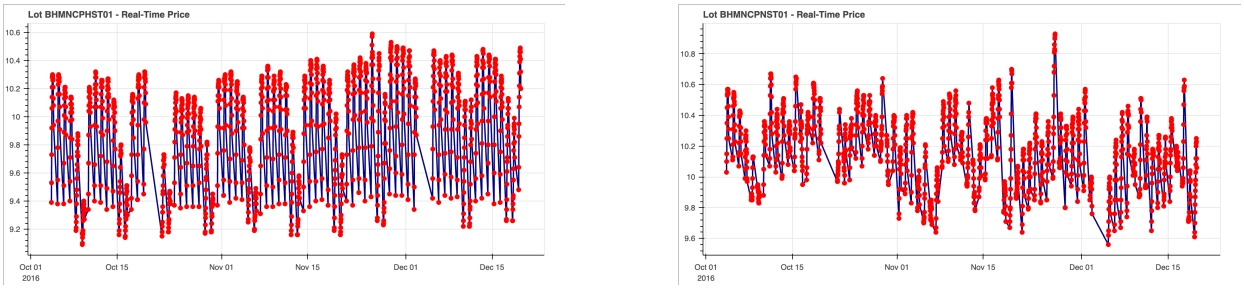
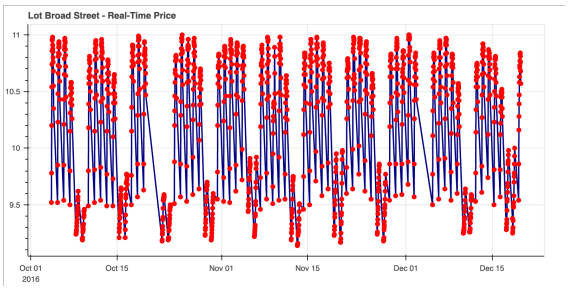


Figure 3: Lot 5 and Lot 6



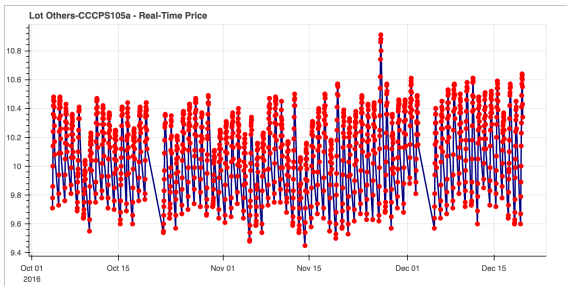
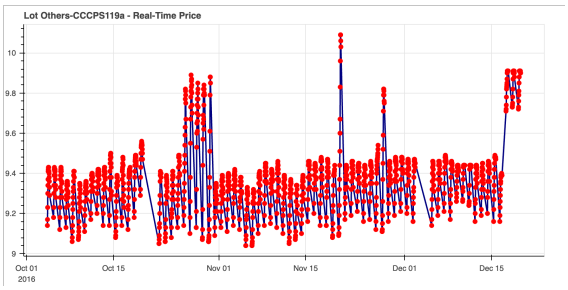


Figure 4: Lot 7 and Lot 8



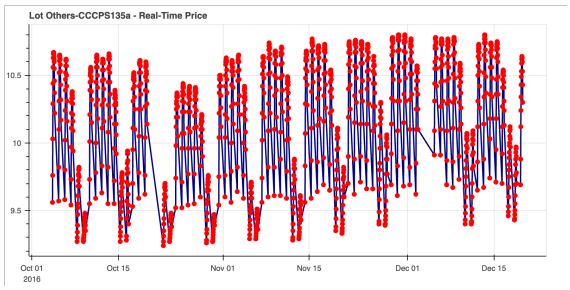
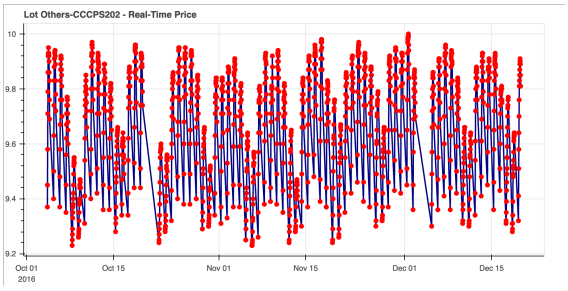


Figure 5: Lot 9 and Lot 10



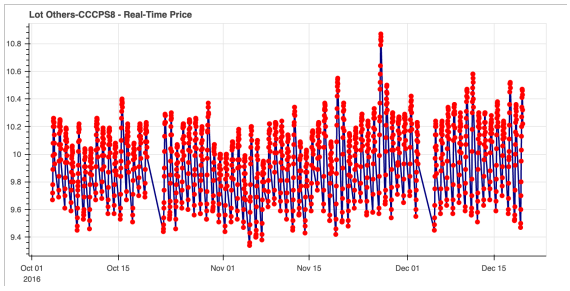
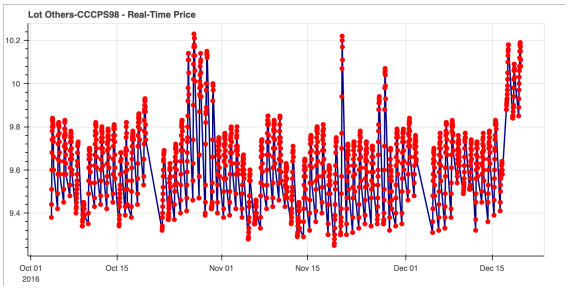


Figure 6: Lot 11 and Lot 12



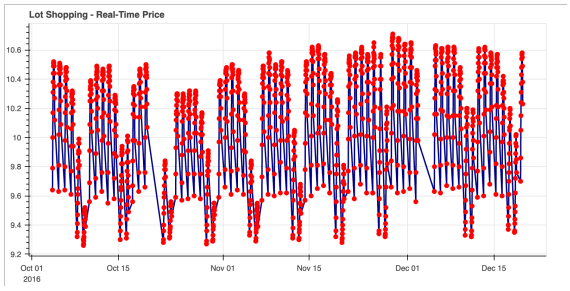


Figure 7: Lot 13 and Lot 14

Lot-wise Price Visualizations (Model 2)

This section presents daily dynamic pricing plots for each parking lot (Lot 1 through Lot 14) under Model 2.

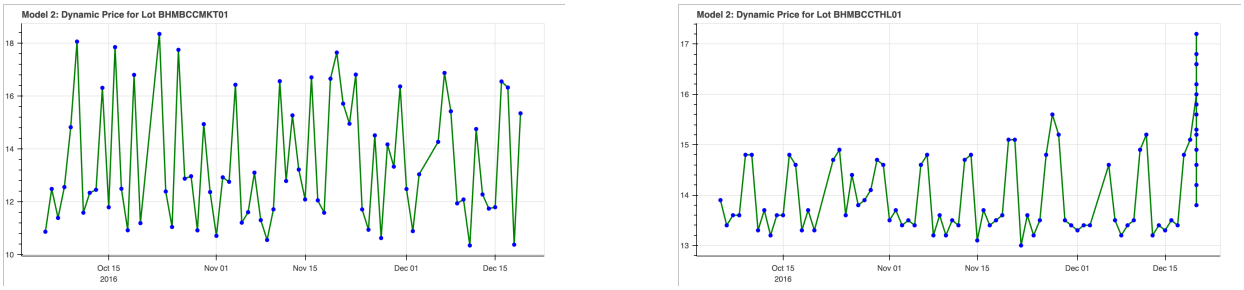


Figure 8: Lot 1 and Lot 2

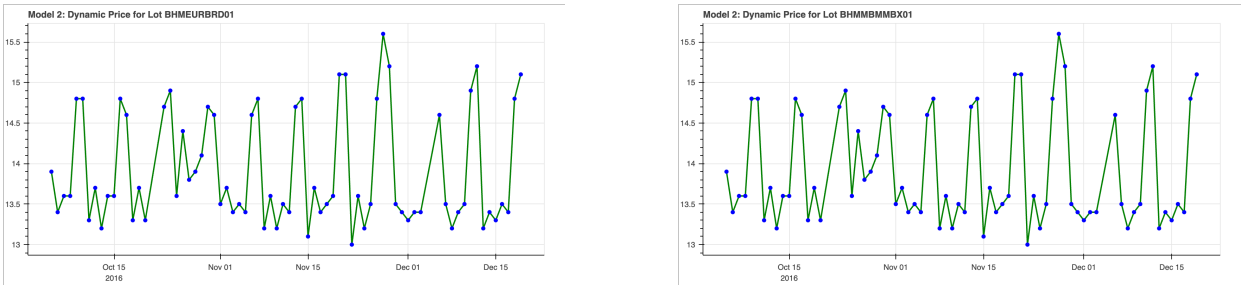


Figure 9: Lot 3 and Lot 4

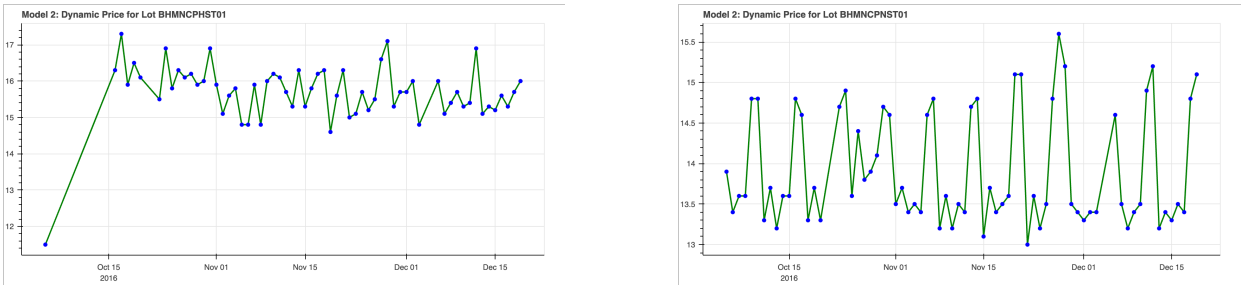
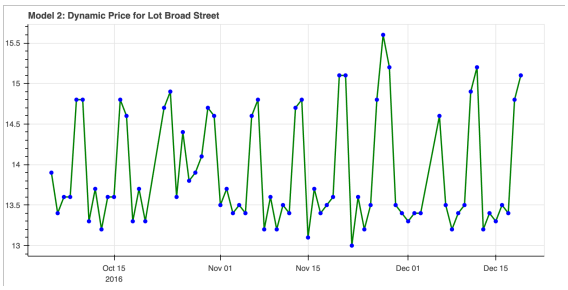


Figure 10: Lot 5 and Lot 6



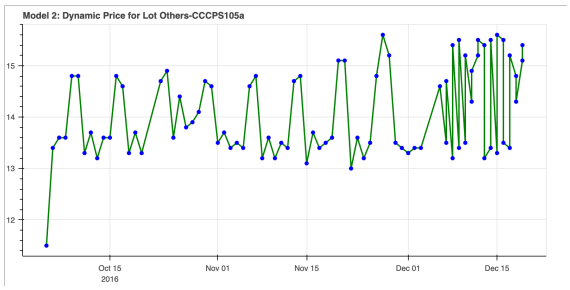
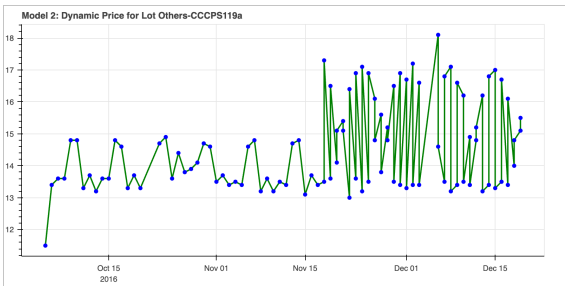


Figure 11: Lot 7 and Lot 8



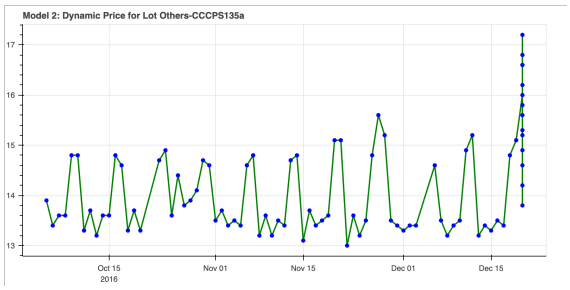
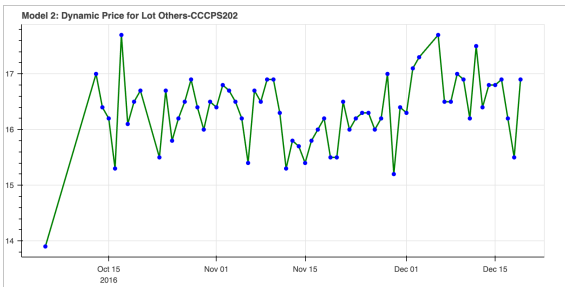


Figure 12: Lot 9 and Lot 10



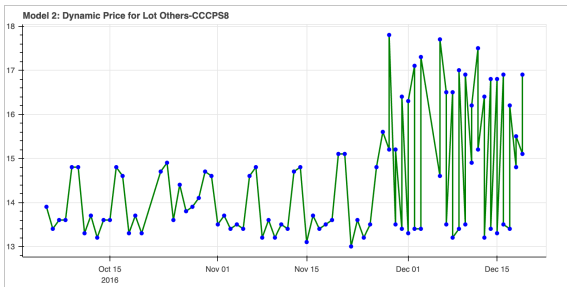
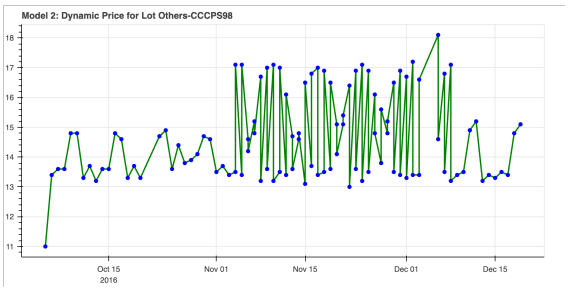


Figure 13: Lot 11 and Lot 12



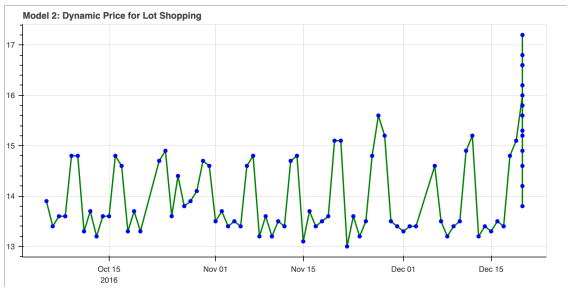


Figure 14: Lot 13 and Lot 14

Discussion and Insights

Behavioral Impact

Model 2 encourages users to park at off-peak times or use lots with lower demand.

Competitive Pricing

Although competition from nearby lots is not modeled directly, price differentiation emerges naturally from traffic and occupancy patterns.

Limitations and Future Work

- Incorporate nearby lot pricing as a competitive input
- Model hourly rather than daily prices using sliding windows
- Introduce machine learning (e.g., gradient boosting) for forecasting

Conclusion

Dynamic pricing using live stream processing allows more efficient and adaptive management of urban parking infrastructure. Among the models, the continuous demand-based approach (Model 2) provides smoother, fairer, and more accurate price estimation and is suitable for real-world deployment. Visualization with Bokeh helps monitor pricing behavior over time.

References

- Pathway Documentation: `https://pathway.com`
- Bokeh Plotting Library: `https://docs.bokeh.org`
- Panel Dashboard Toolkit: `https://panel.holoviz.org`