

DOCTORAL THESIS



INTERNATIONAL DOCTORAL SCHOOL

*Doctoral Programme in Computer Technology and
Environmental Engineering*

Design and Implementation of a Framework to Model the
Climatic Conditions of Car Parking Lots

Author:

Hyacinthe Marie Nshuti

Supervisors:

Prof. Andrés Muñoz Ortega

Prof. Fernando Terroso Sáenz

Murcia, February 2026

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THESIS SUPERVISORS' AUTHORISATION FOR THESIS SUBMISSION

Prof. Andres Muñoz Ortega and Prof. Fernando Terroso Sáenz, as Supervisors¹ of the Doctoral Thesis 'Design and Implementation of a Framework to Model the Climatic Conditions of Car Parking Lots' by Mr Hyacinthe Marie Nshuti in the Doctorate Programme Computer Technology and Environmental Engineering, **authorise its submission**, given that it meets the required conditions for its defence.

Which we hereby sign in compliance with Spanish Royal Decree 99/2011, of 28 January, in Murcia, on 18 March, 2026.

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ABSTRACT

This doctoral research introduces **CLIMATICPARK**, a decision-support framework and innovative simulator designed to address energy efficiency, thermal comfort, and climate adaptation challenges in urban parking facilities. Parking areas, often neglected in sustainability discourse, represent critical urban surfaces that influence local microclimates, vehicle cabin conditions, and energy demands. By integrating contextual factors such as shading, solar irradiance, user parking behavior, and weather variability, CLIMATICPARK provides a multi-dimensional platform for analyzing and optimizing parking infrastructure performance.

The study combines empirical data collection, computational modeling, and scenario-based simulations to evaluate the interplay between parking lot design, thermal dynamics, and energy-saving opportunities. A case study at the Catholic University of Murcia (UCAM) validates the framework, demonstrating how data-driven insights can inform more sustainable urban design and climate-resilient parking management strategies. Results highlight the significant impact of ambient weather conditions, shading structures, and behavioral patterns on thermal loads and energy use. Moreover, the research emphasizes the potential of parking lots as leverage points for mitigating urban heat islands and enhancing user comfort.

By bridging gaps in existing literature, this work contributes both methodological innovations and practical tools for city planners, policymakers, and engineers. Ultimately, CLIMATICPARK demonstrates that rethinking parking infrastructures is essential for advancing sustainable mobility, energy efficiency, and urban resilience in the context of climate change.

RESUMEN

Esta investigación doctoral presenta **CLIMATICPARK**, un marco innovador de simulación y apoyo a la toma de decisiones diseñado para abordar los retos de eficiencia energética, confort térmico y adaptación climática en instalaciones de aparcamiento urbano. Los aparcamientos, a menudo ignorados en el discurso sobre sostenibilidad, constituyen superficies urbanas críticas que influyen en los microclimas locales, las condiciones térmicas del habitáculo de los vehículos y la demanda energética. Al integrar factores contextuales como la sombra, la radiación solar, el comportamiento de los usuarios y la variabilidad meteorológica, CLIMATICPARK proporciona una plataforma multidimensional para analizar y optimizar el rendimiento de las infraestructuras de estacionamiento.

El estudio combina la recogida de datos empíricos, la modelización computacional y simulaciones basadas en escenarios para evaluar la interacción entre el diseño del aparcamiento, la termodinámica y las oportunidades de ahorro energético. Un estudio de caso realizado en la Universidad Católica de Murcia valida el marco, demostrando cómo los datos pueden orientar el diseño urbano hacia estrategias más sostenibles y resilientes frente al clima. Los resultados obtenidos ponen de manifiesto el impacto significativo de los materiales superficiales, las estructuras de sombreado y los patrones de uso sobre las cargas térmicas y el consumo de energía. Asimismo, la investigación enfatiza el potencial de los aparcamientos como puntos de intervención para mitigar las islas de calor urbanas y mejorar el confort de los usuarios.

Al cerrar las brechas existentes en la literatura, este trabajo aporta innovaciones metodológicas y herramientas prácticas para planificadores urbanos, responsables políticos e ingenieros. En última instancia, CLIMATICPARK demuestra que repensar las infraestructuras de estacionamiento es esencial para avanzar hacia una movilidad sostenible, una mayor eficiencia energética y una resiliencia urbana frente al cambio climático.

KEYWORDS

Simulation, Cabin temperature, Energy efficiency, Smart parking systems, Urban microclimate, Sustainability, Ambient conditions

PALABRAS CLAVE

Simulación, Temperatura de cabina, Eficiencia energética, Sistemas de aparcamiento inteligente, Microclima urbano, Sostenibilidad, Condiciones ambientales

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ACRONYMS AND ABBREVIATIONS

AI, Artificial Intelligence

AM, Ambient Module

ANN, Artificial Neural Network

API, Application Programming Interface

CNN, Convolutional Neural Network

CTM, Cabin Temperature Module

DG, Demand Generator

DM, Demand Module

DL, Deep Learning

EV, Electric Vehicle

GCNN, Graph Convolutional Neural Network

GNN, Graph Neural Network

GPS, Global Positioning System

IoT, Internet of Things

KPI, Key Performance Indicator

LSTM, Long Short-Term Memory

MDPs, Major Decision Points

ML, Machine Learning

MLP, Multi-Layer Perceptron

OOP, Object-Oriented Programming

POM, Parking Occupancy Module

PV, Photovoltaic

RNN, Recurrent Neural Network

RMSE, Root Mean Square Error

SMA, Shading and Microclimate Analysis

SQL, Structured Query Language

TPL, Target Parking Lot

UHI, Urban Heat Island

UML, Unified Modeling Language

VMSSs, Variable Message Signs

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I – INTRODUCTION

I – INTRODUCTION

1.1. MOTIVATION OF THE STUDY

Over the past decade, the transportation sector has accounted for approximately 25% of global energy consumption, with private vehicles responsible for about 44% of this share (Conti et al. 2016; Jia et al. 2025). Private cars remain the most common means of commuting worldwide. In the United States, for example, 91% of adults commute to work by car (Bureau of Transportation Statistics 2017), while similar patterns are observed in Europe, with 70% in France and 68% in Germany (Brutel and Pages 2021; Statistischen Bundesamtes 2022). In general, mobility in Europe continues to be dominated by the use of private vehicles: 50% of individuals commute daily by car, compared to only 16% who use public transport and 12% who cycle (Giménez-Nadal, Molina, and Velilla 2022). This heavy dependence on private vehicles contributes significantly to greenhouse gas emissions, with road transport alone accounting for almost 15% of annual CO₂ emissions in the European Union in 2021 (Komnos et al. 2022). Consequently, the transition to sustainable mobility solutions has become a central priority in efforts to reduce emissions and achieve the EU's climate neutrality targets.

In addition to fuel combustion, the auxiliary systems within vehicles further increase the energy demand. Notably, air-conditioning systems account for approximately 2.8% of the total energy consumption of a vehicle, and this figure may rise to nearly 10% when operating at full capacity (Johnson 2002). This proportion is higher than that of several other critical components, such as brake systems (2.5%) or aerodynamic drag (5.3%). The disproportionate impact of air-conditioning highlights its importance as a target for energy-saving measures.

One promising avenue to mitigate both energy consumption and emissions lies in the design of optimized parking facilities. Across Europe, municipalities with

more than 20,000 inhabitants provide an estimated 21.8 million off-street parking spaces (Pierik, Königsberg-Brouns, and Klinge 2017). However, the vast majority of these are surface-level lots with very limited shaded areas, as illustrated in Fig. 1. Vehicles parked in unshaded spaces are often exposed to direct solar radiation, the intensity and duration of which vary by time of day, season, and spatial location within the lot. As a result, cabin temperatures can exceed 60°C during prolonged exposure to sunlight (Scott, Simpson, and McPherson 1999; D. Liu et al. 2025). In contrast, shading structures such as trees or artificial covers can reduce cabin temperatures by more than 15°C , significantly improving comfort and reducing dependence on air conditioning.

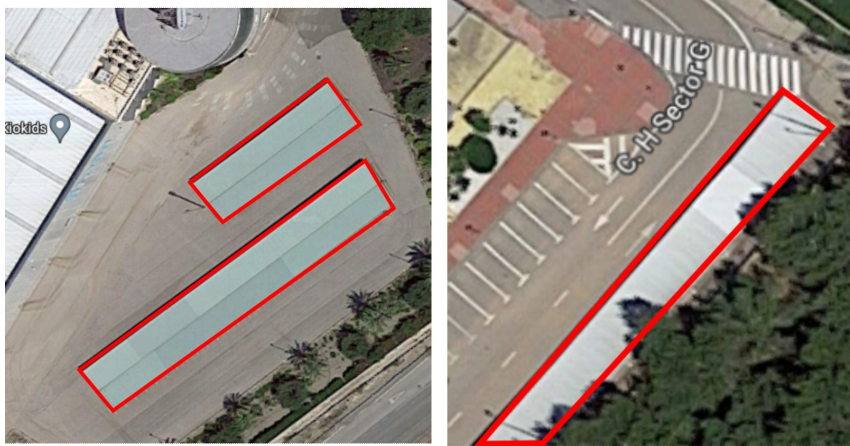


Figure 1: Aerial view of two parking facilities with shaded spaces highlighted in red.

Building on these observations, this thesis adopts the hypothesis that reducing vehicle cabin temperature prior to use lowers the subsequent energy demand of the air-conditioning system. In other words, the cooler the cabin temperature at the time of re-entry, the less energy is required to achieve a comfortable environment, thereby reducing both overall fuel consumption and greenhouse gas emissions.

To this end, the research proposes **CLIMATICPARK**, a framework model for the climatic simulation of car parking facilities. Implemented as the Python library `climaticpark-py`, the system enables the simulation of different shading configurations and their impact on cabin temperatures and fuel consumption. Its modular structure allows parking-lot operators and planners to test various

designs and placements of sunshades, optimizing coverage and functionality before physical installation. Beyond its technical contribution, CLIMATICPARK supports the United Nations Sustainable Development Goal 11: Make cities and human settlements inclusive, safe, resilient, and sustainable¹.

1.2. TECHNOLOGICAL FOUNDATIONS OF PARKING MANAGEMENT SYSTEMS

A combination of different technologies, such as Internet of Things (IoT), data analysis, and machine learning, is used to develop parking management systems. In this section, these technologies are defined and explained through related studies.

1.2.1. IoT

The Internet of Things (IoT) refers to a network of physical devices embedded with sensors, software, and connectivity features that allow them to collect and exchange data (Rath, Khang, and Roy 2024). These devices, which range from household appliances to industrial machines, communicate over the Internet or other networks to automate processes, monitor conditions, and enhance efficiency (P. Sun et al. 2025). IoT is widely used in applications such as smart homes, healthcare monitoring, agriculture, manufacturing, and urban infrastructure (Aouedi et al. 2024). By enabling real-time data exchange and automation, IoT contributes to improved decision-making, energy efficiency, and overall convenience.

One specific and impactful application of IoT is in vehicle parking management. Figure 2 shows a typical example of an IoT based smart parking system. IoT-enabled smart parking systems use sensors installed in parking spaces to detect vehicle presence and transmit real-time data to a centralized platform (Alam et al. 2023). This information can be accessed by drivers through mobile apps, allowing them

¹<https://unstats.un.org/sdgs/report/2016/goal-11/>

to locate available parking spots quickly, thereby reducing traffic congestion and saving time (Jung 2020). Additionally, city administrators can use the collected data for monitoring usage patterns, enforcing regulations, and planning infrastructure upgrades (Mangiaracina et al. 2017). This integration of IoT in parking management not only enhances user convenience but also supports efficient urban mobility and sustainability goals.

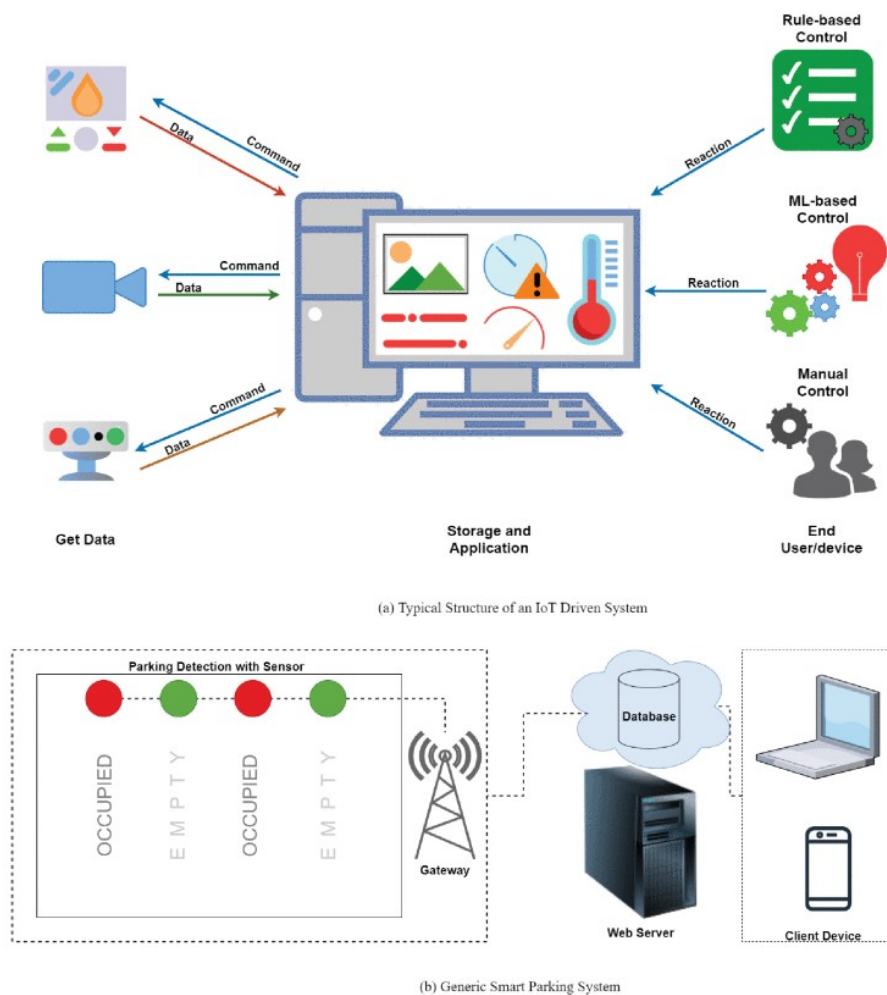


Figure 2: IoT-based smart parking. (Alam et al. 2023).

1.2.2. Big Data

Big Data refers to extremely large and complex datasets that are difficult to manage, process, and analyze using traditional data processing tools (Sagiroglu and Sinanc 2013). It encompasses structured, semi-structured, and unstructured data gathered from various sources like sensors, social media, mobile devices, and enterprise systems (Daas et al. 2015). Data analysis involves examining, cleaning, transforming, and modeling data to discover useful insights, support decision-making, and identify trends or patterns (Natividade Joergensen and Zaggl 2024). Together, Big Data and data analysis are used across industries such as transport, healthcare, finance, marketing, public administration, and urban planning to improve efficiency, enhance customer experience, and drive innovation.

In the context of vehicle parking management and city planning, Big Data has specific and impactful applications. By collecting real-time data from IoT sensors embedded in parking spots, GPS-enabled vehicles, and mobile payment apps, cities can analyze parking behavior, optimize space utilization, and reduce traffic congestion (Whitney et al. 2023). For example, predictive analytics can inform drivers about available parking spaces, minimizing search time and reducing emissions (Sikarwar et al. 2024). On a broader scale, urban planners use big data to assess transportation flows, plan infrastructure upgrades, and develop smart city initiatives that improve livability and sustainability (Elena et al. 2024).

1.2.3. Machine Learning

Machine Learning (ML) is a field of Artificial Intelligence that focuses on developing algorithms that allow computers to learn from and make decisions based on data (S. Ray 2019). Unlike traditional programming, where explicit instructions are given, ML systems identify patterns and relationships in the data to improve their performance over time. These algorithms can be trained using labeled

data (supervised learning), unlabeled data (unsupervised learning), or through trial-and-error (reinforcement learning) (J. He 2025), making them highly adaptable for a wide range of applications.

In general, ML algorithms are widely applied across industries to automate complex tasks, uncover insights, and support predictive analytics. For example, in healthcare, ML assists in diagnosing diseases by analyzing medical images (Binson et al. 2024). The versatility of ML enables industries to increase efficiency, reduce operational costs, and improve user experience by making smarter, data-driven decisions (Gao et al. 2024).

In the context of vehicle parking management and urban planning, ML algorithms are particularly valuable. They can forecast parking demand by analyzing historical occupancy data, traffic patterns, and even weather conditions (Alymani et al. 2025). This helps in dynamic pricing, optimized allocation of parking spots, and better signage for available spaces. In urban planning, ML models analyze large datasets such as GPS traces, zoning maps, and census information to support infrastructure development, reduce congestion, and improve mobility planning (Robi and George 2025). These technologies help cities become more efficient, sustainable, and responsive to the needs of residents.

ML algorithms constitute the foundation of the intelligent parking framework we have developed, as they enable real-time analysis and automated decision-making beyond the capacity of conventional systems. The proposed solution employs predictive models to estimate parking availability, ambient conditions, and vehicle cabin temperatures within parking facilities while dynamically adapting to fluctuations in demand. Through their adaptability and capacity for continuous learning, ML algorithms enhance the accuracy and efficiency of the system over time, ultimately delivering a seamless user experience and contributing to the advancement of smart city infrastructure and urban planning initiatives.

1.2.4. Deep Learning

Deep Learning (DL) models have become central to predictive modeling across diverse domains such as energy demand forecasting, intelligent transportation systems, parking management systems, and financial time-series analysis (LeCun, Y. Bengio, and Hinton 2015; X. Li et al. 2023; Yuldashev, Aung, and Cho 2023). In particular, recent advances have applied DL to enhance parking management, ranging from real-time occupancy detection using CNNs (Yuldashev, Aung, and Cho 2023), to spatial-temporal availability prediction using Transformer architectures with multi-source data fusion (Huang et al. 2024), and accessible parking enforcement via object-detection pipelines (vehicle, license, badge detection) (Neupane et al. 2023). DL architectures, including feed-forward, convolutional, recurrent, and hybrid models, demonstrate strong performance in capturing complex nonlinear relationships and temporal dependencies in sequential data (Goodfellow, Yoshua Bengio, and Courville 2016; G. Zhang, Zheng, and Q. Yang 2018; Yoshua Bengio 2021). Building on this discussion of deep learning applications and their demonstrated strengths in parking management, we now examine the most relevant deep learning architectures in detail.

- **MLP:** A Multi-Layer Perceptron (MLP) is a feed-forward artificial neural network composed of an input layer, one or more hidden layers with nonlinear activations, and an output layer (Yi, S. Xu, and Jiang 2023; Boccato, G. Silva, and Rocha 2024). Although historically associated with classification, contemporary work shows that MLPs remain competitive for regression and time series forecasting, especially with architectural and frequency domain refinements that enhance global context capture and mitigate information bottlenecks (Jian Wang, Rui Chen, and W. Zhang 2024; Kim, Park, and Lee 2025).
- **CNN:** Convolutional Neural Networks (CNNs) apply learned convolutional filters to extract local, translation-invariant features, followed by

pooling/normalization and dense heads (Krichen and Ben Said 2023; L. Zhao, H. Sun, and W. Li 2024). Although best known for image processing, CNNs can be adapted for regression and time series by viewing sequences as 1D signals, enabling automatic feature extraction over local receptive fields that stack to capture longer-range structure (Rangel, Costa, and Almeida 2024; Yan Liu, T. Xu, and J. Ma 2024).

- **LSTM:** Long Short-Term Memory (LSTM) networks are gated recurrent architectures with cell, input, output, and forget gates, designed to preserve and update a latent state over long horizons, thereby addressing vanishing gradients and capturing long-range temporal dependencies (Mienye and Yi Sun 2024; Shi, Chen Zhang, and Yu Liu 2024). LSTMs remain strong baselines (and building blocks) for sequential regression and forecasting, and are often combined with attention/Transformer components (Waqas, S. Khan, and A. Ali 2024; Dai, K. Zhou, and Q. Yu 2024; Albeladi and R. Khan 2023).
- **CNN-LSTM (Hybrid):** CNN-LSTM hybrids use CNN blocks to learn local/short-range features from raw sequences (or sequence windows) and feed the resulting feature maps into LSTMs that model temporal dependencies, yielding a division of labor that often improves forecasting accuracy in energy/load and other demand-like domains (Abumohsen and Hassan 2024; Q. Wang, T. He, and Luo 2024). Variants include wavelet or attention-augmented CNN-LSTM, and extended LSTM stacks (Buratto, R. Silva, and Torres 2024; Salman and I. Rahman 2024; L. Guo, X. Chen, and B. Zhao 2025).

These architectures have been increasingly applied in vehicle parking management, where accurate demand forecasting supports dynamic pricing, congestion reduction, and optimal resource allocation. MLPs and CNNs have been used to learn spatiotemporal patterns of parking occupancy from sensor or camera data, while LSTMs and hybrid CNN-LSTMs are particularly effective in modeling temporal dependencies and traffic flow, enabling real-time predictions

of parking space availability. Such approaches improve efficiency in smart city mobility systems and support sustainable urban planning (S. Yang, Wei, et al. 2023; L. Yu and S. Liu 2023; U. Ali, Ramzan, and Naqvi 2024).

1.3. TOWARD THE DESIGN OF THE CLIMATICPARK FRAMEWORK MODEL

As urban populations expand and private vehicle use continues to dominate mobility patterns, the demand for sustainable parking solutions has become increasingly urgent. As we have seen in the previous section, existing IoT-based parking systems primarily emphasize space utilization and traffic flow optimization; they often overlook the environmental dimension, particularly the influence of vehicle cabin temperatures on both energy demand and passenger comfort. Therefore, this research seeks to bridge this gap by integrating environmental and occupancy data into an intelligent framework for energy-efficient parking management.

In the literature, computer-based simulation models have been widely proposed for representing and analyzing complex real-world systems (Pylianidis et al. 2022). Within the transportation domain, most of the applications of these models have focused on optimizing vehicle flow and planning traffic at the network level (Jafari et al. 2023; Fan et al. 2022; Argota Sánchez-Vaquerizo 2022). However, far fewer contributions address the micro-level dynamics of parking facilities, particularly those that incorporate both user behavior and environmental variables such as cabin heat accumulation in parked vehicles. As highlighted earlier, managing these climatic factors is essential for developing energy-conscious solutions that reduce air-conditioning loads, enhance efficiency, and mitigate greenhouse gas emissions.

Recent studies have begun to explore IoT-enabled parking systems that consider sustainability beyond space management, integrating real-time environmental sensing and predictive modeling (Biswas, Choudhury, and R. Ray 2021; M. Ali, Hussain, and Rehman 2022). Similarly, machine learning and digital twin

approaches are increasingly being applied to urban mobility problems to model and forecast demand while accounting for contextual variables such as weather and user behavior (Moreno, García, and Martínez 2021; Y. Sun, J. Wang, and H. Guo 2023). Nevertheless, research that explicitly connects parking management with climatic and thermal comfort considerations remains limited, underscoring the novelty of the present approach.

To address these challenges, this research introduces **CLIMATICPARK**, an intelligent parking framework model designed to simulate the climatic conditions of parking lots and support energy-aware management strategies. The framework combines environmental variables such as ambient temperature and shading effects with predictive models of user mobility to optimize parking allocation. Its overarching goal is to minimize heat build-up in parked vehicles, thereby reducing subsequent air-conditioning energy demand, improving driver comfort, and lowering associated emissions. This approach not only enhances operational efficiency in parking management, but also aligns with broader sustainability goals by reducing environmental impact and mitigating health risks from excessive cabin heat.

The proposed architecture of CLIMATICPARK is structured around two key dimensions:

- **Demand Patterns:** This component models the temporal and spatial dynamics of parking demand, including the timing of vehicle arrivals and departures, as well as the specific distribution of vehicles across available spaces. Such modeling enables accurate real-time and predictive assessments of occupancy levels.
- **Climatic Factors:** This component accounts for environmental variables within the parking facility, such as temperature variations and shading dynamics caused by architectural elements or sunshades. By integrating these factors, the simulator can estimate vehicle cabin temperatures and the energy required for cooling upon vehicle departure.

Through the combination of these two dimensions, CLIMATICPARK enables a holistic simulation of parking facilities that incorporates both operational and environmental considerations, thereby offering a novel tool for advancing sustainable mobility solutions.

1.4. BACKGROUND OF THE STUDY

Parking facilities play a crucial role in the transportation system of modern communities and have a significant impact on their economic viability. Therefore, they are a major concern for public administrators, business owners, shoppers, workers, students, and anyone who drives a vehicle. Although widely studied and discussed, parking facilities remain a persistent problem when it comes to issues of energy efficiency and greenhouse gas emissions (Sethy, Behera, and Panda 2020). According to (Khayyam et al. 2011), the air conditioning system in the vehicle provides comfort to passengers, but also increases the energy consumption of the vehicle, greenhouse gas emissions, and negatively impacts vehicle performance. Other studies have shown that the mechanical compressor of the air conditioning system itself can increase fuel consumption by 12–17% in sub-compact to mid-size vehicles (Lambert and Jones 2006). As there is increasing demand for more fuel-efficient vehicles, energy management systems for vehicles and their components are being developed. These systems are designed to consider various factors that impact energy usage in the vehicle cabin, including vehicle attributes, environment, driving habits, etc. However, a more effective strategy to deal with the mentioned issues is needed, especially in extreme weather conditions.

As an example, in Murcia, Spain, where the UCAM Catholic University of Murcia is located, the high summer temperatures can make the inside of a parked vehicle extremely hot, causing discomfort for the drivers upon re-entry and posing health-threatening conditions. Furthermore, the intense heat can damage the interior of the vehicle and release harmful gases. Particular research has shown that the temperature inside a parked vehicle in direct sunlight can reach 72°C in summer

with an outdoor temperature of 34°C and a solar radiation of around 88 W/m² (Mao, Ji Wang, and J. Li 2018). To cool down a vehicle, the driver must start the engine and turn on the air conditioning at the maximum level. However, this method takes time to cool down the vehicle and is associated with several disadvantages, such as increased fuel consumption and greenhouse gas emissions. In addition, when a vehicle is operating at idle, the fuel is not completely burned, leading to a build-up of carbon around the valve and an increase in harmful emissions that pollute the environment (S. A. Rahman et al. 2014). Given that the transportation sector is one of the largest contributors to greenhouse gas emissions, accounting for approximately 14% of total emissions in Europe (Khalili et al. 2019), improving the efficiency of air conditioning systems, particularly in parked vehicles, becomes crucial to reducing energy consumption and mitigating environmental impact.

Beyond energy use, several studies have emphasized the significant public health risks associated with overheated vehicles. For instance, research in pediatric safety has demonstrated that children and vulnerable passengers can experience life-threatening heatstroke in less than 30 minutes of being left unattended in a parked vehicle exposed to direct sunlight (McLaren, Null, and Quinn 2005). Similar risks apply to elderly passengers and pets, highlighting that vehicle overheating is not only an energy problem but also a pressing safety issue.

Recent advances in smart parking infrastructure and intelligent shading solutions have attempted to address this problem. Smart shading technologies, such as photovoltaic (PV) canopies, provide dual benefits by both reducing cabin temperature and generating renewable energy for auxiliary services (N. Gupta, Kumar, and Malvoni 2021). Additionally, urban heat island (UHI) studies suggest that widespread adoption of shaded and vegetation-integrated parking lots could significantly reduce local microclimate temperatures, improving both thermal comfort and air quality (Sailor, Elley, and Gibson 2011). Such strategies align with sustainable urban mobility plans and contribute to achieving climate-neutral city goals under the European Green Deal.

In this regard, there is a growing interest in integrating the IoT technologies into parking facilities to monitor environmental conditions, predict cabin heating patterns, and optimize shading solutions dynamically (Al-Turjman and Malekloo 2018). These innovations, when combined with simulation frameworks like CLIMATICPARK, can provide municipalities and private operators with robust decision-making tools to design sustainable parking facilities that minimize both energy consumption and environmental impact.

1.5. PUBLICATIONS

Journal details
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Authors - Affiliations
Name: Hyacinthe-Marie Nshuti University: Catholic University of Murcia, Spain
Name: Juan Morales-García University: University of Alicante, Spain
Name: Andrés Muñoz University: University of Cadiz, Spain
Name: Pedro J. Navarro University: Technical University of Cartagena, Spain
Name: Diego Alonso University: Technical University of Cartagena, Spain
Name: Pedro Sanchez University: Technical University of Cartagena, Spain
Name: Bárbara Álvarez University: Technical University of Cartagena, Spain
Name: Fernando Terroso-Saenz University: Technical University of Cartagena, Spain

II – STATE OF THE ART

II – STATE OF THE ART

Given the diverse research areas the proposed framework addresses, including vehicle traffic simulation, vehicle parking management systems, and cabin temperature modeling and forecasting, this chapter offers a general overview of each domain.

2.1. VEHICLE TRAFFIC SIMULATION

The potential of traffic simulation technology extends beyond conventional modeling, offering support for sustainable urban traffic planning, efficient traffic control, and accurate recording of large-scale vehicular data (Jafari et al. 2023). For example, a framework integrating Digital Twins with edge AI technologies has been proposed to achieve comprehensive control over diverse vehicle types, including connected and automated vehicles (CAVs), connected vehicles (CVs), and human-driven vehicles (HVs) (Fan et al. 2022).

2.1.1. Traffic Flow Simulation Tools

Several software platforms have been developed to model traffic flow and vehicle interactions at different scales. *CORSIM* (Halati, Lieu, and Walker 1997) combines the capabilities of *NETSIM* (Network Simulation), which simulates traffic operations on urban streets, and *FRESIM* (Freeway Simulation), which simulates traffic on freeways and high-speed multi-lane facilities, to simulate detailed traffic flow, congestion, and vehicle interactions on both freeways and surface streets. Operating at a macro-to-meso scale, it allows researchers to examine complex interactions across large traffic networks. Another widely used tool is *SUMO* (Krajzewicz et al. 2012), an open-source platform for traffic management, vehicular communication,

and network modeling. Thanks to its scalability and flexibility, *SUMO* enables the simulation of large-scale transportation systems, providing insights into traffic flow, congestion patterns, and vehicle interactions. For example, a large-scale microsimulation of traffic flows in Barcelona, Spain was developed using *SUMO*; calibrated with real cell phone and survey data, the model evaluated two dynamic assignment methods, incorporated stochastic adaptive routing, and produced a realistic 24-hour representation of urban mobility (Argota Sánchez-Vaquerizo 2022).

TransCAD (Caliper Corporation 2025) is another comprehensive transportation planning software that supports multimodal analysis across different geographic scales, ranging from local to global contexts. It enables the modeling of passenger and freight transport, network analysis, and facility location, thereby offering an extensive platform for evaluating broad transportation systems. In contrast, *ABMTrafSimCA* (Górka and Małeckı 2024) captures micro-scale road traffic dynamics through the integration of cellular automata (CA) and a multi-agent approach. Its primary focus lies on vehicle-level behaviors such as acceleration, braking, and distance management, providing detailed information on the interactions of individual vehicles within traffic flows.

2.1.2. Parking and Energy Management Simulation

Simulation has also been applied to the integration of parking systems and energy management. For instance, a software platform was proposed to manage the solar energy generated by parking-lot installations while balancing the charging demand of electric vehicles (Varone et al. 2024). Similarly, (Ayaz et al. 2024) introduced a smart parking system that embeds a charging station energy management algorithm to optimize station performance.

Focusing more directly on parking dynamics, (X.-Y. Ni and D. Sun 2018) introduced an agent-based simulator to address the problem of limited parking availability. The study highlighted the role of variable message signs (VMSs) at

major decision points (MDPs) defined as intersections where drivers alter routes upon learning that a parking lot is full, and demonstrated how simulation can evaluate the effectiveness of different VMS placements. In later work, (X.-Y. Ni, D. Sun, et al. 2024) presented a cellular automaton approach to assess the efficiency of automated parking robot systems responsible for transporting vehicles to designated spaces.

However, it is important to note that while the aforementioned studies emphasize data collection within vehicles, they largely overlook the potential applications of emerging technologies to address challenges related to thermal management of vehicle interiors. As highlighted in a recent survey (J. Guo et al. 2022), simulation models hold considerable promise for supporting Internet of Vehicles (IoV) system design. Nevertheless, the integration of such models into IoV-based system development and deployment remains insufficiently explored.

For the sake of clarity and completeness, Table 1 provides a comparative overview of the simulators discussed in the two previous sections, outlining their scope, the primary simulation techniques employed, the key traffic and contextual outcomes produced, and the metrics used to evaluate their accuracy.

Table 1: Comparison between different traffic simulators. Acronyms: AS-agent-based simulation, CA-cellular automation simulation, CFM-car following model, CR-cumulative reward, DL-deep learning, LCM-lane changing model, NRMSE-normalised root mean square error, ML-machine learning, MAE-mean absolute error, MAPE-mean absolute percentage error, ME-mean error or bias, PPO-proximal policy optimization, RBA-rule-based algorithm, RMSE-root mean squared error, WT-waiting time.

Ref.	Scope	Simulation techniques	Traffic outcomes	Contextual outcomes	Evaluation metrics
(Fan et al. 2022)	Transportation	PPO	Vehicle traffic	-	CR
(Argota Sánchez-Vaquerizo 2022)	Transportation	CFM, LCM	Vehicle traffic	-	RMSE, NRMSE

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Table 1 – *Continued from previous page*

Ref.	Scope	Simulation techniques	Traffic outcomes	Contextual outcomes	Evaluation metrics
(Varone et al. 2024)	Parking lot	RBA	Demand behaviour	Power demand and generation	MAE, MAPE, ME
(Ayaz et al. 2024)	Parking lot	DL	Demand behaviour	Power demand and generation	RMSE, MAE
(X.-Y. Ni and D. Sun 2018)	Parking lot	AS	Message signs location	Traffic paths	-
(X.-Y. Ni, D. Sun, et al. 2024)	Parking lot	CA	Parking robot systems' behaviour	Arrival rates and parking duration	WT

2.2. VEHICLE PARKING MANAGEMENT SYSTEMS

Vehicle parking management has become an increasingly critical component of urban mobility, particularly in the context of growing populations, limited parking infrastructure, and the rise of connected and automated vehicles. Research in this area encompasses a range of approaches, from IoT-based smart systems that provide real-time information and optimize parking allocation to simulation-based models and predictive analytics that support planning and operational efficiency. The following subsections review the main technological directions, tools, and methodologies developed to enhance parking management, highlighting both practical implementations and data-driven innovations.

2.2.1. IoT-based Smart Parking Architectures

Within the field of vehicle parking management, existing research often emphasizes the design of IoT-based architectures aimed at developing smart parking systems (Sasaki 2021). For example, a two-step method was proposed for optimizing camera placement and generating training data to monitor parking spots (Sekkat et al. 2023). Although effective, vision-based systems of this kind require precise camera positioning to avoid obstructions from vehicles or infrastructure, and they rely heavily on large volumes of labeled training data, where data quality and diversity are critical for handling rare or complex scenarios.

Similarly, (Suthir et al. 2022) presented a conceptual framework for a smart parking system tailored to Industry 4.0. In this approach, each parking spot is equipped with an IoT-enabled infrastructure combining sensors and embedded systems, thereby enabling users to access real-time information on space availability and to select the most suitable option. The study envisions a fully automated parking facility that integrates image analysis with sensor-equipped spaces and introduces one-time password (OTP) generation to enhance security.

The design and fabrication of an IoT-based smart parking system using Raspberry Pi 4 B+, integrating multiple sensors for vehicle detection along with a graphical user interface (GUI) for intuitive monitoring, was presented in (Jabbar et al. 2021). In a related study, the application of advanced IoT technologies in parking management was demonstrated, reporting improvements in accuracy, user convenience, congestion reduction, revenue collection, and system scalability (Kanakaraja et al. 2021).

Several studies further emphasize the use of IoT sensors for real-time detection and visualization of parking space occupancy. For instance, (Dheeven et al. 2024) developed a parking information system incorporating IoT sensors and a web-based dashboard to monitor occupancy status in real time. Likewise, (M. M. Abo-Zahhad and M. Abo-Zahhad 2024) proposed a system employing infrared sensors to estimate

parking availability, transmitting the data to a mobile application for user access. A comparable vision-based method was introduced by (Arunkumar et al. 2024), which uses camera perception to determine occupancy levels.

Expanding beyond conventional sensing systems, the study (X.-Y. Ni, D. Sun, et al. 2024) investigated the use of parking robot systems to mitigate urban parking challenges. Their work introduced a two-stage allocation model to optimize robot navigation by minimizing both empty-loaded and loaded travel times. This system incorporates a cellular automaton simulation combined with priority-based conflict management rules. Validated within a university parking facility in Shanghai, the proposed method achieved notable reductions in queue lengths and vehicle waiting times when compared to a simpler one-stage model.

The work described in (Yu Liu et al. 2021) explored smart city logistics by addressing freight parking management in last-mile delivery. Their study conceptualizes urban freight transportation as a self-aware and self-organized system, with a particular emphasis on mobility, safety, and sustainability. Through the case of Smart City Logistics Parking (SCLP), the authors examined conceptualization, modeling, and implementation, making one of the earliest contributions to the application of Digital Twins for urban facilities. In this approach, multi-source data are systematically organized across multiple scales, from individual objects to complex system structures and semantics.

Beyond logistics, several tools have been developed to optimize parking allocation and scheduling. The software *SPA* (Jiazao Lin et al. 2019) schedules parking spaces according to demand while estimating vehicle parking durations, applying policies such as Worst-Fit (WF-SPA), Best-Fit (BF-SPA), and Parking Behavior Forecast (PBF-SPA). Its main objective is to enhance the efficiency of parking resource management.

For the sake of clarity and completeness, Table 2 provides a comparative overview of the discussed IoT-based smart parking systems, highlighting their scope, the primary technologies and system architectures employed, the main functional

outcomes achieved, and the application scope used to evaluate their performance.

Table 2: Overview of IoT-based smart parking systems. Abbreviations: IoT–Internet of Things, GUI–Graphical User Interface, OTP–One-Time Password, WF–Worst-Fit, BF–Best-Fit, PBF–Parking Behavior Forecast.

Ref.	Scope	System/Techniques	Functional Outcomes	Application scope
(Sasaki 2021)	Smart parking systems	IoT-based architectures, big data analytics	System design frameworks, architecture classification	-
(Sekkat et al. 2023)	Smart parking monitoring	Vision-based system, camera placement optimization, training data generation	Real-time parking spot monitoring, optimized camera placement	Accuracy of spot detection
(Suthir et al. 2022)	Industry 4.0 smart parking	IoT sensors, embedded systems, automated access, OTP-based security	Real-time availability, automated parking, enhanced security	-
(Jabbar et al. 2021)	Smart parking system	Raspberry Pi 4 B+, multiple sensors, GUI	Vehicle detection, intuitive monitoring	System accuracy, usability

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Table 2 – Continued from previous page

Ref.	Scope	System/Techniques	Functional Outcomes	Application scope
(Kanakaraja et al. 2021)	Advanced IoT parking management	IoT-enabled system, sensor integration, automated operations	Accuracy, congestion reduction, revenue collection, scalability	Accuracy, user convenience
(M. M. Abo-Zahhad and M. Abo-Zahhad 2024)	Parking lot information	Infrared sensors, mobile app	Real-time space availability updates	Detection accuracy, update latency
(Arunkumar et al. 2024)	Parking lot information	Camera-based perception, mobile app	Parking space occupancy detection	Detection accuracy
(Yu Liu et al. 2021)	Freight/last-mile parking	Digital Twin framework, multi-scale data integration	Freight parking management, mobility, safety, sustainability	System performance, operational efficiency
(Jiazao Lin et al. 2019)	Parking allocation	SPA software, WF/BF/PBF policies	Optimized parking allocation, duration estimation	Allocation efficiency, resource utilization

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Table 2 – Continued from previous page

Ref.	Scope	System/Techniques	Functional Outcomes	Application scope
(Dheeven et al. 2024)	Occupancy monitoring	IoT sensors, web-based dashboard	Real-time occupancy tracking and visualization	Detection accuracy, dashboard usability
(X.-Y. Ni, D. Sun, et al. 2024)	Robotic parking allocation	Parking robots, two-stage allocation, cellular automaton, priority rules	Reduced queue lengths and waiting times, optimized robot movement	Operational efficiency in high-density areas

2.2.2. Simulation-based Parking Solutions

Simulation-based approaches have been developed to address parking dynamics at both macroscopic and microscopic levels. *PyPML* (Codeca, Erdmann, and Harri 2018), for instance, enriches *SUMO* with parking management capabilities by incorporating real-time occupancy, occupancy evolution over time, and vehicle-type-specific intentions to use parking facilities. Moreover, it supports multi-parking scenarios, as demonstrated in simulations covering the Principality of Monaco and surrounding French cities. Together, *SUMO* and *PyPML* enable the analysis of large-scale traffic network dynamics in relation to parking infrastructure.

At a more microscopic level, (Vo, Waerden, and Wets 2016) proposed a parking lot simulator built on the agent-based modeling framework *NetLogo*,

designed to capture driver behavior during the process of occupying available spaces. Similarly, (Gu et al. 2021) introduced a microscopic simulator for modeling occupancy behavior in both on-street and off-street parking facilities with limited capacity. These approaches provide fine-grained insights into individual driver decisions and localized parking dynamics.

For the sake of clarity and completeness, Table 3 provides a comparative overview of the discussed simulation-based parking solutions, highlighting their scope, the primary simulation techniques employed, the traffic and contextual outcomes captured, and the metrics used to evaluate their performance.

Table 3: Comparison of simulation-based parking solutions. Acronyms: PyPML–Python Parking Management Library, SUMO–Simulation of Urban Mobility, ABM–Agent-Based Modeling.

Ref.	Scope	Simulation Techniques	Traffic/Contextual Outcomes	Application scope
(Codeca, Erdmann, and Harri 2018)	Multi-parking management	PyPML extension, SUMO integration	Real-time occupancy, occupancy evolution, vehicle-type-specific intentions, multi-parking scenarios	Occupancy accuracy, scenario validation
(Vo, Waerden, and Wets 2016)	Parking lot	Agent-based modeling, NetLogo	Driver behavior, space occupancy, parking decision-making	Simulation accuracy, behavioral fidelity

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Table 3 – *Continued from previous page*

Ref.	Scope	Simulation Techniques	Traffic/Contextual Outcomes	Application scope
(Gu et al. 2021)	On-street/ off-street parking	Microscopic simulation	Occupancy behavior, limited capacity management	Occupancy prediction accuracy, parking duration

2.2.3. Predictive Parking Availability Models

A significant body of research has focused on predictive solutions to forecast future parking demand. For instance, (S. Yang, W. Ma, et al. 2019) pioneered a dual GCNN–LSTM architecture that integrates parking-meter transactions, traffic speed, and weather data to provide 30-minute-ahead occupancy forecasts in Pittsburgh, achieving a mean absolute percentage error (MAPE) of 10.6%. In a similar vein, (Sasaki et al. 2023) employed a graph-to-sequence model that leverages real-time data and graph neural networks (GNNs) to capture both spatial and temporal dependencies in parking availability prediction.

Other contributions rely on sensor data and machine learning techniques. (Caicedo, Blazquez, and Miranda 2012) emphasized the real-time estimation of parking space availability by combining sensor data processing, historical analysis, and machine learning models. Along the same line, (Provoost et al. 2020) addressed real-world availability forecasting by integrating traffic and parking sensors, Web of Things (WoT) nodes, weather forecasting services, and historical occupancy rates. The authors applied a variety of machine learning algorithms, including neural networks and random forests, to build effective predictive models.

Alternative approaches explore additional data sources. For example, (Gonzalez-Vidal, Terroso-Sáenz, and Skarmeta 2022) enhanced availability

prediction by incorporating human mobility flows across urban districts, applying deep learning algorithms for time-series forecasting. Likewise, (Tiedemann et al. 2015) introduced the concept of a “data thread” for real-time occupancy prediction in Berlin, combining sensor streams with historical patterns to dynamically optimize the use of urban parking resources.

For the sake of clarity and completeness, Table 4 provides a comparative overview of predictive parking availability models, summarizing their scope, primary techniques, the types of data and outcomes considered, and the metrics used to evaluate predictive performance.

Table 4: Comparison of predictive parking availability models. Abbreviations: GCNN–Graph Convolutional Neural Network, LSTM–Long Short-Term Memory, GNN–Graph Neural Network, ML–Machine Learning, WoT–Web of Things, MAPE–Mean Absolute Percentage Error, RMSE–Root Mean Squared Error, MAE–Mean Absolute Error.

Ref.	Scope	Techniques	Data/Outcomes	Application scope/ Evaluation Metrics
(S. Yang, W. Ma, et al. 2019)	Urban parking	GCNN–LSTM (dual architecture)	Parking-meter transactions, traffic speed, weather; 30-min ahead occupancy forecasts	MAPE
(Sasaki et al. 2023)	Urban parking	Graph-to-sequence, GNNs	Real-time parking data; spatial-temporal dependencies	Prediction accuracy

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Table 4 – *Continued from previous page*

Ref.	Scope	Techniques	Data/Outcomes	Application scope/ Evaluation Metrics
(Caicedo, Blazquez, and Miranda 2012)	Parking occupancy estimation	Sensor data processing, ML models	Historical and real-time sensor data; space availability	Prediction error metrics
(Provoost et al. 2020)	Urban parking	ML algorithms (neural networks, random forests), WoT integration	Traffic and parking sensors, weather, historical occupancy; real-world forecasting	RMSE, MAE, accuracy
(Gonzalez-Vidal, Terroso-Sáenz, and Skarmeta 2022)	Urban mobility	Deep learning time-series forecasting	Human mobility flows, historical occupancy; availability prediction	Forecast accuracy
(Tiedemann et al. 2015)	Urban parking (Berlin)	Data thread concept	Sensor streams, historical patterns; real-time occupancy prediction	Prediction performance
(Antolín et al. 2018)	Parking behavior modeling	Empirical analysis, user heterogeneity	Preferences, behaviors; policy optimization	-

2.3. CABIN TEMPERATURE MODELLING AND FORECASTING

In recent years, considerable research has examined the environmental conditions inside vehicles in different scenarios. For instance, the study in (Fikfak et al. 2020) demonstrates that the greenhouse effect can significantly increase in-vehicle temperatures, even when the ambient air is relatively cold and the sky is partially cloudy. This work primarily addresses the challenge of monitoring elevated cabin temperatures in vehicles parked in open and sun-exposed areas during summer, with particular emphasis on the conditions encountered when individuals return to their cars after work. However, it does not investigate the temperature variations in large-scale parking facilities that include diverse structural features, such as different types of sunshades.

Another relevant study is presented in (Lan et al. 2023), which introduces a method to manage cabin temperature by aligning cooling strategies with the specific microclimatic conditions encountered on the road and the thermal comfort requirements of passengers. The study highlights a delay associated with manual cabin adjustments, which complicates the maintenance of a stable thermal environment in real time. Similarly, (Ce Zhang et al. 2024) propose a physics–data hybrid model that combines a first-principles cabin energy balance with an LSTM residual corrector to provide 10-minute temperature forecasts with a root mean square error (RMSE) of less than 0.5°C. In addition, a companion classifier predicts passenger thermal sensation with over 91% accuracy. Notably, this framework requires only a short calibration drive to adapt to a new vehicle, making it particularly suitable for fleet-scale deployment where minimal sensor recalibration is desired.

Several studies have demonstrated that the most effective approach for reducing cabin temperature is the use of sunshades. For example, (Jasni and Nasir 2012) reported that sunshades can achieve a substantial 21% reduction in cabin temperature. In a separate study, (Lv et al. 2021) proposed a novel car cover designed to mitigate interior temperature increases in outdoor parking by leveraging daytime

radiative cooling effects. The results indicated that, under intense solar irradiation ($>900 \text{ W/m}^2$), the novel cover reduced the cabin air temperature by 31.1°C and 19.6°C compared to a vehicle without a cover and one with a traditional cover, respectively. However, this approach has limitations: Even with the new cover, cabin temperatures during hot days often remain significantly above the human comfort range ($23\text{--}28^\circ\text{C}$). These findings highlight the need for more robust strategies to address thermal discomfort in vehicles, particularly in extreme weather conditions.

In the context of microclimate simulation and forecasting, the `climate-library` (Tripathi 2023) offers functions for preprocessing climate data and computing derived indices. Additionally, `ENVI-met` (ENVI-met 2025) is a well-established numerical tool for microclimate simulation, employing computational fluid dynamics to model environmental conditions. Some recent studies, such as (Zanchi, Zapperi, and La Porta 2023), have also applied deep learning techniques to forecast microclimate parameters. However, it is important to note that these libraries and tools do not specifically address the modeling of temperature conditions within vehicle cabins in parking areas.

Concerning mechanisms to anticipate the cabin temperature of a road vehicle in different settings, it is also possible to find some remarkable works in the existing literature. In (Grundstein, Meentemeyer, and Dowd 2009), the authors conducted an assessment of the highest achievable temperature within the passenger compartment of a 2005 Honda Civic, accounting for various weather conditions. They determined that the maximum temperature reached was 76°C . Furthermore, they devised a temperature prediction model that considered external temperature, solar radiation, and cloud cover as input parameters. In (Dadour et al. 2011), a more extensive study is presented that encompasses a broader timeframe and various car models. This study included the development of a temperature prediction model for a 2008 Ford Sedan. The model was based on a linear regression approach and took into account factors such as the car's orientation to solar radiation, body colour, and window opening levels. It should be noted that the authors acknowledged that they did not account for certain weather conditions, such as

windy days. In contrast, the prediction model proposed in the study by (Horak et al. 2017) factored in the wind speed as input to the system. Unlike previous studies, this work utilized temperature data from six different vehicles to create a dataset for training a linear regression model. Another recent approach (X. He et al. 2022) introduced the utilization of Deep Learning models. This work suggested the implementation of a Graph Neural Network (GNN) to predict interior vehicle temperature by encoding temperature correlations across different areas of the passenger compartment. However, the validation of the model was conducted using data from a single vehicle.

Table 5 summarizes the comparison between the aforementioned works. This table focuses on the target goal of the tool, the technology adopted to collect the data used to build the simulator, and the scope of application of each work.

Table 5: Comparison between different solutions to study a vehicle's cabin temperature. Acronyms: SI-satellite imagery, TS-temperature sensors, WD-weather data, AT-Ambient temperature, SR-solar radiation, WS-wind speed.

Ref.	Model target	Data feeds	Application scope
(Fikfak et al. 2020)	Cabin temperature	TS, WD, SI	Information system
(Lan et al. 2023)	Cabin temperature	TS, WD	Driver behaviour model
(Ce Zhang et al. 2024)	Cabin temperature, passenger thermal	TS, WD	Predictive HVAC control
(Jasni and Nasir 2012)	Cabin temperature	TS	Definition of cooling strategies
(Lv et al. 2021)	Cabin temperature	TS, WD	New car cover design

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Table 5 – *Continued from previous page*

Ref.	Model target	Data feeds	Application scope
(Grundstein, Meentemeyer, and Dowd 2009)	Cabin temperature	AT, SR, cloud cover	Hazard/forensic temperature estimation
(Dadour et al. 2011)	Cabin temperature	AT, SR	Parked vehicle temperature prediction
(Horak et al. 2017)	Cabin temperature	AT, SR, WS	Multi-vehicle linear regression prediction
(X. He et al. 2022)	Cabin temperature	Cabin temp sensors	GNN temperature prediction for HVAC optimization

2.4. PARKING SYSTEMS IN THE ERA OF ARTIFICIAL INTELLIGENCE

Artificial Intelligence (AI) is transforming intelligent transportation systems, and parking management is emerging as one of the domains that is experiencing significant innovation. Traditional parking solutions, which relied primarily on static rules and basic sensor technology, are increasingly being supplemented by AI-driven frameworks that integrate machine learning, computer vision, and predictive analytics. These technologies enable real-time identification of available parking spaces, improved driver guidance systems, and dynamic optimization of parking resources. As highlighted by (Shinde et al. 2021) and (M. Gupta and Singhal 2018), AI-enabled parking systems reduce congestion by predicting space availability and guiding drivers efficiently, thereby reducing both search time and traffic-related emissions.

Beyond operational efficiency, AI-based parking systems also support sustainable and user-centric urban mobility. Predictive algorithms can process historical and real-time occupancy data to forecast demand, minimize unnecessary driving within parking facilities, and recommend optimal space allocations. Deep reinforcement learning approaches, such as those described in (H. Li, Ota, and Dong 2020) and (Alotaibi, Alshehri, and Abouelmehdi 2021), dynamically assign parking spaces by taking into account driver preferences, current traffic conditions, and energy consumption. Moreover, research by (Badii, Al-Obaidi, and Patel 2018) and (Derycke, Lamotte, and Dalmaso 2021) demonstrates that integrating AI with Internet of Things (IoT) infrastructures facilitates adaptive and scalable smart parking ecosystems, reducing environmental impact while enhancing the overall user experience.

Recent developments at the intersection of AI, computer vision, and edge computing are further reshaping parking systems. Edge-based AI processing minimizes latency in real-time parking detection and guidance, which is critical in densely populated urban areas (L. Zhang, J. Ni, and P. Yang 2020). Concurrently, computer vision techniques have been successfully applied for automatic space recognition, license plate detection, and autonomous vehicle parking (W. Yang, Rong Chen, and Y. Zhang 2023; Jun Lin, X. Wang, and L. Zhou 2021). Emerging paradigms that combine AI with 5G and cloud computing enable scalable, city-wide parking services (Mousa, Alkhayyat, and Al-Rubaye 2022). Collectively, these innovations illustrate how AI-driven parking systems are evolving from simple space management tools into intelligent, sustainable, and adaptive mobility infrastructures, aligning with the broader objectives of smart city initiatives.

For the sake of clarity and completeness, Table 6 provides a comparative overview of AI-driven parking systems, highlighting their scope, primary techniques, functional outcomes, and application scope.

Table 6: Comparison of AI-driven parking systems. Acronyms: AI–Artificial Intelligence, ML–Machine Learning, DRL–Deep Reinforcement Learning, IoT–Internet of Things, CV–Computer Vision, 5G–Fifth Generation Mobile Network.

Ref.	Scope	Techniques	Functional Outcomes	Application scope
(Shinde et al. 2021)	Intelligent parking management	ML, predictive analytics	Real-time space availability, driver guidance, congestion reduction	Search time reduction, occupancy prediction accuracy
(M. Gupta and Singhal 2018)	Smart parking systems	AI-based frameworks, sensor integration	Space availability prediction, traffic guidance	Search time, traffic efficiency
(H. Li, Ota, and Dong 2020)	Dynamic parking allocation	Deep Reinforcement Learning (DRL)	Dynamic space assignment, considers driver preferences and traffic	Allocation efficiency, driver satisfaction
(Alotaibi, Alshehri, and Abouelmehdi 2021)	Parking resource optimization	DRL, predictive models	Optimized parking assignments, reduced energy consumption	Resource utilization, energy efficiency
(Badii, Al-Obaidi, and Patel 2018)	IoT-enabled AI parking	IoT integration, ML	Adaptive and scalable smart parking, improved user experience	Occupancy prediction, system scalability

Continued on next page

Table 6 – *Continued from previous page*

Ref.	Scope	Techniques	Functional Outcomes	Application scope
(Derycke, Lamotte, and Dalmasso 2021)	IoT and AI parking ecosystems	IoT sensors, AI analytics	Real-time monitoring, environmental impact reduction	Prediction accuracy, environmental metrics
(L. Zhang, J. Ni, and P. Yang 2020)	Edge-based AI parking	Edge computing, AI inference	Low-latency real-time parking detection and guidance	Detection latency, accuracy
(W. Yang, Rong Chen, and Y. Zhang 2023)	Computer vision parking systems	Computer vision, ML	Automatic space recognition, license plate detection	Detection accuracy, recognition rate
(Jun Lin, X. Wang, and L. Zhou 2021)	Autonomous vehicle parking	CV and AI	Automated vehicle parking, space utilization optimization	Parking success rate, occupancy efficiency
(Mousa, Alkhayyat, and Al-Rubaye 2022)	City-wide AI parking services	AI, 5G, cloud computing	Scalable, real-time parking management	System scalability, occupancy prediction

2.5. SUMMARY

A critical review of the literature reveals that, while substantial progress has been made in vehicle traffic simulation, parking management systems, AI-driven parking optimization, and cabin temperature modeling, existing studies exhibit notable limitations. Most prior research focuses either on traffic and parking infrastructure, predictive occupancy, or microclimate modeling in isolation, without integrating these dimensions into a cohesive, context-aware framework. In particular, conventional parking simulators and predictive models often overlook the thermal conditions of vehicle cabins, the effects of shading and sun exposure, vehicle orientation, and local weather dynamics factors that are crucial for assessing both user comfort and energy requirements.

The majority of existing solutions for predicting parking availability and occupancy rely on sensor data, historical usage patterns, and user behavior. These approaches primarily aim to optimize parking resource utilization based on real-time and past data, but typically do not account for climate-based variables such as vehicle cabin heat, localized weather conditions, or the influence of shading and sun exposure on parked vehicles. Despite the availability of microclimate simulation tools and deep learning forecasting libraries, current models rarely incorporate environmental conditions into parking behavior predictions or cabin temperature estimation.

In response to these gaps, **CLIMATICPARK** integrates contextual factors, including vehicle cabin thermal conditions, dynamic shading within parking facilities, user parking behavior, and local meteorological data. A key feature of CLIMATICPARK is its ability to estimate the energy required to cool vehicle interiors post-parking, an aspect largely neglected in prior models. Unlike existing systems, which often treat parking occupancy and traffic flows independently of ambient conditions, CLIMATICPARK explicitly models cabin temperatures under varying shelter types, such as awnings or partial shade structures, thereby addressing a significant gap in ambient-aware transportation simulation.

The framework incorporates a machine learning-based estimator for vehicle cabin temperature, enabling real-time and predictive modeling across diverse vehicle configurations and environmental settings. By combining crowd-sensed data collection with climate-aware modeling, CLIMATICPARK enhances predictive accuracy and provides actionable insights into how environmental factors influence parking decisions, energy consumption, and user comfort. This integration of environmental and vehicle-specific parameters represents a novel contribution to urban mobility research, bridging the gap between microclimatic modeling and sustainable parking system design.

Ultimately, CLIMATICPARK offers a comprehensive, purpose-built simulation environment for analyzing the interplay between climate, infrastructure, and human behavior in parking systems. Its potential to inform the design of thermally optimized parking facilities and support energy-efficient mobility strategies positions it as a valuable tool for urban planners, system designers, and sustainability focused initiatives.

III – OBJECTIVES

III – OBJECTIVES OF THE STUDY

The primary objective of this research is to develop **CLIMATICPARK, an intelligent, climate-aware parking lot simulation framework aimed at enabling energy-efficient and environmentally conscious parking management.** The system is designed to model a target parking lot (TPL), enabling realistic simulation of both occupancy levels and the cabin temperatures of parked vehicles. CLIMATICPARK integrates multiple contextual factors, including vehicle cabin temperatures, shading and shadow dynamics within parking areas, user parking behavior, and local meteorological data. A distinctive feature of the framework is its capability to estimate the energy required to cool vehicle interiors after they have been parked, thereby supporting sustainable vehicle operation and contributing to the reduction of greenhouse gas emissions.

To achieve this overarching aim, the research is guided by the following Specific Objectives (SO):

- SO-1: To model and simulate the thermal behavior of vehicle cabins in different parking scenarios, considering exposure to direct sunlight, shading structures, and seasonal variations.
- SO-2: To develop predictive algorithms that incorporate user parking patterns and mobility behaviors for optimized parking space allocation.
- SO-3: To integrate environmental data, including temperatures and solar radiation, into the simulation framework to improve accuracy and reliability.
- SO-4: To quantify the energy consumption associated with vehicle air-conditioning systems based on cabin temperature predictions, enabling assessment of potential energy savings.
- SO-5: To provide a modular and extensible simulation software for parking lot

operators and urban planners to evaluate and optimize shading configurations prior to physical implementation.

IV – MATERIAL AND METHODS

IV – DESIGN OF CLIMATICPARK FRAMEWORK

4.1. CLIMATICPARK ARCHITECTURE

In this section, we describe the inner architecture of CLIMATICPARK. As mentioned in Chapter III, the main goal of the system is to generate a model of a target parking lot (TPL) able to simulate its occupancy level in a realistic manner, along with the cabin temperatures of the simulated vehicles. To do so, we firstly state its general modular design, and then describe each component in detail.

4.1.1. General Overview

Fig. 3 shows the general architecture of the framework (comprising four modules) along with its key processing steps. CLIMATICPARK takes as input the target date (d_{target}) and hour (h_{target}), which are processed by the *Ambient Module* (AM) to simulate the state of the TPL and to determine the shadow coverage rate of each parking space for each hour. The inference of shadow coverage is primarily based on the geometric projection of the TPL roofs ($C(d, h)$). In addition, the AM incorporates the ambient temperature in the TPL ($\mathcal{T}(d, h)$), not because temperature affects the shadow geometry, but because it provides contextual information on solar irradiance and thermal conditions. This allows the framework to couple geometric shading patterns with the impact of ambient temperature on parked vehicles. At the same time, the *Demand Generator* (DG) estimates the arrivals and exits of drivers in the TPL for such a day and hour ($\mathcal{D}_{(d, h)}$). These records are processed by the *Parking Occupancy Module* (POM) to compute the state of the TPL spaces ($\mathcal{O}_{(d, h)}$), that is, which ones are occupied by a vehicle and which ones are empty. Lastly, all this information is processed by the *Cabin Temperature Module* (CTM) so as to compute the cabin temperature of each of the simulated vehicles parked in the TPL.

As a result, CLIMATICPARK generates the current state of the parking lot, $\mathcal{E}_{(d,h)}^{TPL}$ comprising 1) the parking spaces that are occupied on the target date and hour and 2) the cabin temperatures of the vehicles located in such spaces.

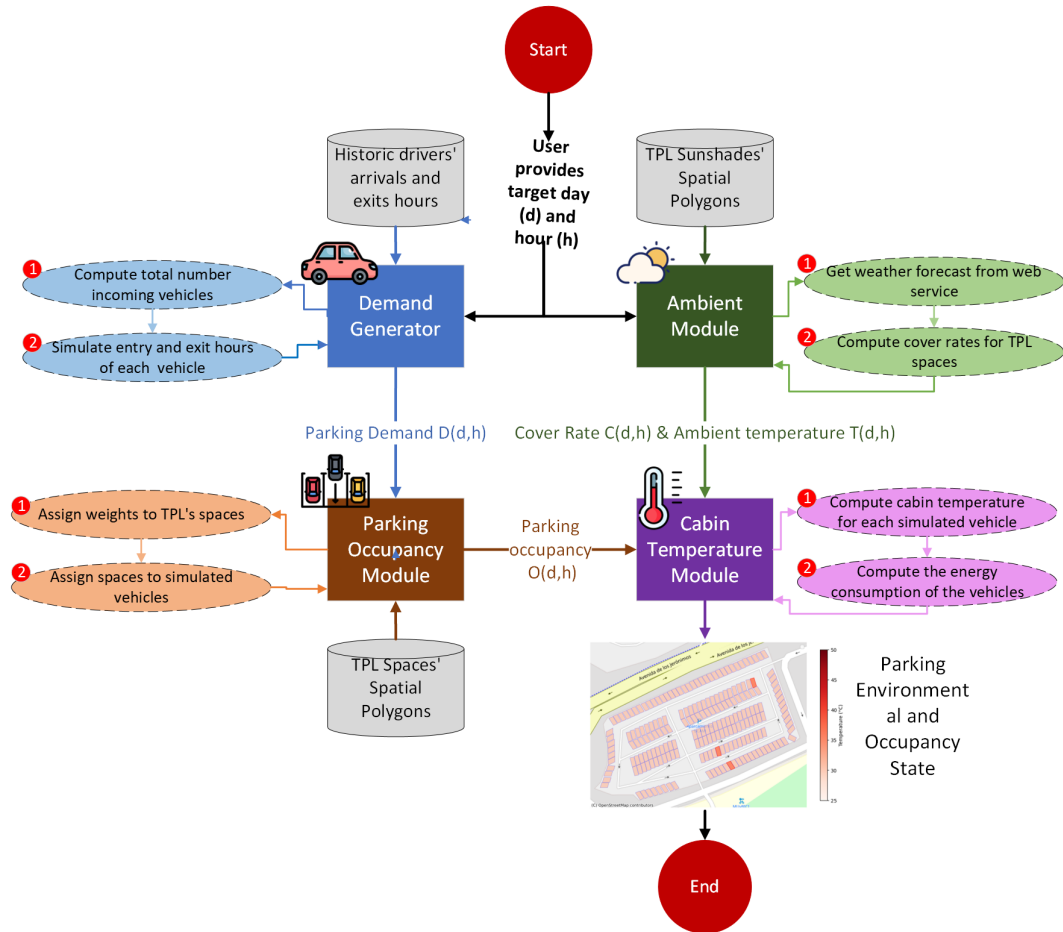


Figure 3: General architecture of the proposed system. The dashed arrows represent the input of the modules during their configuration. The solid arrows represent the flow of information during the production stage. For each module, the tasks to be performed are represented as ellipses.

The subsequent sections begin by presenting the configuration parameters necessary to instantiate CLIMATICPARK. This is followed by a comprehensive discussion of the four internal modules that collectively constitute the framework's processing pipeline, thereby providing a structured understanding of its operational components.

4.1.2. Configuration Parameters

To simulate the desired behaviour of the TPL, CLIMATICPARK first needs to receive five input items, namely,

1. The spatial polygons that define the location, shape, size, and orientation of the different sunshades or roofs installed in the TPL. Let us call this set C_{TPL} , where $c \in C_{TPL}$ represents the 2-dimensional spatial polygon of a particular sunshade or roof structure.
2. The spatial polygons that define the location, shape, size, and orientation of the parking spaces included in the TPL. Let us call this set S_{TPL} , where $s \in S_{TPL}$ represents the 2-dimensional spatial polygon of a particular parking space in the TPL.
3. The bi-variate timeseries $\mathcal{A}_{TPL}$, comprising the historical sequence of arrival and exits of drivers to the TPL during a certain period of time. Hence, this timeseries can be regarded as an ordered sequence of n triplets, $\mathcal{A}_{TPL} = \langle (d, h_a, h_e)_0 \rightarrow (d, h_a, h_e)_1 \rightarrow (d, h_a, h_e)_2 \rightarrow \dots \rightarrow (d, h_a, h_e)_n \rangle$, where the i -th element $(d, h_a, h_e)_i$ indicates that a driver arrived in the parking lot on date d_{target} at time h_a and left at time h_e .
4. The spatial points indicating the location of the different entrances and exits of vehicles of the TPL. Let us call this set $\mathcal{G}_{TPL}$.
5. The number of hours preceding the target hour h_{target} that CLIMATICPARK must consider to make certain inferences. As explained later, this information is rather domain-dependent, and it should be defined by the user. Let us call this time lag ℓ_{TPL} .

4.1.3. Ambient Module (AM)

The Ambient Module (AM) of CLIMATICPARK focuses on modelling the ambient conditions that will affect the cabin temperature of the vehicles in the TPL. To do so, AM takes as input the spatial polygons C_{TPL} described in the previous section. Next, each time this module receives a new target date and hour (d, h) to simulate, it performs the computation explained next.

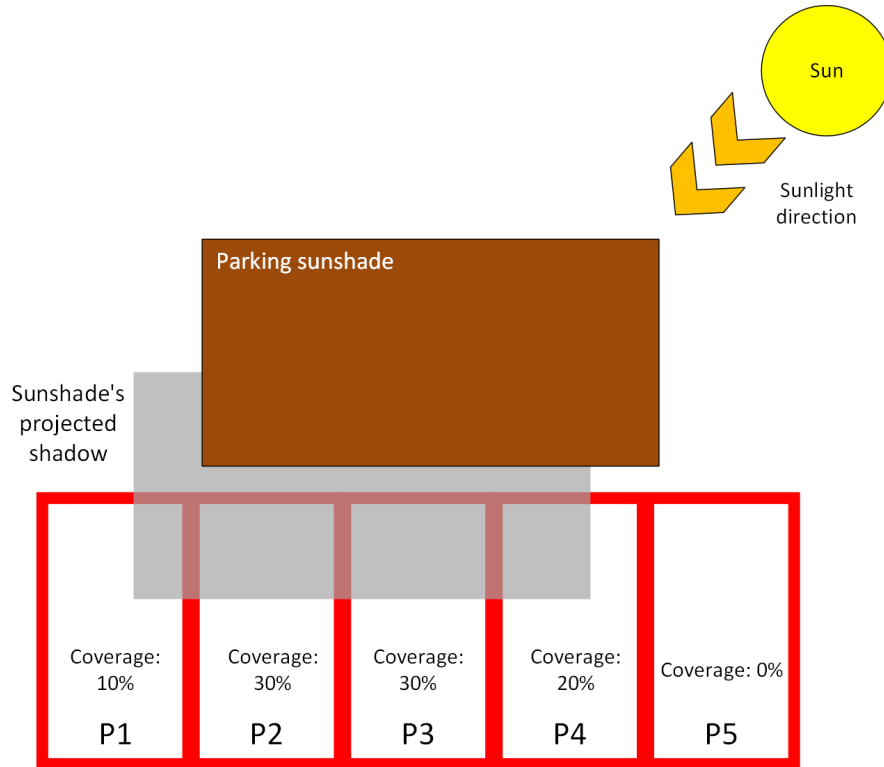


Figure 4: An illustrative example of the coverage rate concept for a parking lot with five spaces (P1, ..., P5) and a sunshade. Given the sun's position, the shadow projected by the sunshade results in spaces P2 and P3 having 30% of their spatial area covered by shadow, whereas space P5 has no coverage, giving it a coverage rate of 0%.

First, the AM captures the current weather conditions of the TPL's surrounding area by means of third-party weather data providers such as, for example, *World Weather API*¹. This third-party service allows retrieving, among other variables, the current and forecast temperature per hour up to 14 days, $t_{forecasted}^h$. Then, the shadow movements projected by the roofs or sunshades in the TPL are calculated

¹<https://www.worldweatheronline.com/weather-api/>

to estimate the cabin temperature. Such an assessment is contingent on the Sun's positioning during different seasons.

As a result, the AM returns the outdoor temperature of the parking lot for the target date and hour $\mathcal{T}_{(d,h)}$ and the overall shield rate of the parking lot, $C_{(d,h)}$. In this manner, for each space s in the TPL, its *coverage* level $c_{(d,h)}^s \in C_{(d,h)}$ represents the rate of the space's area that is covered by the shadow of the TPL sunshades, as shown in Fig. 4.

4.1.4. Demand Generator (DG)

The Demand Generator (DG) module focuses on estimating the total number of entries and exits that will occur in the TPL on the target date and time. To do so, a two-step procedure is implemented. First, it computes the total number $a_{(d,h)}^{total}$ of drivers arriving at the TPL on date d_{target} between hours $h - \mathcal{L}_{TPL}$ and h_{target} . By considering a certain number of hours before the target hour, it is possible to provide a more accurate estimate of the total number of vehicles that will be located inside the infrastructure by hour h_{target} . As a matter of fact, many car parks exhibit a cyclical pattern, with a large number of cars entering in the morning and a significant number departing in the evening. In these cases, considering the last 24 hours of TPL entries and exits seems a suitable approach.

For this first step, DG relies on an ensemble model combining two deep-learning networks, namely a Convolutional Neural Network and a Long Short-Term Memory one (CNNLSTM). Thus, this model features a convolutional network, but instead of the typical fully connected MLP layer at the end, it incorporates an LSTM network. This setup allows the CNN to automatically extract input features, while the LSTM is responsible for recalling past events and generating the regression results.

Once $a_{(d,h)}^{total}$ has been computed, the second step involves generating the particular entry and exit hours of each driver that the CNNLSTM has forecast during the time interval $[h - \mathcal{L}_{TPL}, h)$. To perform this computation, DG relies on Gaussian

Mixture Models (GMMs). In brief, a GMM is a probabilistic model that assumes all data points are generated from a finite mixture of Gaussian distributions with unknown parameters (Reynolds et al. 2009). Mixture models can be viewed as a generalization of the well-known k-Means clustering algorithm, incorporating information about both the covariance structure of the data and the centers of the latent Gaussians. GMMs can also serve as generative models, capable of creating synthetic data points based on the latent distribution of the input dataset. However, it is also important to note the instability of k-Means, which primarily arises from its sensitivity to the initial choice of centroids. As k-Means is typically initialized randomly, different initializations can lead to different final clusters, especially when the data has a complex structure or contains overlapping clusters. This randomness can result in variability in the algorithm’s output (Jain 2010). Additionally, k-Means optimizes a non-convex objective function, meaning that it can converge to local minima, further contributing to the variability in results. In that sense, several strategies have been proposed to mitigate this instability, such as running k-Means multiple times with different random initializations and then selecting the solution that minimizes the within-cluster sum of squares (WCSS), which can reduce the impact of poor initializations (Bradley and Fayyad 1998).

More in detail, we feed a GMM instance, $\mathcal{G}_{TLP}$, with the data distribution of entry and exit hours of the bi-variate timeseries $\mathcal{A}_{TLP}$ (see sec. 4.1.2.). Next, we use such an instance to generate a set $\mathcal{H}_{(d,h)}$ of entry and exit hours ($|\mathcal{H}_{(d,h)}| = a_{(d,h)}^{total}$). These hours represent the synthetic demand of TPL for the target date and hour, $\mathcal{D}_{(d,t)}$, that CLIMATICPARK will use in downstream modules.

4.1.5. Parking Occupancy Module (POM)

Once the DG component has generated the $\mathcal{H}_{(d,h)}$ set, the drivers’ behaviour regarding their entry and departure times from the TPL has been simulated in CLIMATICPARK. At this point, there is an important detail to be addressed: the specific space of the TPL that each of these drivers will occupy upon arrival. The

POM module is tasked with simulating that aspect of the system operation.

The Parking Occupancy Module (POM) relies on the hypothesis that drivers tend to park their cars as close to the parking lot exits as possible. This assumption is based on previous studies about outdoor parking cruising (Millard-Ball, Hampshire, and Weinberger 2020). Building on this idea, the POM includes a parking space assignment system designed to simulate the spaces within the TPL that each synthetic driver will occupy.

The assignment mechanism takes as input a list of TPL parking spaces, $\mathcal{S}_{TPL}$. Then, we define for each space $s_i \in \mathcal{S}_{TPL}$ a normalized weight $\omega_{s_i} = \frac{e^{1-\delta_{s_i}}}{\sum_{j=1}^{|\mathcal{S}_{TPL}|} e^{1-\delta_{s_j}}}$ where $\delta_{s_i} = \frac{\delta_{min}^{s_i}}{\delta_{max}^{TPL}}$, $\delta_{min}^{s_i}$ is the distance of the space s_i to its closest entry or exit gate and δ_{max}^{TPL} is the maximum distance in the TPL between a space and an entry or exit gate. Hence, the closer a space is to an entry or exit gate, the larger its assigned weight.

Next, for each incoming vehicle, the module assigns a space by means of a weighted random sampling of all the available spaces, considering the aforementioned weights. At the same time, when any vehicle leaves the TPL, its assigned space becomes available again for the sampling process.

This list is ordered based on the distance of each space to its closest entry or exit point in the set $\mathcal{G}_{TPL}$ (see sec. 4.1.2.). Hence, when a new car enters the TPL, it is assigned the space at the top of the list, and such a space is temporarily removed from $\mathcal{S}_{TPL}$. Similarly, when a vehicle leaves the TPL, its assigned space is inserted into the $\mathcal{S}_{TPL}$ list in the order given.

Consequently, the POM generates the set of spaces occupied by a vehicle on date d_{target} and hour h_{target} , $\mathcal{O}_{(d,h)}$. This set is eventually sent to the Cabin Temperature Module, whose description is stated next.

4.1.6. Cabin Temperature Module (CTM)

The Cabin Temperature Module (CTM) is responsible for estimating the temperatures of vehicle cabins, whether the vehicles are covered by a roof or exposed, as well as calculating the energy required to cool the cabin to a comfortable level. In the following subsections, we explain how these two steps are carried out.

4.1.6.1. Cabin temperature predictor

For a given user u and a parking space s in the TPL, the estimation is performed using a regression model ($\mathcal{P}$) expressed as follows:

$$\mathcal{P}(h_{(d,h)}^u, t_{(d,h)}^u, \Delta_u, t_{forecasted}^h, c_{(d,h)}^s) \rightarrow \hat{t}_{(u,\Delta_u)}^s$$

where the independent variables of the model are the arrival time of u at the TPL ($h_{(d,h)}^u \in \mathcal{H}_{(d,h)}$), the cabin temperature of the vehicle when it arrives to the TPL $t_{(d,h)}^u$, the total number of hours the car stays in the TPL, Δ_u (computed as the difference between the target and arrival hours ($h - h_{(d,h)}^u$)), the estimated temperature in the TPL at the target hour h_{target} ($t_{forecasted}^h$), and the sun coverage rate of s during the same time period ($c_{(d,h)}^s \in \mathcal{C}_{(d,h)}$). As a result, the predictor generates the estimated cabin temperature of a vehicle parked in s after Δ_u hours, $\hat{t}_{(u,\Delta_u)}^s$.

In order to estimate the initial cabin temperature of a vehicle $t_{(d,h)}^u$, we have considered the report from the Spanish National Institute of Statistics (INE) that claimed that 72,1% of the vehicles in Spain include an air-conditioning system among their features². For that reason, CLIMATICPARK uses this figure to estimate whether the incoming vehicle includes such a feature or not. If that is the case, $t_{(d,h)}^u$ is set to 22°C; otherwise, $t_{(d,h)}^u$ is set to the ambient temperature of the TPL at arrival time.

²<https://shorturl.at/fA5o2>

Using a Vector Autoregression (VAR) model, the CTM captures the interdependencies among variables such as ambient temperature, solar irradiance, and the vehicle's cabin thermal response. By incorporating these interactions, it is able to forecast cabin temperature trajectories with improved accuracy compared to univariate approaches, effectively representing the complex thermal dynamics inside vehicles (Lütkepohl 2013). As a result, this mechanism generates the set $\mathcal{T}_{(d,h)}^{cabin}$ comprising the cabin temperatures of all the vehicles in the TPL at date d_{target} and hour h_{target} . More in detail, each element $t^{cabin} \in \mathcal{T}_{(d,h)}^{cabin}$ is defined as a tuple $t^{cabin} = \langle s, t_s \rangle$ reporting that the space s of the TPL is occupied by a vehicle whose cabin temperature at the target hour h_{target} is t_s . Hence, the CTM returns the current state of the TPL, $\mathcal{E}_{(d,h)}^{TPL} (= \mathcal{T}_{(d,h)}^{cabin} \cup \mathcal{O}_{(d,h)})$. This set indicates the current number of vehicles in the TPL, the currently occupied spaces, and the cabin temperatures of each of the vehicles in those spaces at hour h_{target} .

4.1.6.2. Fuel consumption predictor

Another function of the CTM is to use the $\mathcal{T}_{(d,h)}^{cabin}$ sets to estimate the energy consumption of the simulated vehicles. This is done based on two dimensions: the cooling time and the fuel consumption in the air conditioning system of the simulated vehicles. To compute them, we first need to determine the rate of temperature change inside the vehicle cabin. In that sense, we rely on the differential equation based on the energy balance proposed in (Çengel and Boles 2014). Assuming that the air conditioning unit of a vehicle provides constant cooling power $P_{cooling}$, we can express the rate of temperature decrease in the cabin as:

$$\frac{dt_{cabin}}{dt} = -\frac{P_{cooling}}{\rho \cdot V_{cabin} \cdot c_p},$$

where:

- $t_{cabin} \in \mathcal{T}_{(d,h)}^{cabin}$ is the cabin temperature of the target vehicle when leaving the

TPL,

- $P_{cooling}$ is the cooling power of the air conditioning system in watts (W),
- ρ is the air density in kilograms per cubic meter (kg/m^3),
- V_{cabin} is the cabin volume in cubic meters (m^3),
- c_p is the specific heat capacity of air in joules per kilogram per Kelvin ($\text{J}/\text{kg}\cdot\text{K}$).

This equation states that the rate of temperature change, $\frac{dt_{cabin}}{dt}$, is proportional to the cooling power divided by the total heat capacity of the air inside the cabin.

The simulation continues until the cabin reaches a specified target temperature t_{target} . The condition to stop cooling is therefore defined as:

$$t_{cabin} \leq t_{target}.$$

The Time to Reach the Target Temperature (TRTT) required to achieve this target temperature is obtained by solving the differential equation with this condition.

Next, the Fuel Consumption (FC) can be estimated based on the energy requirement to cool the cabin to the target temperature. In that sense, we assume that 1 litre of fuel contains approximately 3.6 million joules (J) (Çengel and Boles 2014) so that such a variable can be calculated as:

$$FC = \frac{P_{cooling} \cdot TRTT}{J_{perliter}},$$

where $J_{perliter}$ ($= 3.6 \times 10^6$) J is the energy content per litre of fuel assumed by CLIMATICPARK. This formula converts the total energy consumed by the air conditioning system during the cooling period into litres of fuel, providing an estimate of the fuel cost based on the energy requirements (Incropera and DeWitt

2002). Hence, the framework is able to estimate the TRTT and the FC for each simulated vehicle.

4.1.6.3. Justification of the approach

In the literature, it is possible to find several works that make use of linear regression coefficients to estimate the cabin temperature of a vehicle such as the one described in (Alkaabi and Raza 2022; Jess et al. 2022; Ghareeb et al. 2024; Ce Zhang et al. 2024).

Although structurally different, these works and our solution share a number of conceptual similarities. First, they rely on data collected online to inform temperature estimation models. For instance, this involves real-time sensing of supply-air temperature, cabin temperature, and load conditions in (Ce Zhang et al. 2024); in our case, temperature forecasts, user-specific metadata, and environmental descriptors such as sun coverage are integrated into a multivariate regression model. Second, these frameworks use least-squares estimation to fit parameters. The work in (Ce Zhang et al. 2024) applies recursive least-squares to identify correction terms in their dynamic thermal model. Similarly, our regression model coefficients can be trained using standard least squares fitting techniques and could be adaptively updated as new data become available. Third, both methods emphasize the influence of external environmental conditions (particularly ambient temperature and solar radiation) on the thermal state of the cabin. While the mechanism in (Ce Zhang et al. 2024) incorporates this through physical heat-balance equations and the modeling of thermal loads, we incorporate them as input variables in the regression.

Regarding the key differences, they include model complexity and physical granularity: the work in (Ce Zhang et al. 2024) derives correction terms from first-principles dynamics and refines regional predictions via grey-modeling, whereas our approach treats thermal evolution as a purely linear combination of predictors. Temporal resolution also diverges: the approach in (Ce Zhang et al.

2024) targets real-time cabin regulation during operation with one-second sampling intervals, while our framework addresses passive temperature rise during inactivity in public parking lots. Additionally, the mechanism in (Ce Zhang et al. 2024) segments the cabin into multiple zones and employs human-machine interaction to predict passenger thermal sensation, whereas our model condenses solar effects into a single sun coverage metric and ignores spatial gradients.

Finally, we remark that our predictor is offered as a proof of concept. To extend it, we propose incorporating physics-driven heat-transfer equations to model conduction and radiation, adopting grey-modeling to correct time-series errors, and subdividing the cabin into zones for detailed solar mapping. Collecting occupant feedback via a human-machine interface could tune comfort indices. Finally, a recursive least-squares scheme would allow coefficients to adapt online, improving predictive accuracy and generalizability across varied climates.

V – USE CASE DESCRIPTION

V – USE CASE DESCRIPTION

This chapter presents the real-world scenario used to evaluate the applicability and performance of the CLIMATICPARK framework. To validate the proposed model under realistic conditions, a representative case study was designed, allowing for the integration of spatial, behavioral, and climatic variables relevant to parking dynamics and vehicle cabin thermal conditions. The selected use case supports the framework's objectives of modeling climate-aware parking management strategies and estimating the energy demands associated with post-parking cooling.

In that sense, the Target Parking Lot (TPL) was selected from among the parking facilities located within the premises of the Catholic University of Murcia (UCAM), Spain¹. This site was chosen due to its representativeness in terms of spatial layout, daily usage patterns, and contextual relevance to the objectives of the study. Its typical Mediterranean climate and frequent vehicle turnover make it an ideal environment for assessing the thermal and energy impacts modeled by the CLIMATICPARK simulator.

5.1. SETTING DESCRIPTION

The target parking lot has barrier-controlled access and covers an area of approximately 5,000 m² with a total of 250 spaces, as shown in Fig. 5. This car park is used by different academic and research teaching staff, together with members of the administration and service staff of the institution. Therefore, its hours of use are highly variable due to the heterogeneity of its users, which makes it an interesting TPL. Furthermore, the university is located in the city of Murcia (south-east of Spain), where the average maximum temperature in June, July and August is above 30°C as we can see from Table 7. This made the TPL particularly challenging for

¹<https://ucam.edu>

CLIMATICPARK.



(a) Aerial view of the parking lot whose spatial boundaries are marked in red with latitude-longitude coordinates (37.992, -1.186).



(b) South access to the parking lot controlled by barriers.



(c) Northeast access to the parking lot controlled by barriers.



(d) Northwest corner of the parking lot.

Figure 5: Target Parking Lot for the evaluation of the framework.

Table 7: Average maximum, minimum, and mean temperatures in Celsius ($^{\circ}\text{C}$) in the city of Murcia (Spain) from 2015 to 2022.

Values	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
High	17	18	20	22.8	26.1	30	32.8	32.8	30	25	20	17.2
Mean	10	11.1	13.9	16.1	20	24.4	27.2	27.2	23.9	19.4	13.9	10.5
Low	4.4	5.6	7.2	10	13.9	18.3	20.6	21.1	17.8	13.3	8.3	5.6

As depicted in Fig. 5, this TPL does not include any covered spaces. In order to provide a reliable study of CLIMATICPARK and, at the same time, show its utility in planning the installation of covered spaces, the evaluation was based on the hypothesis that two configurations of sunshades were evaluated. In the first one, the 250 parking spaces of the TPL spaces were covered by some type of sunshade, whereas in the second one, only a subset of the spaces located in the center of the TPL were covered. For the sake of clarity, Fig. 6 shows the spatial distribution of

these spaces, their associated number scheme, and the simulated sunshades.

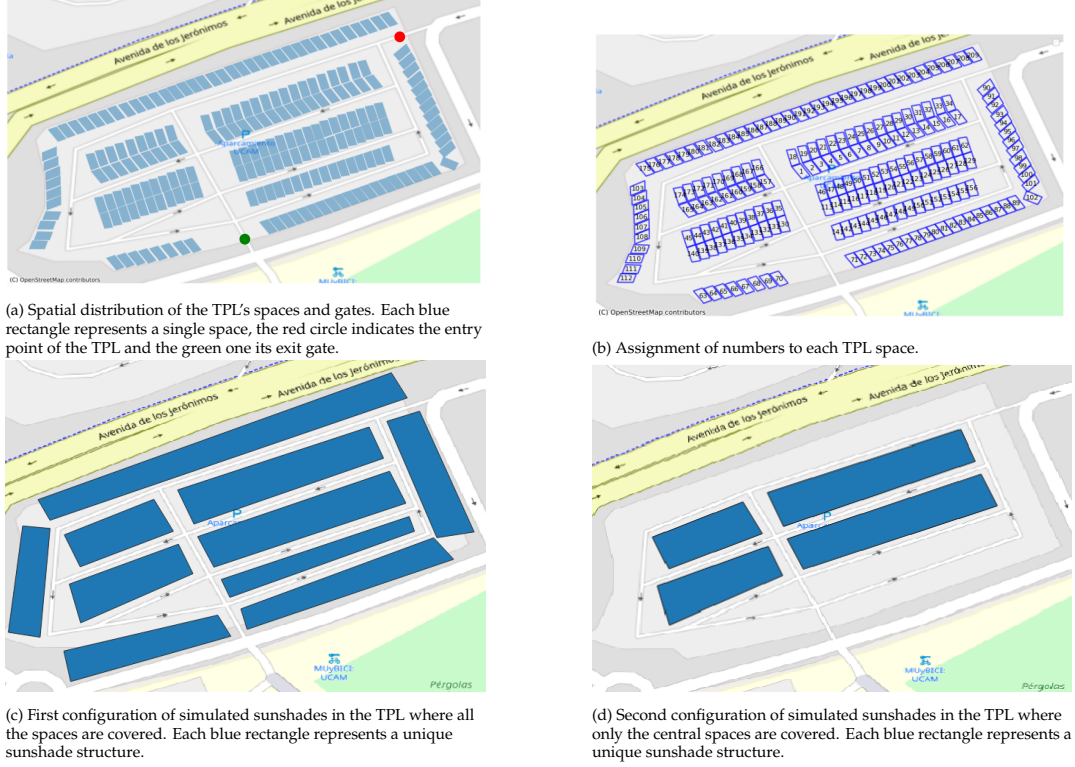


Figure 6: Parking spaces and simulated sunshades at UCAM parking facility.

To evaluate our approach in this TPL, we made use of a historical dataset with 32,053 check-in/check-out records of 367 different users spanning a 6-year period from 2016-09-20 to 2022-10-31. This dataset was obtained from the access-control system of the parking facility, which records every driver's entry and exit. This is made possible by the requirement for drivers to use a personal smart card to enter and leave the parking area. As a result, the dataset consists of a list of tuples, where each tuple $t = (driver_{id}, date_{entry}, date_{exit})$ represents the (anonymized) unique identifier of a driver, along with the corresponding date and time of entry and exit from the parking facility. In that sense, a driver could be included in more than one tuple.

From the aforementioned dataset, Fig. 7 shows the daily number of users in the TPL. As observed, there are no records in August, since the university would remain

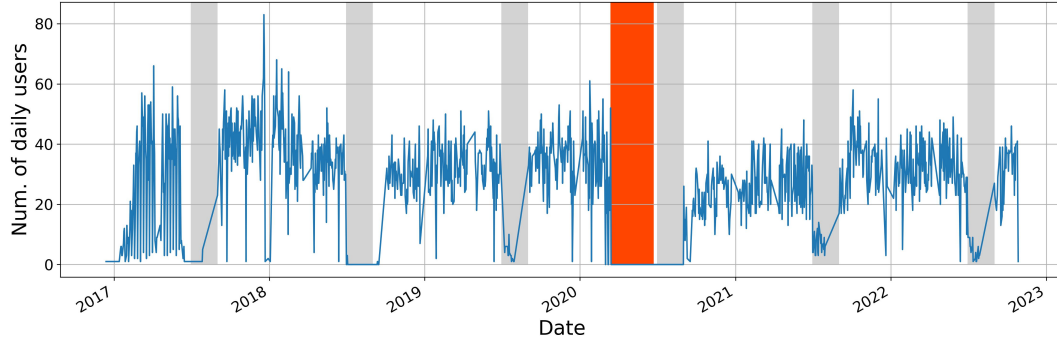


Figure 7: Number of daily users in the TPL. The summer holidays (from July, 1 to August, 31 are marked in grey) and the Spanish COVID-19 lockdown period (from 2020-03-14 to 2020-06-21) is marked in red.

partially closed without any academic activity in that month. Furthermore, it can also be observed that there are no records during the first months of 2020 due to the lockdown caused by the COVID-19 pandemic.

5.2. MEASURING THE CABIN TEMPERATURES WITHIN TPL

To accurately measure cabin temperatures in the TPL, an Elitech Temperature Data Logger² was installed inside the cabins of two different vehicles: a 2018 white Renault Dacia Sandero and a 2010 black Volkswagen Passat. Both vehicles are shown in Fig. 8. In particular, these vehicles belong to two regular users of the TPL.



(a) 2018 white Renault Dacia Sandero.



(b) 2010 black Volkswagen Passat.

Figure 8: Test vehicles used to capture the cabin temperatures in the TPL.

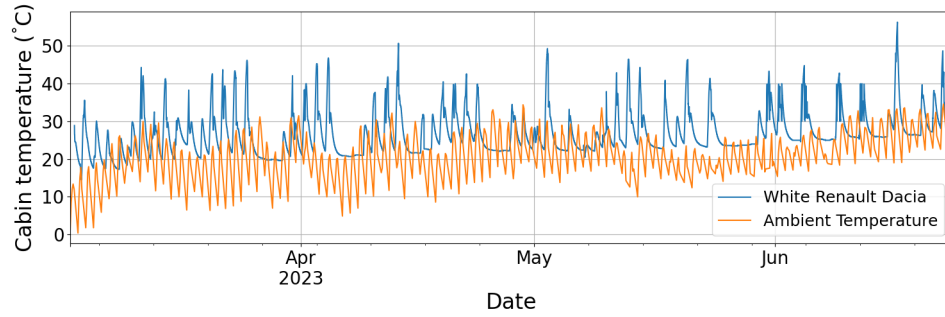
²<https://www.elitech.eu/products/elitech-rc-5plus-temperature-data-logger-reusable-usb-variant=43105462976771>

These sensors recorded data in the two vehicles mentioned above over the period from 2023-03-02 to 2023-06-23 while their drivers used them to enter and exit the TPL. During the data collection, vehicle cabin temperature was recorded under conditions in which the doors and windows were sealed shut, and the front windshield remained unshielded. With a maximum external temperature of 36°C , the interior temperature of the white vehicle reached 56.3°C and 62.3°C in the dark one as illustrated in Figs. 9a and 9b.

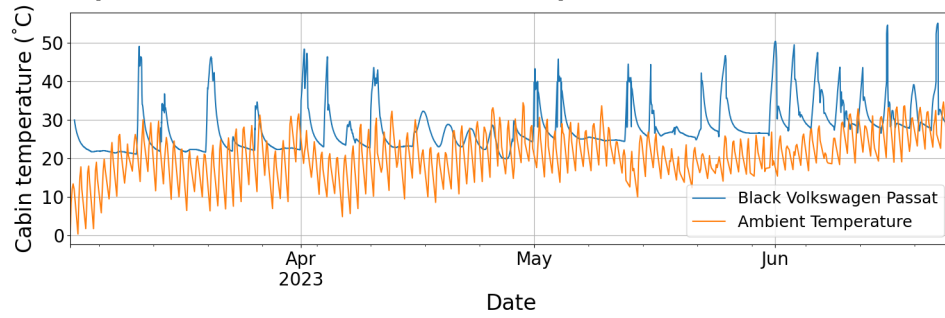
As observed, it becomes evident that as the environmental temperature increases, the cabin temperature continues to rise, even in situations where the environmental temperature change is relatively small. Note that the entrance and exit hours of the test vehicle in TPL were also recorded, as we can see in Figure 9c. Lastly, we also performed a Mann–Whitney U test (McKnight and Najab 2010) that rejected the null hypothesis that the cabin temperature distribution was identical in both vehicles with a p-value of 3.65×10^{-210} . This is consistent with findings in the literature that report the impact of the vehicle’s bodywork color on its inner temperature (Dadour et al. 2011). In utility terms, this allowed to development of two different cabin temperature predictors (sec. 4.1.6.), one for dark-color vehicles and another for light-color ones so that CLIMATICPARK used one model or another depending on the coarse-grained classification of the incoming vehicle’s color.

5.3. TRAINING PREDICTIVE MODELS FOR DEMAND AND CABIN TEMPERATURE

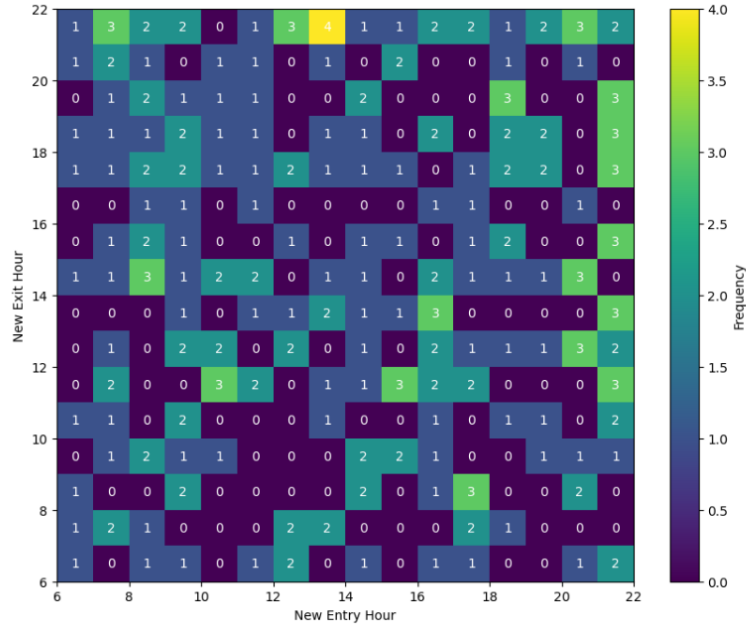
Given the sequence of general entry and exit hours described in sec. 5.1., we trained a CNNLSTM instance to anticipate the demand in the TPL (see sec. 4.1.4.). Furthermore, we also trained 3 alternative Deep Learning predictors, namely a Multilayer Perceptron (MLP), a Convolutional Neural Network (CNN), and a Long Short-Term Memory network (LSTM). A brief description of the models is provided in the next subsection.



(a) Cabin temperature of the white Renault Dacia Sandero and the external temperature in the TPL.



(b) Cabin temperature of the black Volkswagen Passat and the external temperature in the TPL.



(c) Entry and exit hours of the test vehicles.

Figure 9: Temperature records and the distribution of the entry and exit hours of the test vehicles.

The goal was to make a comparison between the CNNLSTM model and these three baselines. This enabled us to validate that the CNNLSTM model, adopted

by CLIMATICPARK, provided the most accurate predictions compared to other well-known deep learning architectures. To achieve this, we first divided the dataset into 90% for training and 10% for testing. From the training portion, 10% was reserved for validation, resulting in a final split of 80% for training, 10% for validation, and 10% for testing. Then, we evaluated all possible combinations of values within the hyperparameter ranges (grid search technique) shown in Table 8, until the best hyperparameters were obtained for each model, as shown in Table 10. The description of these hyperparameters is provided in Table 9. As a time horizon, we set 5 days ahead. In operational terms, this allowed us to set h_{target} 120 hours ahead of the current hour.

Table 8: Range of hyperparameter values evaluated for each model (MLP, CNN, LSTM, CNNLSTM).

HYPERPARAMETER	MLP	CNN	LSTM	CNNLSTM
Filters	-	[16 – 512]	-	[16 – 512]
Kernel size	-	[1 – 16]	-	[1 – 16]
Strides	-	[1 – 8]	-	[1 – 8]
Units	[30 – 300]	-	[30 – 300]	[30 – 300]
Activation function	[ReLU, Tanh]	[ReLU, Tanh]	[ReLU, Tanh]	[ReLU, Tanh]
Batch size	[720 – 8640]	[720 – 8640]	[720 – 8640]	[720 – 8640]
Epochs (+ <i>EarlyStopping</i>)	[100 – 3000]	[100 – 3000]	[100 – 3000]	[100 – 3000]
Optimizer	[Adam, RMSProp, SGD]	[Adam, RMSProp, SGD]	[Adam, RMSProp, SGD]	[Adam, RMSProp, SGD]
Loss function	[MSE, MAE]	[MSE, MAE]	[MSE, MAE]	[MSE, MAE]
Learning rate (+ <i>ReduceLROnPlateau</i>)	[0.0001 – 0.01]	[0.0001 – 0.01]	[0.0001 – 0.01]	[0.0001 – 0.01]

Table 9: Description of hyperparameters used for the models.

HYPERPARAMETER	Description
Filters	Features detector
Kernel size	Filters matrix used to extract the features
Strides	Number of pixels shifts over the input matrix
Units	Number of neurons in the model
Activation function	Function that decides if a neuron should be (or not) activated
Batch size	Size of batch used for training/forecasting
Epochs (+ <i>EarlyStopping</i>)	Number of epochs used in training
Optimizer	Function that optimizes the learning of an AI model
Loss function	Function used to evaluate the error of the model in each epoch
Learning rate (+ <i>ReduceLROnPlateau</i>)	Percentage change with which weights are updated at each iteration

Given this configuration, Table 11 shows four commonly utilized metrics for evaluating model performance, the coefficient of determination (R²), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and the Coefficient of the Variation of the Root Mean Square Error (CVRMSE) of the 4 models under consideration.

Furthermore, Table 11 also comprises the 4 parking availability predictors

Table 10: Hyperparameters used for the MLP, CNN, LSTM, and CNNLSTM models. For each hyperparameter, the set value is shown.

HYPERPAREMETER	MLP	CNN	LSTM	CNNLSTM
Train-Test split	0.9/0.1	0.9/0.1	0.9/0.1	0.9/0.1
Filters	-	64	-	64
Kernel size	-	1	-	2
Strides	-	1	-	1
Units	70	-	70	70
Activation function	Tanh	Tanh	Tanh	Tanh
Batch size	2880	2880	2880	2880
Epochs (+ <i>EarlyStopping</i>)	3000	3000	3000	3000
Optimizer	Adam	Adam	Adam	Adam
Loss function	MSE	MSE	MSE	MSE
Learning rate (+ <i>ReduceLROnPlateau</i>)	0.003	0.003	0.003	0.003

Table 11: Comparison of the demand predictors considered in CLIMATICPARK(Ours) and other existing parking availability predictors in the literature (Literature). Values in parentheses indicate the time horizon used in each work.

Source	Model/Manuscript	R2	RMSE	MAE	CVRMSE
Ours	MLP	0.479	0.684	0.277	0.020
	CNN	0.471	0.683	0.329	0.020
	LSTM	0.001	1.010	0.746	0.029
	CNNLSTM	0.495	0.672	0.319	0.019
Literature	sasaki2023predicting	-	-	4.608 (1h)	-
	PROVOOST2020100301	0.989 (1h)	2.68 (1h)	1.910 (1h)	-
	gonzalez2022parking	-	20.363 (1h)	15.324 (1h)	4.393 (1h)
	YANG2019248	-	-	1.390 (30 min)	-

reviewed in Chapter II that reports any of the aforementioned metrics in the evaluation section of their manuscripts.

Regarding the deep learning architectures under consideration, Table 11 clearly shows that the CNNLSTM network achieved the best R2, RMSE and CVRMSE among the 4 models considered. These results allow to validate the usage of a CNNLSTM instance as the most suitable model among the 4 alternatives to predict the number of incoming vehicles in the TPL. It is important to note that this is a key task within the CLIMATICPARK's pipeline.

Concerning the comparison with existing parking demand predictors, Table 11 shows that our work also outperformed previous solutions. For instance, the MAE of the CNNLSTM of CLIMATICPARK was much lower than the minimum of the other proposals (0.319 vs 1.390). In that sense, it is important to note that such solutions focused on on-street parking lots. This type of parking lot tends to exhibit

a much more heterogeneous and unpredictable behavior of drivers than our TPL, where drivers usually follow a quite regular schedule. This might explain the lower accuracy obtained by the reviewed solutions. In addition, we used the cabin temperature and the entry and exit records of the test vehicle described in the previous section to train the VAR model, which constitutes the core component of the CTM module (sec. 4.1.6.). It is important to note that the VAR model requires specifying just one configuration parameter: the number of lags to be used for forecasting. In our case, this value was selected through a grid-search procedure guided by the Akaike Information Criterion (AIC) (Hu 2007). Based on this process, the optimal lag length for the VAR model was determined to be 4 hours.

Moreover, we fitted the Gaussian Mixture Model (GMM) employed to estimate the entry and exit times of the POM module, denoted as $\mathcal{G}_{TLP}$, using the same dataset utilized for training the demand predictor. Accordingly, Table 12 presents the main configuration parameters of the resulting model.

Table 12: Main configuration parameters of the Gaussian Mixture Model, $\mathcal{G}_{TLP}$, where EM stands for Expectation-Maximization.

Parameter	Value	Brief Description
K	2	Number of Gaussian components in the mixture.
covariance_type	full	Structure of covariance matrices Σ_k .
ϵ	10^{-3}	Convergence tolerance for the EM algorithm.
reg_covar	10^{-6}	Regularization added to each covariance matrix Σ_k to prevent singularities.
max_iter	100	Maximum number of EM iterations.
init_params	Kmeans	Initialization method for component means (μ_k) and responsibilities.

Table 13 presents a comparison of the evaluation metrics obtained by our model with those reported by the existing approaches described in sec. 2.3.. As shown, the RMSE obtained by our model is similar to that of the mechanism proposed in (Lv et al. 2021). Although our model achieved slightly higher RMSE and MAE values compared to the predictor described in (Ce Zhang et al. 2024), it is important to note that the latter focused on a single vehicle, whereas our predictor was trained using data from two different vehicles, resulting in a more heterogeneous setting.

Table 13: Comparison of the cabin temperature predictors considered in CLIMATICPARK and other proposals in the literature. Values are defined in degrees Celsius.

Predictor	RMSE	MAE
(Ce Zhang et al. 2024)	0.11-0.14	0.07-0.10
(Lv et al. 2021)	1.4-2.0	-
CLIMATICPARK	1.84	1.44

VI – RESULTS

VI – RESULTS

In this chapter, we present the main findings of the research carried out in this thesis. The results are structured to highlight both the development and evaluation of the proposed framework, providing evidence of its effectiveness and applicability in real-world contexts. We begin by describing the design and implementation of the dedicated software package, `climaticpark-py`, which operationalizes the framework. This is followed by a detailed evaluation of its performance in the use case described in Chapter V.

6.1. CLIMATICPARK-PY LIBRARY DESCRIPTION

As a primary outcome of the CLIMATICPARK design, a dedicated software package, `climaticpark-py`¹ was developed to operationalize the framework and support its integration into research and practice. The software has been designed with modularity and extensibility in mind, allowing researchers and practitioners to simulate diverse parking scenarios, analyze energy and thermal dynamics, and evaluate climate-sensitive management strategies. In this section, we present a detailed description of the software architecture, including its principal modules, data flows, and processing logic. We also highlight its key functionalities, ranging from parameter configuration and data ingestion to simulation and visualization, and provide representative code to illustrate its practical use. Through these details, the user will gain a clear understanding of both the technical foundations of `climaticpark-py` and its broader impact as a tool for advancing sustainable and climate-aware parking management.

¹<https://github.com/fterroso/climaticpark>

6.1.1. Software architecture

The `climaticpark-py` library has been fully implemented in Python, adopting the Object-Oriented Programming (OOP) paradigm. This approach enables a modular and extensible code structure, facilitating both maintainability and future enhancements. Figure 10 presents the Unified Modeling Language (UML) class diagram of the library, which comprises six distinct classes. A brief description of each class is provided below.

To begin with, the core class of the library is `ClimaticPark` (center in Fig. 10). This class defines the end-point to interact and use the library to launch and simulate different scenarios for a Target Parking Lot (TPL) defined by the client. Hence, its constructor receives different geospatial files as input parameters defining the infrastructure and location attributes of the TPL along with its sunshade structures. Furthermore, it is in charge of orchestrating the interactions and execution of the other classes in the library during a simulation workflow, as we will explain in sec. 6.1.2..

The `AmbientModule` class (AM) in (bottom right corner of Fig. 10) is in charge of computing and generating the simulation aspects related to the climatic conditions in the TPL, based on the geographical location provided to the `ClimaticPark` class. In the current version of the library, this module focuses on estimating the ambient temperature at the geographical location of the parking lot. In terms of implementation, AM relies on a Recurrent Neural Network implemented with `tensorflow` library².

The `ShadowModule` class (SM), depicted in the bottom-left corner of Fig. 10, is responsible for simulating the shadows cast by sunshades in the TPL throughout the designated simulation days. These simulations are based on the position and movement of the sun during the day. From an implementation perspective, the

²<https://www.tensorflow.org>

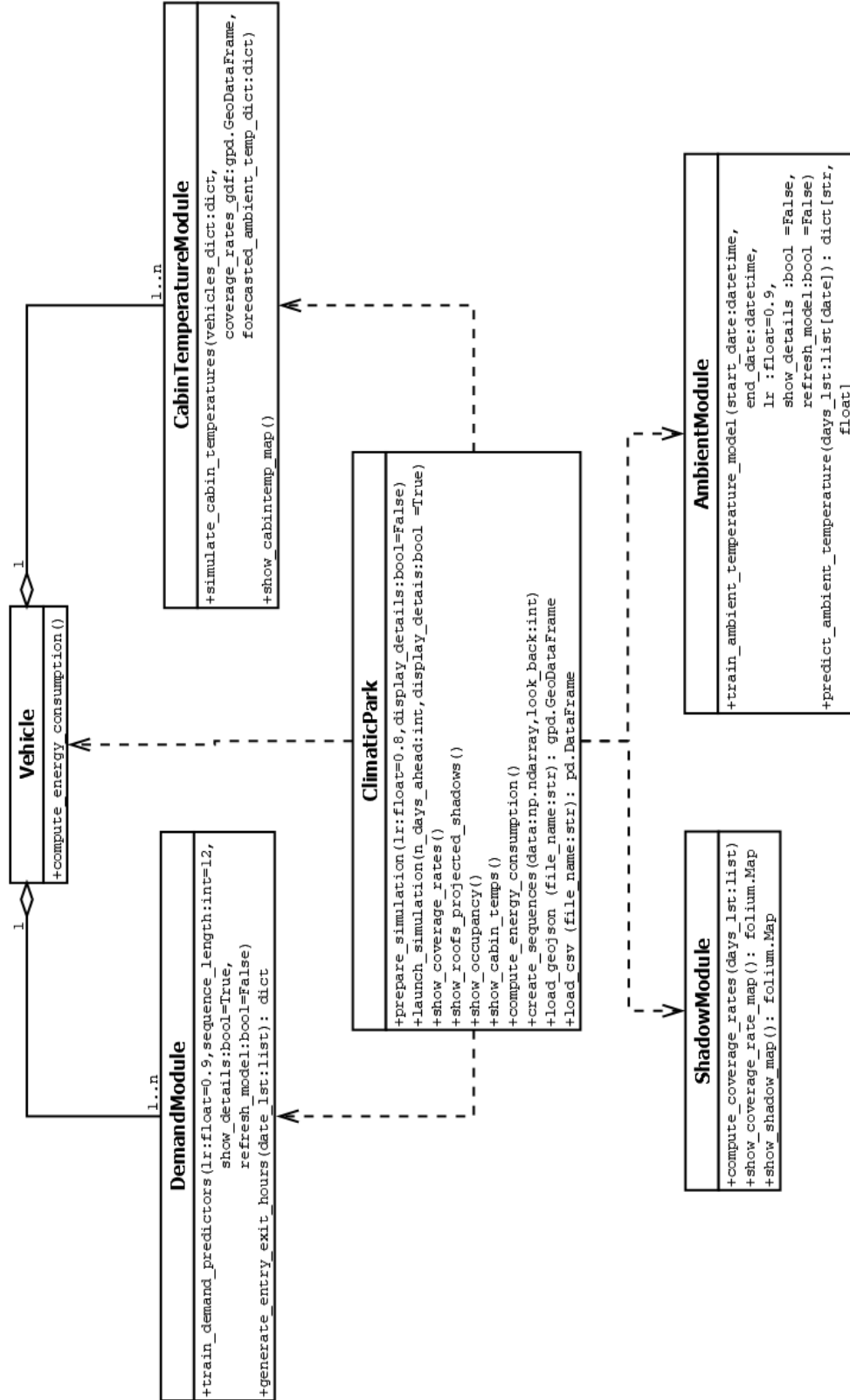


Figure 10: UML class diagram of the library. Each rectangle represents a different class along with its public methods. A dashed line indicates a dependency relationship between two classes, while a solid line indicates a composition relationship. The numbers on the solid line specify the cardinality of the relationship.

module leverages the *pybdshadow* Python package³, which is specifically designed to model sunlight-based shadow projections. To determine the sun's position at each simulation time step, the module integrates the third-party library *suncalc-py*⁴. In addition to generating shadows, the `ShadowModule` calculates the shadow coverage rate for each parking space in the TPL every hour for the entire simulation period. The coverage rate is defined as the proportion of the surface area of a parking space that is covered by shadow.

Regarding the `DemandModule` class (DM) (top left corner of Fig. 10), it oversees the simulation of the drivers' behavioral aspects in the TPL. Such aspects are defined in terms of the entrance and exit hours of the TPL for each driver along with the space occupied by their vehicle during the stay. In order to simulate such occupied spaces, the library assumes that drivers tend to park close to the entry and exit gates of the TPL.

The `CabinTemperatureModule` (CTM) class (top right corner of Fig. 10) provides a key feature of the library, as it is in charge of computing the cabin temperature of the simulated vehicles by the DM. To do so, this module considers the coverage rates of the spaces computed by the SM and the ambient temperature simulated by the AM and integrates them by means of a linear regression model.

Lastly, `Vehicle` (top part in Fig. 10) is an auxiliary class whose instances represent the different cars simulated by the library. In this manner, each object of this class comprises the features computed by the aforementioned modules for a single vehicle, such as its entry and exit hours or its cabin temperature. In addition, this class includes the functionality to estimate the energy consumption required by the vehicle to reduce its cabin temperature to a particular comfort level when it leaves the TPL's premises.

³<https://pypi.org/project/pybdshadow/>

⁴<https://github.com/kylebarron/suncalc-py>

6.1.2. Software workflow

Fig. 12 shows the workflow followed by the library to provide a simulation of the TPL. As we can see from this figure, the library is designed following a pipeline architecture, where data flows through a series of three sequential processing stages, namely, *preparing the simulation*, *launching the simulation*, and *visualization of the results*. Each state performs a specific task and passes its output to the next stage in the pipeline, promoting modularity and ease of maintenance. For completeness, Fig. 11 shows a UML sequence diagram involving the library classes depicted in Fig. 10. The diagram illustrates the ordered sequence of method invocations among these classes to carry out the three aforementioned processing stages.

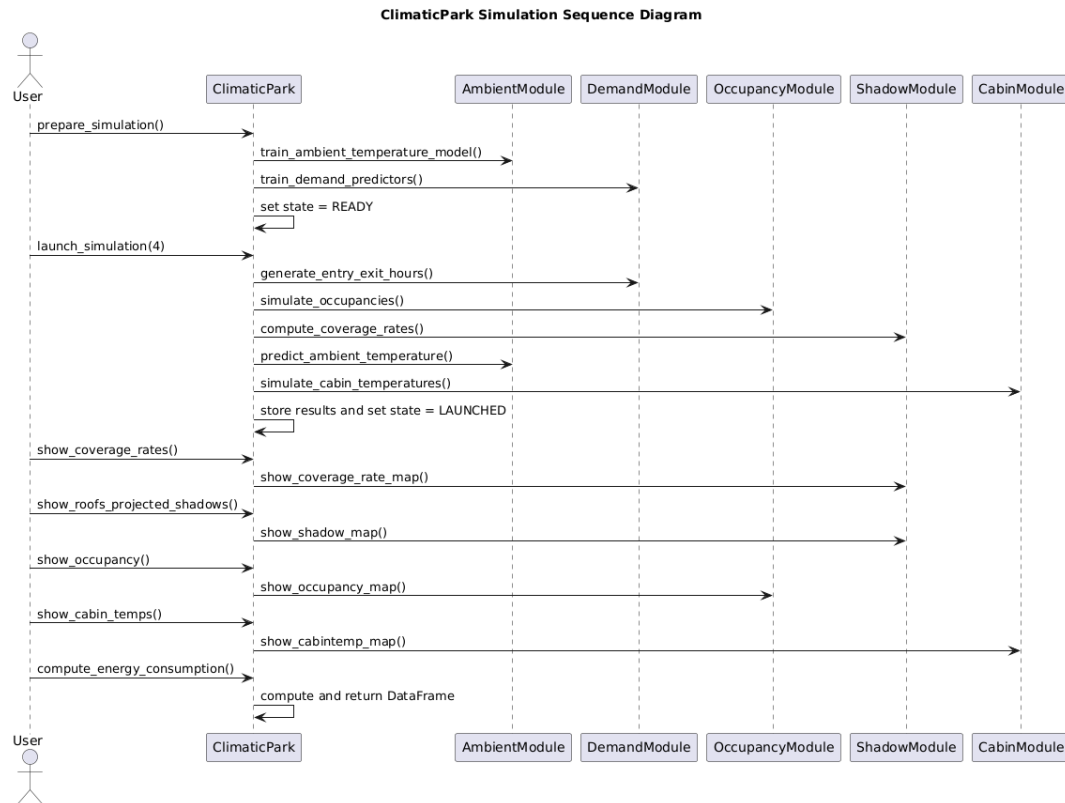


Figure 11: UML sequence diagram of the library.

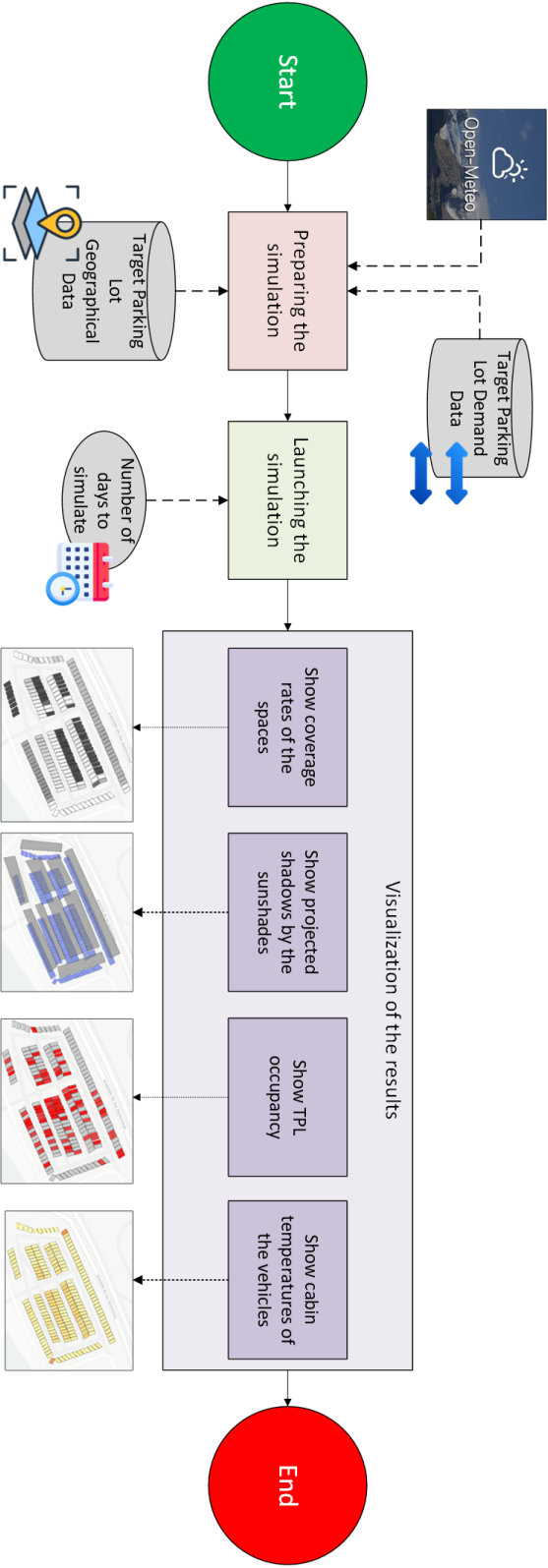


Figure 12: Workflow of the climaticpark-py library.

6.1.2.1. Library inputs

In order to provide a simulation outcome, `climaticpark-py` requires the client to previously gather the following data about the TPL,

- Geographical location and spatial distribution of the spaces.
- Geographical location of the entrance and exit gates.
- Geographical location and spatial distribution of the sunshades.
- Geographical location of the TPL spatial centroid.
- Timeseries comprising an ordered sequence of entry and exit hours of a set of TPL's drivers.

All location data must be encoded as `geopandas GeoDataFrames` where the spaces and sunshades are defined as spatial polygons. Thus, the user can feed the library with different configurations of sunshades and evaluate their impact on existing parking infrastructure. Besides, the time series of entry and exit hours must be provided as a CSV file. This file is used by the library to provide a reliable simulation of the drivers' behavior. For the sake of clarity, Table 14 describes the input parameters of the library and the required file types.

Table 14: Description of the input parameters required by `climaticpark-py`.

Input parameter	Description	Required file type
<code>file_name_lots</code>	Path to the file comprising the spatial distribution of the TPL spaces	GeoJSON
<code>file_name_roofs</code>	Path to the file comprising the spatial data of the roofs installed in the TPL.	GeoJSON
<code>file_name_coords</code>	Path to the file comprising the coordinates in EPSG:4326 of the spatial centroid of the TPL.	CSV
<code>file_name_gates</code>	Path to the file comprising the coordinates in EPSG:4326 with the location of the entry and exit gates of the TPL.	CSV
<code>file_name_cabintem</code>	Path to the file comprising the dataset of cabin temperatures of the vehicles.	CSV

Next, a detailed description of the three steps involved in the user–library interaction is provided, as shown in Figure 12.

6.1.2.2. *Preparing the simulation*

The first step in the library’s pipeline is to prepare the simulation by instantiating the necessary objects. To do so, we first need to instantiate a `ClimaticPark` class by providing all the inputs listed in a `sec` to its constructor. 6.1.2.1.. Next, we call the `ClimaticPark.prepare_simulation` method which creates an object of each of the five modules in the library. Moreover, the `AmbientModule` collects weather data from the *Open-Meteo* web service⁵ for the location of the TPL to feed the ambient temperature predictor that will be used in the following steps. At this point, the instance of `ClimaticPark` that we have created is ready to generate the TPL simulation.

6.1.2.3. *Launching the simulation*

Next, it is necessary to invoke the `ClimaticPark.launch_simulation` method to actually perform a simulation on the TPL. This method receives two input parameters, named `n_days_ahead`, which indicates the total number of days we want to simulate and `allocation_policy`, which allows us to configure the behavior followed by the simulated vehicles in order to occupy the available spaces. In this sense, the library defines three different parking allocation behaviors, namely:

- *Random*, vehicles randomly occupy the available spaces in the parking lot.
- *Minimum distance*, vehicles occupy the available spaces closest to their entrance gate.
- *Random minimum distance*, vehicles tend to occupy the spaces closest to their

⁵<https://open-meteo.com/>

entry gate, with a certain level of randomization.

Consequently, this method triggers the necessary functions in the other library modules to calculate shadow movement, vehicle entry and exit along with their assigned spaces and cabin temperatures, as well as the energy required to cool the cabin. It is important to note that this stage does not produce any direct output for the user, as its primary focus is on performing the underlying computations. The subsequent step in the pipeline is responsible for delivering the simulation results to the client.

6.1.2.4. Visualization of the results

With the aim of retrieving the different simulation outcomes, the library provides different methods to visualize the results. Given the spatiotemporal nature of the simulation, such outcomes are provided as interactive spatial maps that allow the user to easily see the evolution of certain elements of the TPL. The palette of map-visualization methods provided by the library through the `ClimaticPark` object is described below,

- `show_coverage_rates` returns an HTML map showing the distribution of TPL spaces and how the cover rate of each one evolves during the simulated days on an hourly basis.
- `show_roofs_projected_shadows` returns an HTML map showing the shadows projected by the TPL sunshades (given as input to the library, sec. 6.1.2.1.) for each hour of the simulated process. This map allows for a better understanding of the cover rates generated in the previous method.
- `show_occupancy` returns an HTML map that indicates the time evolution of the occupied spaces based on the vehicles previously simulated. Hence, the client can visualize the entry and exit behavior simulated by the `climaticpark-py`.

- `show_cabin_temp` returns an HTML map that enriches the previous one with the cabin temperature of each vehicle in its occupied space on an hourly basis.

These methods provide interactive maps where the user can easily visualize the simulation outcomes. However, they do not provide any data structure that could be manipulated and analyzed later on. For that purpose, the library also provides the method `compute_energy_consumption` through its `Climaticpark` class. This method returns a `pandas DataFrame` comprising all the features of the simulated vehicles. For each vehicle, this data structure returns, among other fields, its entry and exit dates, its occupied space within the TPL, along with its initial and final cabin temperature and energy consumption. This allows clients to use such a data structure in their own downstream processing pipeline.

6.2. CLIMATICPARK-PY LIBRARY EVALUATION

6.2.1. One-week Simulation

To evaluate our model, we used `climaticpark-py` to simulate the behavior of a single work week in the TPL, from Monday 2022-10-24 to Friday 2022-10-28. Each of these dates was used as d_{target} of the framework. The rationale for using this range of dates was that it consisted of a regular period within the university course. This allowed us to assess the feasibility of the library to simulate the regular behavior of the TPL during several days in a row.

First, the `Shadow Module SM` computed the coverage rates of the TPL spaces ($C_{(d,h)}$, $h \in [0,23]$), taking into account each of the five target dates and the two roof configurations shown in Figure 6. Fig. 13 shows a sample of the evolution of coverage rates when all spaces are covered by a roof (see Fig. 6c) on $d_{target}=2022-10-25$. Note that the computed cover rates are consistent with the movement of the sun during the period of study. As a matter of fact, Fig. 13a shows a few spaces with a cover

rate close to 0.0 at 09:00 in the morning. This is consistent with the position of the sun in the east, which projects the shadows of the roofs towards the west (left side of the figure). Later, as the day progresses, we can see that the coverage ratio is more or less stable until the end of the afternoon, where, as observed in Fig. 13f, the spaces located in the lower right corner of the TPL have a slightly lower ratio due to the position of the sun in the west at 19:00.

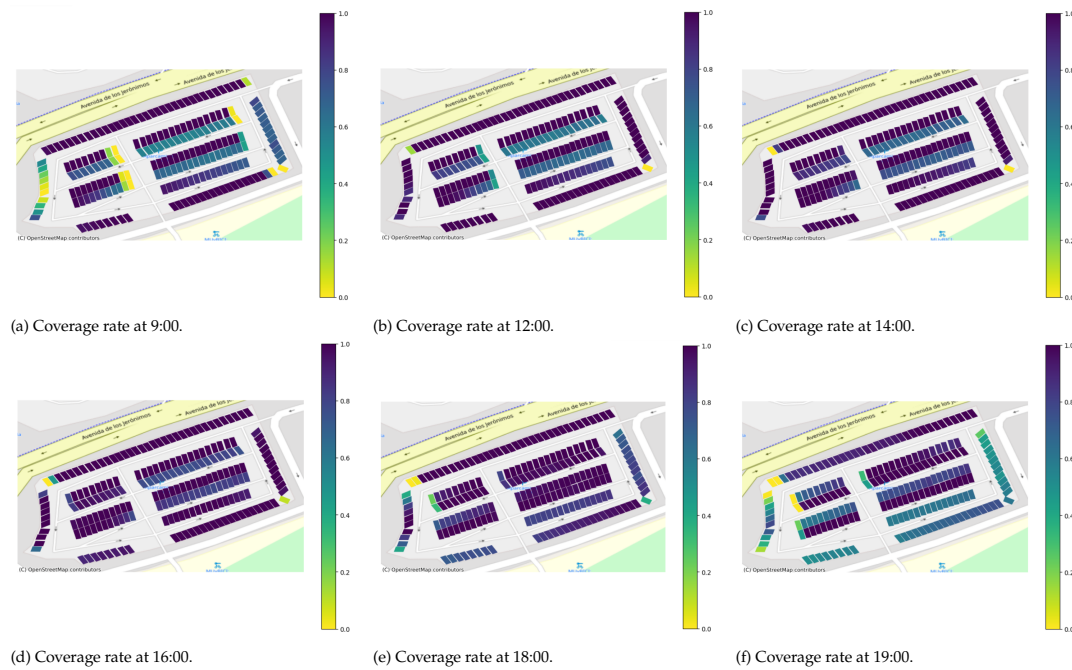


Figure 13: Coverage rate of the TPL spaces for some of the target hours of the use case when all the spaces are covered by a sunshade. Recall that the coverage rate of a space is the proportion of its area that is covered by a shadow.

Moreover, Fig. 14 shows such cover rates when using the smaller roof configuration as depicted in Fig. 6d. Again, the evolution of such rates is consistent with the simulated roofs. More in detail, Fig. 14a clearly illustrates that when a small roof configuration is used, many spaces remain uncovered, and those that are covered have a coverage rate varying between 0.0 at 1.00 in the morning. This corresponds to the sun's position in the east, casting roof shadows towards the west. As the day progresses, the coverage ratio remains relatively stable until late afternoon. As seen in Fig. 14f, the spaces in the lower right corner of the covered area have a slightly lower coverage ratio because of the sun's position in the west at

19:00.

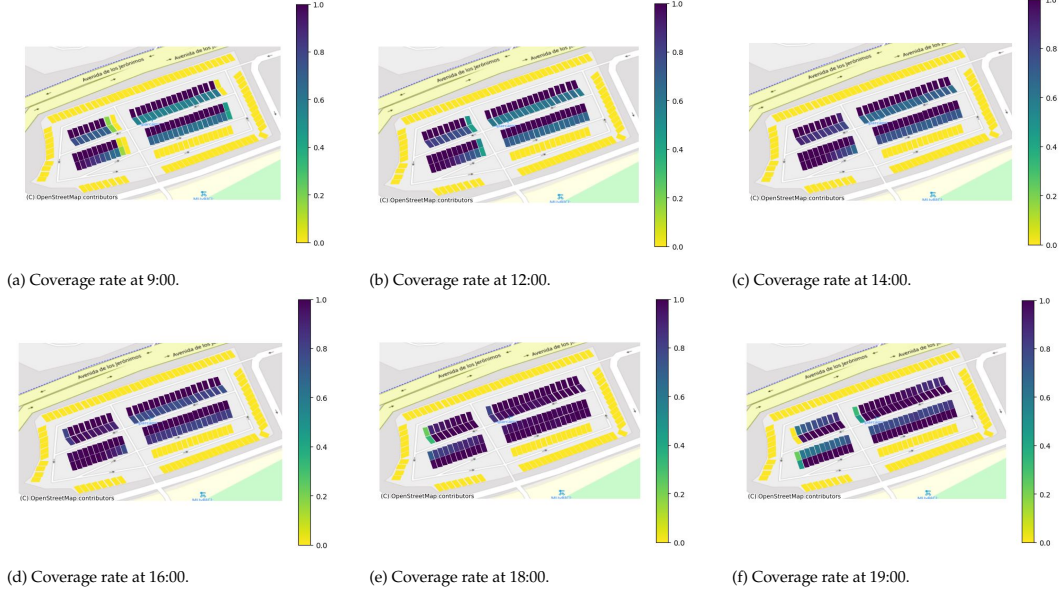


Figure 14: Coverage rate of the TPL spaces for some of the target hours of the use case when only few spaces are covered by a sunshade. Recall that the coverage rate of a space is the proportion of its area that is covered by a shadow.

After computing the coverage rates, the CNNLSTM predictor of the Demand Module estimated the overall number of incoming drivers for each of the target hours, namely, $\langle a_{(2022-10-24,0)}^{total}, a_{(2022-10-24,1)}^{total}, \dots, a_{(2022-10-28,23)}^{total} \rangle$. This estimation is shown in Fig. 15a. For the sake of completeness, Fig. 15b. shows the prediction outcome for the predictor when d_{target} was set to 2022-10-25 and h_{target} from 06:00 to 22:00. As we can see, the predictor was able to estimate the overall pattern of incoming cars in the TPL with the peak number of incoming drivers at 09:00, followed by a smooth decrease in the number of arrivals afterwards. In total, there were 167 incoming vehicles during the whole week and the DM predicted 125.

Given the demand generated by the predictor, the DM also generated the set comprising the synthetic movement of vehicles in and out of the TPL ($\mathcal{H}_{(d,h)}$). As described in sec. 4.1.4., this is done by means of a GMM able to generate synthetic entry and exit hours. The model generated 125 entry-exit tuples, one for each of the incoming drivers predicted by the CNNLSTM.

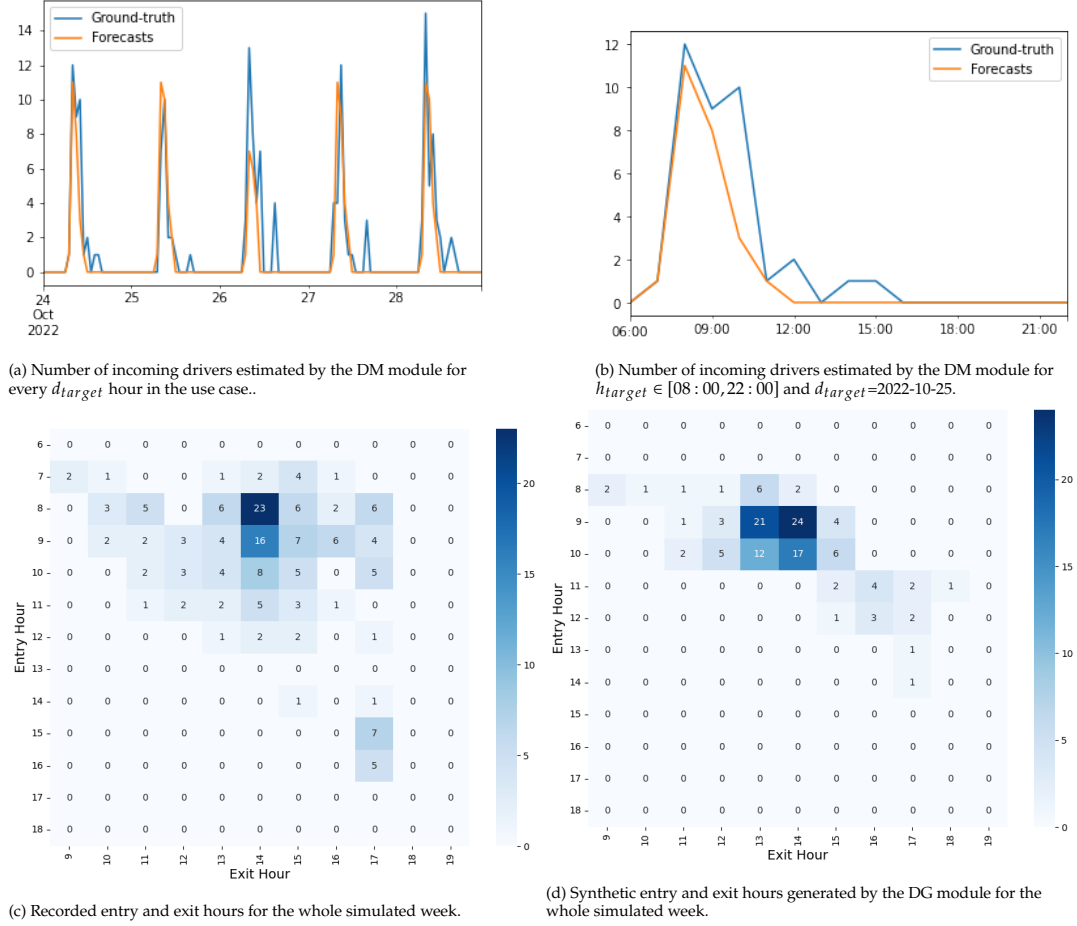


Figure 15: Synthetic demand and entry and exit hours generated by the DM.

For comparison purposes, the distribution of the real entry and exit tuples of the target week is shown in Fig. 15c, and the synthetic tuples of $\mathcal{H}_{(d,h)}$ is shown in Fig. 15d. We can see that `climaticpark-py` simulated a set of users whose arrival time was slightly later than those in the real setting. While most of the real drivers arrived at 8:00 am during the week under consideration, our simulator estimated that most of the drivers entered the TPL around 9:00 am. However, it is also important to note that a large number of the simulated tuples have an exit time around 02:00 and 03:00 pm. This is consistent with the regular schedule of the university where the TPL is located. Since most of the lessons are held in the morning, they usually end during such an hour range that the university staff go home. In order to provide a complete comparison

between these matrices, we followed the procedure suggested in (Rodríguez-Avi, Ariza-López, and Alba-Fernández 2018). In this manner, we performed a one-sample Kolmogorov-Smirnov test (Arnold and Emerson 2011) on them by turning each matrix into a 1D vector. The results yielded a p-value of 0.2270, supporting the acceptance of the null hypothesis that the two distributions are identical.

Lastly, for each incoming vehicle, the DM assigned a parking space by performing a weighted random sampling over the set of currently available spaces, taking into account the previously defined weights. When a vehicle left the TPL, its assigned parking space was released and became available again for subsequent assignments. As a matter of fact, Table 15 shows the content of this set for $d_{target}=2022-10-26$ by providing, for each incoming vehicle, its entry and exit hour and its assigned space number following the policy described in sec. 4.1.5.. The actual location of the space assigned to each driver in this table can be seen in Fig. 6b.

Table 15: Entry and exit hours of each of the simulated drivers and the parking space that they have occupied given $d_{target}=2022-10-26$.

Entry	Exit	Space num.	Entry	Exit	Space num.
08:01	15:19	80	09:23	14:29	97
08:14	10:09	16	09:31	11:08	76
08:30	10:14	75	09:32	14:42	99
08:42	12:54	100	09:33	10:49	32
08:44	14:30	203	09:38	14:23	93
08:47	09:55	17	09:39	12:43	90
08:49	14:44	73	09:49	11:39	202
08:53	14:22	94	09:50	16:43	208
09:01	13:52	207	09:57	14:59	98
09:03	14:47	205	10:06	14:17	61
09:07	13:06	91	10:10	14:13	62
09:09	14:10	96	11:00	13:28	34
09:15	14:45	92	11:23	14:37	33
09:16	13:47	204	12:43	15:22	15
09:21	10:28	129			

As the last step in the simulation, the CTM module took as input the aforementioned occupancy and cover-rate sets ($O_{(d,h)}$, $C_{(d,h)}$) for all the dates and hours of the simulated week and computed the cabin temperature of each vehicle

in the TPL considering the two sunshades configurations (Figs. 6c and 6d). The outcome of this module when $d_{target}=2022-10-26$ for different h_{target} given both configurations is shown in Figs. 16 and 17. As we can see, both figures show that most of the vehicles that entered the TPL at the beginning of the morning occupied a space close to the entry or exit points of the TPL according to the behavior model defined by the DM. Furthermore, from 12:00 to 15:00, the number of occupied spaces remained stationary, which is consistent with the fact that the university staff arrive early in the morning and remain at the university's premises until lunchtime.

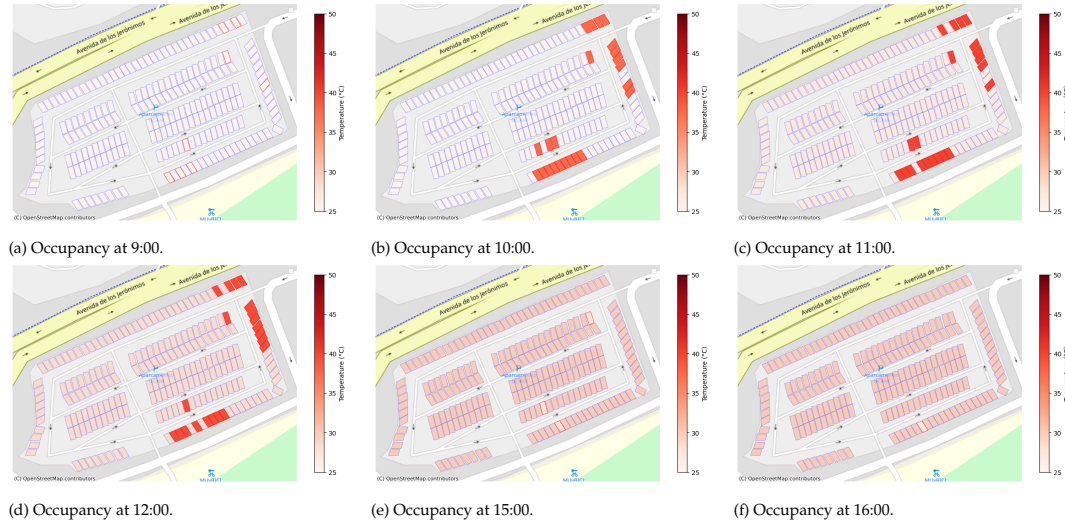


Figure 16: Example of the evolution of the TPL occupancy when the configuration with all the spaces covered by a roof is used when $d_{target}=2022-10-26$. Each occupied space is coloured with the cabin temperature of the vehicle at the specified hour.

The temperature modeling results obtained with `climaticpark-py` exhibit distinct behaviors depending on the roof configuration considered. On the one hand, Fig. 16 shows that the modeled cabin temperature of the vehicles in the TPL was higher than the ambient temperature in all the target hours. As a matter of fact, we observed rather large differences between the cabin temperature of the vehicles and the ambient temperature early in the morning at 09:00 (Fig. 16a). Hence, the vehicles' cabin temperatures were, on average, 29.3°C , but the ambient temperature was 23.1°C . This difference also remained for the other hours under study. For example, at 11:00 the ambient temperature was 27.1°C , whereas the average cabin temperature of the vehicles was 51.5°C . Again, this is consistent with the expected

behaviour of a real parking lot.

On the other hand, Fig. 17 clearly shows that the cabin temperatures of the vehicles were higher when the reduced set of sunshades was used compared to the previous configuration. This makes sense due to the low coverage provided by the simulated sunshades. This is especially noticeable given the vehicles located at the TPL between 15:00 and 16:00 (Figs. 17e and 17f). As we can see, their cabin temperatures were above 35°C , whereas in the full-covered configuration (Figs. 16e and 16f) such temperatures were around 25°C . This is because such vehicles occupied spaces that were not covered at all during the whole day, raising their temperatures well above that of the fully-coverage configuration.

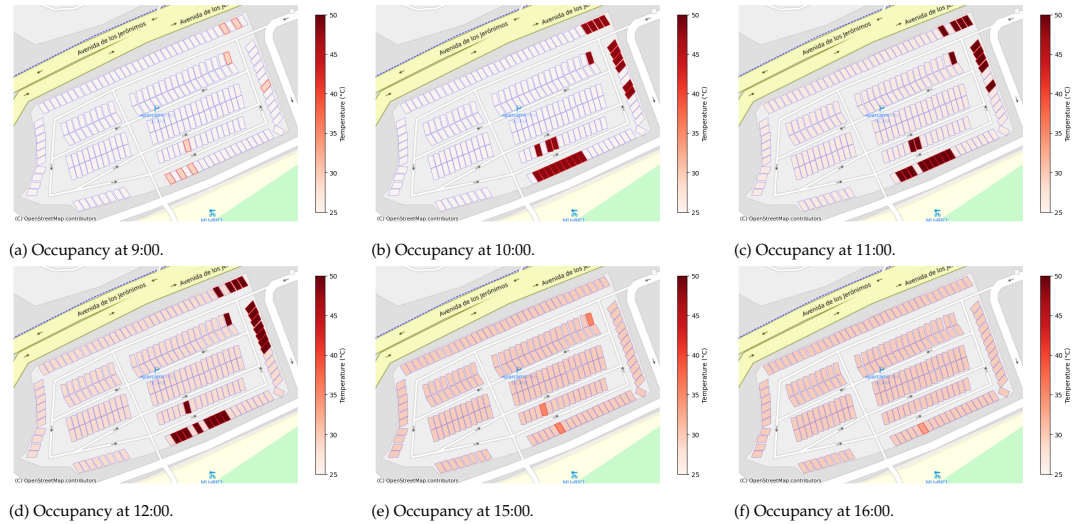


Figure 17: Example of the evolution of the TPL occupancy when the configuration with few spaces are covered by a roof is used when $d_{target}=2022-10-26$. Each occupied space is coloured with the cabin temperature of the vehicle at the specified hour..

As a result, this one-week simulation demonstrates the ability of the developed library to generate realistic behavior for the TPL using synthetic data on both driver behavior and climate conditions. The model revealed that most vehicles arrived between 09:00 and 10:00 in the morning, with the lot becoming nearly empty during the afternoon, a pattern that aligns well with the actual usage profile of the site. Additionally, the computed shading coverage rates for the parking spaces followed the expected solar movement across the simulation period, validating the accuracy

of the shadow modeling component.

The results further show that the parking area was effectively shaded, with an overall coverage rate of 95%. Individual coverage rates were calculated for each parking space and aggregated over several days, offering a comprehensive measure of shadow exposure across the facility. Consequently, the simulated cabin temperatures exhibited a realistic daily evolution, consistently exceeding ambient temperatures throughout the day, a pattern expected under typical Mediterranean conditions. `climaticpark-py` also demonstrated its capacity to assess the effects of different shading configurations on vehicle cabin temperature, highlighting its value for infrastructure planning and climate-adaptive parking design.

Furthermore, Fig. 18 presents the total cabin temperature values per day over the target week, comparing two shading configurations under consideration. This metric represents the sum of the maximum cabin temperatures recorded for each simulated incoming vehicle on a given day. As expected, the blue bars representing a partial coverage scenario where only central spaces were shaded show a noticeable increase in cabin temperatures compared to the full coverage scenario depicted by the orange bars. These results underscore the utility of `climaticpark-py` as a simulation-based decision support tool, enabling evaluation of trade-offs between the cost of roof infrastructure and its thermal benefits, while accounting for actual parking behavior patterns.

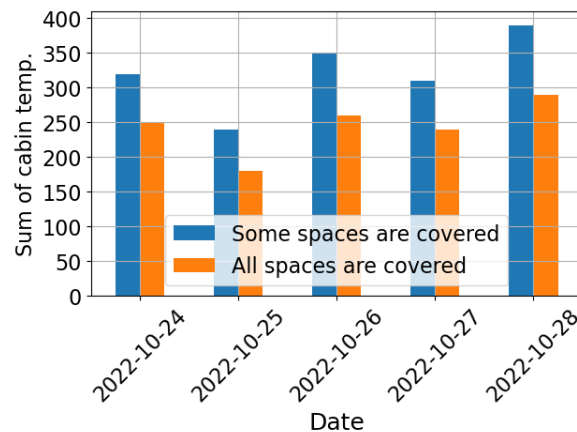


Figure 18: Daily sum of cabin temperatures during the target simulation period.

Regarding the energy consumption computed by the CTM, it was estimated that the Fuel Consumption (FC) of all simulated vehicles over five days, given the first sunshade configuration (Fig. 6c), was 1.81 litres (an average of 0.362 liters per day), and the Time to Reach the Target Temperature (TRTT) was 1,705.25 minutes (341.05 minutes per day on average). Moreover, the overall FC in the second configuration (Fig. 6d) was 2.75 litres (an average of 0.55 liters per day), and the TRTT was 2,187.5 minutes (437.5 minutes per day on average).

According to the performed simulation, fully covering all spaces in the TPL with the first sunshade configuration could reduce FC by approximately 35% over a workweek compared to the alternative configuration, where only the central spaces are covered, as suggested by the second sunshade setting (from 2.75 litres to 1.81 litres). Although the actual benefit of implementing the first configuration over the second should consider additional factors such as the economic and energy costs of installing the sunshades, such analysis is beyond the scope of this thesis.

More specifically, Fig. 19 shows the distribution of the daily average FC and TRTT per vehicle. For example, Fig. 19b shows that 2 vehicles (out of the 125 simulated ones) had an average FC between 0.00384 and 0.00439 litres per day with the first sunshade configuration. As we can see, this configuration allowed 35 cars to have no FC. This was because they were located in spaces that kept their cabin temperature under control, so the air-conditioning system did not need to operate intensively.

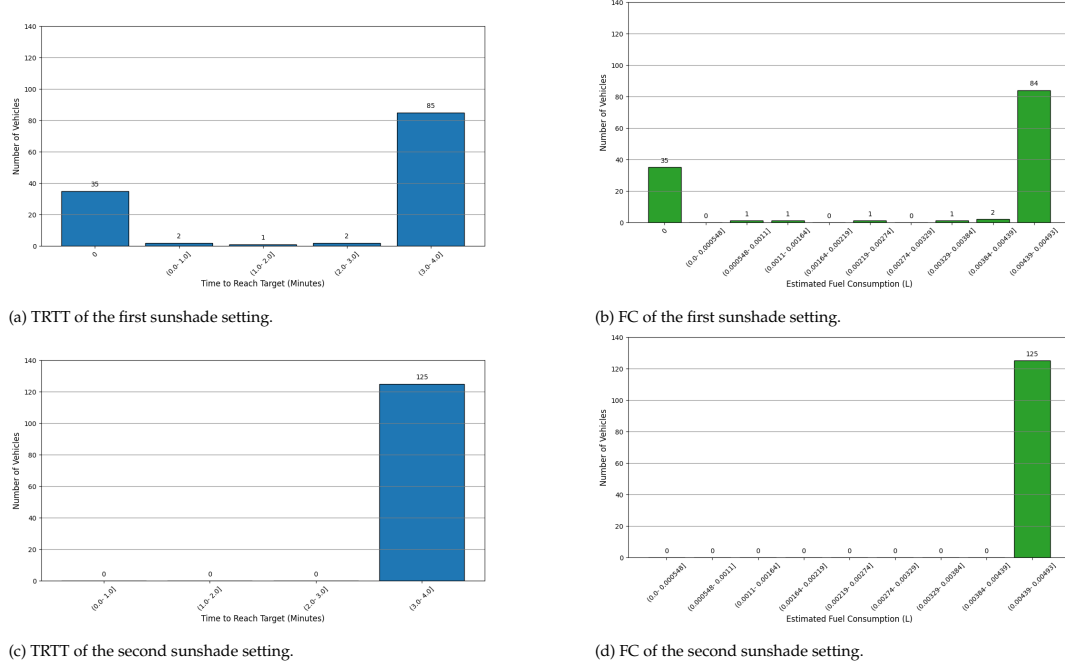


Figure 19: Computation of the energy cost of each roof configuration in the TPL.

6.2.2. Complexity Study

Finally, we studied the execution time of `climaticpark-py` using a MacBook Air with MacOS 11.7, 8GB RAM, and 1.4 GHz Intel Dual-Core i5 CPU as an evaluation platform. In this regard, Fig. 20 shows the time required to simulate each of the 125 vehicles in the five-day simulation under study. This process involves computing their entry and exit times, cabin temperatures, and energy consumption.

The framework required approximately 3.52 seconds to simulate all vehicles. Moreover, the execution time exhibited a linear trend throughout the simulation, indicating consistent efficiency.

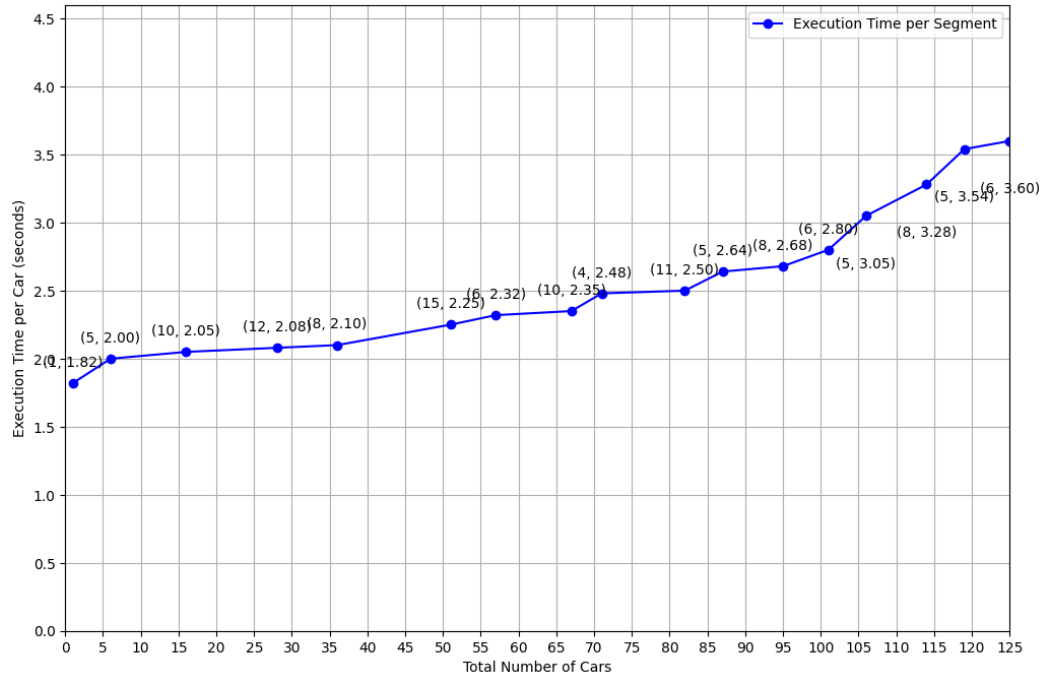


Figure 20: Execution time of `climaticpark-py` to simulate the target vehicles. Each point in the plot is labelled with a tuple indicating the number of vehicles processed and the current execution time.

VII – DISCUSSION

VII – DISCUSSION

In this chapter, we interpret the key findings derived from the CLIMATICPARK framework and its Python-based implementation, `climaticpark-py`. The discussion explicitly links the results to the specific objectives stated in Chapter III, highlighting how each objective has been addressed. These insights illustrate the pivotal role of parking infrastructure in shaping urban energy dynamics and demonstrate how predictive frameworks and simulation tools can inform sustainable urban planning.

The general objective of this research was *"to develop CLIMATICPARK, an intelligent, climate-aware parking lot simulation framework capable of enabling energy-efficient and environmentally conscious parking management"*. The achievement of this objective rests on the integration of thermodynamic modeling, drivers' behavioral forecasting, environmental data embedding, and computational simulation within a coherent architectural system. Conceptually, CLIMATICPARK reframes parking infrastructure as thermodynamically active micro-environments that influence vehicle energy consumption and urban energy demand. This shift moves the focus of sustainability intervention from post-use vehicle efficiency to infrastructure-level exposure management, extending the scope of parking research beyond land-use efficiency and traffic optimization into climate-responsive infrastructure design.

Technically, the framework operationalizes this shift through a modular architecture in which environmental exposure, parking demand, occupancy dynamics, and cabin thermal behavior are explicitly modeled and computationally integrated. The translation of predicted cabin temperatures into cooling energy demand establishes a measurable link between parking configuration and downstream energy consumption, embedding environmental consciousness as a quantifiable performance variable.

The implementation of this architecture with `climaticpark-py` library consolidates the achievement of the general objective. By providing a configurable, scenario-based simulation environment, the research moves from theoretical formulation to decision-support instrumentation. Stakeholders are enabled to test alternative shading geometries, allocation policies, and climatic conditions prior to physical implementation. This capacity for pre-investment evaluation transforms CLIMATICPARK from a descriptive analytical framework into an applied planning tool. Accordingly, the general objective has been achieved at three levels: conceptual (reframing parking as climate-sensitive infrastructure), methodological (integrating thermodynamic and behavioral modeling within a unified architecture), and operational (delivering a modular simulation environment capable of supporting evidence-based planning).

The achievement of the specific objectives (SO) is embodied in the modular architecture of CLIMATICPARK and its computational implementation `climaticpark-py`. Rather than being achieved independently, the objectives are structurally interwoven through the interaction of Ambient Module (AM), Demand Module (DM), Parking Occupancy Module (POM), and Cabin Temperature Module (CTM). Collectively, these main modules form a predictive and simulation pipeline that integrates climatic exposure, behavioral dynamics, occupancy processes, thermodynamic modeling, and energy quantification within a unified analytical system. In what follows, we review how each SO has been achieved.

SO-1: *"To model and simulate the thermal behavior of vehicle cabins in different parking scenarios, considering exposure to direct sunlight, shading structures, and seasonal variations".* This SO was achieved through the design of the Cabin Temperature Module (CTM), which constitutes the thermodynamic core of the CLIMATICPARK framework model. At the conceptual level, CLIMATICPARK formalizes vehicle cabins as thermodynamically responsive units embedded within climate-exposed parking micro-environments. Within this architecture, the CTM defines the multivariate relationships between ambient temperature, solar radiation, shading geometry, and cabin heat accumulation. By incorporating TPL

ambient temperatures and spatial shadow distribution, the framework specifies the governing mechanisms of in-vehicle thermal dynamics under varying exposure conditions.

At the operational level, the integration of this module within the `climaticpark-py` simulator operationalizes the conceptual thermodynamic framework as a computationally executable system. The CTM processes temporally resolved environmental inputs to generate dynamic vehicle cabin temperature trajectories at the level of individual units. This functionality enables micro-scale simulation and the comparative assessment of alternative shading configurations, spatial arrangements, and seasonal scenarios. The simulator reproduces realistic vehicle cabin thermal evolution patterns consistent with anticipated periods of intense solar exposure, thereby validating the thermodynamic rationale embedded in CLIMATICPARK and confirming the effective operationalization of SO-1.

SO-2: *"To develop predictive algorithms that incorporate user parking patterns and mobility behaviors for optimized parking space allocation"* was achieved through the integrated design of the Ambient Module (AM), Demand Module (DM), and Cabin Temperature Module (CTM). The AM employs a Long Short-Term Memory (LSTM) network to forecast environmental conditions affecting thermal exposure. Central to this objective, the DM is built as an ensemble model combining two deep-learning networks, a Convolutional Neural Network (CNN) and an LSTM integrated in a CNN-LSTM configuration, together with Gaussian Mixture Models (GMMs). The CNN-LSTM component captures complex spatiotemporal dependencies in parking demand and user mobility patterns, while the GMMs model probabilistic distributions of arrival and departure behaviors and occupancy variability. This ensemble enables the DM to represent both deterministic temporal dynamics and stochastic behavioral variation within parking systems.

The outputs of the DM, together with environmental forecasts from the AM, are processed by the CTM, which relies on a Vector AutoRegression (VAR) model to generate predicted cabin temperatures at departure. The VAR-based CTM captures

the interdependencies between environmental exposure, occupancy dynamics, and thermal response, producing temporally coherent temperature trajectories for individual vehicles. By integrating deep-learning-based demand forecasting, probabilistic occupancy modeling, environmental prediction, and VAR-driven thermodynamic simulation, CLIMATICPARK advances beyond conventional parking optimization approaches that treat behavioral, environmental, and energy dimensions in isolation. Through this ensemble-driven, modular integration, SO-2 is realized at both algorithmic and systemic levels.

SO-3: *"To integrate environmental data, including temperatures and solar radiation, into the simulation framework to improve accuracy and reliability"* was fulfilled through the combined integration of environmental variables within the Ambient Module (AM) and the Cabin Temperature Module (CTM). The AM provides dynamic forecasts of ambient temperature, solar radiation, and shadow geometry, while the CTM incorporates these environmental inputs directly into cabin thermal modeling. By treating these variables as temporally resolved, endogenous inputs rather than static parameters, the simulator ensures that environmental variability is internalized throughout the predictive and simulation process. This integration enhances both explanatory and predictive accuracy, allowing the pipeline to capture micro-scale thermal dynamics at the level of individual vehicles. Consequently, SO-3 is operationalized within both the architectural and functional dimensions.

SO-4: *"To quantify the energy consumption associated with vehicle air-conditioning systems based on cabin temperature predictions, enabling assessment of potential energy savings"* was achieved through the extended functionality of the Cabin Temperature Module (CTM). Beyond modeling thermal states, the CTM estimates the cooling energy required to restore cabin conditions to a predefined comfort threshold. This establishes a direct analytical sequence linking parking configuration, environmental exposure, occupancy state, cabin temperature evolution, and cooling demand. By translating thermal differentials into energy metrics, the framework advances from descriptive environmental modeling to performance-based sustainability evaluation. The ability to compare shading

strategies and allocation policies in terms of measurable energy savings represents a substantive contribution to climate-aware infrastructure assessment.

SO-5: *"To provide a modular and extensible simulation software for parking lot operators and urban planners to evaluate and optimize shading configurations prior to physical implementation"* was achieved through the development of `climaticpark-py` library. The library integrates the modules mentioned above within a configurable and interoperable software environment designed for scenario-based experimentation. Users can use different shading geometries, spatial arrangements, climatic inputs, and allocation strategies, thereby assessing thermal and energy implications prior to real-world deployment.

The `climaticpark-py` library positions itself as a step toward a new generation of parking-focused simulators. Whereas existing tools such as *PyPML* (Codeca, Erdmann, and Harri 2018) are designed to model macro-level parking availability across urban networks, `climaticpark-py` operates at a micro-scale. This difference is not only technical, but also conceptual. By emphasizing the individual vehicle and its immediate environment, the library foregrounds the user experience and the environmental consequences of small-scale design interventions. Compared to micromobility simulators (Vo, Waerden, and Wets 2016; Gu et al. 2021), which track detailed vehicle movements but often ignore climatic dynamics, `climaticpark-py` integrates human behavior with environmental sustainability, offering a more holistic view of parking systems.

The case study conducted in Spain highlights the practical utility of `climaticpark-py`. The results reveal that the simulator can accurately estimate variations in both parking lot occupancy and vehicle temperatures throughout the day. This outcome provides compelling empirical validation of the model, while also raising critical reflections. For instance, while the Spanish climate provides a rigorous test due to its high solar exposure, the framework's adaptability to colder or cloudier regions remains to be fully tested. This highlights a potential limitation, but also an opportunity for future studies to expand the generalizability of the

model across different climatic zones. More broadly, the findings support the view that urban infrastructure must be reconceptualized as active contributors to climate mitigation strategies, where even seemingly marginal design choices, such as shade distribution, may have significant implications for energy consumption and user comfort.

Taken collectively, specific objectives are mutually reinforcing rather than discrete accomplishments. Thermal modeling, ensemble-based predictive behavioral integration, climatic data embedding, energy quantification, and modular software operationalization converge within a coherent architectural system. The structural alignment between conceptual design, methodological implementation, and computational realization confirms that the objectives have been achieved not merely declaratively but integratively within the logic of the framework itself.

VIII – CONCLUSIONS

VIII – CONCLUSIONS

This doctoral thesis has been designed to address an important but frequently neglected dimension of urban mobility and sustainability: the climatic and energetic dynamics of parking facilities. Traditionally, parking infrastructures have been perceived primarily as functional spaces designed to accommodate vehicles. Their role has been limited to regulating access, pricing, or availability, with little attention paid to their environmental footprint, their impact on local microclimates, or their influence on user comfort and energy consumption. The work presented here challenges this narrow perspective by demonstrating that parking lots are not passive surfaces but rather active components of the urban climate system and significant determinants of energy use in transportation.

The central contribution of this thesis is the design and implementation of **CLIMATICPARK**, an integrated framework and simulation tool capable of modeling the interaction between parking demand patterns, shading and coverage conditions, microclimatic factors, and vehicle cabin thermal behavior. The accompanying Python library, `climaticpark-py`, provides a modular, extensible, and reproducible platform that combines data-driven models with physically inspired parameters. By linking environmental conditions with behavioral and infrastructure variables, the framework fills a major gap in the literature on parking management and sustainable urban design.

The results obtained from the case study at the Catholic University of Murcia provide concrete evidence of the practical value of this approach. The simulations confirmed that even modest design interventions, such as the addition of partial shading structures, can substantially reduce vehicle cabin temperatures and thereby decrease subsequent reliance on air-conditioning systems. This reduction not only improves driver comfort and safety but also leads to tangible energy savings, contributing to the mitigation of greenhouse gas emissions. In other words,

the findings validate the initial hypothesis: lowering cabin temperature prior to vehicle use directly reduces the energy demand of cooling systems, reinforcing the importance of parking lot design as a lever for sustainability.

Beyond quantitative results, the research has broader conceptual implications. It shows that parking lots must be reconceptualized as climate actors within the urban ecosystem. Like building façades, rooftops, and green spaces, parking surfaces contribute to the distribution of heat, the formation of urban heat islands, and the regulation of microclimatic conditions. Recognizing this role transforms parking from an operational concern into a domain of environmental design. This shift has profound consequences for urban planning, as it highlights new opportunities to integrate parking infrastructures into climate adaptation and energy transition strategies.

Another significant contribution of the thesis lies in its methodological innovations. By combining empirical data collection (including cabin temperature measurements, occupancy patterns, and shading geometries) with advanced predictive algorithms (including deep learning models for demand and temperature forecasting), CLIMATICPARK illustrates the power of hybrid approaches that merge real-world data with computational intelligence. This methodological orientation not only enhances accuracy but also enables scalability, making the framework adaptable to diverse urban contexts and climatic conditions. The development of the `climaticpark-py` software further reinforces the reproducibility and accessibility of the work, opening pathways for continued academic research, practical deployment, and interdisciplinary collaboration.

The findings also have implications beyond the use of the parking itself. By highlighting the links between shading, energy consumption, and thermal comfort, the research resonates with broader debates on sustainable mobility, smart cities, and climate-neutral urbanism. Collectively, the research contributes to the United Nations Sustainable Development Goal 11: *Make cities and human settlements*

*inclusive, safe, resilient, and sustainable*¹ by providing data-driven methods to optimize the intersection of infrastructure, climate adaptation, and urban mobility. For instance, the simulations underscore how simple infrastructural decisions, such as sunshades, have measurable effects on both local microclimates and global emissions. These insights can inform cross-sectoral policies that connect transport, energy, and climate agendas, advancing progress towards the United Nations Sustainable Development Goals and the objectives of the European Green Deal.

Equally important are the safety and health dimensions of the research. Overheated vehicles are not only an energy problem but also a public health hazard, with risks ranging from driver discomfort to life-threatening heatstroke for children, elderly passengers, and pets. By demonstrating how predictive models and design strategies can prevent dangerous thermal build-up, CLIMATICPARK extends its relevance to public safety and well-being, strengthening the social justification for adopting its recommendations.

In conclusion, this thesis has made four major contributions. First, it has identified and articulated the overlooked role of parking facilities in shaping energy demand, microclimatic conditions, and user comfort. Second, it has developed a novel simulation framework, CLIMATICPARK, that integrates climatic, infrastructural, and behavioral factors into a unified analytical model. Third, it has provided empirical validation and practical tools, demonstrating the feasibility and value of this approach in real-world contexts. Finally, it has placed parking management within the larger discourse of sustainability, public health, and climate adaptation, thus expanding the boundaries of urban and transportation research.

Collectively, these contributions reinforce the argument that rethinking parking infrastructures is not a marginal concern but a central component of sustainable mobility and resilient urban planning. As cities worldwide grapple with the dual challenges of climate change and urban growth, the lessons from CLIMATICPARK highlight that innovation can emerge not only from high-profile interventions

¹<https://www.unesco.org/en/sdgs>

like electric mobility or renewable energy, but also from reimagining everyday infrastructures such as parking lots. The hope is that the framework developed in this thesis will inspire further research, inform policy decisions, and ultimately contribute to creating cities that are safer, more energy-efficient, and better prepared for a changing climate.

IX – LIMITATIONS AND FUTURE WORK

IX – LIMITATIONS AND FUTURE WORK

Despite the encouraging results obtained with the CLIMATICPARK framework, it is important to critically examine the assumptions, simplifications, and constraints that shape the current implementation. Like most simulation-based systems that operate at the intersection of physical modeling, data-driven learning, and human behavior, CLIMATICPARK represents a trade-off between realism, scalability, and computational feasibility. This chapter provides a comprehensive discussion of the framework's limitations, spanning thermodynamic modeling, data availability, behavioral assumptions, and validation scope. It then outlines a detailed roadmap for future research directions aimed at overcoming these constraints and advancing the framework toward greater automation, accuracy, and real-world applicability.

9.1. LIMITATIONS

From a modeling perspective, the thermodynamic core of CLIMATICPARK necessarily simplifies several environmental processes that influence heat accumulation and dissipation in parking environments. In its current form, the framework primarily relies on ambient air temperature as the main weather input, while other influential meteorological variables such as solar irradiance, humidity, cloud cover, and wind speed are not explicitly modeled. The omission of these variables can affect prediction accuracy under certain conditions. For example, solar irradiance directly governs radiative heat gains on vehicle surfaces, while cloud cover modulates both shortwave and longwave radiation. Wind speed influences convective heat transfer, potentially accelerating cooling in exposed areas, and humidity alters perceived thermal stress as well as evaporation dynamics. As a result, the current formulation may underestimate or overestimate cabin temperatures in regions where these factors exhibit strong variability or extreme values.

Additionally, the thermodynamic model does not yet fully capture secondary environmental effects such as surface albedo variations, heat storage in pavement materials, or the cooling influence of vegetation through shading and evapotranspiration. These processes are particularly relevant in urban contexts where microclimatic conditions can vary substantially across short spatial distances.

Another important limitation concerns the representation of vehicle properties. The current implementation considers only a limited set of generic vehicle attributes, while several key features that influence thermal behavior remain unmodeled. Vehicle size, exterior color, glazing properties, interior materials, and body geometry all play a significant role in determining how quickly a vehicle heats up or cools down when parked. For instance, darker-colored vehicles tend to absorb more solar radiation, leading to higher cabin temperatures, while larger vehicles with greater internal volume may exhibit slower thermal dynamics. By not accounting for such heterogeneity, the simulator currently provides an averaged or idealized representation of vehicle thermal responses, which may not fully reflect real-world fleet diversity.

Furthermore, the deep learning-based Cabin-Temperature Module was trained on a relatively limited dataset comprising only two vehicles. This narrow training scope constrains the range of thermal behaviors learned by the model and limits its ability to generalize across different vehicle types, manufacturers, and interior configurations. Consequently, predictions may be less reliable when applied to vehicle classes that differ significantly from those observed during training.

CLIMATICPARK also depends heavily on the availability and quality of spatial and contextual data describing the parking environment. External elements such as neighboring buildings, trees, roof structures, and other shading or reflective surfaces can significantly alter local thermal conditions. In the current system, such contextual information must be provided explicitly by the user. This requirement introduces two challenges. First, it increases the manual effort needed to configure simulations, reducing usability and scalability. Second, inaccuracies or omissions in

the provided spatial data may propagate into the thermal and demand predictions, thereby affecting the reliability of the results. In many real-world deployments, especially in informal or rapidly evolving urban settings, detailed and up-to-date spatial data may be difficult to obtain.

The framework further relies on a number of behavioral and operational assumptions that simplify real-world complexity. These include assumptions such as a fixed proportion of air-conditioning-equipped vehicles (e.g., 72%), constant cooling power during operation, and typical parking preferences such as a tendency to park near exits. While these assumptions are grounded in empirical observations and are reasonable for an initial model, real driver behavior is often far more heterogeneous. In practice, drivers may deviate from recommended parking allocations, exhibit varying tolerance to thermal discomfort, or prioritize factors such as convenience or security over thermal optimization. Such deviations introduce stochasticity and non-compliance that are not fully captured by the current demand and allocation mechanisms. As a result, the effectiveness of parking guidance or optimization strategies may be overestimated under idealized compliance assumptions.

A further limitation relates to the geographic and climatic scope of validation. The `climaticpark-py` library has been validated using data from a Mediterranean climate (Murcia), which is characterized by relatively stable seasonal patterns and high solar exposure. While this provides a valuable proof of concept, it does not guarantee equivalent performance in colder climates, tropical regions, or areas with highly variable weather conditions. Applying the library to new locations requires a nontrivial recalibration process. This includes retraining the Ambient Module using at least one year of local weather data, recalibrating the Cabin-Temperature Module through short-term in-site measurement campaigns across a representative vehicle sample, and fine-tuning the Demand Generator using local entry and exit logs. In cases where such data are unavailable, transfer learning techniques must be employed, introducing additional uncertainty.

Finally, the accuracy and robustness of the framework are constrained by data availability. Reliable weather, shading, and occupancy data are not always accessible, particularly in smaller cities or privately operated parking facilities. Missing, sparse, or noisy data can degrade model performance and limit applicability. These data-related challenges highlight the need for methods that are more resilient to incomplete information.

9.2. FUTURE WORK

Future work will focus on several complementary research directions aimed at addressing the limitations outlined above and extending the scope of CLIMATICPARK. An important next step is to deploy and evaluate the simulator in a broader range of parking environments. Future studies will extend beyond off-street surface parking lots to include on-street parking and underground parking facilities. These environments present fundamentally different thermal dynamics, shading patterns, and user behaviors. On-street parking, in particular, introduces complex microclimates shaped by trees, buildings, and traffic, while underground facilities require alternative thermal modeling approaches due to reduced solar exposure.

Another key direction involves enriching both environmental and vehicle representations. Future versions of the simulator will incorporate additional weather variables, including wind speed, humidity, and direct and diffuse solar irradiance. At the same time, vehicle metadata such as color, size, and body type will be integrated to better capture fleet heterogeneity. Extending the framework to explicitly support electric vehicles is also a critical priority, given their growing prevalence. Electric vehicles introduce new thermal and energy considerations, including battery thermal management and charging-related heat generation, which are not addressed in the current model.

A major methodological shift in future work will be the integration of AI

agents to reduce reliance on manual configuration. Instead of requiring users to explicitly define parking layouts, spatial features, and contextual elements, future implementations will allow users to grant access to a location. AI agents will then automatically infer parking geometry, shading structures, entrances, and surrounding context using geospatial data, remote sensing, and pre-trained computer vision or graph-based models. This transition will move the framework away from rule-based programming toward adaptive, learning-based approaches, improving scalability and usability while reducing configuration errors.

To better capture real-world complexity, future work will incorporate behavioral heterogeneity through agent-based modeling. This approach will allow individual drivers to be represented with distinct preferences, compliance levels, and decision-making strategies. Such models can capture emergent system-level behavior arising from interactions between users, infrastructure, and guidance policies, providing a more realistic assessment of intervention effectiveness. From an application standpoint, comparative studies across diverse climatic regions and urban typologies will be conducted to assess robustness and transferability. These studies will help identify climate-specific sensitivities and guide regionally adapted calibration strategies. Future implementations of `climaticpark-py` will also include optimization routines, such as automated sunshade placement and adaptive parking guidance, as well as a web-based interface to improve accessibility for planners and practitioners.

Finally, moving from simulation to real-world deployment requires attention to governance and institutional factors. Future research will explore regulatory frameworks, data-sharing mechanisms, and public-private partnerships that enable the practical adoption of climate-aware parking management systems. Addressing these non-technical dimensions is essential for translating technical advances into tangible societal impact.

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XI – APPENDIXES

X – APPENDICES

APPENDIX 1. A PYTHON CODE SNIPPET FROM THE CLIMATICPARK-PY LIBRARY

A Python code snippet from the `climaticpark-py` library that defines three sequential stages of processing.

```
import lib.climaticpark as cp

# Step 1: Preparing the simulation
park = cp.ClimaticPark()
park.prepare_simulation()

# Step 2: Launching the simulation.
## We want to simulate 4 4-day
park.launch_simulation(4)

# Step 3: Visualization of the results
cr_map= park.show_coverage_rates()
ps_map= park.show_roofs_projected_shadows()
occ_map= park.show_occupancy()
ct_map= park.show_cabin_temps()

vehicle_consumption_df = park.compute_energy_consumption()
print(vehicle_consumption_df)
```

APPENDIX 2. METADATA

Table 16: Code metadata.

Nr.	Code metadata description	Metadata
C1	Current code version	v1.0
C2	Permanent link to code/repository used for this code version	https://github.com/fterroso/climaticpark
C3	Permanent link to Reproducible Capsule	https://mybinder.org/v2/gh/fterroso/climaticpark/0d818f2dd89655ee5afd73d8594ff7d338f874f0?urlpath=lab%2Ftree%2Fdemo.ipynb
C4	Legal Code License	GPL 2.0.
C5	Code versioning system used	git
C6	Software code languages, tools, and services used	python 3.10
C7	Compilation requirements, operating environments & dependencies	numpy, pandas, scipy, scikit-learn, matplotlib, folium, tensorflow, keras, geopandas, fiona, suncalc-py
C8	If available Link to developer documentation/manual	
C9	Support email for questions	fernando.terroso@upct.es

