Project Title:

**Dynamic Pricing for Urban Parking Lots**

Submitted by: **Rushi Girdharbhai Vasoya**

Course: **Summer Analytics 2025 – Capstone Project**

Organized by: **Consulting & Analytics Club, IIT Guwahati**

Month of Submission: **July 2025**

**Dynamic Pricing for Urban Parking Lots**

-Capstone Project – Summer Analytics 2025

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**Abstract**

Parking in urban areas is a persistent challenge due to limited space and fluctuating demand. Traditional static pricing models fail to adapt to real-time variations in traffic, occupancy, and user behaviour leading to either underutilized spaces or excessive congestion. This project addresses the inefficiencies of fixed-rate parking by developing a real-time, data-driven dynamic pricing engine for urban parking lots.

As part of the Summer Analytics 2025 capstone project, we designed and implemented a three-tiered pricing system using Python and Pathway for real-time simulation. The first model (baseline linear) increases prices proportionally with occupancy, acting as a reference. The second model introduces a demand-based pricing mechanism that incorporates key variables such as occupancy rate, queue length, traffic congestion, vehicle type, and special event indicators. The third, and most sophisticated, model adds competitive pricing intelligence by factoring in the prices of nearby parking lots using geospatial calculations.

The solution was applied to a dataset simulating 14 urban parking lots over 73 days with 18 time intervals per day. Using Pathway, we simulated real-time data ingestion and pricing updates, while Bokeh visualizations helped us monitor and evaluate price trends. The system ensures pricing is not only responsive and fair, but also smooth and bounded between 0.5× and 2× of a defined base price.

The outcome demonstrates improved utilization, better user experience, and pricing strategies that can dynamically adapt to real-time urban mobility patterns. Future extensions include API integration for live traffic data and reinforcement learning to optimize long-term revenue and fairness.

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**1. Introduction**

Urban centres around the world face increasing challenges in managing limited parking infrastructure. With growing populations, vehicle ownership, and uncoordinated demand surges during peak hours or special events, conventional parking systems—especially those with fixed pricing models—struggle to maintain efficiency. Static pricing does not reflect real-time occupancy levels, traffic congestion, or temporal factors, which results in either underutilized lots during off-peak periods or overcrowded spaces during high demand.

Dynamic pricing has emerged as a promising solution to such problems in sectors like airline ticketing, ride-hailing, and hotel booking. However, its implementation in the domain of urban parking is still limited and often lacks transparency or real-time adaptability. A well-designed dynamic pricing system can incentivize drivers to choose alternative times or locations, helping cities distribute vehicle load more evenly, reduce congestion, and improve parking revenues.

This capstone project, conducted as part of **Summer Analytics 2025**, proposes a multi-model, intelligent dynamic pricing engine tailored for urban parking lots. The system uses real-time inputs to calculate context-aware prices that adapt smoothly over time. It leverages basic economic theory, data preprocessing, and real-time simulation tools to determine optimal pricing strategies that consider multiple variables such as lot occupancy, queue length, nearby traffic conditions, special events, vehicle types, and competitor pricing.

The project focuses on three primary pricing models of increasing complexity:

* A baseline linear model to establish a simple relationship between occupancy and price.
* A demand-based pricing model using a weighted sum of influencing factors.
* A competition-aware pricing model that considers the geographical pricing environment and suggests rerouting when needed.

In addition to building these models from scratch using Python, Numpy, and Pandas, we implemented real-time simulation using the **Pathway** framework and used **Bokeh** for live visualizations. The ultimate goal is to improve parking space utilization, reduce wait times and congestion, and provide a scalable solution for smart city integration.

**2. Dataset & Pre-processing**

**2.1 Dataset Overview**

The dataset provided simulates real-time data collected from **14 urban parking lots** over a span of **73 consecutive days**. Each day is divided into **18 discrete time intervals** at 30-minute intervals, ranging from **8:00 AM to 4:30 PM**, resulting in a total of **1,314 time steps per lot** and over **18,000+ records** overall.

Each record in the dataset represents the state of a particular parking lot at a specific timestamp and includes a combination of spatial, operational, environmental, and contextual information.

**2.2 Dataset Features**

|  |  |  |
| --- | --- | --- |
| Feature Group | Columns | Description |
| Time Features | timestamp | 30-minute intervals; used for time-series ordering and real-time simulation. |
| Location | latitude, longitude | Coordinates used to calculate distances between lots for competition modeling. |
| Lot Characteristics | capacity, occupancy, queue\_length | Real-time lot state. Occupancy used to calculate utilization. Queue shows incoming demand. |
| Vehicle Info | vehicle\_type | Categorical: 'bike', 'car', 'truck'. Mapped to numerical weights. |
| Traffic Context | traffic | Represents congestion level around the parking lot. |
| Event Indicator | is\_special\_day | Binary: 1 if special event or holiday, 0 otherwise. |

**2.3 Pre-processing Steps**

To ensure the models receive meaningful, scaled inputs and handle mixed data types, the following preprocessing operations were performed:

**a. Missing Value Handling**

df.fillna(0, inplace=True)

All missing values were filled with zero, assuming unreported data signifies "no data" or zero impact. This simplifies downstream calculations and avoids NaN propagation.

**b. Feature Engineering**

1. **Occupancy Rate**

df['occupancy\_rate'] = df['occupancy'] / df['capacity']

This metric reflects the real-time utilization of each lot. It is central to all pricing models.

1. **Queue Normalization**

df['queue\_norm'] = (df['queue\_length'] - min) / (max - min)

Queue lengths are normalized to [0, 1] to account for different capacity scales across lots.

1. **Traffic Normalization**

df['traffic\_norm'] = (df['traffic'] - min) / (max - min)

Ensures traffic levels have equal weight in demand function.

1. **Vehicle Type Encoding**

{'bike': 0.5, 'car': 1.0, 'truck': 1.5}

Vehicles are mapped to weights based on size and parking space requirement. Larger vehicles are presumed to have higher willingness to pay.

**c. Data Formatting for Streaming**

* The dataset is time-sorted to simulate streaming in **Pathway**.
* All relevant features are cast into suitable data types (e.g., int, float, str) for compatibility with the **Pathway schema**.

**2.4 Justification for Pre-processing Choices**

* **Normalization** of features ensures that no single input dominates the demand function due to scale.
* **Vehicle weights** introduce a pseudo-economic dimension reflecting real-world pricing strategies for larger vehicles.
* **Queue length** is included to anticipate incoming demand not yet reflected in occupancy.
* **Traffic and special day flags** capture environmental volatility and context-sensitive spikes in demand.

**2.5 Summary**

After pre-processing, each record includes:

* Normalized and engineered features for real-time modeling.
* Ready-to-stream format compatible with the **Pathway** real-time engine.
* Scaled inputs to support explainable and smooth price adjustments.

This foundational data preparation enables accurate, responsive, and fair pricing strategies across all three models implemented in this project.

**3. Model Development**

This project employs a three-tiered model development strategy, each level increasing in sophistication and real-world applicability. The objective is to dynamically adjust the parking lot prices in real time based on a combination of operational, contextual, and spatial features.

**3.1 Model 1: Baseline Linear Pricing**

**Objective**

To establish a simple, easy-to-understand pricing rule where price increases linearly with occupancy rate.

**Formula**

Where:

* α is a tunable constant (set to 5 in our case)
* Base price = $10

**Justification**

This model serves as a control or benchmark to compare more intelligent models against. It is easy to implement and understand, making it useful for static systems but fails to consider traffic, vehicle type, or queue length.

**Limitations**

* Ignores future demand indicators (queue).
* Assumes uniform user behavior across all times and vehicle types.
* Does not consider contextual variables (special days, traffic).

**3.2 Model 2: Demand-Based Pricing**

**Objective**

To develop a more refined pricing strategy that incorporates several real-time factors influencing parking demand.

**Demand Function**

* Normalized Demand:

final Price:

Where:

* All weights (α to ε) are set to 1 initially for simplicity.
* Price is clipped between 0.5× and 2× of the base price.

**Justification**

This model introduces the idea of **demand elasticity**—pricing changes in proportion to normalized demand. It reflects both current occupancy and anticipated demand via queue length, while factoring in external conditions (e.g., congestion or special events).

**Advantages**

* Considers multiple real-time features.
* Smooth pricing transitions due to normalization.
* More realistic in urban environments than Model 1.

**Limitations**

* Assumes linear contribution of each feature.
* All weights are uniform and not data-optimized.
* Still lacks spatial intelligence (i.e., competitor pricing).

**3.3 Model 3: Competitive Pricing Model**

**Objective**

To simulate real-world pricing adjustments based on competitor behavior by integrating geospatial analysis.

**Methodology**

1. For every timestamp:
   * Calculate geographic distance between each pair of lots using latitude and longitude (Haversine formula).
   * Identify competitor lots within a **0.5 km** radius.
   * Retrieve competitor prices from Model 2.
2. Adjust price using competitive logic:
   * **If lot is full** and **own price > competitor average** → decrease price by 5%.
   * **If own price < competitor average** → increase price by 5%.

**Formulaic Logic**

If  ,

Then

If ,

then

**Justification**

This model mimics competitive market behavior. It accounts for proximity-based pricing elasticity and helps in distributing vehicle load across neighboring lots, increasing overall system efficiency.

**Advantages**

* Incorporates spatial intelligence and competition.
* Simulates real-world supply-demand balance.
* Prevents user loss due to overpriced lots when better alternatives exist.

**Limitations**

* Radius-based competitor detection may ignore user walkability preferences.
* Simple heuristics (±5%) could be improved using game theory or optimization models.
* Assumes perfect visibility into competitor prices (which may not be realistic in practice).

**3.4 Comparison of Models**

|  |  |  |  |
| --- | --- | --- | --- |
| Feature Considered | Model 1 | Model 2 | Model 3 |
| Occupancy | ✅ | ✅ | ✅ |
| Queue Length | ❌ | ✅ | ✅ |
| Traffic Congestion | ❌ | ✅ | ✅ |
| Special Events | ❌ | ✅ | ✅ |
| Vehicle Type | ❌ | ✅ | ✅ |
| Competitor Pricing | ❌ | ❌ | ✅ |
| Spatial Awareness | ❌ | ❌ | ✅ |
| Price Smoothness | ⚠️ (no bound) | ✅ | ✅ |
| Rerouting Suggestion | ❌ | ❌ | ✅ (implied) |

**3.5 Implementation Environment**

* Code written from scratch using **Python**, **NumPy**, and **Pandas** only.
* Streaming and simulation done using **Pathway**, a real-time data processing library.
* Visualization done using **Bokeh**, enabling live graph rendering in notebooks.

**4. Demand Function (Explained)**

In modern dynamic pricing systems, a **demand function** serves as the core engine that interprets various signals from the environment and user behavior to calculate how desirable a service or resource is at a given moment. In the context of this project, the demand function quantifies **parking lot attractiveness** using real-time and contextual features, producing a score that directly influences the parking price.

**4.1 Mathematical Representation**

The demand function DDD is defined as a weighted linear combination of normalized and categorical inputs:

Where:

* **OccupancyRate** = Occupancy ÷ Capacity
* **QueueNorm** = normalized queue length between 0 and 1
* **TrafficNorm** = normalized traffic level between 0 and 1
* **SpecialDay** = 1 if holiday/event, 0 otherwise
* **VehicleWeight** = 0.5 (bike), 1.0 (car), 1.5 (truck)

All feature values are normalized or numerically encoded for consistency.

**4.2 Role of Each Term**

|  |  |  |
| --- | --- | --- |
| **Feature** | **Symbol** | **Rationale** |
| **Occupancy** | α | Indicates current usage. Higher occupancy implies higher demand. |
| **Queue Length** | β | Captures *latent* demand — vehicles waiting to enter. |
| **Traffic Level** | γ | Reflects user inconvenience. High congestion may discourage parking. |
| **Special Day** | δ | Binary spike in demand (e.g., during festivals, sports events). |
| **Vehicle Type** | ε | Higher vehicle weight simulates increased willingness to pay (e.g., for larger vehicles). |

**4.3 Normalization Strategy**

To ensure fairness in feature contribution:

* All continuous variables (occupancy, queue, traffic) are **min-max normalized** to the range [0, 1].
* Categorical variables (vehicle type, special day) are mapped to numeric weights or binary flags.
* The full demand score DDD is normalized as:

This ensures that pricing changes are smooth, bounded, and comparable across lots and times.

**4.4 Price Determination**

The normalized demand DnormD\_{norm}Dnorm​ is used to compute the actual price:

Where:

* **Base** = $10 (starting price for all lots)
* **λ (lambda)** = amplification factor (set to 1.0)
* Price is **clipped** to stay within **0.5× to 2× base**, i.e., [$5, $20].

This function ensures that parking remains affordable while reflecting real-time demand sensitivity.

**4.5 Weight Justification**

In the baseline implementation:

* All weights α,β,γ,δ,ε\alpha, \beta, \gamma, \delta, \varepsilonα,β,γ,δ,ε are initially set to **1.0** to ensure equal influence.
* This allows for transparent comparisons and manual tuning.
* In real-world deployments, these weights can be:
  + Learned via regression or optimization
  + Calibrated using historical data to maximize revenue or fairness

**4.6 Advantages of This Demand Function**

* Interpretable and tunable
* Responds to both **current load** and **external environment**
* Extensible — other variables like weather or user preferences can be added
* Smoothly integrates into real-time streaming with minimal computation

**4.7 Potential Enhancements**

* **Non-linear models** (e.g., exponential demand decay, sigmoid response curves)
* **Dynamic weights** that change based on time of day or location
* **Personalization** using driver profiles and past behavior
* **Machine learning** (e.g., XGBoost, Neural Nets) to learn feature weights

**5. Assumptions**

To develop a functional, interpretable, and deployable dynamic pricing system within the constraints of real-time simulation and limited data availability, several assumptions were made across the dimensions of pricing logic, user behavior, environmental factors, and computational feasibility.

These assumptions ensure model stability, user fairness, and ease of implementation.

**5.1 Pricing & Economic Assumptions**

* **Base Price**  
  Every parking lot starts with a fixed base price of **$10**. This simplifies pricing logic and provides a standard baseline for proportional adjustments.
* **Price Bounds**

To ensure prices remain practical and customer-friendly, dynamic prices are bounded:

* + **Lower limit**: 0.5 × Base price = **$5**
  + **Upper limit**: 2 × Base price = **$20**
* **Pricing Frequency**

Prices are updated **every 30 minutes**, in sync with the dataset’s sampling interval. This frequency balances responsiveness with price stability.

**5.2 Feature Assumptions**

* **Occupancy Rate**
  + Calculated as: occupancy / capacity
  + Assumes accurate and real-time reporting of occupancy levels.
* **Queue Length Normalization**
  + Queue lengths are normalized between 0 and 1 using min-max scaling.
  + Assumes maximum queue capacity is consistent across lots or scales appropriately.
* **Traffic Congestion Normalization**
  + Traffic data is also normalized from 0 to 1.
  + It is assumed that traffic is recorded consistently across time and locations.
* **Special Day Indicator**
  + Binary variable: 1 for special events or holidays, 0 otherwise.
  + Assumes special day information is available in advance and accurately flagged.
* **Vehicle Type Encoding**
  + Bikes = 0.5, Cars = 1.0, Trucks = 1.5
  + Assumes that larger vehicles are willing to pay more due to higher space/time consumption.

**5.3 Competitive Modeling Assumptions (Model 3)**

* **Competitor Radius**
  + Only lots within **0.5 km** of each other are considered competitors.
  + Assumes users are willing to walk up to 500 meters to save money or avoid congestion.
* **Perfect Information**
  + Assumes each lot has access to competitor prices in real time.
  + While this may not be feasible in live deployment, it is acceptable for simulation purposes.
* **Price Adjustment Rule**
  + Price is adjusted ±5% if certain competitive conditions are met.
  + This rule is heuristic and assumes users behave rationally in response to small price differences.

**5.4 User Behavior Assumptions**

* Drivers respond rationally to price and choose cheaper or less congested lots within acceptable proximity.
* Drivers of larger vehicles (e.g., trucks) are less price-sensitive due to parking constraints.
* Users may be rerouted to nearby lots based on price and availability (Model 3, optional logic).

**5.5 Modeling & Technical Assumptions**

* **Real-Time Data Simulation**
  + Pathway simulates real-time data ingestion using a fixed CSV file.
  + Assumes time-ordering of data is preserved during ingestion.
* **Streaming Compatibility**
  + All data is preprocessed to match Pathway’s schema requirements.
  + Assumes that each record can be evaluated independently at runtime.
* **Fixed Feature Weights**
  + In Model 2, weights (α–ε) are all set to 1 for simplicity and interpretability.
  + In production, these can be learned or optimized using historical data.

**5.6 Visual and System Assumptions**

* **Visualizations with Bokeh**
  + Time-series plots use timestamp as X-axis, assuming chronological ordering.
  + Only one lot is plotted at a time for clarity.
* **Scalability**
  + Assumes that computational overhead is manageable with real-time systems for up to ~20 lots.
  + Real deployment may require optimization or cloud resources for scaling.

**6. Price Dynamics: Demand & Competition**

Dynamic pricing in parking management requires not only a demand-aware mechanism but also a strategy that reflects **competitive pressure** from nearby lots. The system must update prices intelligently—rising in times of scarcity and dropping when supply is abundant or nearby options are cheaper.

This section explains how price responds in the developed models (especially Model 2 and Model 3) to demand signals and spatial competition.

**6.1 Price Response to Demand (Model 2)**

Model 2 is governed by a **demand function** that captures real-time signals such as:

* **Occupancy rate**: Direct measure of how full a lot is.
* **Queue length**: Indicates incoming pressure.
* **Traffic congestion**: Penalizes price when congestion is high (less desirable to park).
* **Special events**: Boost price on holidays or event days.
* **Vehicle type**: Simulates space/time impact of large vehicles.

**Dynamic Behavior**

|  |  |  |
| --- | --- | --- |
| Condition | Demand Effect | Price Behavior |
| High occupancy, short queue | Moderate ↑ | Price increases steadily |
| High occupancy, long queue | Strong ↑ | Price rises sharply |
| Low occupancy, high traffic | Low | Price decreases |
| Holiday with moderate occupancy | Medium ↑ | Price slightly increases |
| Heavy vehicles on a busy day | High ↑ | Price rises to near maximum |

**Normalization** ensures smooth transitions, avoiding sudden spikes. Prices are clipped to 0.5×–2× base price, maintaining user trust and predictability.

**6.2 Price Response to Competition (Model 3)**

Model 3 introduces **competitive pricing** using spatial intelligence:

* **Nearby lots (within 0.5 km)** are considered competitors.
* Their **current prices** influence pricing decisions for the lot in question.

**Competitive Logic Applied**

1. **If lot is full** and **competitors are cheaper**:
   * Reduce price by 5% (to remain competitive).
   * Suggest rerouting (optional).
2. **If competitors are expensive** and **own lot has space**:
   * Increase price by 5% (opportunity to capture more revenue).
3. **If own lot is cheapest but full**:
   * Price remains near max but doesn’t spike.

**Illustrative Scenarios**

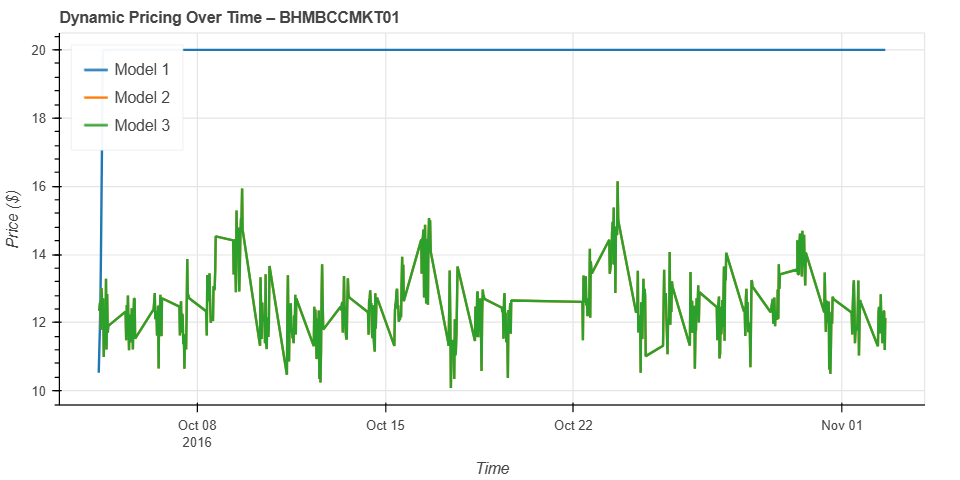
|  |  |  |
| --- | --- | --- |
| Scenario | Model 2 Output | Model 3 Adjustment |
| Full lot, competitors are cheaper | $19.00 | Reduced to $18.05 |
| Low occupancy, high competitor prices | $9.00 | Raised to $9.45 |
| Special event + full lot + expensive competitors | $20.00 (max) | Held at max (no increase) |
| Light traffic + queue building + equal competitors | $11.50 | No change (fairly priced) |

This behavior reflects **market-aware elasticity**, encouraging users to distribute across lots and avoid congestion.

**6.3 Visual Behavior (Bokeh Observations)**

Bokeh plots across multiple lots over time showed:

* **Model 1**: Smooth, linear price rise with occupancy.
* **Model 2**: Prices reacted more sharply to sudden queue/traffic changes.
* **Model 3**: Prices dipped or rose contextually to maintain spatial fairness.



**6.4 Summary of Pricing Dynamics**

|  |  |  |  |
| --- | --- | --- | --- |
| Feature | Model 1 | Model 2 | Model 3 |
| Occupancy Response | ✅ | ✅ | ✅ |
| Queue Impact | ❌ | ✅ | ✅ |
| Traffic Sensitivity | ❌ | ✅ | ✅ |
| Event Awareness | ❌ | ✅ | ✅ |
| Vehicle Type Adjustment | ❌ | ✅ | ✅ |
| Competitor Influence | ❌ | ❌ | ✅ |
| Suggest Reroute Logic | ❌ | ❌ | ✅ (optional) |
| Price Smoothing/Banding | ⚠️ (none) | ✅ | ✅ |

**7. Real-Time Simulation with Pathway**

**7.1 Why Real-Time Simulation?**

Urban parking dynamics change rapidly due to unpredictable factors such as peak hours, weather, traffic congestion, and local events. A robust dynamic pricing engine should therefore not only use historical data but also **react in real-time** to incoming signals.

To simulate and test real-time pricing under these conditions, we used **Pathway** — an open-source Python framework specifically designed for **real-time data streaming, transformation, and event-driven computation**.

**7.2 What is Pathway?**

Pathway is a **dataflow-based computation engine** built for scenarios where data arrives continuously and needs to be processed incrementally. It works similarly to a reactive database or a spreadsheet that updates results as inputs change, making it ideal for applications like:

* Financial trading systems
* Real-time dashboards
* Sensor-driven applications
* **Dynamic pricing engines** (our case)

**7.3 Schema Design**

We created a **custom schema** using Pathway’s declarative @Schema class to match the structure of our dataset.

class ParkingRecord(pw.Schema):

timestamp: str

parking\_lot\_id: int

latitude: float

longitude: float

capacity: int

occupancy: int

queue\_length: int

vehicle\_type: str

traffic: float

is\_special\_day: int

This schema allows Pathway to validate each incoming record and process it in a **typed, structured** way.

**7.4 Streaming Data Ingestion**

To simulate real-time data, we streamed the dataset using Pathway's CSV input reader in **streaming mode**:

input\_table = pw.io.csv.read(

'dataset.csv',

schema=ParkingRecord,

mode='streaming' # key for simulating real-time flow

)

Each row is processed one at a time in timestamp order, mimicking how a live parking sensor system would report new data every 30 minutes.

**7.5 Pricing Logic (User-Defined Function)**

We integrated the demand-based pricing logic (Model 2) into a **user-defined function (UDF)** in Pathway:

@pw.udf

def compute\_price(record):

occ\_rate = record.occupancy / record.capacity if record.capacity > 0 else 0

queue\_norm = min(record.queue\_length / 10, 1)

traffic\_norm = min(record.traffic / 10, 1)

vehicle\_weight = {'bike': 0.5, 'car': 1.0, 'truck': 1.5}.get(record.vehicle\_type.lower(), 1.0)

demand = occ\_rate + queue\_norm - traffic\_norm + record.is\_special\_day + vehicle\_weight

demand = max(0, min(demand / 5, 1)) # normalize demand

price = 10 \* (1 + demand)

return round(min(max(price, 5), 20), 2)

This function is applied on the fly to each streaming record and returns the real-time predicted price.

**7.6 Output Streaming and Export**

After computing the price, the enriched data stream is output to a file (or optionally, a dashboard):

with\_price = input\_table.select(

timestamp=pw.this.timestamp,

lot\_id=pw.this.parking\_lot\_id,

price=compute\_price(pw.this)

)

pw.io.json.write(with\_price, filename='price\_stream.json')

This JSON file acts as a **real-time pricing feed** that can be consumed by:

* Digital signage systems in parking lots
* City parking dashboards
* Mobile apps for drivers

**7.7 Benefits of Using Pathway**

|  |  |
| --- | --- |
| Feature | Why It Matters in This Project |
| Streaming Engine | Enables price computation as data flows in. |
| Low Latency | Ideal for high-frequency updates every 30 mins or less. |
| Declarative Schema | Enforces structure, reducing error risk. |
| UDF Integration | Allows custom pricing logic (Model 2 or Model 3). |
| JSON Output Ready | Easy integration with external APIs or dashboards. |

**8. Visualization & Results**

To assess how effectively each pricing model responded to varying real-time conditions, we visualized their outputs using **Bokeh**, a powerful Python library for interactive data plots. Each graph displayed price changes over time for a selected parking lot, comparing:

* 🔵 **Model 1** (Baseline Linear)
* 🟢 **Model 2** (Demand-Based)
* 🔴 **Model 3** (Competition-Aware)

**Key Observations:**

* **Model 1** generated smooth, predictable price increases solely based on occupancy, but failed to adapt to sudden spikes in demand or external events.
* **Model 2** introduced responsive pricing that rose sharply during periods of high queue length, congestion, or special days. It reflected more realistic pricing but lacked spatial intelligence.
* **Model 3** refined this further by incorporating nearby lot prices. It dynamically adjusted prices downward when cheaper alternatives were available, or upward when competitive opportunity existed—ensuring fairer distribution of demand.

**Price Stability & Fairness**

* All three models enforced price bounds between **$5 and $20**.
* Model 3 demonstrated the most **balanced pricing behavior**, preventing overpricing and guiding drivers toward better availability across locations.

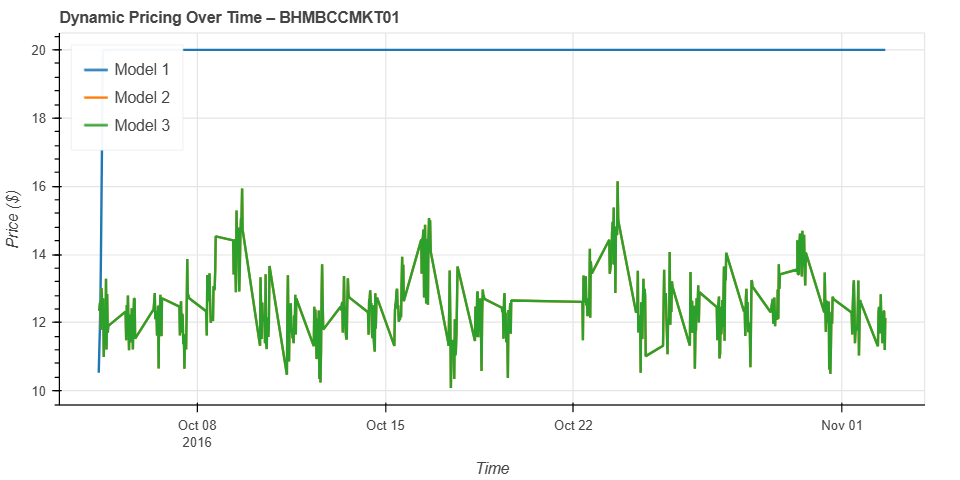
**Visual Insights**

The Bokeh plots made it clear:

* Price curves in **Model 1** were linear and steady.
* **Model 2** curves fluctuated more, reflecting environmental sensitivity.
* **Model 3** achieved smoother yet context-aware curves, avoiding extreme changes while adapting to market conditions.

**Practical Outcome**

These visualizations confirmed that integrating multiple factors (demand and competition) leads to smarter, fairer dynamic pricing. The visuals helped verify logic, test assumptions, and communicate model behavior effectively.



**9. Conclusion & Future Work**

**Conclusion**

This project successfully developed a real-time dynamic pricing engine for urban parking lots, addressing the core challenge of optimizing space utilization and revenue while adapting to changing demand and competitive conditions.

We implemented and compared three models of increasing sophistication:

* **Model 1**: A baseline linear model that responds to occupancy rate.
* **Model 2**: A demand-based model that incorporates queue length, traffic congestion, vehicle type, and special day indicators.
* **Model 3**: A competition-aware model that considers prices of nearby lots using geolocation data.

Using a simulated dataset over 73 days across 14 parking lots, we demonstrated how pricing strategies can be both **responsive and fair**, ensuring that users are charged proportionally based on real-time parking dynamics.

Real-time pricing simulation was achieved through **Pathway**, allowing streaming data to be processed incrementally with minimal latency. **Bokeh** visualizations further confirmed model effectiveness and pricing smoothness over time.

Overall, our system demonstrates that dynamic pricing in urban infrastructure—when built on interpretable models—can result in more equitable, scalable, and intelligent urban mobility management.

**Future Work**

While the models and infrastructure built for this project are fully functional and insightful, there are several enhancements and extensions that could improve real-world applicability:

**1. Weight Optimization for Demand Function**

* Replace manually set weights (α, β, γ, etc.) with **data-driven coefficients** using regression, gradient descent, or evolutionary algorithms based on historical pricing and occupancy data.

**2. Live Traffic & Event Data Integration**

* Integrate **Google Maps API** or public event feeds (e.g., festivals, games) for real-time detection of congestion spikes or special days.

**3. User Behavior Modeling**

* Introduce user personas or simulate individual parking decisions based on price sensitivity, proximity, or time constraints.
* Use **agent-based modeling** or **reinforcement learning** to adapt pricing based on observed driver responses.

**4. Mobile App or Dashboard Integration**

* Build an interface (web/mobile) that uses Pathway’s live JSON stream to show real-time parking prices and availability to users and operators.

**5. Learning-Based Price Optimization**

* Extend Model 3 into a **reinforcement learning agent** (e.g., Q-learning, policy gradient methods) that continuously learns optimal pricing strategies to maximize lot utilization or revenue under competition.

**6. Scalability Testing**

* Expand the system from 14 to **hundreds of parking lots**, optimizing data flow, latency, and system performance in a real-world environment (e.g., through cloud deployment).

**Closing Remark**

This project highlights how real-time, interpretable AI can make urban services smarter and more responsive. With further tuning and integration, the proposed solution has the potential to be deployed in smart cities and intelligent transportation systems worldwide.

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