Predictive Standby Dispatch: Machine Learning-based Smart Elevator Idle Positioning

Student Name	:	TEN YEE CHERN
Student ID	:	0381084
Supervisor	:	Prof. Afizan Azman

INTRODUCTION


ATTENTION
ACCESSIBLE RESTROOMS ARE LOCATED IN THE BASEMENT AND ON FLOORS 6, 7, AND 15.
COLLOQUIA AND ACADEMIC NOTICES ONLY
How do brands like Apple and Gucci and Vespa design for 'desirability'?

INTRODUCTION

- Traditional elevator control strategy: Send the nearest and heading elevator to the calling floor, and **stay at where they lastly unload** passengers (closet car algorithm, CCA)
- This makes idle elevators often stay at low-demand frequency floors
- When high-demand frequency floors are making calls, the elevator needs to take time to arrive at calling floors, increasing waiting time
- When buildings become taller, this situation becomes worse

Solution:
Elevator's Predictive Standby Dispatch

- A system that allows the elevator to predict future calls
- Reposition the idle elevator according to the predicted calls
- Therefore, reducing users' waiting time

Problem Statement, Research Questions & Objectives

PROBLEM STATEMENT

- **Waiting Time Gap:** A reactive dispatch control system only sends the elevator once a call is received, even though there are several optimising strategies, but the time the elevator takes to reach the calling floors cannot be eliminated.

- **System's Effectiveness in different scenarios:** The developed predictive system might not improve much in demand-saturated scenarios, as it only repositions the elevator when it is idle.

- **Cost-Benefit balance:** It can be expected that waiting time can be reduced significantly if we send the elevator to stand by at every possible floor, but the cost also increases.

RESEARCH QUESTION

- Can machine learning algorithms reliably predict future hall calls (floor and direction) before they occur?
- Does using prediction to reposition idle elevators (standby dispatch) reduce waiting time compared to baseline in different scenarios (high and low demand)?
- How should the system trade off between decreasing waiting time and minimising repositioning movement/energy cost?

RESEARCH OBJECTIVE

- Develop and validate machine learning models that predict future hall calls (floor and direction) with satisfactory accuracy.

- Implement and simulate the predictive standby dispatching strategy, and compare its average waiting time (AWT) versus a baseline reactive dispatch strategy in different scenarios (high and low demand).

- Design a framework or strategy to balance between AWT reduction and movement cost.

LITERTURE REVIEW

Domain Research (Elevator Dispatch Optimisation)

- Reactive: CV occupancy-aware (Wang et al., 2021); Dispatch control RL Opti (Crites & Barto, 1995);
- Proactive: Standby floor scoring system(-AWT:~24%) (Tsai et al., 2025); Arrival time prediction based on users' trajectory (Zhang et al., 2022)

Dataset

- All previous similar work using a simulator
- Poisson process (Crites & Barto, 1995) and Gaussian-based (Tsai et al., 2025) arrival rate

Predictor

- Statistical Models: (ARIMA, SARIMA)
  - Easy to implement
  - Computationally efficient and low-cost
  - Design for regression, not suitable for classification task (Fatima & Rahimi, 2024)
- RNNs: (RNN, LSTM, GRU)
  - Able to capture long-term dependencies
  - Gradient explosion/vanishing problem limit dependencies range (Sherstinsky, 2020)
- TCN:
  - Able to capture longer-range dependencies compared to RNNs
  - High training efficiency (D. Kim, 2023)

- Transformers:
  - Able to process extremely long-range dependencies
  - Able to capture global temporal dependencies
  - Outperform RNNs and TCN in a longer range of dependencies (Hall & Rasheed, 2025)
  - Require higher computation and memory (Kong et al., 2025)

Interesting study:

- Encoder-decoder separated LSTM (W. Zhang et al., 2019)
- Hybrid model GRU-TCN (Nanni et al., 2021)

METHODOLOGY

DATA & ENVIRONMENT SIMULATIONS

Arrival Simulation

- A formula to decide the global arrival rate in time (Gaussian Based) :

$$\boldsymbol{\lambda(t)} = \boxed{\boldsymbol{A_1 \cdot exp(-\frac{(t-\mu_1)^2}{2\sigma_1^2})}} + \boldsymbol{A_2 \cdot exp(-\frac{(t-\mu_2)^2}{2\sigma_2^2}) + A_3 \cdot exp(-\frac{(t-\mu_3)^2}{2\sigma_3^2}) + \varepsilon}$$

- Determine the traffic pattern in time:

  Workday:

  - Morning up-peak (7-10:00): predominantly upward movement (lobby/carpark -> upper)
  - Lunchtime peak (11-14:30): mainly inter-floor trips
  - Evening down-peak (16-21:00): predominantly downward movement (upper/carpark ->lobby)
- Weekday/Weekend/Holiday differentiation:
  - Using A_i to control the number of arrival
  - Larger A_i in weekday, lower in weekend and holiday
- Dense Level Control
  - Adjusting A_i to generate two set of data, different in demand level (low and high)

Building Simulation

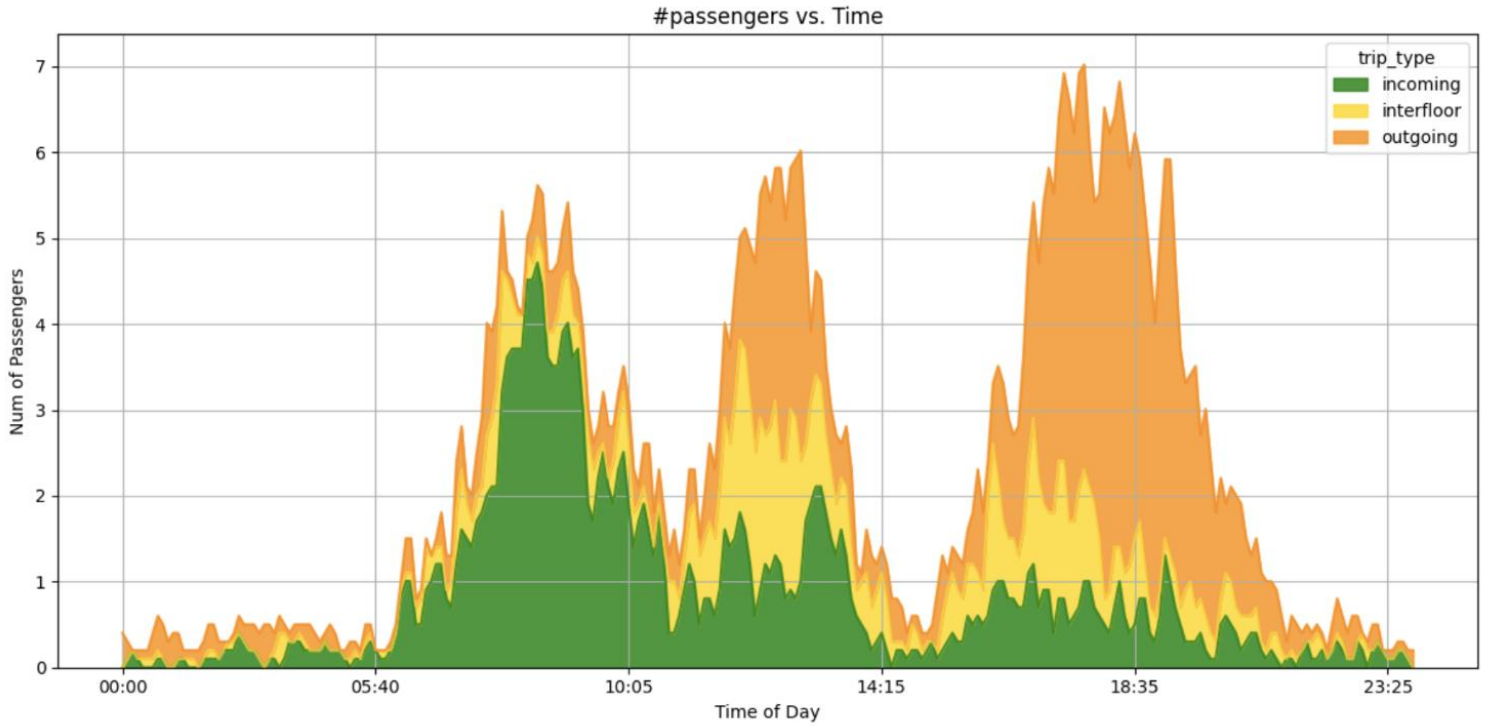
- Two profiles:
  - Low-rise: 10-floor, 1 elevator, no carpark
  - High-rise: 40-floor, 4 elevator, 2-5 floor are the carparks

Elevator Simulation

- Capacity: 15 units
- Moving speed: 2s/floor
- Load/Unload time:

$$T(n_{load}, n_{unload}) = C + \sum_{k=0}^{n_{load}-1} 3 \times 0.5^k + \sum_{k=0}^{n_{unload}-1} 3 \times 0.5^k$$

- Dispatch rule: Closet Car Algorithms (CCA)



Daily traffic profile from **Tsai et al. (2025)**

Machine Learning

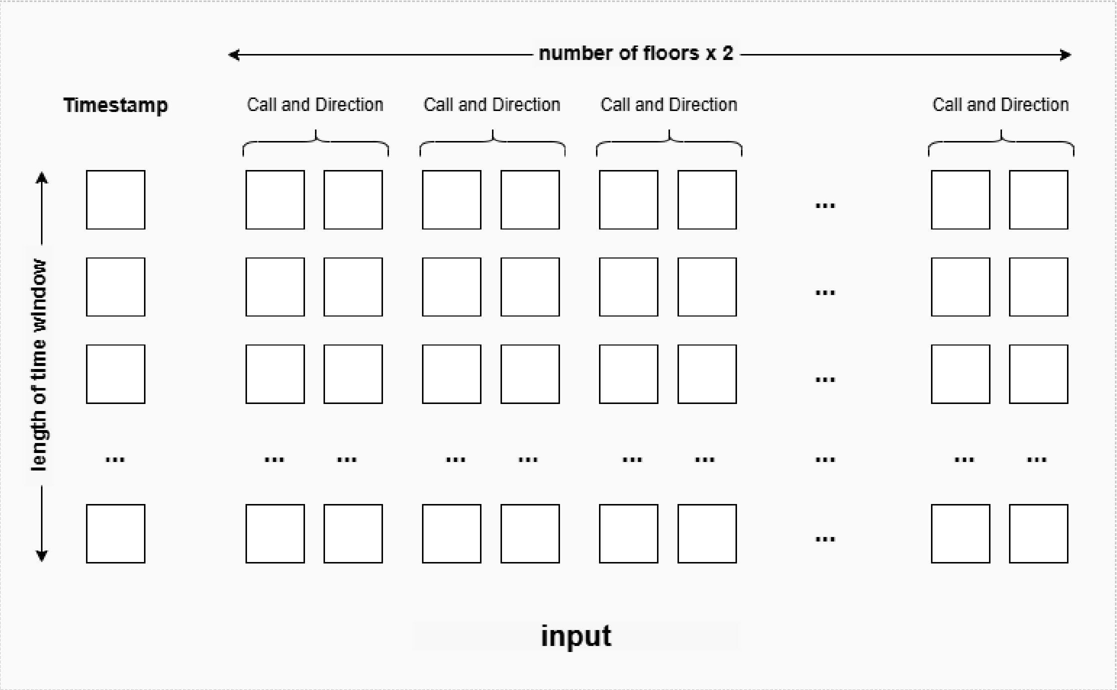
- Task type: Multi-label Classification
- Model: TCN & GRU-TCN
- Criterion: Binary Cross-Entropy (BCE) (consider implementing weight if unbalanced)
- Optimiser: Adam
- Input:

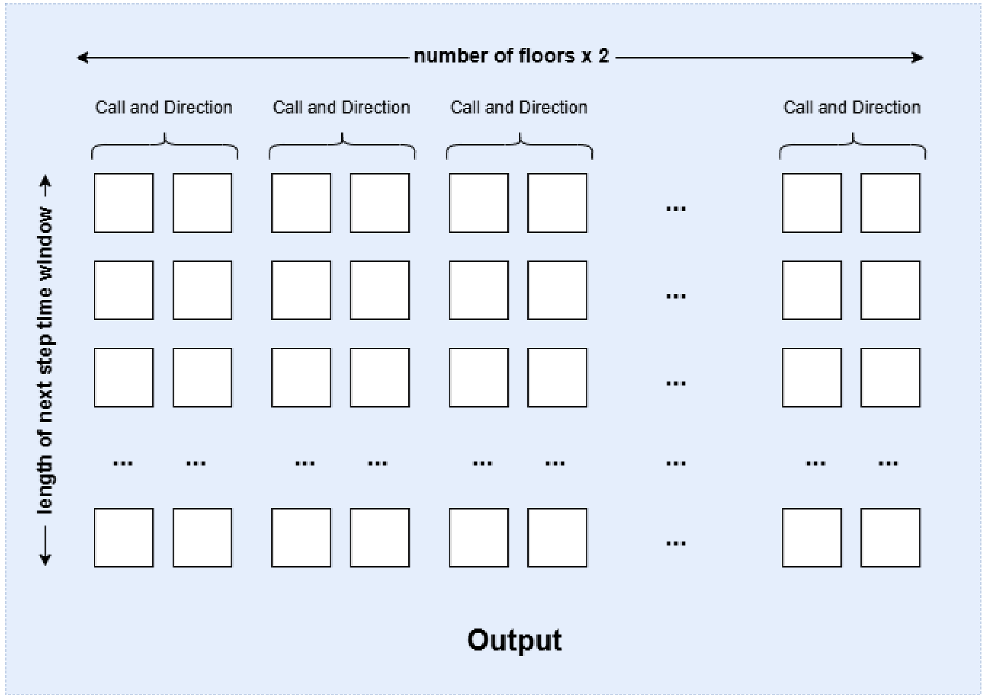
A matrix of features within a time window that consists of *Timestamp* & One-hot encode *call and direction record* of floors (0/1)

- Output:

One-hot encode *call and direction record* of floors (0/1) in the future time window

- Evaluation: Accuracy, Precision, Recall



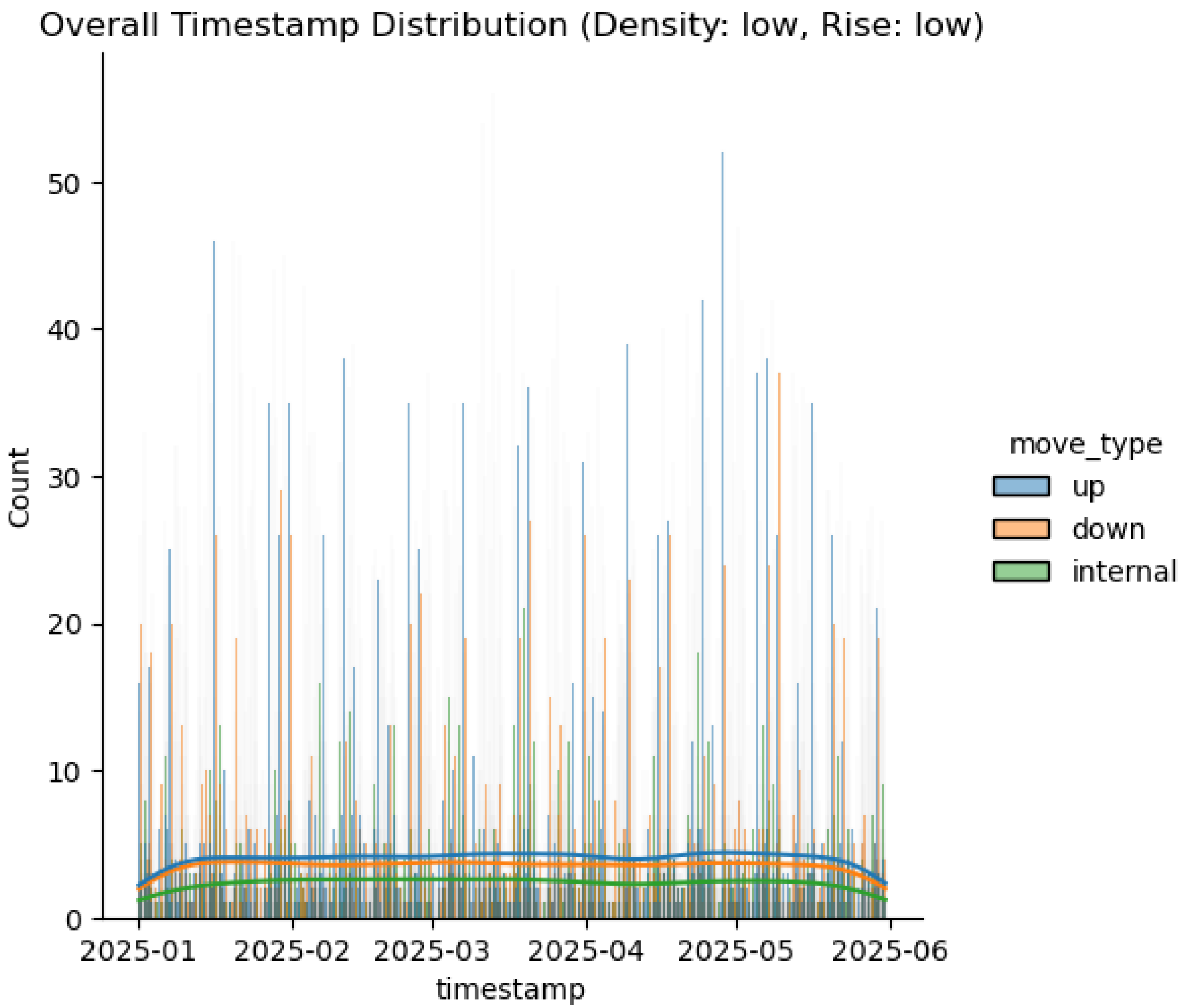


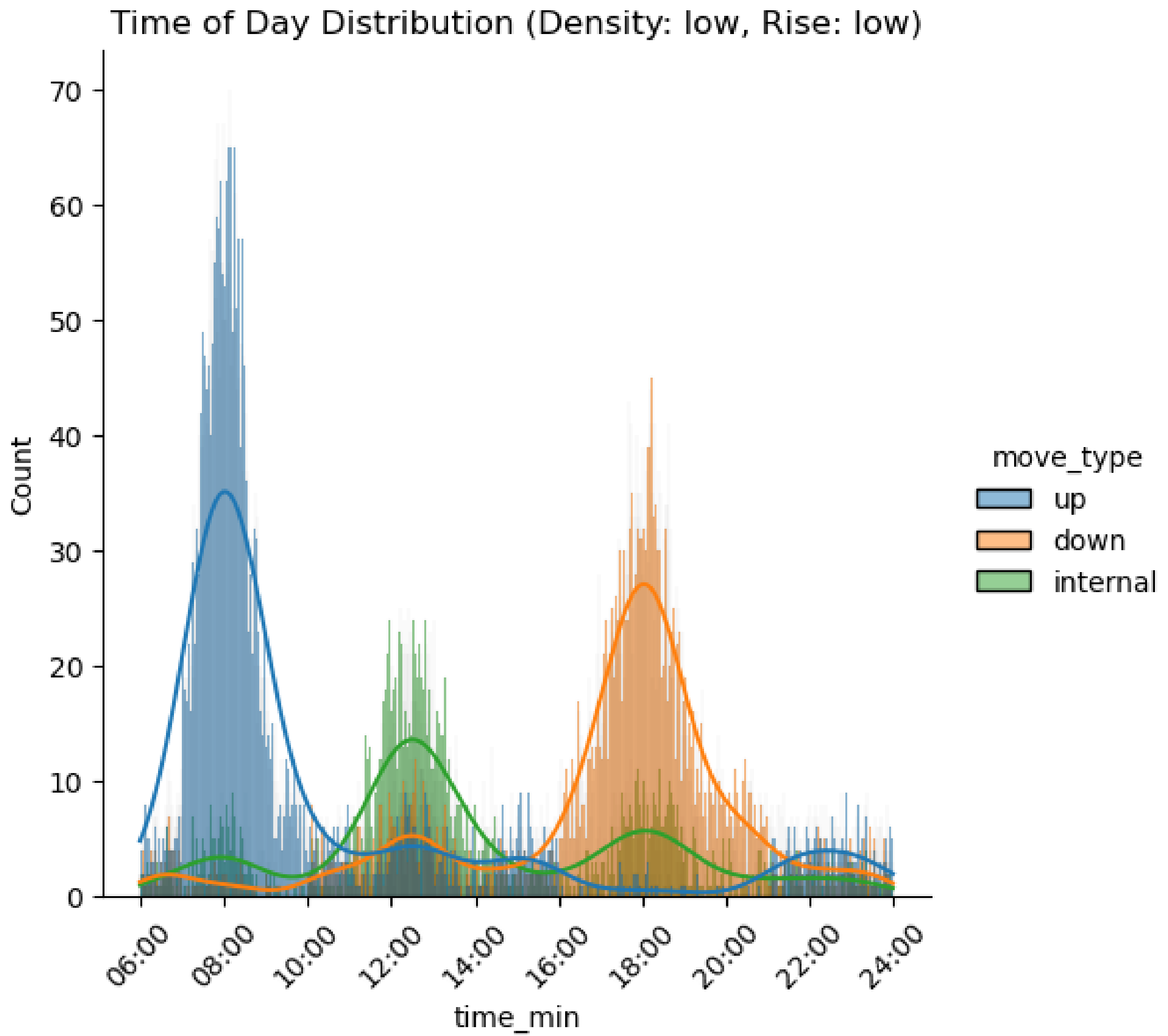
Improvement evaluation & Cost-benefit balancing

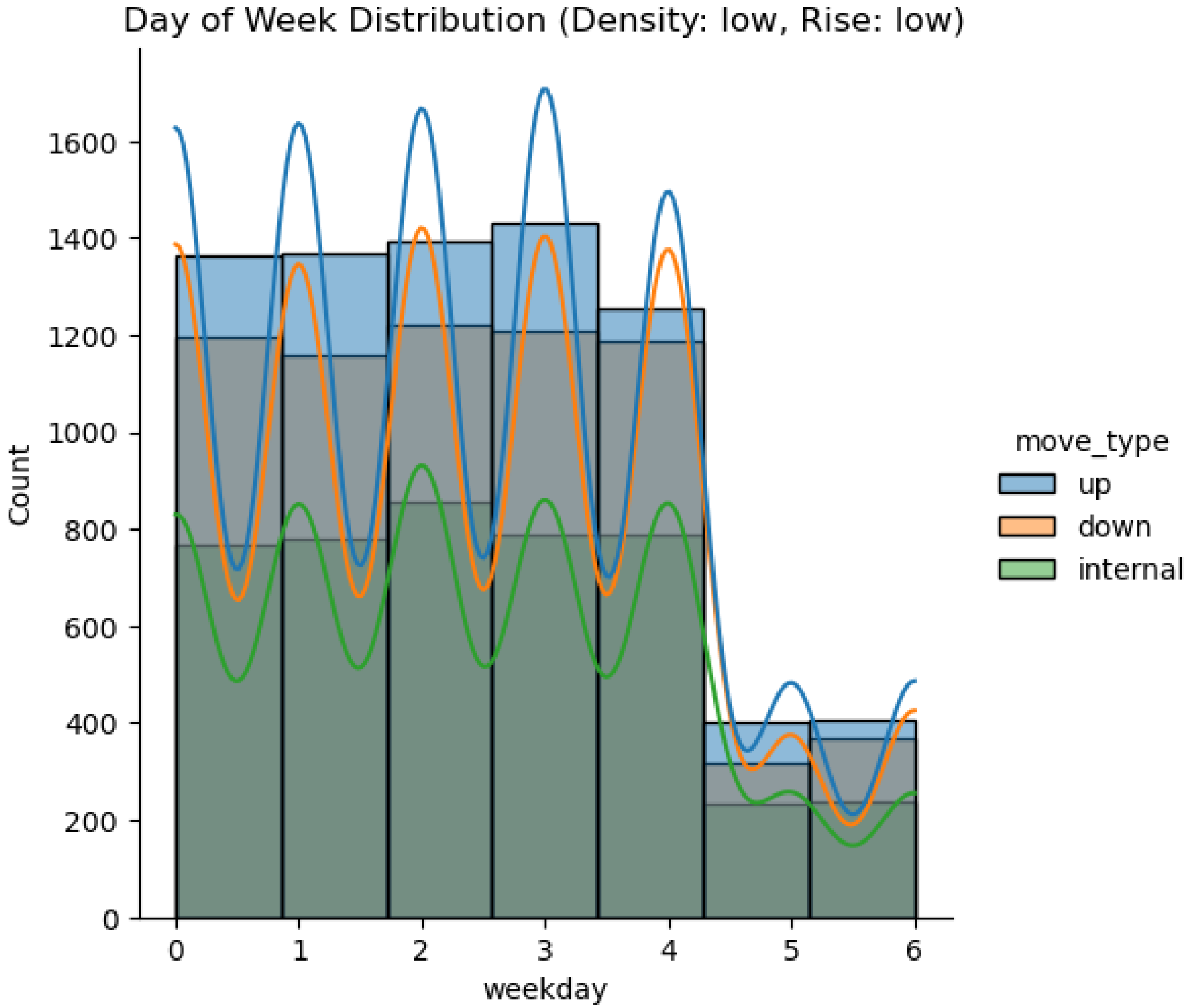
- Using an elevator simulator to run and record the waiting time, compare the average waiting time with baseline strategies (CCA, Tsai's standby scoring system)
- Cost Optimisation:
  - Adjusting standby threshold
  - Implement probability decay: $P'(d) = P \times \lambda^{d}$

PROOF-OF-CONCEPT

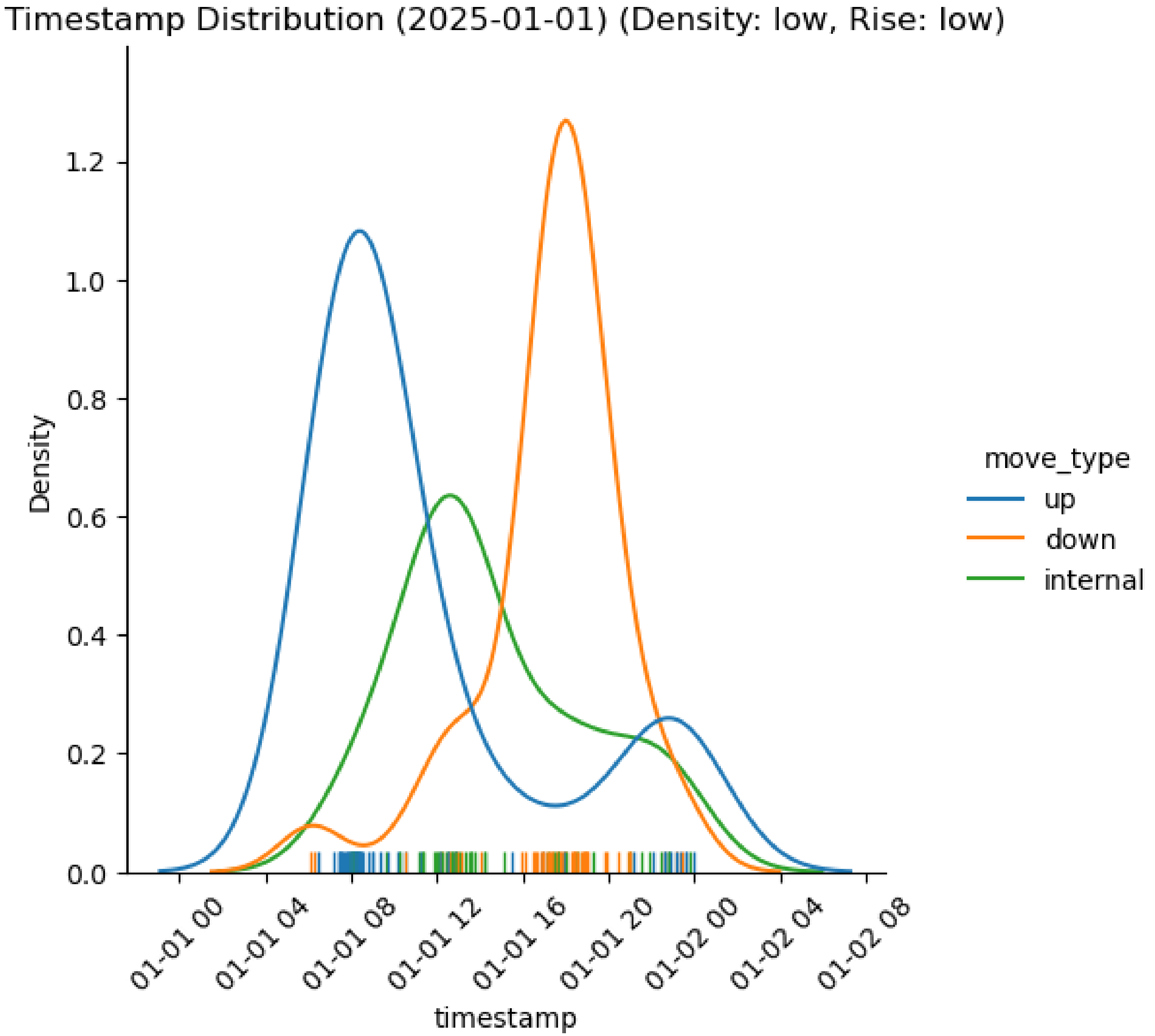
Data Simulation





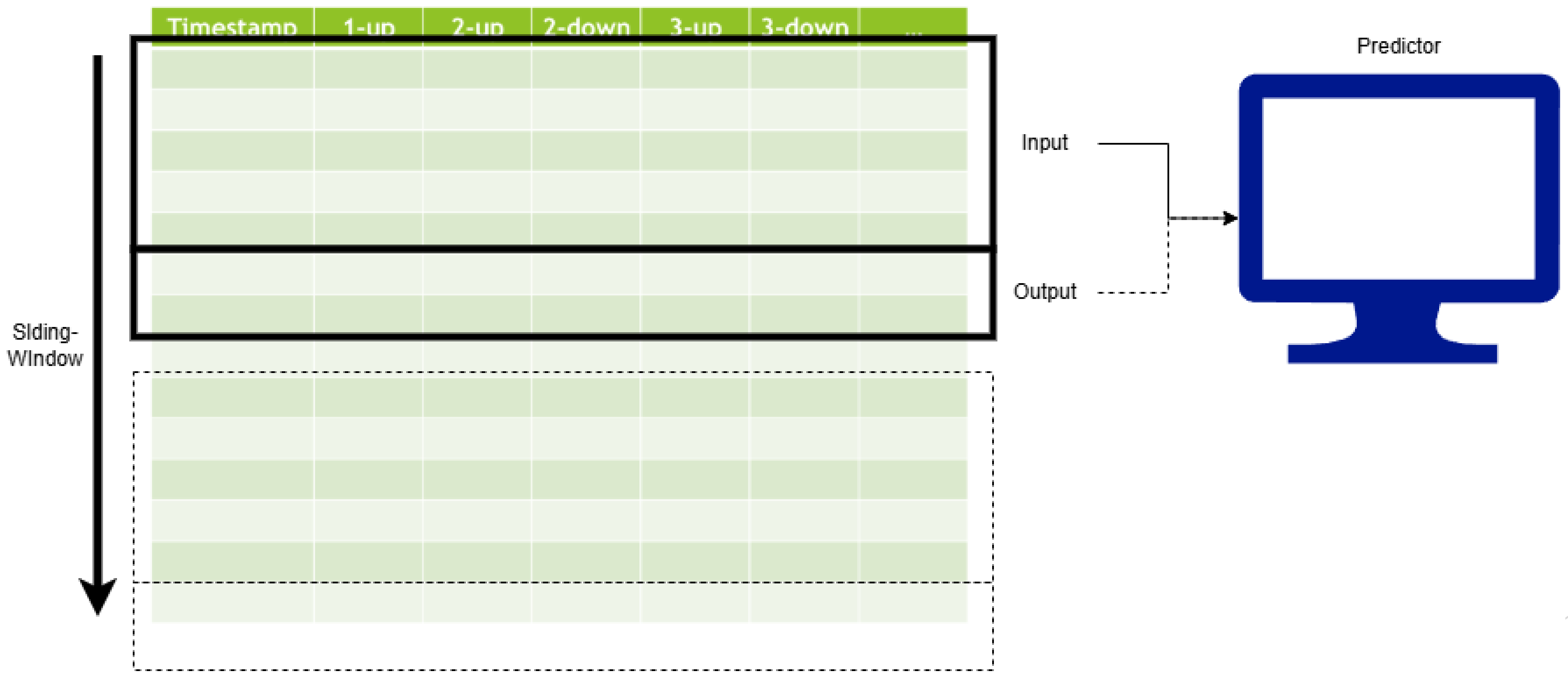


Day of Week Distribution (Density: low, Rise: low)
Count
weekday
move_type
up
down
internal

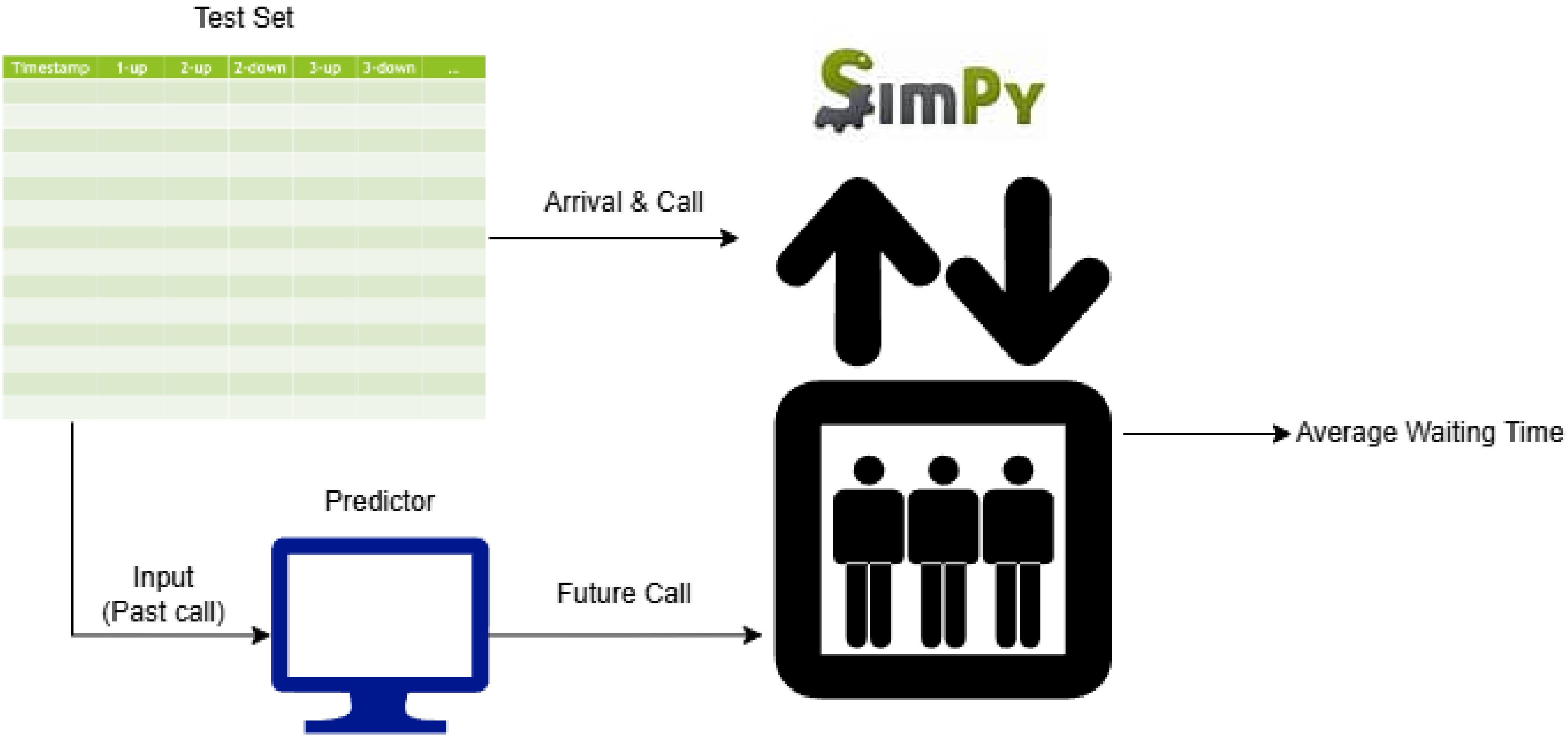


Timestamp Distribution (2025-01-01) (Density: low, Rise: low)
Density
timestamp
move_type
up
down
internal

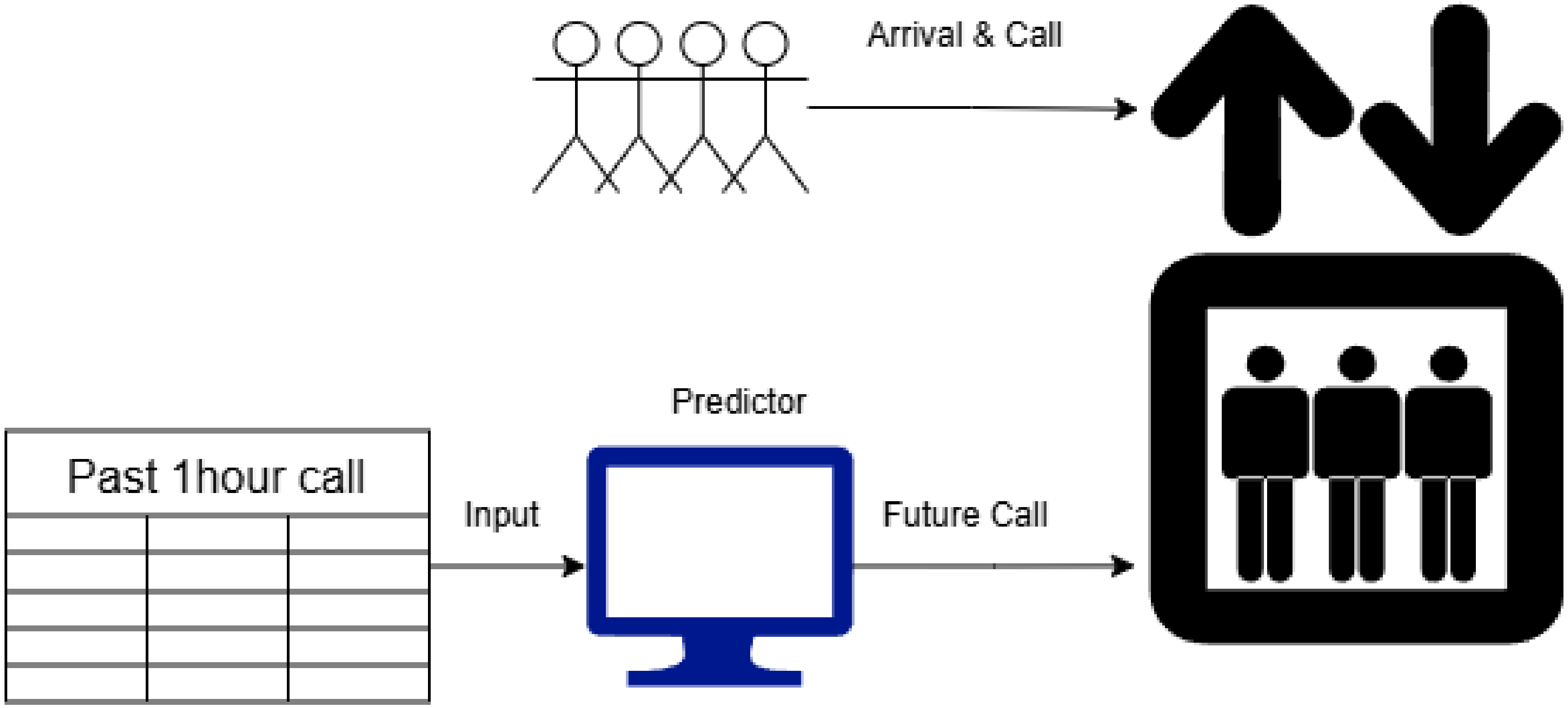
Training & Testing Process



Improvement Evaluation



Deployment



PROJECT MANAGEMENT AND TIMELINE

Gantt Chart

LLM-Driven Verification of Video Content Credibility																	
Description	September Block1 (September 2025 - November 2025)								September Block2 (November 2025 - January 2025)								
	Week1	Week2	Week3	Week4	Week5	Week6	Week7	Week8	Week9	Week10	Week11	Week12	Week13	Week14	Week15	Week16	Week17
Proposal Phase																	
Finalize Project Proposal																	
Project Proposal Presentation																	
Optimise Project Proposal																	
Submission of Project Proposal																	
ImplementationPhase																	
Project Planning & Preparation																	
System Development																	
System Testing																	
System Optimizing																	
Project Report Documentation																	
System Demonstration																	
Submission of Final Projec Report																	

	Progress
	Deadline

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