

Project Report

1. Problem Statement

Urban areas are experiencing exponential growth in vehicle ownership, causing traffic congestion, inefficient parking, and underutilization of spaces. Traditional fixed-rate pricing models fail to adapt to real-time demand and do not reflect the dynamic nature of parking availability. The aim of this project is to create a dynamic pricing system for urban parking spaces using real-time streaming, machine learning, and clustering techniques.

2. Project Overview

This solution dynamically calculates parking prices using three models:

- **Model 1:** Linear pricing based on occupancy rate.
- **Model 2:** Demand-based pricing using a weighted ML formula.
- **Model 3:** Competitive pricing adjusted for local cluster averages.

Real-time visualization is powered by **Bokeh** and **Panel**, while data streaming is simulated using **Pathway**.

3. Technologies & Libraries Used

Python Libraries:

- **pandas:** For data handling
- **numpy:** For numerical operations
- **sklearn:**
 - `LabelEncoder` (categorical encoding)
 - `MinMaxScaler` (normalization)
 - `KMeans` (clustering)
- **matplotlib:** Basic plotting (used optionally)
- **bokeh:** Interactive plotting
- **panel:** Bokeh dashboard hosting
- **threading & time:** Simulated real-time data updates

- **pathway:** For schema definition and time-windowed streaming pipeline
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4. Feature Engineering

The dataset contains:

- Occupancy & Capacity
- Vehicle Type
- Traffic Conditions
- Queue Length
- Special Day Indicator
- Latitude & Longitude

Engineered Features:

- $\text{OccupancyRate} = \text{Occupancy} / \text{Capacity}$
 - VehicleWeight (mapped from type)
 - RawDemand using:
 - OccupancyRate
 - QueueLength
 - TrafficEncoded
 - IsSpecialDay
 - VehicleWeight
 - NormalizedDemand scaled to [0, 1]
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5. Pricing Models Explained

Model 1: Linear Pricing

Simple baseline model:

$$\text{Price} = \text{BasePrice} + \alpha * \text{OccupancyRate}$$

- Alpha is a sensitivity factor (e.g., 2)
- Encourages higher prices for fuller lots

Model 2: Demand-Based Pricing

Combines multiple real-time features:

$$\text{RawDemand} = 1.5 * \text{OccupancyRate} + 1.2 * \text{QueueLength} - 0.8 * \text{Traffic} + 1.0 * \text{IsSpecialDay} + 0.7 * \text{VehicleWeight}$$

- Scaled between 0 and 1

- Used to calculate price: $\text{Price} = 10 * (1 + 0.5 * \text{NormalizedDemand})$
- Clipped between 5 and 20 for fairness

Model 3: Competitive Pricing

Applies local adjustments using clustering:

- Clusters created using Latitude & Longitude (via KMeans)
 - Compares price to cluster average
 - Adjusts downward if $\text{OccupancyRate} > 0.9$
 - Adjusts upward if cluster mean > current price
 - Final price clipped to [5, 25]
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6. Pathway Streaming Pipeline

- **Schema Defined:** ParkingSchema with Timestamp, Occupancy, Capacity, Model Prices
 - **Replay CSV:** Data is streamed at 100 records/sec using Pathway's `replay_csv`
 - **Tumbling Window:** Aggregates prices daily
 - **Reducers:** Mean prices and min/max occupancy captured
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7. Real-Time Dashboard

Using Bokeh + Panel:

- Daily average prices for each model are plotted
 - Interactive tooltips show all prices per date
 - Streaming is simulated using threading and sleep
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8. Scalability Discussion

This model is highly extensible:

- Can ingest real-time IoT sensor data
 - Scales to multiple cities via clustering
 - Easy to integrate with APIs for payment & parking systems
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9. Limitations & Future Work

- Currently uses simulated streaming
- Demand weights are hand-tuned

- No true real-time IoT or camera feed integration
- Limited to 3 pricing models; could expand to reinforcement learning or RL agents

Next Steps:

- Integrate with live city parking APIs
- Add forecasting for peak times
- Introduce anomaly detection in price jumps