When can I park?-A Physics-Informed Deep Learning Method for Waiting Time Estimation in Saturated Parking Garages

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Short summary

This study addresses the problem of estimating waiting time for vehicles queuing outside saturated parking garages—a metric more directly useful to drivers than traditional parking occupancy predictions. We propose a cascaded queuing framework to model the interaction between the external queue and the parking system under saturation. A saturation balance equation is derived to estimate saturation duration and individual waiting times using only vacancy data and real-time queue length. To enhance flexibility and robustness, a Physics-Informed Deep Learning (PIDL) approach is introduced to learn key system parameters while preserving physical consistency. The method is validated through both simulation and real-world data collected at the Kennedy Town Car Park in Hong Kong. Results show that the proposed approach achieves accurate waiting time prediction and outperforms baseline methods, while maintaining strong interpretability.
Keywords: Parking waiting time estimation; saturated parking systems; cascaded queue model; saturation balance equation; physics-informed deep learning (PIDL);

1 Introduction

Parking spaces are a scarce resource in urban areas worldwide, and the difficulty of finding available parking leads to significant economic and societal losses. According to statistics, drivers in the United States spend over $73 billion annually searching for parking spaces (INRIX, 2017). In Munich, Germany, a single district incurs an estimated EUR 20 million in annual losses due to parking search behavior (Caliskan et al., 2007). Hong Kong is among the cities with the highest parking demand, where curbside parking spaces are occupied more than 80% of the time. As a result, off-street parking garages have become a common alternative, helping to reduce cruising when availability exists. However, our statistical analysis reveals that over 30% of garages in Hong Kong experience saturation, with approximately 30% of these being heavily saturated, as illustrated in Figure 1. A key contributor to these losses is the lack of information regarding parking availability. Providing accurate waiting time estimates for saturated garages can help drivers make informed decisions, reduce cruising behavior, and consequently alleviate congestion, emissions, and time loss (Sun et al., 2024).

Previous studies have shown that parking-related information—such as occupancy status (Caicedo et al., 2006), parking search time (Ibeas et al., 2014), and acceptable search duration (Chaniotakis & Pel, 2015)—is highly valued by drivers and significantly influences their decisions (Caicedo et al., 2012). Most existing research focuses on predicting parking occupancy to bridge the information gap. However, these approaches often assume that drivers will leave when encountering a full garage and therefore overlook waiting time estimation under saturation.

Data-driven approaches have demonstrated strong performance in prediction tasks (Inam et al., 2022; Morell et al., 2023; Jose & V, 2021), but they typically require large amounts of historical data and are difficult to apply in scenarios where waiting time observations are scarce or unavailable. In contrast, model-based approaches, such as queueing models, can describe system dynamics with limited data. For example, Xiao (Xiao et al., 2018) modeled garage occupancy using an $M/M/C/C$ queue, assuming Poisson arrivals and no waiting buffer. Caliskan (Caliskan et al., 2007) applied a Markov chain–based queueing model to estimate parking availability. Other studies (Lu et al., 2009; Millard-Ball et al., 2014) have also used queueing theory to analyze parking systems but generally ignore the behavior of vehicles waiting outside during saturation.

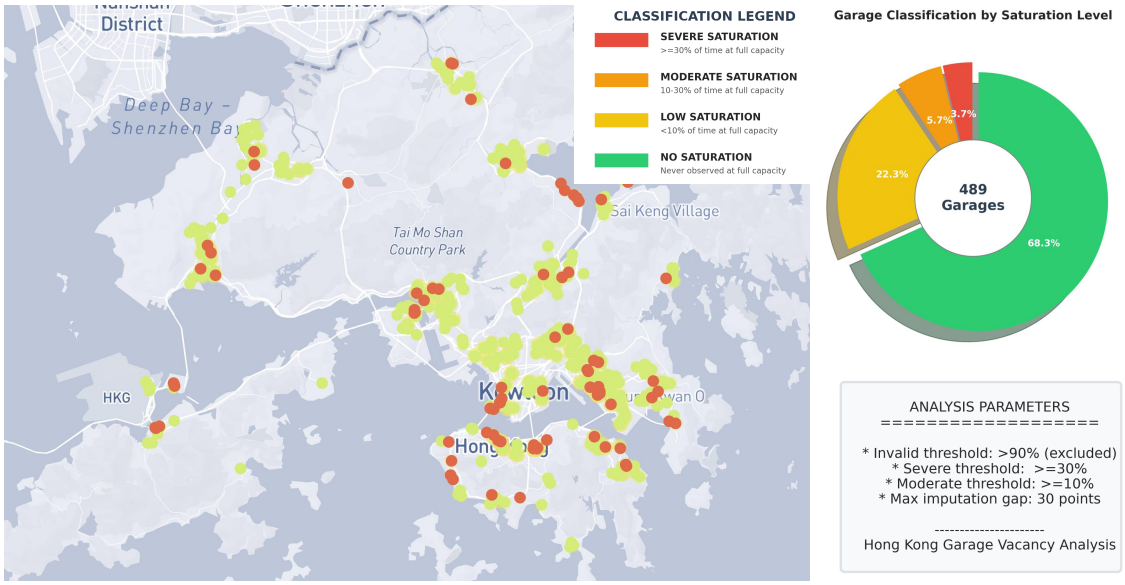


Figure 1: Saturation patterns of parking garages in Hong Kong. Red areas denote the occurrence of saturation events based on historical data.

However, field observations in Hong Kong indicate that drivers often choose to wait in line rather than search for alternative parking, contradicting the assumptions of most prior studies. This highlights the need to explicitly model and estimate waiting time in saturated conditions.
A major challenge in waiting time estimation is the lack of observable queue data, including both queue length and individual waiting times. Classical waiting time formulations rely on known arrival and service processes, which are rarely available in practice. Moreover, theoretical results such as those by Kawakami (Kawakami et al., 1994) have not been validated using real-world data. To address these limitations, we propose a cascaded queueing framework that separates the internal parking system and the external waiting queue. The arrival process is modeled as a temporal point process, specifically a Hawkes process, capturing self-exciting behavior (Zhou et al., 2025), while the service process follows a Gamma distribution.
To compensate for the lack of observed queue data, we first conduct simulation studies under these assumptions. The results reveal a nontrivial relationship between queue length and waiting time, which motivates further analytical investigation. We formally define the cascaded queueing system and derive a saturation balance equation that enables waiting time estimation using only vacancy data and real-time queue length. Based on this formulation, we develop a Physics-Informed Deep Learning (PIDL) approach to estimate key model parameters. The proposed method is validated using real-world observations from Hong Kong. The remainder of this paper is organized as follows: we present the model formulation, followed by the solution methodology, simulation study, real-world validation, and performance evaluation.

2 Methodology

In this section, we first formulate a cascaded queuing system with a buffer zone to represent a garage with limited capacity and a waiting queue that forms outside during saturation. We then define the conditions for saturation and unsaturation, as well as the dynamic transitions within and between these states.

System Overview

The garage operates as a finite-capacity queueing system with the following characteristics:

- **Arrival Process of under–saturated State**: The arrival process is modeled as a time-dependent Hawkes process with intensity:

$$\lambda^*(t) = \mu(t) + \sum_{t_i<t} \alpha e^{-\beta(t-t_i)}, \tag{1}$$

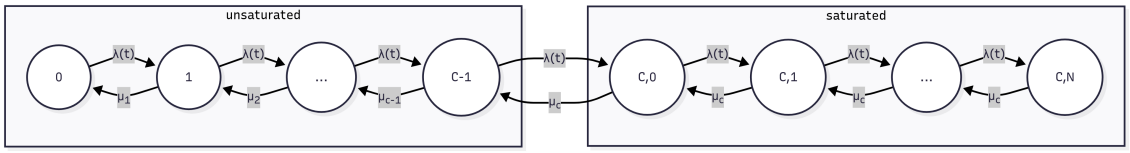


Figure 2: The values in the circles represent the state of the system, which evolves based on arrival rates λ and departure rates μ.

where $\mu(t)$ is a piecewise-constant base rate (e.g., higher during peak hours), and α, β control the self-exciting behavior.

- **Service Process**: Parking durations follow a Gamma distribution: $S \sim \text{Gamma}(k, \theta)$, with mean service time $\mathbb{E}[S] = k\theta$ and variance $\text{Var}(S) = k\theta^2$. Accordingly, the average service (departure) rate per parking minute is:

$$\mu = \frac{1}{\mathbb{E}[S]} = \frac{1}{k\theta}. \tag{2}$$

When the garage reaches capacity C, arriving vehicles are held in an external queue (buffer zone) outside the garage, the system enters a saturated state, and a secondary queue begins to form outside the garage. In this state:

- **Arrival Process of saturated state**: The rate at which vehicles enter the external queue is based on the most recent arriving process during the under–saturated state, scaled by a time-dependent decreasing function $f(t)$, reflecting the physical limitation of the buffer zone and driver hesitation:

$$\lambda_{\text{sat}}(t) = \lambda^*(t^-) \cdot f(t), \tag{3}$$

- **Departure Process of Saturated State**: The garage remains full so the departure process is assumed to follow the same Gamma distribution as before and approximates the recent under–saturated departure pattern. Assuming all C parking spaces operate independently and in parallel, the maximum aggregate departure rate of the garage is:

$$\mu_{\text{sat}} = \frac{C}{k\theta}. \tag{4}$$

- **Queue Discipline**: First-In-First-Out (FIFO) with a queue limited to the length of N. The ratio of saturated arrival to departure, known as traffic intensity $\rho(t) = \lambda_{\text{sat}}(t)/\mu_{\text{sat}}$, becomes less than 1 over time. Indicating that the queue length in the buffer zone will eventually decrease as arrival slows and departure remains steady.

System Dynamics

To better understand the above queuing system, the state transition mechanisms have been explained in the following section and illustrated in Figure 5 in detail. Let $N(t)$ denote the number of vehicles in the garage, and $Q(t)$ the length of the external queue at time t. The system exhibits two primary states:
Under-Saturated State: new arrivals enter the garage immediately.

$$0 \leq N(t) < C \quad \text{and} \quad Q(t) = 0.$$

Saturated State: new arrivals join the external queue.

$$N(t) = C \quad \text{and} \quad 0 \leq Q(t)0 \leq N.$$

Transition to saturation state from under-saturated state is when an arrival occurs at $N(t^-) = C - 1$, then the system will update its state as:

$$N(t) = C, \quad Q(t) = Q(t^-) + 1.$$

as shown in Figure 5, this process can be written as:

$$(N(t^-) = C - 1, Q(t^-) = 0) \xrightarrow{\text{Arrival}} (N(t) = C, Q(t) = 1).$$

similarly, the transition from saturation state back to the under-saturated state occurs when a departure happens when $N(t^-) = C$ and $Q(t^-) = 0$, then:

$$N(t) = C - 1, \quad Q(t) = 0.$$

which results in a condition of

$$(N(t^-) = C, Q(t^-) = 0) \xrightarrow{\text{Exit}} (N(t) = C - 1, Q(t) = 0).$$

Besides, there is another state called Sustained Saturation when a departure occurs at $Q(t^-) > 0$, the garage remains saturated:

$$(N(t^-) = C, Q(t^-) = k) \xrightarrow{\text{Exit}} (N(t) = C, Q(t) = k - 1), \quad k \geq 1.$$

the duration of Sustained Saturation can be called T_s.
When in under-Saturated state, $N(t) < C$ and the occupancy evolves as:

$$N(t + h) = N(t) + A(h) - D(h), \tag{5}$$

where $A(h)$ is the number of arrivals and $D(h)$ the departures in h. When $N(t) = C$, the queue length follows:

$$Q(t + h) = Q(t) + A(h) - E(h), \tag{6}$$

where $E(h)$ is the number of vehicles entering the garage from the queue (each entry requires a departure event).

Waiting Time Estimation

The cascaded queuing framework enables estimation of waiting times using limited observable data. In practice, only vacancy data $V(t) = C - N(t)$ and real-time queue length are available.
Consider a parking system:

$$\text{Arriving} \xrightarrow{\text{buffer}} \text{Entering} \xrightarrow{\text{garage}} \text{Departing}. \tag{7}$$

Let A_i and E_i denote the arrival and entrance times of vehicle i.

Definition 1 (Waiting Time)**.**

$$W_i = E_i - A_i.$$

Definition 2 (Queue Length)**.**

$$Q(t) = \sum_i \mathbf{1}\{A_i \leq t < E_i\}.$$

Under a FIFO discipline, the waiting time depends only on vehicles ahead in the queue. Assuming a constant service rate μ_{sat}:

$$W_i(t) = \frac{Q_i(t) + 1}{\mu_{\text{sat}}}. \tag{8}$$

Saturation Balance Equation

During the Saturated State, the departure rate μ_{sat} is assumed to remain constant as shown in Equation 4, while the arrival rate $\lambda_{sat}(t)$ may evolve over time. We model $\lambda(t)$ as a function scaled by the pre-saturation arrival rate ($\lambda^*(t^-)$):

$$\lambda_{sat}(t) = \lambda^*(t^-)\theta(t), \quad \lambda_{sat}(t) > 0, \tag{9}$$

where $\theta(t)$ is to be estimated during the elapsed time period t since the onset of saturation. Given an observed saturation duration $T_s = t_e - t_a$, we exploit the *saturation balance equation*, which states that the total arrivals equal the total departures over the saturation period:

$$\int_{t_a}^{t_e} \lambda_{sat}(t)\, dt = \mu_{sat} T_s. \tag{10}$$

For a given $(\lambda^*(t^-), \mu_{sat}, \theta(t))$, the predicted saturation duration $\hat{T}_s$ is obtained by solving Eq. (10) numerically and $\theta(t)$ can be estimated by minimizing the mean squared error between $\hat{T}_s$ and T_s over all training saturation events:

$$\min_{\boldsymbol{\theta}} \frac{1}{N} \sum_{i=1}^{N} \left[\hat{T}_s^{(i)}(\boldsymbol{\theta}) - T_s^{(i)} \right]^2. \tag{11}$$

In real-world scenarios, the arrival rate $\lambda(t)$ and service rate $\mu(t)$ are typically not directly observable. Instead, the number of available parking spaces (vacancy), denoted by $V(t)$, or its rate of change, is readily measurable. Therefore, we introduce the net inflow rate:

$$\delta(t) = \lambda(t) - \mu(t),$$

as the core modeling quantity. This formulation is both more consistent with observable data and leads to a simpler model structure.

Relationship Between Vacancy Dynamics and $\delta(t)$

Let $V(t)$ denote the number of vacant spaces at time t, and let C be the total parking capacity. Assuming that the number of vehicles currently being served is negligible, we have:

$$Q(t) + V(t) \approx C,$$

where $Q(t)$ is the queue length.
Taking the derivative with respect to time:

$$\frac{dV(t)}{dt} = \mu(t) - \lambda(t) = -\delta(t).$$

Key insight: The rate of change of vacancy is directly equal to $-\delta(t)$, which is observable from data.

Reformulation of the Saturation Balance Condition

The classical balance equation during a saturation period $[t_a, t_e]$ is:

$$\int_{t_a}^{t_e} \lambda_{\text{sat}}(t)\, dt = \mu_{\text{sat}}\, T_s,$$

where $T_s = t_e - t_a$.
Substituting $\lambda(t) = \mu(t) + \delta(t)$ yields:

$$\int_{t_a}^{t_e} [\mu_{\text{sat}} + \delta(t)]\, dt = \mu_{\text{sat}}\, T_s.$$

This simplifies to:

$$\int_{t_a}^{t_e} \delta(t)\, dt = 0.$$

Physical interpretation: Over a saturation period, the cumulative net inflow is zero. That is, the queue first builds up and then dissipates, returning the system to equilibrium.

General Functional Form of $\delta(t)$

Instead of assuming a specific parametric form (e.g., quadratic), we consider $\delta(t)$ as a general integrable function:

$$\delta(t) = \delta(t^-) f(t; \boldsymbol{\theta}),$$

where $f(\cdot)$ may be represented by a flexible model such as a neural network, and $\boldsymbol{\theta}$ denotes its parameters.
The saturation condition becomes:

$$\int_{t_a}^{t_e} \delta(t^-) f(t; \boldsymbol{\theta})\, dt = 0. \tag{12}$$

Equivalently, using the vacancy dynamics:

$$\int_{t_a}^{t_e} \delta(t)\, dt = -\int_{t_a}^{t_e} \frac{dV(t)}{dt}\, dt = V(t_a) - V(t_e).$$

Thus, we obtain:

$$\int_{t_a}^{t_e} f(t;\boldsymbol{\theta})\, dt = \Delta V_{\text{target}},$$

where

$$\Delta V_{\text{target}} = V(t_e) - V(t_a)$$

is directly observable from data.
Given an observed ΔV_{target}, the saturation duration $T_s = t_e - t_a$ can be obtained by solving:

$$\int_{0}^{T_s} f(t;\boldsymbol{\theta})\, dt = \Delta V_{\text{target}}. \tag{13}$$

This formulation allows for both analytical solutions (if f is simple) and numerical solutions (for general learned models) for $\boldsymbol{\theta}$. Thus with the learned $\boldsymbol{\theta}$ and the initial value δ_0, we can figure out $\hat{T}_s$ by a predictive model using Equation 12. A boundary condition that the arrival rate vanishes at the end of saturation (i.e., $\lambda(t_e) \approx 0$). Since

$$\delta(t) = \lambda(t) - \mu(t),$$

we approximate:

$$\mu \approx -\delta(T_s).$$

Thus, the predicted service rate during saturation is:

$$\hat{\mu_{\text{sat}}} = -\delta(T_s).$$

The waiting time is then figured out by the above Equation!8. In practice, using the observed queue length $Q(t)$ at arrival time:

$$W_i(t) \approx \frac{Q(t)}{\hat{\mu_{\text{sat}}}}.$$

The full pipeline can be summarized as:

$$\boldsymbol{\theta} \;\rightarrow\; \delta(t) \;\rightarrow\; T_s \;\rightarrow\; \mu_{\text{pred}} \;\rightarrow\; W_i(t).$$

Physics-Informed Deep Learning

Building upon the above formulation, we propose a *Physics-Informed Deep Learning* (PIDL) framework to learn the dynamics of the net inflow function $\delta(t)$ directly from observable data. Unlike earlier approaches that assume a fixed parametric form for $\lambda(t)$, our method models $\delta(t)$ as a flexible function while enforcing physical consistency through the saturation balance constraint.
Neural Network Parameterization: We represent the net inflow rate as:

$$\delta(t) = \delta(t^-) f_{\text{NN}}(t; \mathbf{x}, \boldsymbol{\theta}),$$

where $f_{\text{NN}}(\cdot)$ is a feedforward neural network parameterized by $\boldsymbol{\theta}$, and $\mathbf{x}$ denotes observable inputs such as pre-saturation vacancy trends and contextual features. The network captures the temporal evolution of $\delta(t)$ without imposing a restrictive functional form.
Physics-Constrained Loss Function: Instead of directly supervising waiting time or saturation duration, we enforce the saturation balance equation derived earlier. The training loss is defined as:

$$\mathcal{L} = \frac{1}{N} \sum_{i=1}^{N} \left[\int_{0}^{T_s^{(i)}} \delta^{(i)}(t)\, dt - \Delta V_{\text{target}}^{(i)} \right]^2, \tag{14}$$

where $\Delta V_{\text{target}}^{(i)} = V(t_e^{(i)}) - V(t_a^{(i)})$ is directly observed from data. This formulation ensures that the learned $\delta(t)$ satisfies the conservation relationship between arrivals and departures.
Saturation Duration Prediction: Given a trained model and initial condition $\delta_0 = \delta(t^-)$, the saturation duration $\hat{T}_s$ is obtained by solving:

$$\int_{0}^{\hat{T}_s} \delta(t)\, dt = \Delta V_{\text{target}}. \tag{15}$$

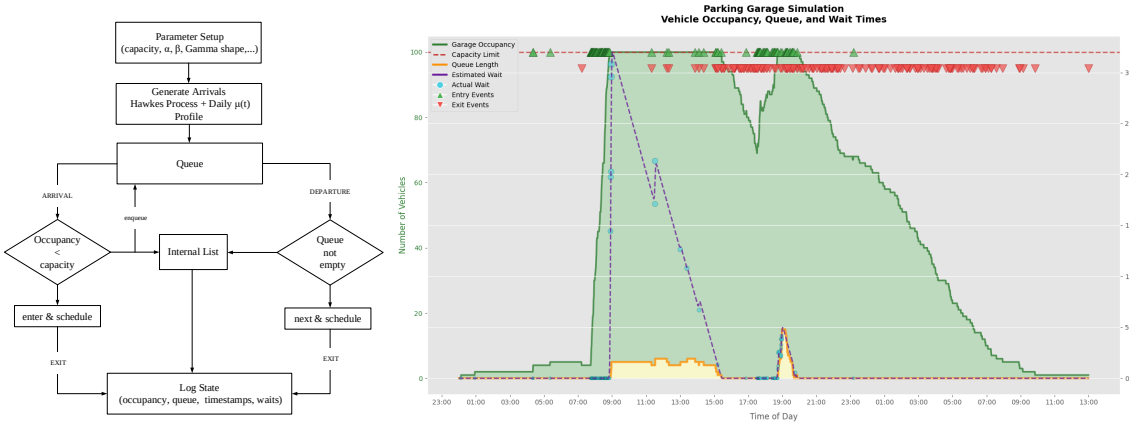


Figure 3: Simulation framework (left) and resulting parking dynamics (right).

This can be computed numerically for general learned functions.
Service Rate Estimation: Using the boundary condition that the arrival rate vanishes at the end of saturation (i.e., $\lambda(t_e) \approx 0$), we estimate the service rate as:

$$\hat{\mu}_{\text{sat}} = -\delta(\hat{T}_s).$$

Real-Time Waiting Time Estimation: Finally, under a FIFO discipline, the waiting time for a vehicle arriving at time t is estimated as:

$$W_i(t) \approx \frac{Q(t)}{\hat{\mu}_{\text{sat}}}, \tag{16}$$

where $Q(t)$ is the observed queue length.
Summary: The overall pipeline integrates learning and physical constraints:

$$\boldsymbol{\theta} \;\to\; \delta(t) \;\to\; \hat{T}_s \;\to\; \hat{\mu}_{\text{sat}} \;\to\; W_i(t).$$

3 Results and Discussion

This section presents simulation results, real-world observations, and model performance evaluation. The aim is to analyze the temporal evolution of parking congestion and validate the proposed method under both synthetic and real conditions.

Simulation Study

To investigate the temporal evolution of a parking garage under both under-saturated and saturated states, we developed an event-driven simulation framework that combines a self-exciting Hawkes arrival process with a Gamma-distributed service process. Vehicle arrivals follow a Hawkes process, where the baseline intensity varies with time of day to capture peak and off-peak demand, and the parameters control self-excitation and decay rates. Parking durations follow a Gamma distribution to reflect realistic variability in departures. The simulation processes events in continuous time using a priority queue, handling arrivals by either admitting vehicles directly if capacity is available or placing them in an external queue, and handling departures by freeing capacity and admitting queued vehicles if present. The system naturally transitions between under-saturated states, where arrivals are served immediately, and saturated states, where excess demand is queued. Throughout the simulation, we record occupancy, queue length, and vehicle trajectories, enabling calculation of estimated and actual waiting times as well as waiting time distributions overall and during peak periods, which allows quantitative evaluation of congestion patterns and service efficiency under varying demand conditions.

On-site Observation

on 28 June 2025, 26 July 2025, and 10 August 2025, we conducted on-site observations at the Kennedy Town Car Park in Hong Kong to record real-world vehicle arrival and entrance times

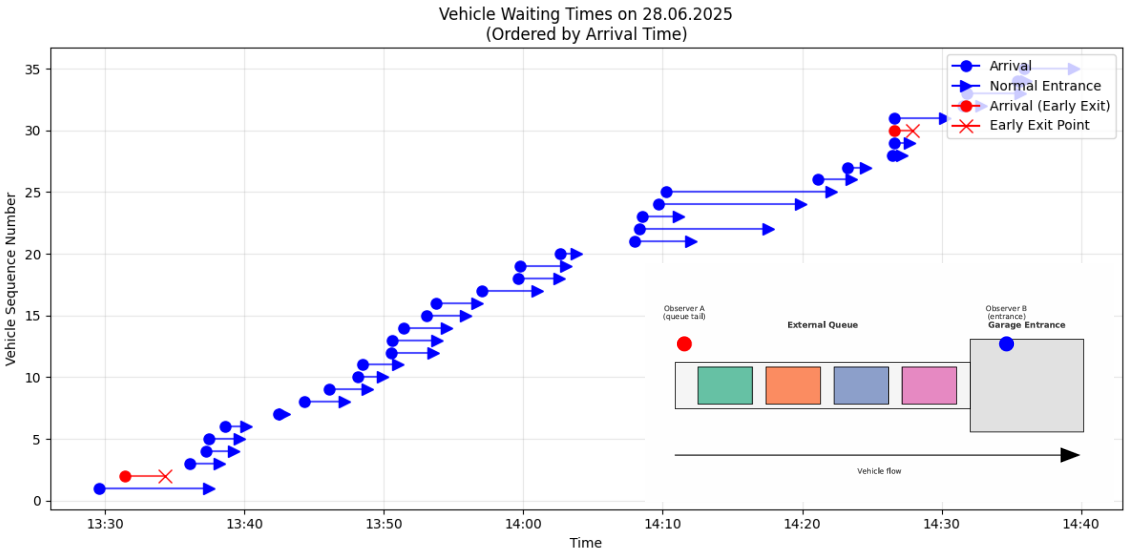


Figure 4: Field observation setup and measured waiting time distributions.

under saturated conditions. Two observers were positioned at different locations: one at the end of the external queue to record the arrival time of each vehicle joining the queue, and another at the garage entrance to record the time each vehicle entered the facility. For each vehicle, we noted an anonymized car ID, arrival time, entrance time, and any special remarks (e.g., vehicles that left the queue without entering). To protect driver privacy, actual license plate numbers were not recorded; instead, anonymized identifiers were created by combining different letters and numbers to distinguish individual vehicles. This setup allowed us to capture detailed queuing and entry dynamics, enabling subsequent analysis of actual waiting times, queue turnover, and driver behavior during peak demand periods.

Model Performance

Finally, we compared the estimated results with real observations and proved the efficiency of the proposed method.

Experimental Setup

To evaluate the proposed saturation duration estimation framework and waiting time prediction, we utilized two types of data from the Kennedy Town Car Park in Hong Kong. First, historical vacancy records collected at 1-minute(A)/15-minute(B) intervals were processed to identify saturation intervals, characterized by zero vacancy over continuous periods. For each saturation event, we extracted features including the duration, arrival and departure rates before and during saturation, using a 30-minute window around the event. Events with valid data and duration longer than five minutes were selected, with all dates before June 28, 2025, used for training and after (including) June 28, 2025, reserved for testing. Second, on 3 selected days, on-site observations were conducted. These observations were synchronized with the historical vacancy data and queue length records. The trained model was applied to estimate saturation durations and waiting times based on observed queue lengths and arrival/departure rates, with results validated by comparing predicted waiting times against the ground truth from on-site measurements using mean absolute error and visual analyses.

Model Comparision

We compared four different methods for predicting parking waiting times. The fitted polynomial (FP) method applies simple polynomial regression to model the relationship between input features and saturated duration, serving as a basic baseline. The XGBoost method employs a gradient boosting tree ensemble capable of capturing complex nonlinear patterns with high accuracy. The PIDL (physics-informed deep learning) approach incorporates physical domain knowledge into the learning process, achieving a balance between interpretability and predictive performance. Finally, the pure DL (deep learning) method relies entirely on data-driven neural networks without

Table 1: MAE comparison of different methods for saturation duration T_s and waiting time W_i

Task	Date	XGBoost	Pure DL	FP	PIDL
T_s	28.06.2025 (A)	3.68	3.32	3.88	**2.82**
	28.06.2025 (B)	3.53	3.06	3.13	**2.91**
	10.08.2025	25.79	25.54	25.34	**25.06**
	26.07.2025	21.64	21.93	20.40	**21.94**
W_i	28.06.2025 (A)	2.82	2.73	2.79	**1.93**
	28.06.2025 (B)	2.78	2.47	3.00	**1.85**
	10.08.2025	5.18	5.31	4.75	**4.49**
	26.07.2025	5.24	5.69	4.73	**3.84**

physical constraints, yielding competitive accuracy but lacking meaningful physical parameters, which prevents it from producing a final fitted duration or waiting time (W_i).

4 Discussion

Performance Analysis

We evaluated four decreasing function forms $f(t)$ within the FP baseline. The quadratic polynomial achieved the best overall performance, with the lowest MAE for T_s and competitive W_i. Combining this choice with the results in Table **??**, we find that the PIDL + quadratic polynomial configuration offers a strong balance between accuracy and interpretability. The strong performance of the quadratic polynomial also suggests that the vehicle arrival rate during the saturation stage exhibits a slight initial increase, possibly due to the clustering of vehicles arriving just before saturation, followed by a subsequent decline.

Table 2: Performance of different decreasing functions $f(t)$ based on the fitted polynomial (FP) model

	Quadratic	Exponential	Inverse	Linear
MAE (minutes)				
T_s	4.21	7.79	38.76	7.61
W_i	1.60	1.19	2.77	1.24

Queue Length vs. Waiting Time

By combining the simulation results with on-site observations, we find that the waiting time is not strictly proportional to the queue length. As shown in the plots, a longer queue length does not necessarily correspond to a longer waiting time. This discrepancy can be attributed to several factors, including the timing of vehicle arrivals to the queue, the variability in departure rates, and transient fluctuations in garage occupancy. For instance, a long queue formed just before a batch of vehicles exits the garage can dissipate relatively quickly, whereas a shorter queue formed during low departure rates may persist for a longer period. These findings highlight the importance of incorporating both arrival dynamics and service processes when estimating waiting times, rather than relying solely on instantaneous queue length.

5 Conclusion

This study addresses the longstanding challenge of estimating parking garage waiting times under saturated conditions, where direct observations of queue length and waiting time are largely unavailable. By introducing a cascaded queuing model that separately represents the under-saturated

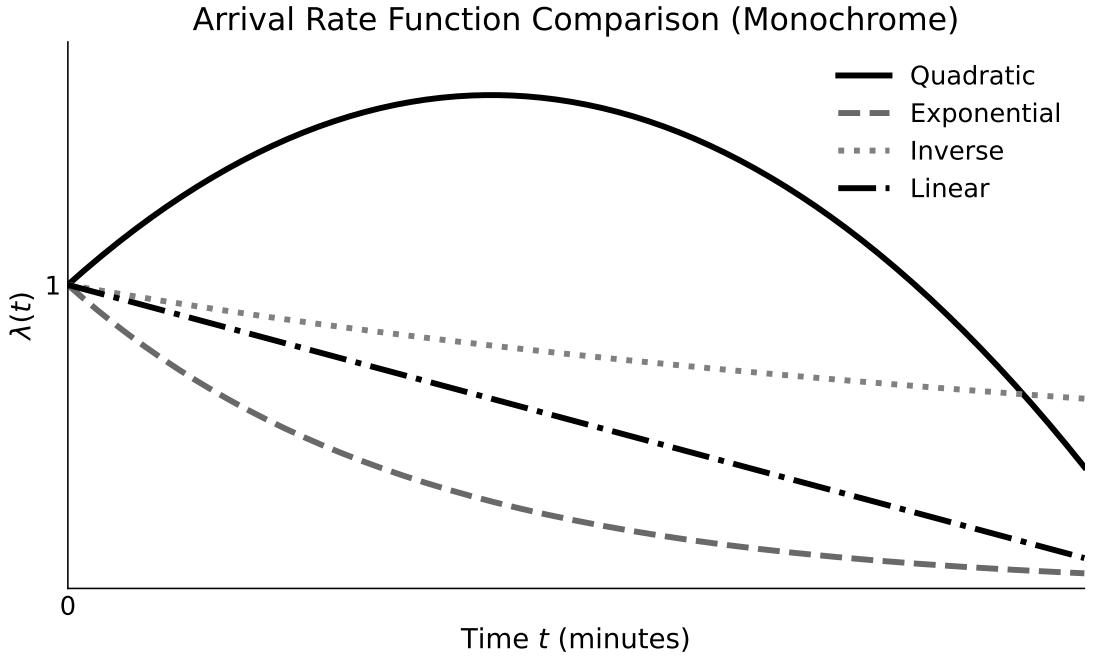


Figure 5: Visualization of different decreasing function.

garage and the external queue, and by modeling arrivals and services using a Hawkes process and Gamma distribution respectively, we establish a framework capable of linking vacancy data to queue dynamics. Simulation studies reveal an indirect but robust relationship between queue length and waiting time, enabling the derivation of a saturation balance equation that forms the basis for our estimation method. The proposed Physics-Informed Deep Learning (PIDL) approach leverages this formulation to optimize dynamic arrival rate estimation while maintaining physical interpretability. Validation with on-site observations from the Kennedy Town Car Park in Hong Kong demonstrates that the PIDL method, particularly when paired with a quadratic arrival rate model, provides superior accuracy over traditional polynomial fitting and purely data-driven deep learning approaches. The results highlight the potential of integrating queueing theory, temporal point process modeling, and physics-informed learning for practical, interpretable, and accurate waiting time estimation in real-world parking systems. Future work will focus on extending the approach to multi-garage networks and incorporating stochastic variations in service patterns.

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