4.1 Model 1: Short-Term Passenger Flow Prediction (Task 1)

4.1.1 Purpose of the Model

In order to support proactive elevator dispatching and parking decisions, it is necessary to anticipate near-future passenger demand.
Based on the exploratory data analysis presented in Section 3, elevator hall-call arrivals show two key characteristics:

1. **Strong regularity within a day**, with recurring peaks during lunchtime and evening hours.
2. **Short-term dependence**, where demand in the next few minutes is closely related to recent demand levels.

Motivated by these observations, we develop a mathematical model to predict the **total number of hall calls in the next 5-minute time interval**. The model is designed to be simple, interpretable, and suitable for real-time implementation in an elevator group control system.

4.1.2 Notation and Time Discretization

Time is divided into consecutive 5-minute intervals. Let

$$y_t = \text{number of hall calls occurring during the } t\text{-th 5-minute interval.}$$

The objective of Task 1 is to estimate the expected demand in the next interval:

$$\hat{y}_{t+1} = \mathbb{E}[y_{t+1} \mid \mathcal{F}_t],$$

where $\mathcal{F}_t$ represents all information available up to time t.

To account for the significant behavioral differences observed between weekdays and weekends, we introduce a regime indicator:

$$w_t = \begin{cases} 1, & \text{if interval } t \text{ occurs on a weekday,} \\ 0, & \text{if interval } t \text{ occurs on a weekend.} \end{cases}$$

4.1.3 Time-of-Day Baseline Demand

Exploratory analysis reveals that passenger arrivals follow a highly repeatable daily pattern. To capture this regularity, we define a **time-of-day baseline demand**.

Let $\tau(t)$ denote the position of interval t within a day (e.g., the index of a 5-minute interval from midnight). For each regime $w \in \{0,1\}$, we define:

$$\mu_w(\tau) = \mathbb{E}[y_t \mid w_t = w, \tau(t) = \tau].$$

This baseline represents the typical number of hall calls expected at a given time of day under weekday or weekend conditions. In practice, $\mu_w(\tau)$ is estimated using historical averages from the available data.

4.1.4 Short-Term Adjustment Using Recent Observations

While the baseline captures long-term regularity, actual demand may temporarily deviate from typical levels due to local fluctuations. To account for this effect, we introduce a deviation term:

$$e_t = y_t - \mu_{w_t}(\tau(t)).$$

Empirical observations indicate that these deviations tend to persist over short time horizons. Therefore, we model the deviation using a first-order autoregressive structure:

$$e_t = \phi_{w_t} e_{t-1} + \varepsilon_t,$$

where $\mid \phi_{w_t} \mid < 1$ and ε_t represents short-term random variability with zero mean.

4.1.5 One-Step-Ahead Forecasting Formula

Combining the baseline demand with the short-term adjustment yields the following prediction for the next interval:

$$\boxed{\hat{y}_{t+1} = \mu_{w_{t+1}}(\tau(t+1)) + \phi_{w_t}\left[y_t - \mu_{w_t}(\tau(t))\right]}$$

This formulation reflects two intuitive components:

- the **expected demand at the next time of day**, and
- a **correction term** based on whether recent demand has been higher or lower than usual.

4.1.6 Parameter Estimation

The baseline demand $\mu_w(\tau)$ is estimated by averaging historical hall-call counts for the corresponding regime and time-of-day interval.

The autoregressive parameter ϕ_w is estimated separately for weekdays and weekends using standard least-squares regression on the deviation series $\{e_t\}$. This separation ensures that the model reflects the distinct temporal dynamics observed under different operating regimes.

4.1.7 Interpretation and Model Applicability

The proposed model captures both **systematic daily patterns** and **short-term demand persistence**, enabling reliable prediction of near-future passenger flow. Its simplicity allows for efficient real-time computation, making it well suited for integration into elevator group control systems.

The predicted value $\hat{y}_{t+1}$ serves as a key input for:

- traffic mode identification (Task 2), and
- proactive elevator parking decisions (Task 3).

4.1.8 Limitations

The model is designed to describe typical operating conditions and may not fully capture rare, unexpected events such as large unscheduled gatherings. Nevertheless, its transparency and robustness make it an appropriate foundation for short-term demand forecasting in this application.

4.2 Model 2: Real-Time Traffic State Classification (Task 2)

4.2.1 Objective of the Model

Elevator traffic within a high-rise building is not uniform throughout the day. Instead, it evolves through a small number of recurring operational modes, such as morning up-peak, lunchtime transitions, and evening down-peak.
Identifying the current traffic state in real time is essential, since different elevator control and parking strategies are appropriate for different modes.

The objective of Task 2 is therefore to develop a **real-time classification model** that automatically assigns the building to a traffic state based on observable elevator call characteristics. The resulting state label serves as a decision signal for the dynamic parking strategy developed in Task 3.

4.2.2 Definition of Traffic States

Based on exploratory data analysis and common elevator traffic theory, we define the following set of discrete traffic states:

$\mathcal{S}$
$= \{\text{Night Idle,Morning Up-Peak,Lunch Down-Peak,Afternoon Mixed,Evening Down-Peak,Weekend Low-De}$

Each state corresponds to a distinct pattern of passenger behavior and directional flow, and therefore requires different operational responses.

4.2.3 Real-Time Feature Construction

To classify the current traffic state, we extract a set of features from the most recent 5-minute observation window, consistent with the forecasting horizon in Task 1.

Let the following quantities be defined for time interval t:

- C_t: total number of hall calls,
- C_t^{up}: number of upward hall calls,
- C_t^{down}: number of downward hall calls,
- $r_t = \frac{C_t^{up}}{C_t}$: proportion of upward calls,
- $p_{1,t}$: proportion of hall calls originating from Floor 1,
- H_t: spatial entropy of call distribution across floors, measuring how concentrated or dispersed the demand is.

These features are combined into a feature vector:

$$\mathbf{x}_t = (C_t, r_t, p_{1,t}, H_t).$$

All quantities are directly observable in real time and require no historical model training.

4.2.4 Rule-Based State Classification Model

Rather than relying on data-driven black-box classifiers, we adopt a **rule-based classification approach**. This ensures transparency, interpretability, and robustness, all of which are desirable in operational elevator control systems.

The traffic state at time t, denoted s_t, is determined by the following decision rules:

$$
s_t = \begin{cases} \text{Night Idle}, & C_t < \theta_1, \\ \text{Morning Up-Peak}, & C_t \geq \theta_2, r_t \geq \alpha_1, p_{1,t} \geq \beta_1, \\ \text{Evening Down-Peak}, & C_t \geq \theta_3, r_t \leq \alpha_2, \\ \text{Lunch Down-Peak}, & C_t \geq \theta_2, \alpha_2 < r_t < \alpha_3, \\ \text{Weekend Low-Demand}, & w_t = 0, \\ \text{Afternoon Mixed}, & \text{otherwise}. \end{cases}
$$

Here:

- $\theta_1, \theta_2, \theta_3$ are demand intensity thresholds,
- $\alpha_1, \alpha_2, \alpha_3$ define directional dominance,
- β_1 captures the concentration of lobby-originated traffic.

Threshold values are determined empirically using historical quantiles of the corresponding features, ensuring adaptability to different building scales and usage levels.

4.2.5 Interpretation of Classification Logic

Each classification rule reflects an intuitive interpretation of observed traffic behavior:

- **Night Idle** corresponds to minimal system activity, typically during late-night hours.
- **Morning Up-Peak** is characterized by high demand, strong upward directionality, and heavy concentration at the lobby.
- **Lunch Down-Peak** reflects a temporary downward migration of occupants, often involving multiple floors.
- **Evening Down-Peak** exhibits the strongest downward dominance as occupants exit the building.
- **Afternoon Mixed** represents intermediate periods with balanced inter-floor movement.
- **Weekend Low-Demand** captures the fundamentally different usage patterns observed on weekends.

This structure allows the system to respond not only to demand magnitude, but also to demand direction and spatial distribution.

4.2.6 Role in the Integrated Framework

The output of Model 2 is a discrete traffic state label $s_t \in \mathcal{S}$, updated every 5 minutes.

This label is used in Task 3 to select appropriate elevator parking and repositioning strategies, enabling a state-aware and demand-responsive control policy.

4.2.7 Advantages and Limitations

Advantages

- Fully interpretable and transparent decision logic,
- No training data or computational overhead required,
- Easily adaptable to other buildings by recalibrating thresholds.

Limitations

- The rule-based structure may not capture rare or atypical traffic patterns,
- Threshold selection depends on historical data quality.

Despite these limitations, the model provides a reliable and operationally meaningful representation of real-time elevator traffic states.

4.3 Model 3: Dynamic Elevator Parking Strategy (Task 3)

4.3.1 Objective of the Parking Strategy

When an elevator becomes idle, its parking location has a significant impact on future passenger waiting times and system efficiency. A poorly chosen parking strategy may lead to long response times, unnecessary empty travel, and uneven elevator utilization.

The objective of Task 3 is to develop a **dynamic elevator parking strategy** that determines:

1. where idle elevators should be parked,
2. how many elevators should be positioned at key locations, and
3. when repositioning should occur,

based on predicted near-future demand (Task 1) and the current traffic state (Task 2).

4.3.2 Decision Framework and Inputs

The parking strategy operates in discrete 5-minute decision intervals, consistent with the time scale used in Tasks 1 and 2.

At time interval t, the decision framework takes the following inputs:

- $\hat{y}_{t+1}$: predicted total hall-call demand in the next 5-minute interval (Task 1),
- $s_t \in \mathcal{S}$: current traffic state identified by the classification model (Task 2),
- $\{f_k\}$: current floor locations of all idle elevators.

The output of the model is a set of parking assignments for idle elevators.

4.3.3 Candidate Parking Floors

Rather than allowing elevators to park arbitrarily at any floor, we define a limited set of **candidate parking floors** based on spatial demand patterns observed in the exploratory data analysis:

$$\mathcal{L} = \{\text{Lobby}, \text{Mid-Zone}, \text{Upper-Zone}\}.$$

These zones represent:

- **Lobby**: the primary origin point during up-peak periods,
- **Mid-Zone**: floors with consistently high daytime activity,
- **Upper-Zone**: floors associated with concentrated downward demand during evening periods.

Restricting parking locations to a small number of zones simplifies decision-making and enhances operational robustness.

4.3.4 Conceptual Objective Function

The parking strategy is designed to optimize overall system performance. Conceptually, we consider the following multi-objective function:

$$\min\ J = \alpha \cdot \text{AWT} + \beta \cdot P(\text{Wait} > \tau) + \gamma \cdot \text{Empty Travel},$$

where:

- **AWT** denotes average passenger waiting time,
- $P(\text{Wait} > \tau)$represents the proportion of long-wait incidents exceeding a threshold τ,
- **Empty Travel** measures unnecessary elevator movement without passengers,
- $\alpha, \beta, \gamma$are non-negative weighting parameters.

This objective guides the structure of the parking rules but does not require explicit numerical optimization.

4.3.5 State-Dependent Parking Policy

We propose a **state-dependent rule-based parking policy**, where parking decisions are determined primarily by the identified traffic state s_t.

(1) Night Idle State

When $s_t =$ Night Idle, overall demand is minimal.

Policy:

- Maintain a small number of elevators at the lobby,
- Park remaining idle elevators at their most recent stop floors to minimize unnecessary movement.

(2) Morning Up-Peak State

During morning up-peak periods, most passenger requests originate from the lobby and travel upward.

Policy:

- Allocate the majority of idle elevators to the lobby,
- Minimize repositioning to upper zones unless demand predictions indicate unusually high activity.

(3) Lunch Down-Peak State

Lunchtime traffic involves significant downward movement from multiple occupied floors.

Policy:

- Distribute idle elevators across the mid-zone,
- Reduce reliance on lobby parking to avoid delayed responses to upper-floor calls.

(4) Afternoon Mixed State

In the afternoon, traffic is characterized by balanced inter-floor movement.

Policy:

- Evenly distribute idle elevators among lobby, mid-zone, and upper-zone,

- Aim to minimize the maximum distance between any idle elevator and potential call locations.

(5) Evening Down-Peak State

Evening traffic exhibits strong downward dominance, often originating from upper floors.

Policy:

- Pre-position a larger share of idle elevators in the upper-zone,
- Maintain limited lobby presence to handle residual arrivals.

(6) Weekend Low-Demand State

Weekend traffic is sparse and less structured.

Policy:

- Keep a minimal number of elevators active at the lobby,
- Park remaining elevators at nearby floors and prioritize energy-saving behavior.

4.3.6 Role of Demand Prediction in Repositioning Timing

The predicted demand $\hat{y}_{t+1}$ is used as a trigger for proactive repositioning.

If $\hat{y}_{t+1}$ exceeds a predefined demand threshold, idle elevators may be repositioned **before** new calls are registered. This anticipatory behavior reduces response delays during emerging peak periods and prevents reactive congestion.

4.3.7 Discussion of Strategy Characteristics

The proposed parking strategy exhibits several desirable properties:

- **Interpretability**: all decisions are based on transparent rules linked to observable traffic states,
- **Adaptability**: the strategy automatically adjusts as the traffic state changes throughout the day,
- **Efficiency**: unnecessary elevator movement is avoided during low-demand periods,
- **Practicality**: the policy can be implemented as a software-level enhancement to existing group control systems.

4.3.8 Limitations

The strategy is designed for typical daily operating patterns and may not fully address rare, unexpected events. In such cases, manual overrides or adaptive threshold adjustments may be required. Nevertheless, for routine operations, the proposed policy provides a robust and effective approach to elevator parking management.

Summary Sheet

Problem B: The Elevator Pitch

Background and Problem Statement

In modern high-rise buildings, elevator efficiency strongly affects passenger experience, energy consumption, and system wear. A critical but often overlooked component of elevator group control is the **parking strategy**—deciding where idle elevators should wait for future calls. Static strategies, such as leaving elevators at their last stop or sending all idle cars to the lobby, fail to adapt to time-varying traffic patterns and may result in long waiting times and unnecessary empty travel.

Using 30 days of operational data from a bank of eight elevators in a mixed-use building, this study develops a set of mathematical models to support **predictive, state-aware, and dynamic elevator parking decisions**.

Task 1: Short-Term Passenger Flow Prediction

To anticipate near-future demand, we model the total number of hall calls in the next 5-minute interval. Exploratory data analysis reveals strong **time-of-day regularity**, clear **weekday–weekend differences**, and **short-term temporal dependence**.

We propose a regime-based time-series model that decomposes demand into:

1. a **time-of-day baseline**, representing typical passenger behavior at each moment of the day, and
2. a **short-term adjustment**, capturing recent deviations from typical levels.

The resulting model predicts future demand using both historical daily patterns and recent observations. The forecasted passenger flow serves as an early indicator of emerging congestion and provides input for subsequent traffic classification and parking decisions.

Task 2: Real-Time Traffic State Classification

Elevator traffic does not evolve continuously but instead switches among a small

number of recurring operational modes. Based on data analysis and elevator traffic theory, we define discrete traffic states including **Morning Up-Peak**, **Lunch Down-Peak**, **Afternoon Mixed**, **Evening Down-Peak**, **Night Idle**, and **Weekend Low-Demand**.

A rule-based classification model is developed using real-time features such as:

- total hall call volume,
- proportion of upward calls,
- concentration of lobby-originated requests, and
- spatial distribution of calls across floors.

Transparent decision rules map these features to traffic states without requiring model training. This approach ensures interpretability and enables reliable real-time identification of the building's current operating mode.

Task 3: Dynamic Elevator Parking Strategy

Using the predicted demand (Task 1) and identified traffic state (Task 2), we design a **state-dependent dynamic parking strategy** for idle elevators. Candidate parking locations are grouped into functional zones, including the lobby, mid-level floors, and upper-level floors.

For each traffic state, tailored parking rules determine:

- where idle elevators should be positioned,
- how many elevators should be allocated to each zone, and
- when proactive repositioning should occur.

The strategy is guided by a conceptual objective that balances average waiting time, long-wait occurrences, and unnecessary empty travel. By pre-positioning elevators near expected demand sources, the proposed policy improves responsiveness during peak periods while conserving energy during low-demand intervals.

Conclusions

Together, the three models form an integrated framework that links **prediction**, **classification**, and **decision-making**. The proposed approach replaces static parking rules with a flexible, data-informed strategy that adapts to changing traffic conditions throughout the day. This framework enhances passenger experience, improves system efficiency, and provides a practical foundation for smarter elevator group control systems.

Memo to Building Management and Elevator Maintenance Company

Subject: Proposal for a Dynamic Elevator Parking Strategy Based on Building Traffic Patterns

To: Building Management Team and Elevator Maintenance Company
From: MCM Modeling Team
Date: *[Insert Date]*

Executive Summary

This memo proposes a **dynamic elevator parking strategy** designed to reduce passenger waiting times, decrease unnecessary elevator movement, and improve overall system efficiency.
Unlike traditional static approaches—such as leaving elevators at their last stop or returning all idle elevators to the lobby—our strategy adapts in real time to changing traffic conditions within the building.

Using historical operational data and observed traffic patterns, we recommend a state-aware parking policy that positions idle elevators closer to where future demand is most likely to occur.

Why Current Parking Strategies Are Inefficient

Conventional parking strategies are simple but inflexible:

- **Leaving elevators at their last stop** often places idle cars far from the next passenger request.
- **Sending all idle elevators to the lobby** increases empty travel, energy consumption, and congestion during non–up-peak periods.

Our analysis shows that elevator demand varies significantly throughout the day. Traffic patterns during morning arrivals, lunchtime movement, afternoon activity, and evening departures are fundamentally different. A single static parking rule cannot perform well across all these scenarios.

Overview of the Proposed Strategy

The proposed approach integrates three key components:

1. **Short-term demand anticipation**
   Near-future passenger demand is estimated using recent activity and time-of-day patterns.
2. **Traffic state identification**

The building's current operating mode (e.g., morning up-peak, evening down-peak, low-demand periods) is identified using simple, transparent rules based on real-time data.

3. **State-dependent parking decisions**
   When an elevator becomes idle, its parking location is determined by the current traffic state rather than a fixed default rule.

This allows the system to respond proactively rather than reactively.

How the Strategy Works in Practice

- **Morning Up-Peak:**
  Most idle elevators are positioned at the lobby to quickly serve incoming passengers.
- **Lunchtime and Afternoon Periods:**
  Elevators are distributed across mid-level floors where inter-floor movement is most common.
- **Evening Down-Peak:**
  More elevators are pre-positioned at upper floors to reduce response time for departing occupants.
- **Nighttime and Weekends:**
  Only a minimal number of elevators remain active at the lobby, while others remain parked to minimize energy use and wear.

This adaptive behavior ensures that elevators are closer to anticipated demand, reducing response delays.

Expected Benefits

Implementing this dynamic parking strategy is expected to deliver several benefits:

- **Reduced passenger waiting times**, particularly during peak periods.
- **Fewer long-wait incidents**, improving occupant satisfaction.
- **Lower energy consumption**, by minimizing unnecessary empty travel.
- **More balanced elevator usage**, reducing uneven wear and maintenance burden.

Importantly, the strategy relies on rule-based logic and does not require complex optimization algorithms, making it practical to integrate into existing group control systems.

Implementation Considerations

- The strategy can be implemented as a **software-level enhancement** without changes to elevator hardware.
- Decision rules and thresholds can be adjusted to reflect building-specific characteristics.
- The approach is transparent and interpretable, allowing operators to understand and fine-tune system behavior.

Conclusion

By replacing static parking rules with a dynamic, traffic-aware strategy, the building can significantly improve elevator performance and operational efficiency.
The proposed solution aligns with real-world usage patterns, is easy to implement, and provides a scalable foundation for smarter elevator management.

We recommend pilot testing this strategy during selected operating hours to evaluate its performance and refine parameters before full deployment.