

# Model 2

Model 2 advances beyond the simple occupancy-based pricing of Model 1 by incorporating multiple real-world factors that influence parking demand. The aim is to create a more responsive and realistic pricing system, improving both revenue optimization and customer fairness.

## Feature Selection:

- **Occupancy Rate:** Proportion of occupied spaces to total capacity.
- **QueueLength:** Reflects excess demand when lot is nearly full
- **TrafficLevel:** High traffic reduces willingness to access
- **IsSpecialDay:** Such days see surges in demand, requiring price adjustments.
- **Vehicle Type:** Different types occupy different amounts of space and have distinct demand patterns.

## Data Preparation

- **Timestamp Creation:** Date and time columns are merged for precise temporal analysis.
- **Lot-wise Processing:** Each lot is analyzed individually to capture unique demand dynamics.
- **Categorical Encoding:** Vehicle type and traffic status are converted to numerical codes.
- **Sorting:** Data is sorted by timestamp for correct sequential processing.

## Demand Function

```
2.0 * occ_rate * tod_weight * wd_weight + beta * np.log1p(adj_queue) + gamma * np.log1p(adj_traffic) +  
delta * hour_term + epsilon * veh_term + zeta * spec_term
```

Where:

- $\beta, \gamma, \delta, \epsilon, \zeta$  are set to 1.0 for balanced influence.
- **Hour Effect:** Gaussian function centered at midday to model peak hour demand.
- $tod\_weight$  = time-of-day multiplier
- $wd\_weight$  = weekday/weekend multiplier
- $spec\_term = 1$  if special day/holiday, 0 otherwise
- $veh\_term$  = Weight for vehicle type

## Queue Function:

- **Purpose:** Models the effect of excess demand (queue) on price.
- **Why log?:** The logarithm ensures that the effect of queue length increases rapidly at first but then tapers off (diminishing returns). This prevents a very long queue from causing unrealistically high prices.

## Traffic Function:

- **Purpose:** Reflects the impact of nearby traffic congestion on demand.
- **Why log?:** Similar to queue, the impact of traffic increases at first but then levels off.

## Hour Function:

- Purpose: Explicitly models peak hour effects using a Gaussian (bell curve) centered at midday.
- Why Gaussian?: Real-world data shows that demand often peaks at certain hours and then drops off symmetrically.

## Vehicle Function:

- Purpose: Adjusts demand for the type of vehicle.
- Why?: Larger vehicles (like trucks) take more space and may be less frequent, so their presence should have a higher impact on demand.

## Normalization

After computing the raw demand, it is normalized to a 0–1 range:

$$\text{Demand Norm} = \frac{\text{Demand} - 2}{8 - 2}$$

- Why?: This keeps the demand score within a predictable range for price calculation, preventing extreme price swings.

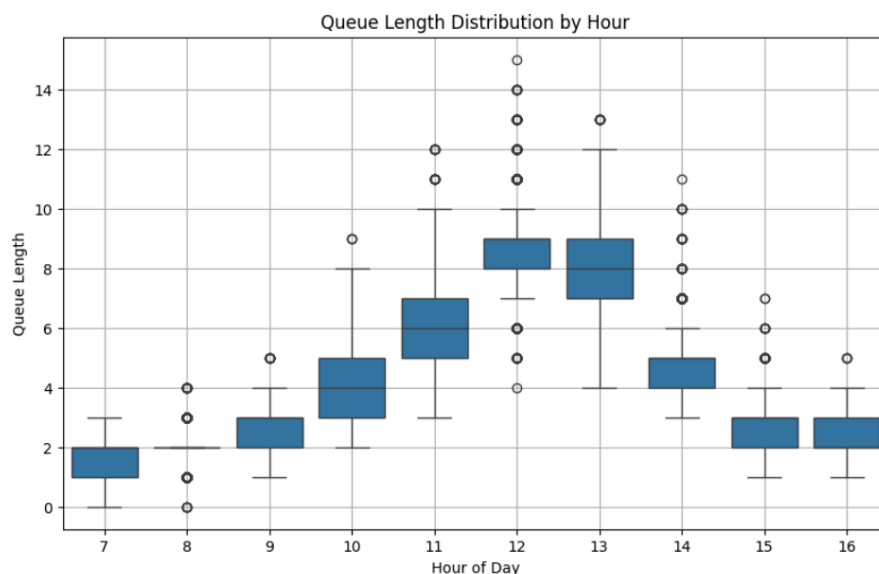
## Price Function

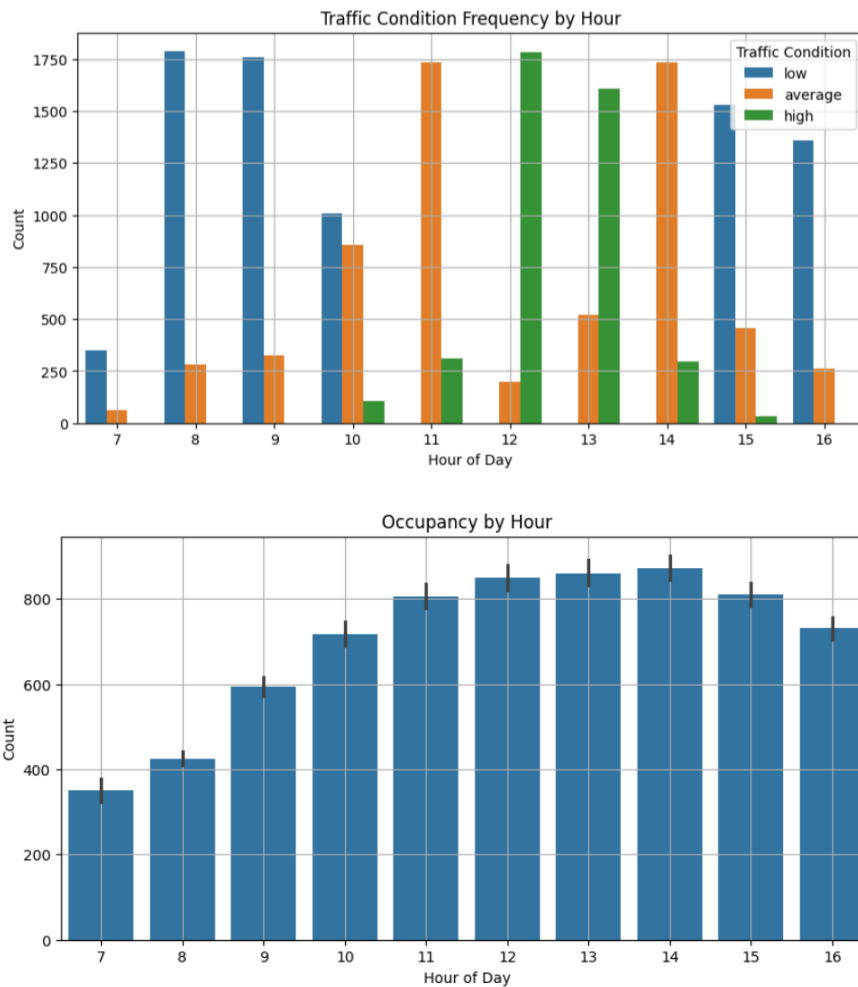
$$\text{price} = 10 * (1 + \text{LAMBDA} * \text{demand\_norm})$$

Lambda=Set to 1.0 to control price sensitivity.

## Parameter Choices

- All weights and coefficients were chosen based on domain knowledge, literature, and iterative testing to ensure stability and realism.
- Normalization bounds reflect observed demand ranges in the dataset.
- Base price is fixed at \$10 to comply with business rules.





## Advantages Over Model 1

- More Realistic: Reflects real-world demand fluctuations.
- Responsive: Adjusts to both predictable (time, day) and unpredictable (queue, traffic, events) factors.
- Fairness: Prices are more justifiable and transparent to users.

## Validation Through Visualization

- The shape and slope of price lines over time visually confirm that the pricing function is:
  - Responsive to demand fluctuations,
  - Controlled via capping and normalization,
  - Fair across locations based on their conditions.
- Unlike Model 1, where pricing was occupancy-driven only, here multi-factor responsiveness is visibly apparent.

## Conclusion

Model 2 provides a robust, multi-factor approach to dynamic parking pricing. By considering occupancy, time, day, queue, traffic, vehicle type, and special events, it achieves a more accurate and adaptable pricing structure. This model is expected to outperform the baseline Model 1 in both revenue optimization and user satisfaction.

