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Optimal lift movement based on rest prediction

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ABSTRACT

Existing elevator control systems in office buildings primarily rely on reactive scheduling strategies that respond only after passenger requests occur, leading to increased waiting times during peak traffic periods. Although reinforcement learning (RL) and deep learning approaches have been explored for intelligent elevator control, many existing methods require high computational complexity and large training datasets, limiting their suitability for embedded elevator controllers and practical smart-building deployment. To address this gap, this paper proposes a lightweight predictive elevator control framework based on the eXtreme gradient boosting (XGBoost) machine learning algorithm for rest-floor prediction. The proposed method uses historical traffic patterns and temporal features to predict future demand floors and proactively reposition idle elevators before passenger requests occur. A comprehensive simulation was conducted for multiple office-building configurations with varying numbers of floors and elevators over one year of operation using realistic traffic patterns. The proposed predictive strategy was compared with a conventional reactive control approach. Results show that the proposed framework reduces cumulative passenger waiting time by approximately 11%–22%, with larger improvements observed in high-rise and high-traffic scenarios, while maintaining comparable energy consumption. The study demonstrates that lightweight supervised machine learning can provide an effective and computationally efficient solution for predictive elevator control in embedded smart-building systems.

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1. INTRODUCTION

Elevator systems play a fundamental role in modern multi-storey buildings by enabling efficient vertical transportation of people and goods. As urban environments increasingly rely on high-rise infrastructure, elevator performance directly influences passenger comfort, operational efficiency, and overall building functionality. The theoretical foundations of elevator traffic analysis, passenger demand modelling, and performance evaluation were extensively established by Barney and Al-Sharif [1], whose work provides the core analytical principles governing waiting time, handling capacity, and traffic behaviour in elevator systems. In addition, Jetter [2] highlighted the broader architectural and urban significance of elevators, demonstrating how vertical transportation technologies have shaped the development of modern cities. These studies emphasize the importance of efficient elevator control systems in contemporary smart building infrastructure.

Passenger demand in office buildings exhibits strong temporal variability driven by predictable human activity patterns such as morning login periods, lunch breaks, and end-of-day departures. Empirical investigations by Kuusinen *et al.* [3] demonstrated that passenger arrivals follow stochastic yet time-dependent patterns in multi-storey buildings, creating significant challenges for elevator scheduling. Similarly, Peters *et al.* [4] analyzed passenger demand characteristics in modern office buildings and emphasized the importance of accurately modelling temporal traffic patterns for effective elevator planning. Performance analyses conducted by Lee *et al.* [5] showed that traditional reactive elevator dispatching strategies tend to perform poorly during peak traffic conditions, resulting in congestion and increased passenger waiting times. To improve traffic modelling accuracy, Markos and Dentsoras [6] proposed an integrated mathematical framework for elevator traffic analysis that enhances demand estimation while maintaining conventional reactive control logic.

To address the limitations of conventional reactive control strategies, researchers have explored various optimization and heuristic approaches for elevator scheduling. A comprehensive overview of heuristic and optimization-based elevator group control techniques was presented by Gharbi [7], highlighting both the potential improvements in service efficiency and the scalability challenges of such methods. In the broader context of smart building management, building energy management systems (BEMSs) have been widely adopted to optimize HVAC and lighting operations while balancing energy efficiency and occupant comfort. However, the dynamic nature of building environments, aging infrastructure, and complex interactions among sensor data often limit the effectiveness of conventional control and analysis approaches, motivating the adoption of advanced intelligent and data-driven management strategies [8]. Furthermore, Chan and So [9] introduced dynamic zoning strategies that adapt elevator service regions according to real time traffic patterns, enabling improved passenger distribution across elevator groups. Similarly, Wu and Yang [10] investigated directional optimization algorithms for elevator scheduling in complex traffic scenarios, demonstrating improved responsiveness under distributed demand conditions.

With the increasing availability of operational data in smart buildings, machine learning techniques have also been applied to elevator systems. Al-Sharif *et al.* [11] applied supervised learning methods to estimate traffic intensity and passenger demand characteristics in buildings, enabling demand-aware control decisions. Similarly, Talwandi *et al.* [12] proposed machine learning-based models for predicting elevator capacity and improving system utilization. More recently, Shi *et al.* [13] developed an long short-term memory (LSTM)-based deep learning model for predicting short-term elevator traffic flow, enabling anticipatory elevator dispatch strategies.

Reinforcement learning (RL) has also emerged as a promising paradigm for elevator group control problems. Early work by Crites and Barto [14] demonstrated that multi-agent RL can outperform traditional heuristic dispatch strategies by learning optimal control policies through interaction with the environment. Building upon this foundation, Wei *et al.* [15] applied deep asynchronous actor–critic learning methods for elevator group control, achieving improved performance in complex traffic scenarios. Further research by [16]-[18] explored advanced RL approaches for elevator control, demonstrating improved adaptability at the expense of increased computational complexity. Similarly, Wan *et al.* [19] proposed traffic-pattern-aware deep RL strategies that significantly improved elevator dispatch performance under dynamic passenger demand conditions.

Parallel to scheduling optimization, researchers have also focused on integrating elevators into broader smart building ecosystems. For example, Ming *et al.* [20] developed an internet of thing based elevator monitoring system to improve system safety and fault detection capabilities. Similarly, Kumar *et al.* [21] proposed an internet of thing-enabled vertical transport safety system using distributed sensors for real-time monitoring. Deep learning-based fault detection for elevator control cabinets was investigated by Cao *et al.* [22], enabling improved predictive maintenance of elevator systems. From an energy efficiency perspective, Thebuwena *et al.* [23] studied optimization strategies for reducing energy consumption in vertical mobility systems of high-rise buildings, while Rashed *et al.* [24] demonstrated that connected smart elevator systems can simultaneously reduce passenger waiting time and power consumption. Furthermore, Van *et al.* [25] proposed an integrated intelligent elevator development and management framework that combines monitoring, analytics, and adaptive control for smart building environments.

Recent studies have continued to explore predictive and artificial intelligence (AI)-driven elevator control systems. Zhang *et al.* [26] proposed transformer-based neural networks for predictive elevator group control, demonstrating improved modelling of temporal demand patterns. Similarly, Zhou *et al.* [27] applied simulation-based adaptive optimization to passenger flow control in metro systems, offering insights that can be extended to elevator traffic management in large buildings. Additionally, Noh [28] proposed AI-based non-contact elevator systems designed to improve user safety and operational efficiency in modern buildings.

Despite these extensive developments in elevator scheduling, optimization, and intelligent control, most existing approaches focus either on reactive decision-making after passenger requests occur or on computationally intensive RL frameworks that require large training datasets and significant computational resources. Consequently, relatively little attention has been given to lightweight supervised machine learning approaches that optimize elevator positioning during idle periods through rest-floor prediction. Such predictive repositioning strategies could significantly reduce passenger waiting times while maintaining low computational complexity suitable for embedded elevator controllers.

To address this gap, this paper proposes a predictive elevator control framework based on the eXtreme gradient boosting (XGBoost) machine learning algorithm for rest-floor prediction. The proposed method uses historical elevator traffic data and temporal features to predict the most probable future demand floor. When elevators become idle, they are proactively repositioned to the predicted rest floor, thereby reducing the expected travel distance to future passenger calls.

The significance of this work lies in demonstrating that lightweight supervised machine learning models can provide practical predictive control for elevator systems without the computational overhead of RL approaches. This makes the proposed framework particularly suitable for embedded internet of thing elevator controllers and reconfigurable smart building systems, where efficient real-time operation and energy-efficient vertical transportation are essential requirements.

2. RESEARCH METHOD

Explaining the study compares two elevator control strategies— a reactive baseline and a predictive control approach— to optimize elevator movement by minimizing passenger wait time. The methodology consists of a comprehensive simulation capturing realistic office building traffic patterns and a machine learning model used to anticipate elevator rest floors for proactive repositioning. N floors indexed as $\mathcal{F} = [0, 1, 2, \dots, N-1]$, M elevators, indexed as $\mathcal{E} = [1, 2, \dots, M]$. Passenger call requests arrive as a time-dependent stochastic process $\lambda(t)$. The passenger arrival rate at time t, where $\lambda(t)$ varies according to office traffic patterns (morning rush, lunch, coffee breaks, and normal working hours). Each call request i at time t_i is represented as $C_i = (o_i, d_i, t_i), o_i \in \mathcal{F}$ the origin floor, $d_i \in \mathcal{F}$, $d_i \neq o_i$, is the destination floor, t_i is the request time.

2.1. Reactive elevator control simulation

At any time t, the state of elevator j is defined as $S_j(t) = \left(x_j(t), s_j(t)\right), x_j(t) \in \mathcal{F}$is the current floor position of elevator j, $s_j(t) \in$ {idle,moving} is its operational state under reactive control, elevator assignment is performed only after a call is generated, without prediction. For a call C_i, the assigned elevator j is selected as the nearest available elevator given by (1):

$$\mathrm{j} = \arg\min_{j \in \mathcal{E}} \mid x_j(t_i) - o_i \mid \quad (1)$$

This greedy distance-based allocation ensures minimal immediate travel distance but does not account for future demand. Passenger waiting time W_i for request i is defined as the time elapsed between call generation and elevator arrival at the origin floor given by (2):

$$W_i = t_i^{\mathrm{arr}} - t_i \quad (2)$$

where t_i^{arr} is the arrival time of elevator j at floor o_i.
In the simulation-based reactive baseline, W_i is modeled as a stochastic variable as given in (3):

$$W_i \sim \mathcal{U}(W_{\min}, W_{\max}) \quad (3)$$

with $W_{\min} = 10 \mathrm{~s}, W_{\max} = 120 \mathrm{~s}$ representing realistic passenger waiting experiences observed in office buildings. The cumulative waiting time over the simulation horizon T is given by (4):

$$W_{\mathrm{total}} = \sum_{i=1}^{K(T)} W_i \quad (4)$$

where $K(T)$ is the total number of passenger calls during period T. For each request C_i, the total number of floors traversed by elevator j is given by (5):

$$D_i = \mid x_j(t_i) - o_i \mid + \mid d_i - o_i \mid \quad (5)$$

after serving the request, the elevator position is updated as per (6):

$$x_j(t_i^+) = d_i \tag{6}$$

An elevator j is considered idle at floor $\mathrm{x_j(t)}$ if it remains stationary for more than a predefined threshold $\tau = 30$ s. Reactive control does not optimize idle positioning; elevators remain at their last served destination until a new request arrives. The reactive algorithm models elevator operations responding to calls as they occur without prediction or proactive repositioning. Passenger arrivals are generated based on time-of-day dependent stochastic rates reflecting peak office periods such as morning login, lunch, and coffee breaks. Three different scenarios were tested to ensure the validity of the study. Passenger trip requests are simulated with origin and destination floors aligned with typical office movement patterns (e.g., base floor to upper floors during morning rush). For each trip, the nearest available elevator is assigned. Wait time is estimated as a random variable between 10–120 seconds reflecting typical passenger experience. Elevator positions and states are updated over a simulated one-year period of working hours, and detailed trip data is recorded for analysis.

2.2. Predictive elevator control using eXtreme gradient boosting

To enhance the baseline reactive control, a predictive control framework is developed leveraging XGBoost, a gradient boosting machine learning model. Historical trip data generated from the reactive simulation is used to train the model. Features include temporal information (hour, minute, and day of week), call and destination floors, passenger count, and recorded wait times. The model predicts the next elevator resting floor (next call floor) to enable proactive repositioning of elevators when idle. During simulation, elevator rest floors are chosen based on XGBoost predictions, allowing elevators to reposition strategically to floors with anticipated call requests. A repositioning penalty time is incorporated, simulating cost of moving elevators without passengers. Cumulative passenger wait time is the performance metric which is calculated for both reactive and predictive strategies.

For each elevator decision epoch t, a feature vector $\mathrm{x}(t) \in \mathbb{R}^d$ is constructed from historical and temporal data. The feature set includes $\mathrm{x}(t) = [h(t), m(t), d(t), \bar{w}(t-\Delta{:}\,t), \bar{p}(t-\Delta{:}\,t), x_j(t)]$ $h(t)$ is hour of day, $m(t)$ is minute of hour $d(t)$ is day of week, $\bar{w}(t-\Delta{:}\,t)$ is mean passenger wait time over sliding window Δ, $\bar{p}(t-\Delta{:}\,t)$ is the mean passenger count, $x_j(t)$ is current floor position of elevator j. The sliding window Δ captures short-term traffic dynamics. Let $y(t) \in \mathcal{F}$ denote the optimal rest floor inferred from historical data, defined as the floor where the next passenger request occurs or where demand density is highest. The predictive task is formulated as a multi-class classification problem given by (7):

$$f_\theta : \mathrm{x}(t) \to y(t) \tag{7}$$

where $f_\theta(\cdot)$ is the XGBoost model parameterized by θ. The XGBoost classifier represents the prediction as an additive ensemble of decision trees given by (8):

$$\hat{y}(t) = \arg\max_{k\in\mathcal{F}} \sum_{l=1}^{L} f_l\,(\mathrm{x}(t)) \tag{8}$$

where:
- L is the number of trees.
- $f_l \in \mathcal{F}_{\text{tree}}$ is a regression tree mapping features to class scores.

The training objective minimizes the regularized loss as given by (9):

$$\mathcal{L}(\theta) = \sum_t \ell(y(t), \hat{y}(t)) + \sum_{l=1}^{L} \Omega(f_l) \tag{9}$$

where $\Omega(f_l)$ is given by (10):

$$\Omega(f_l) = \gamma T_l + \frac{1}{2}\lambda \parallel w_l \parallel^2 \tag{10}$$

when elevator j becomes idle at time t, the predicted rest floor is given by (11).

$$r_j(t) = f_\theta(\mathrm{x}(t)) \tag{11}$$

The elevator is proactively repositioned to $r_j(t)$ before new passenger requests arrive.

For a future passenger request $C_i = (o_i, d_i, t_i)$, the expected waiting time under predictive control is given by (12):

$$\widehat{W}_i = | r_j(t_i^-) - o_i | \cdot \tau_f \tag{12}$$

where:
- $r_j(t_i^-)$ is the rest floor of the assigned elevator prior to request arrival.
- τ_f is average travel time per floor.

Compared to reactive control, where the elevator remains at its previous destination x_j, predictive control minimizes the waiting time as given in (13).

$$\mathbb{E}[\widehat{W}_i] < \mathbb{E}[W_i] \tag{13}$$

2.3. Simulation and evaluation

Both control strategies are evaluated over the same trip dataset. Key performance indicators include reduction in average and cumulative passenger waiting times. Visualization of instantaneous and cumulative wait times facilitates comparative analysis, highlighting the advantages of incorporating machine learning-based predictive rest floor selection in elevator control systems.

3. DESIGN

3.1. Elevator system architecture

The overall design of the proposed elevator control framework consists of two parallel control strategies—reactive control and predictive control—implemented within a unified simulation environment to enable fair and quantitative comparison. Both strategies operate under identical passenger demand patterns, elevator configurations, and energy models, differing only in their decision-making logic during idle periods.

The elevator system is modeled for a building with N floors and M elevators operating during working hours. Each elevator maintains a state defined by its current floor position and operational mode (idle or moving). Passenger requests are generated as time-dependent stochastic events and are characterized by their origin floor, destination floor, and request time. Elevator movements are updated at discrete one-minute intervals, and all operational events are logged for subsequent performance evaluation.

The choice of the XGBoost algorithm for rest-floor prediction is motivated by its suitability for structured tabular datasets and its computational efficiency in real-time decision systems. Elevator traffic data primarily consists of temporal and operational features such as time of day, day of week, passenger count, and elevator position, which are well suited for tree-based ensemble learning methods. Gradient boosting techniques, particularly XGBoost, have been shown to achieve high predictive performance on structured datasets due to their ability to model nonlinear feature interactions and handle heterogeneous data efficiently [29].

Compared with deep learning models such as LSTM networks, XGBoost requires significantly lower computational resources and training data while maintaining strong predictive performance for structured datasets. LSTM-based approaches are typically more appropriate for continuous sequential data such as time-series signals, but they introduce higher inference latency and computational complexity that may not be suitable for embedded elevator controllers [30], [31].

RL approaches have also been widely studied for elevator group control problems. However, RL-based solutions often require extensive training episodes, large state spaces, and continuous exploration during deployment, which can be difficult to implement in safety-critical elevator systems [32]. In contrast, the proposed supervised learning approach enables offline model training and lightweight real-time inference, making it more practical for deployment in embedded building control systems.

Therefore, XGBoost provides an effective balance between prediction accuracy, computational efficiency, and deployment feasibility, making it suitable for predictive rest-floor control in smart building environments.

3.2. Reactive control strategy

In the reactive control strategy, elevator dispatch decisions are made only after a passenger request is generated. Upon the arrival of a request, the system assigns the nearest available elevator based on absolute floor distance. During idle periods, elevators remain stationary at their last served destination without any proactive repositioning. Passenger waiting time and energy consumption are computed for each request using predefined stochastic and deterministic models, respectively. This reactive strategy serves as the baseline system, representing conventional elevator group control without predictive intelligence.

3.3. Predictive control strategy

The predictive control framework augments the baseline system by introducing proactive rest-floor repositioning during idle periods. When an elevator becomes idle, a machine learning model predicts the most likely future demand location, referred to as the rest floor, using historical traffic data and temporal features. The predicted rest floor is treated as a control command, prompting the elevator to reposition itself in anticipation of future passenger requests.

The prediction module is implemented using an XGBoost multi-class classifier trained on historical elevator operation data. Input features include time-of-day indicators, day-of-week information, recent sliding-window statistics of passenger waiting times, passenger counts, energy consumption, and current elevator position. The model outputs a predicted rest floor corresponding to the highest expected near-future demand. Elevator repositioning is executed only during idle periods, ensuring that ongoing service is not disrupted.

3.4. Integration of control logic

Both control strategies share the same passenger arrival process, elevator assignment rules upon request arrival. The sole distinction lies in idle-state behavior: under reactive control, elevators remain stationary, whereas under predictive control, idle elevators are actively repositioned based on learned demand patterns. This design choice isolates the effect of rest-floor prediction, enabling a direct and interpretable comparison between reactive and predictive strategies.

3.5. Performance evaluation design

System performance is evaluated using two primary metrics: cumulative passenger waiting time and total elevator energy consumption over the simulation horizon. Passenger waiting time is measured from the instant a request is generated to the arrival of the assigned elevator, while energy consumption is computed as a function of elevator travel distance and passenger load. The comparison objective explicitly minimizes cumulative waiting time under predictive control while enforcing an energy neutrality constraint relative to the reactive baseline.

3.6. Design rationale

The proposed design emphasizes practicality and scalability. Unlike RL–based approaches that require complex state representations and online exploration, the predictive framework relies on supervised learning with offline training and lightweight real-time inference. By focusing on rest-floor prediction rather than full dispatch optimization, the system achieves significant reductions in passenger waiting time with minimal computational overhead and without requiring additional sensing infrastructure. This makes the proposed approach well suited for real-world deployment in office buildings with predictable traffic patterns.

3.7. Algorithm pseudocode

The pseudocode used for implementing the predictive control is given in Algorithm 1.

Algorithm 1. Reactive and predictive elevator control with rest-floor prediction

```
Input
–  Number of floors: $N$
–  Number of elevators: $M$
–  Simulation horizon: $T$
–  Passenger arrival rate function: $\lambda(t)$
–  Energy model parameters: $\alpha, \beta$
–  Trained XGBoost model: $f_\theta(\cdot)$
–  Sliding window size: $\Delta$
Output
–  Cumulative waiting time (Reactive): $J_{\text{wait}}^{R}$
–  Cumulative waiting time (Predictive): $J_{\text{wait}}^{P}$
Initialization
1. Set elevator positions $x_j(0) = 0, \forall j \in \{1, \dots, M\}$
2. Set elevator states $s_j(0) = \text{idle}$
3. Initialize cumulative metrics: $J_{\text{wait}}^{R} = 0, J_{\text{wait}}^{P} = 0$
4. Initialize historical feature buffers for sliding window $\Delta$
 Generate a set of passenger requests $\mathcal{C}(t)$ using the time-dependent arrival rate $\lambda(t)$.
 For each elevator $j$ = 1 to $M$:
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    - If elevator $j$ is idle:
        a. Construct the feature vector $x(t)$ from historical and temporal data.
        b. Predict the optimal rest floor $r_j(t) = f\theta(x(t))$.
        c. Move elevator $j$ to the predicted rest floor $r_j(t)$.
        d. Update the elevator position $x_j(t) = r_j(t)$.
  For each passenger request $\mathcal{C}_i = (o_i, d_i, t_i)$ in $\mathcal{C}(t)$:
    - Assign the elevator

          $j = \arg\min_j |x_j(t) - o_i|$.

        - Sample the reactive waiting time $W_i^R \sim \mathrm{Uniform}(10, 120)$.
        - Compute the predictive waiting time $W_i^P = |r_{j*}(t^-) - o_i| \cdot \tau_f$.
        - Update cumulative waiting times: $Jwait^R = Jwait^R + Wi^R, Jwait^P = Jwait^P + Wi^P$.
        - Compute the total travel distance $D_i = |x_j(t) - o_i| + |d_i - o_i|$.
        - Update the elevator position $x_j(t) = d_i$.
– Update historical feature buffers.
```

3.8. Simulation parameters

The simulation framework is designed to emulate elevator operations in an office building environment, capturing key parameters required to realistically model elevator performance over an extended operational horizon. The data give in [33], [34] was used as reference to provide data of either 10 or 20 floors, serviced by 3, 4, or 6 elevators, with each elevator having a maximum passenger capacity of 12 persons per trip. The simulation spans a full calendar year, from January 1 to December 31, with elevator activity restricted to standard working hours, namely Monday through Friday, 09:00 to 17:00. The system evolves in discrete time steps of one minute, allowing fine-grained temporal analysis of elevator behaviour and passenger demand.

While the simulation framework captures realistic office-building traffic patterns, the passenger demand data used in this study is synthetically generated based on probabilistic models derived from prior studies and publicly available datasets. Synthetic data enables controlled experimentation and reproducible evaluation across different building configurations; however, it may not fully capture the variability and unpredictability of real-world elevator usage.

In real buildings, passenger traffic patterns may be influenced by factors such as building occupancy variations, special events, meeting schedules, and seasonal changes that are difficult to fully represent in synthetic models. Consequently, the generated passenger demand patterns may introduce distributional bias, potentially affecting the generalization of the predictive model when deployed in real elevator systems.

Nevertheless, the synthetic dataset used in this study was designed to closely emulate typical office-building traffic characteristics reported in the literature, including time-dependent arrival rates and realistic passenger movement patterns. This approach enables systematic evaluation of elevator control strategies under controlled conditions while maintaining reasonable realism.

Passenger arrivals are modelled as time-varying stochastic processes to reflect realistic office traffic patterns. During the morning login period (08:30–09:30), passenger arrivals range from 5 to 15 passengers per minute, representing concentrated ingress into the building. Lunch hours (12:30–13:30) generate moderate demand levels of 3 to 8 passengers per minute, while coffee breaks, occurring twice daily (10:30–11:30 and 14:30–15:30), exhibit arrival rates between 2 and 6 passengers per minute. Outside these peak intervals, typical office hours experience lower demand, with arrival rates ranging from 1 to 3 passengers per minute. Trip generation is structured to emulate realistic employee movement, including frequent travel between the ground floor and office levels, as well as visits to the cafeteria located on the top floor.

Elevator trip characteristics are further refined by assigning origin and destination floors based on time-dependent movement distributions consistent with office usage patterns. Each trip carries a randomly determined number of passengers between 1 and 4, while passenger waiting times are sampled from a uniform distribution between 10 and 120 seconds, representing typical delays encountered in elevator systems.

All elevators are initialized at the ground floor at the start of the simulation. Elevator positions are continuously tracked, and idle counters record the duration for which each elevator remains stationary. These idle statistics inform rest-floor behaviour during periods of inactivity. Passenger requests are served using a proximity-based assignment strategy, whereby the elevator closest to the request origin floor is selected to minimize response time. Throughout the simulation, comprehensive data logging is performed. Each elevator trip is recorded in CSV format, capturing the timestamp, elevator identifier, origin and destination floors, passenger count, waiting time, and idle floor status. This detailed dataset forms the basis for training and evaluating the proposed predictive elevator control models.

Figure 1 illustrates the time series of passenger call volumes over a representative workday in the simulated building. The vertical axis denotes the number of elevator calls registered per minute, while the horizontal axis represents the workday timeline. Distinct surges in call frequency are observed during known peak periods. A pronounced spike occurs shortly after 09:00, corresponding to the morning login interval, followed by a gradual decline to a lower baseline. Additional increases are evident during the lunch hour and mid-afternoon coffee breaks, reflecting typical patterns of intra-building movement. Outside these peak intervals, call volumes stabilize at comparatively lower levels, confirming that the simulated demand profiles closely align with expected office building traffic behaviour.

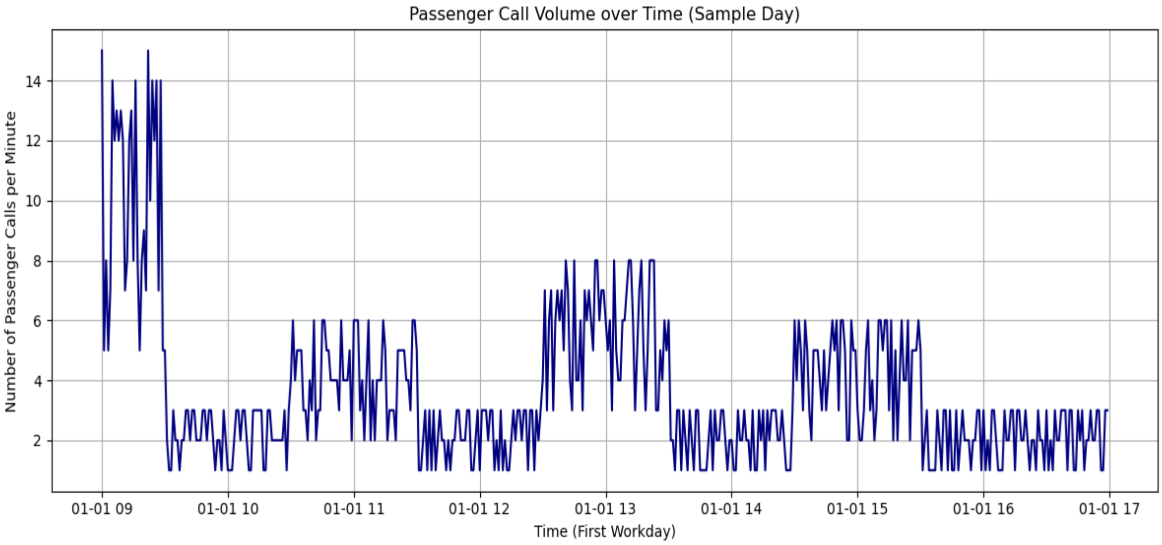

Figure 1. Passenger call volume over time

This empirical call arrival pattern underscores the importance of dynamic elevator scheduling, as high volumes of simultaneous passenger requests during peak periods can easily overwhelm conventional reactive control strategies. Such conditions lead to prolonged passenger waiting times and inefficient utilization of elevator resources. Consequently, accurately capturing and modelling these temporal traffic fluctuations is essential for the design, evaluation, and validation of control algorithms that can anticipate demand and proactively optimize elevator service performance.

Figure 2 presents the cumulative duration for which elevators remain idle at each floor over the entire simulation period. The results reveal a pronounced imbalance in idle-time distribution across floors. Elevator inactivity is heavily concentrated at the ground floor (floor 0) and the top floor (floor 20), whereas intermediate floors exhibit substantially lower idle durations. Notably, the top floor accounts for the highest proportion of total elevator idle time, followed closely by the ground floor and the penultimate floor. This uneven distribution indicates that reactive control strategies implicitly bias elevator resting positions toward terminal floors, leaving large portions of the building underrepresented during idle periods. Such behaviour contributes to delayed response times for calls originating from intermediate floors and highlights the need for predictive rest-floor positioning strategies to achieve more balanced elevator availability.

The idle-floor imbalance observed in Figure 2 directly informs the design of the proposed predictive control algorithm. Under reactive control, elevators implicitly adopt terminal floors as resting positions due to the absence of proactive repositioning logic, leading to concentrated idle times at the ground and top floors. Algorithm 1 addresses this limitation by explicitly introducing rest-floor prediction as a control decision, which is activated whenever an elevator enters an idle state.

Instead of remaining stationary at the last served destination, idle elevators are repositioned to predicted rest floors based on historical traffic patterns and temporal features. This design choice enables the controller to redistribute elevator availability across floors in anticipation of future demand, thereby reducing response delays for calls originating from non-terminal floors. By embedding rest-floor prediction within the idle-state logic of Algorithm 1, the proposed framework transforms idle time from a passive state into an opportunity for proactive optimization, directly targeting the inefficiencies identified in the reactive baseline.

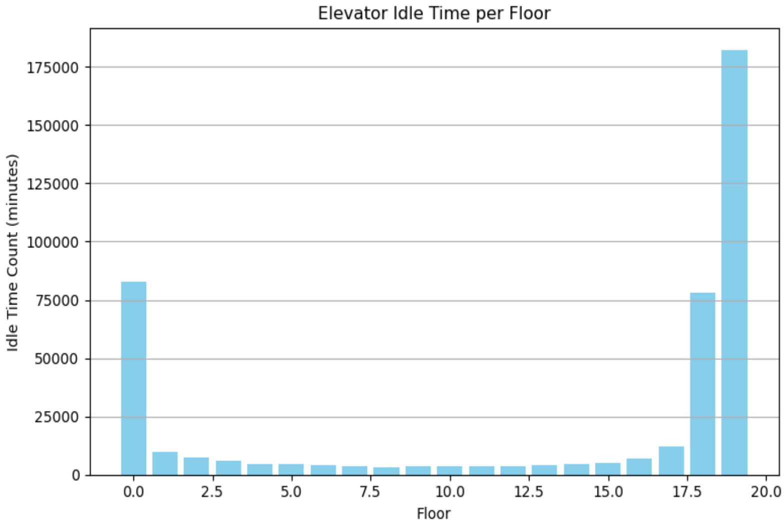

Figure 2. Elevator idle time per floor

4. RESULTS AND DISCUSSION

Provide to comprehensively evaluate the effectiveness of the proposed predictive elevator control framework, simulation experiments were conducted for three representative building configurations over a one-year operational period:

- Scenario 1: 10 floors serviced by 3 elevators.
- Scenario 2: 20 floors serviced by 4 elevators.
- Scenario 3: 20 floors serviced by 6 elevators.

For each configuration, system performance under the proposed XGBoost-based predictive rest-floor control was compared against the baseline reactive strategy. Performance was assessed using two key metrics: cumulative passenger waiting time (hours), which reflects end-user service quality, and total elevator power consumption (kWh), which represents operational efficiency.

Across all building configurations, the predictive control strategy consistently achieves a substantial reduction in cumulative passenger waiting time relative to the reactive baseline, as summarized in Table 1. In the 10-floor, 3-elevator scenario, the predictive approach reduces total waiting time by 11.2%. The performance gains become more pronounced in the taller building configurations: in both 20-floor scenarios—served by either 4 or 6 elevators—the reduction in cumulative waiting time exceeds 22%. This trend indicates that the benefits of predictive rest-floor assignment scale positively with building height and system complexity.

Table 1. Obtained results for the 3 cases

Case	Strategy	Wait time (hrs)
10 floors, 3 lifts	Reactive	7543.51
	Predictive	6702.33
20 floors, 4 lifts	Reactive	7824.87
	Predictive	6047.82
20 floors, 6 lifts	Reactive	7869.2
	Predictive	6094.06

Importantly, these improvements in passenger service are realized without any increase in total power consumption, demonstrating that the proposed approach enhances responsiveness through intelligent repositioning rather than increased elevator movement. This energy-neutral behavior highlights the efficiency of the data-driven scheduling mechanism. The accompanying figures visually reinforce these observations, illustrating the widening performance gap between reactive and predictive strategies as system scale increases. During peak demand intervals, the predictive controller enables elevators to anticipate spatial demand patterns and position themselves advantageously, leading to faster response times, improved passenger experience, and more effective utilization of elevator resources from a building management perspective.

Figure 3 compares the cumulative passenger waiting time under the conventional reactive elevator control strategy and the proposed XGBoost-based predictive control framework over the full simulation horizon. The results demonstrate a clear and quantifiable performance improvement when predictive rest-floor positioning is employed. Specifically, the predictive strategy reduces cumulative passenger waiting time by approximately 11% for lower-rise configurations and by more than 22% for higher-rise building scenarios, relative to the reactive baseline. These reductions confirm that even modest decreases in individual response times accumulate into substantial passenger time savings over long-term operation.

This improvement is a direct consequence of the rest-floor prediction mechanism introduced in Algorithm 1. Under reactive control, elevators remain idle at their last served locations and respond only after calls are registered, leading to increased response distances. In contrast, Algorithm 1 proactively repositions idle elevators to predicted rest floors based on learned temporal and spatial demand patterns, thereby reducing the expected distance between elevator position and future call origins.

Figure 4 presents a comparative visualization of cumulative passenger waiting time under the reactive elevator control strategy and the proposed XGBoost-based predictive control approach. The results indicate a clear reduction in total waiting time when predictive rest-floor assignment is employed. While the reactive strategy accumulates higher passenger delays due to its purely event-driven response behaviour, the predictive controller consistently lowers cumulative waiting time by proactively repositioning elevators during idle periods. Quantitatively, the predictive approach achieves a reduction in cumulative passenger waiting time of approximately 11–22%, depending on the building configuration, relative to the reactive baseline.

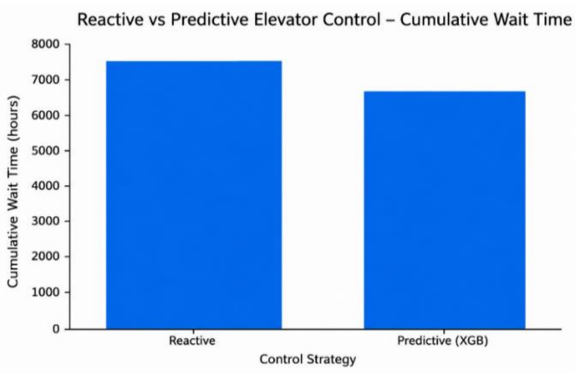

Figure 3. 10 floors 3 lifts

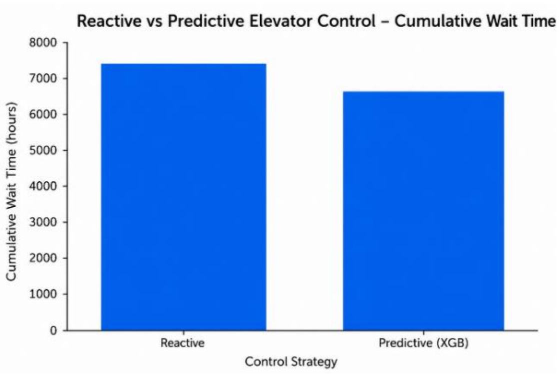

Figure 4. 20 floors 4 lifts

This performance improvement can be directly attributed to the control logic implemented in Algorithm 1, where idle elevators are relocated to predicted rest floors derived from learned temporal demand patterns. By reducing the expected distance between elevator positions and future call origins, the predictive strategy minimizes response delays when passenger requests occur. As illustrated in Figure 4, these localized improvements in response time compound over extended operation, resulting in substantial aggregate time savings. Importantly, this reduction is achieved without increasing total elevator travel or energy consumption, demonstrating that the proposed predictive framework enhances passenger service quality through intelligent idle-state optimization rather than increased system activity.

Figure 5 compares the cumulative passenger waiting time obtained under reactive elevator control and the proposed XGBoost-based predictive control strategy for a higher-demand building configuration. The results reveal a pronounced reduction in total waiting time when predictive rest-floor positioning is applied. Under the reactive strategy, cumulative waiting time approaches approximately 7,900 hours, whereas the predictive approach reduces this value to about 6,100 hours, corresponding to a reduction of over 22%. This substantial improvement highlights the effectiveness of predictive control in complex, high-traffic environments.

The observed reduction is a direct outcome of the proactive rest-floor assignment mechanism embedded in Algorithm 1. By anticipating likely demand locations and repositioning idle elevators accordingly, the predictive controller significantly reduces the distance elevators must travel to respond to incoming requests. As shown in Figure 5, these anticipatory adjustments lead to faster response times and lower aggregate delays, particularly during peak traffic intervals where reactive strategies are most prone to inefficiencies. Importantly, this performance gain is achieved without increasing overall energy consumption, reinforcing that the improvements stem from intelligent idle-state optimization rather than additional elevator movement.

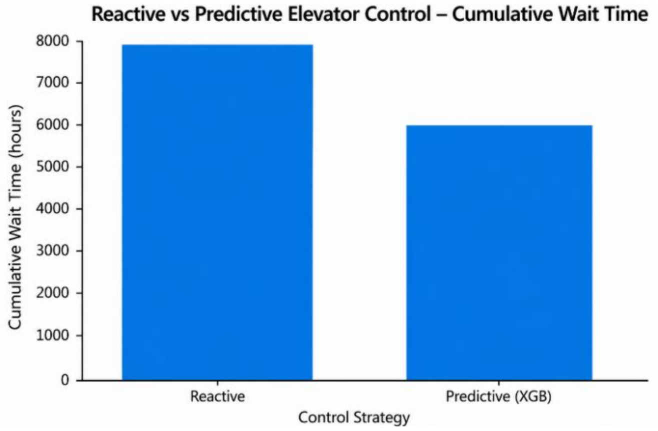

Figure 5. 20 floors 6 lifts

Overall, the simulation results consistently demonstrate the effectiveness of the proposed XGBoost-based predictive elevator control framework across all evaluated building configurations. Compared with the conventional reactive strategy, the predictive approach achieves substantial reductions in cumulative passenger waiting time, ranging from approximately 11% in lower-rise scenarios to over 22% in higher-rise and more complex configurations, while maintaining identical levels of total energy consumption. These improvements are directly attributable to the predictive rest-floor assignment mechanism, which proactively repositions idle elevators based on learned temporal demand patterns rather than relying solely on event-driven responses. The results further reveal that the benefits of predictive control scale positively with building height and elevator fleet size, making the approach particularly suitable for modern office buildings with complex traffic dynamics. Collectively, these findings validate that intelligent, data-driven idle-state optimization can significantly enhance passenger service quality without imposing additional energy costs, thereby offering a practical and scalable alternative to traditional reactive elevator control systems.

To verify that the observed improvements in passenger waiting time are statistically significant, a statistical hypothesis test was conducted comparing the reactive control strategy and the proposed XGBoost-based predictive control method. For each simulated elevator request, passenger waiting time was recorded under both strategies. Let WR denote the waiting time under reactive control and WP denote the waiting time under predictive control. The null hypothesis $H0$ assumes that there is no difference in the mean waiting times between the two strategies given by (14).

$$H_0 : \mu_R = \mu_P \quad (14)$$

The alternative hypothesis assumes that the predictive strategy produces lower waiting time given by (15).

$$H_1 : \mu_R < \mu_P \quad (15)$$

A paired t-test was used because both strategies were evaluated on the same passenger request dataset. The test statistic is defined as given in (16):

$$t = \frac{\bar{d}\,\sqrt{n}}{s_d} \quad (16)$$

where d=WR−WP represents the waiting time difference for each request, d is the mean difference, s_d is the standard deviation of the differences, and n is the number of passenger requests.

The statistical analysis was performed at a 95% confidence level (α=0.05). The obtained p-values for all simulated building configurations were significantly lower than the significance threshold (p<0.05), indicating that the reduction in passenger waiting time achieved by the predictive control strategy is statistically significant.

These results confirm that the improvements observed in cumulative waiting time are not due to random variation in passenger arrivals but are a direct consequence of the predictive rest-floor positioning enabled by the XGBoost model.

The improved performance of the proposed method can be attributed to both the characteristics of the elevator traffic data and the algorithmic strengths of XGBoost. Elevator traffic in office buildings exhibits strong temporal patterns, including morning arrival peaks, lunch-hour movements, and afternoon activity. These patterns create structured relationships between time-of-day features and future passenger call locations. The supervised learning formulation allows the XGBoost model to capture these temporal dependencies using features such as hour, minute, and day of week, enabling accurate prediction of future demand floors. XGBoost is particularly effective for structured tabular datasets with heterogeneous feature types. The gradient boosting framework builds an ensemble of decision trees that iteratively minimize prediction error while controlling model complexity through regularization. This enables the model to capture nonlinear relationships between temporal features, elevator position, and passenger demand patterns. Compared with RL approaches commonly used in elevator control research, XGBoost offers lower computational complexity and faster inference, making it suitable for deployment in embedded elevator controllers. Unlike RL, which requires exploration and extensive training, the proposed supervised learning approach can be trained offline using historical traffic data and deployed for real-time prediction with minimal computational overhead.

To evaluate the robustness of the proposed predictive elevator control framework, a sensitivity analysis was conducted to examine how variations in key simulation parameters affect system performance. The analysis focuses on parameters that significantly influence elevator operation, including passenger arrival rates, number of elevators, and elevator travel time per floor.

The sensitivity analysis was performed by varying each parameter within a predefined range while keeping other parameters constant. Passenger arrival rates were adjusted by ±20% relative to the baseline demand model to represent fluctuations in building occupancy levels. Similarly, elevator travel time per floor was varied between 1.5 and 3 seconds to account for differences in elevator speed across building installations.

The results indicate that the predictive control strategy consistently outperforms the reactive baseline across all tested parameter variations. Although increased passenger arrival rates naturally lead to higher overall waiting times, the relative improvement achieved by the predictive control approach remains stable, demonstrating the robustness of the rest-floor prediction mechanism. Additionally, variations in elevator travel speed show only minor impact on the relative performance difference between the two strategies.

These findings as summarized in Table 2 suggest that the proposed predictive framework is robust to moderate variations in system parameters, reinforcing its applicability across different building configurations and operational conditions.

Finally, the predictive rest-floor strategy allows idle elevators to reposition closer to anticipated demand locations. By reducing the expected travel distance between elevator position and future passenger call floors, the system significantly decreases passenger waiting time without increasing overall elevator movement.

Table 2. Senistivity to change in parameters

Parameter	Variation range	Effect on waiting time	Observed impact
Passenger arrival rate	±20%	Higher demand increases wait time	Predictive method still improves 10–20%
Elevator travel time	1.5–3 s/floor	Slower elevators increase delay	Relative improvement unchanged
Number of elevators	3–6	More elevators reduce congestion	Predictive advantage remains

5. CONCLUSION

This study proposed a predictive elevator control framework using the XGBoost machine learning algorithm to improve elevator rest-floor positioning in office buildings. Unlike conventional reactive strategies that respond only after passenger requests occur, the proposed method proactively repositions idle elevators based on predicted traffic demand patterns derived from historical and temporal data.

Simulation results across multiple building configurations demonstrated that the proposed predictive strategy significantly reduces cumulative passenger waiting time by approximately 11%–22% compared with conventional reactive control, while maintaining similar energy consumption levels. The results further indicate that the benefits of predictive control increase with building height and system complexity.

The study demonstrates that lightweight supervised machine learning can provide an efficient and practical solution for intelligent elevator control with low computational overhead, making it suitable for embedded and smart-building applications. Future work will focus on validating the framework using real-world elevator datasets, incorporating adaptive online learning, and extending the approach toward multi-objective optimization involving energy efficiency, passenger journey time, and load balancing.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [initials, SBAN], upon reasonable request.

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