Dynamic Pricing for Urban Parking Lots

Fluctuation-Based Pricing Report

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Executive Summary

This report presents the implementation and analysis of a novel fluctuation-based dynamic pricing model for urban parking lots. The model leverages daily occupancy variance as a key indicator of demand volatility to determine optimal pricing strategies. Using real-time data processing through Pathway and temporal windowing techniques, the system successfully demonstrates smooth price transitions while maintaining business viability across 14 parking stations over a 73-day period.

1. Model Architecture and Implementation

1.1 Theoretical Foundation

The fluctuation-based pricing model operates on the economic principle that price volatility should reflect demand uncertainty. Unlike traditional occupancy-based models that respond to instantaneous demand levels, this approach captures the underlying demand dynamics through daily variance patterns.

Core Formula:

Price = Base_Price + (Occupancy_Max - Occupancy_Min) / Capacity Where:

- Base Price: Fixed minimum price floor (\$10)
- Occupancy_Max: Peak occupancy observed within the time window
- Occupancy_Min: Minimum occupancy observed within the time window
- Capacity: Maximum parking capacity for normalization

1.2 Technical Implementation

Data Schema Definition: The system processes structured streaming data through a defined Pathway schema:

```
class ParkingSchema(pw.Schema):

Timestamp: str # ISO format timestamp
Occ_Cap_Norm: float # Normalized occupancy ratio
IsSpecialDay: int # Binary special day indicator
Traffic: float # Traffic congestion level
```

VehicleTypeWeight: float # Vehicle type impact factor QueueLength_Normalized: float # Normalized queue length SystemCodeNumber_Encoded: int # Parking station identifier

Real-time Processing Pipeline: The model utilizes Pathway's temporal windowing for continuous data processing:

```
delta_window = data_with_time.windowby(
   pw.this.t, # Event time column for temporal ordering
   instance=pw.this.day, # Daily logical partitioning
   window=pw.temporal.tumbling(datetime.timedelta(days=1)),
   behavior=pw.temporal.exactly_once_behavior()
)
```

This architecture ensures exactly-once processing semantics while maintaining temporal consistency across all parking stations.

1.3 Key Innovation: Demand Volatility Quantification

The model's primary innovation lies in its interpretation of occupancy fluctuation as a proxy for demand volatility. High fluctuation indicates strong demand variations justifying premium pricing, while low fluctuation suggests stable demand patterns maintaining base-level prices.

2. Results and Performance Analysis

2.1 Price Performance Overview

The model demonstrates robust performance across all 14 parking stations, with prices ranging from \$10 (base) to approximately \$18.50 during peak demand periods. The attached visualizations show representative pricing patterns:

- Station 0 (Figure 1): Consistent price variations with spikes reaching \$18+, indicating high demand volatility periods
- Station 7 (Figure 2): Similar pricing behavior with occasional peaks around \$19, successfully capturing demand patterns
- Station 12 (Figure 3): More moderate fluctuations (\$11-18 range), suggesting stable demand patterns

2.2 Key Performance Metrics

Technical Achievements:

• Price stability within reasonable bounds (10-18.5 range)

- Smooth transitions avoiding erratic price jumps
- Station-specific pattern recognition
- Successful outlier management without price instability

Business Benefits:

- Dynamic revenue capture during high-demand periods
- Predictable pricing enhancing customer experience
- Real-time processing with minimal computational overhead
- Robust error handling through exactly-once processing semantics

3. Model Assessment and Future Directions

3.1 Current Limitations

While the schema includes comprehensive features (Traffic, VehicleTypeWeight, QueueLength_Normalized, IsSpecialDay), the current implementation focuses primarily on occupancy patterns. This represents an opportunity for enhanced multi-factor integration.

3.2 Enhancement Opportunities

Immediate Improvements:

- Leverage existing schema features (Traffic, VehicleTypeWeight, QueueLength_Normalized)
- Implement time-of-day weighting for granular pricing
- Add price bounds to prevent extreme variations

Future Vision:

- Machine learning integration for demand prediction
- Competitive pricing analysis using geospatial data
- Multi-objective optimization balancing revenue and utilization

4. Conclusion

The fluctuation-based pricing model successfully demonstrates the viability of using occupancy variance as a primary driver for dynamic pricing in urban parking scenarios. Despite having access to comprehensive data features through the ParkingSchema (Traffic, VehicleTypeWeight, QueueLength_Normalized, IsSpecialDay), the model's focus on occupancy fluctuation provides a solid foundation that achieves key objectives of smooth price transitions, business viability, and real-time responsiveness.

Key Achievements:

- Smooth, explainable price variations (10-18.5 range)
- Real-time processing with Pathway streaming architecture
- Robust performance across all 14 stations
- Business-viable pricing maintaining customer satisfaction

Scalable technical implementation with exactly-once processing

The visualizations clearly demonstrate the model's ability to capture demand patterns across different stations while maintaining price stability. This implementation establishes a strong baseline for dynamic pricing systems and provides valuable insights for future development incorporating the additional schema features for more sophisticated urban parking management solutions.

References:

- 1. Pathway Documentation Real-time Data Processing
- 2. Summer Analytics 2025 Project Requirements

Figures:

- Figure 1: Daily Clamped Price for Station 7 (October-December 2016)
- Figure 2: Daily Clamped Price for Station 12 (October-December 2016)
- Figure 3: Daily Clamped Price for Station 0 (October-December 2016)





