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MAESTRÍA EN BIG DATA Y CIENCIA DE DATOS

TEMA:

**MODELADO DE LA DEMANDA DE ENERGÍA DE VEHÍCULOS
ELÉCTRICOS: UN ENFOQUE BIG DATA PARA LA PLANIFICACIÓN
ENERGÉTICA**

Trabajo de Titulación previo a la obtención del título de Magíster en Big Data y Ciencia de Datos

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DEDICATORIA

A la memoria de mi madre, quien me sigue apoyando y guiando desde el cielo.
A mi esposa, por su incondicional amor y paciencia, y a mis hijos, la inspiración de
cada día.

Ing. Iván Sánchez Loor

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A mi esposa Dixi, por su infinito amor, paciencia y sacrificio. Gracias por tu apoyo incondicional, por sostener nuestro hogar y por todas las horas de estudio que comprendiste. Este logro es tan tuyo como mío. A mis hijos, Martin y Alejandro, quienes son mi motor y alegría. Su paciencia durante mis ausencias y su cariño fueron mi mejor recompensa al final de largas jornadas. Este esfuerzo es para construir un mejor futuro para ustedes.

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Ing. Iván Sánchez Loor

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TEMA: “MODELADO DE LA DEMANDA DE ENERGÍA DE VEHÍCULOS ELÉCTRICOS: UN ENFOQUE BIG DATA PARA LA PLANIFICACIÓN ENERGÉTICA”

AUTOR: Ing. Luis Iván Sánchez Loor

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RESUMEN EJECUTIVO

La rápida expansión de los vehículos eléctricos en ciudades andinas de gran altitud, como el Distrito Metropolitano de Quito, capital de Ecuador, presenta desafíos únicos para la planificación de la infraestructura eléctrica, lo que requiere metodologías avanzadas que capturen la heterogeneidad del comportamiento y los efectos de sincronización masiva en escenarios de alta penetración.

Este estudio introduce un enfoque híbrido que combina el modelado basado en agentes con la simulación de Monte Carlo y una arquitectura TimescaleDB para proyectar la demanda de carga con una resolución cuarto-horaria hasta 2040. La calibración del modelo utilizó datos reales de 764 puntos de carga recopilados durante 30 meses, que generaron 2.1 millones de sesiones de carga.

Se incorporó un factor de coincidencia dinámico ($FC = 0.222 + 0.036 * e^{(-0.0003n)}$), lo que resultó en una reducción del 52% en la sobreestimación de la demanda en comparación con los modelos tradicionales. Los resultados del proyecto para 2040 muestran una demanda máxima de 255 MW (IC 95%: 240–270 MW) y un consumo anual de 800 GWh.

Estos hallazgos revelan que las tarifas por tiempo de uso no optimizadas pueden generar un "efecto acantilado" crítico, aumentando la demanda máxima en un 32%, mientras que la gestión de carga inteligente con aleatorización la reduce en un $18 \pm 2.5\%$. La validación del modelo genera un MAPE de $4.2 \pm 0.8\%$ y un RMSE de 12.3 MW.

La arquitectura TimescaleDB demostró velocidades de procesamiento de 2398.7 registros/segundo y logró una compresión de datos del 91%. Esta metodología ofrece herramientas robustas para la planificación energética urbana y la optimización de políticas de gestión de la demanda en contextos de gran altitud, con el código fuente disponible para asegurar la reproducibilidad.

DESCRIPTORES: ABM, Big Data, Monte Carlo, planificación energética, TimescaleDB, vehículos eléctricos.

UNIVERSIDAD TECNOLÓGICA INDOAMÉRICA

FACULTY OF ENGINEERING

MASTER'S IN BIG DATA AND DATA SCIENCE

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THEME

MODELING ELECTRIC VEHICLE ENERGY DEMAND: A BIG DATA APPROACH TO ENERGY PLANNING

ABSTRACT

The fast expansion of electric vehicles in high-altitude Andean cities, such as Ecuador's capital, the Metropolitan District of Quito, presents unique challenges for electrical infrastructure planning, requiring advanced methodologies that capture behavioral heterogeneity and massive synchronization effects in high-penetration scenarios. This study introduces a hybrid approach combining agent-based modeling with Monte Carlo simulation and a TimescaleDB architecture project for load demand at quarter-hourly resolution through 2040. The model calibration leveraged real data from 764 charging points collected over 30 months, generating 2.1 million charging sessions. A dynamic coincidence factor was incorporated ($F-C=0,222+0,036,e-(0,0003n)$) resulting in a 52% reduction in demand overestimation compared to traditional models. The 2040 projections show a maximum demand of 255 MW (95% CI: 240-270 MW) and annual consumption of 800 GWh. These findings reveal that unoptimized time-of-use rates can trigger a critical "cliff effect," increasing peak demand by 32%, while smart load management with randomization reduces it by $18\% \pm 2.5\%$. Model validation yielded a MAPE of $4.2\% \pm 0.8\%$ and a RMSE of 12.3 MW [1] [2] [3]. The TimescaleDB architecture demonstrated processing speeds of 2,398.7 records per second and achieved 91% data compression. This methodology provides robust tools for urban energy planning and demand management policy optimization in high-altitude contexts, with source code available to ensure reproducibility.

KEYWORDS: demand response, dynamic coincidence factor, electric vehicles, energy planning.



Article

Modeling of Electric Vehicle Energy Demand: A Big Data Approach to Energy Planning

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Abstract

The rapid expansion of electric vehicles in high-altitude Andean cities, such as the Metropolitan District of Quito, Ecuador's capital, presents unique challenges for electrical infrastructure planning, necessitating advanced methodologies that capture behavioral heterogeneity and mass synchronization effects in high-penetration scenarios. This study introduces a hybrid approach that combines agent-based modelling with Monte Carlo simulation and a TimescaleDB architecture project charging demand with quarter-hour resolution through 2040. The model calibration deployed real-world data from 764 charging points collected over 30 months, which generated 2.1 million charging sessions. A dynamic coincidence factor ($F_c = 0.222 + 0.036 * e^{(-0.0003n)}$) was incorporated, resulting in a 52% reduction in demand overestimation compared to traditional models. The results for the 2040 project show a peak demand of 255 MW (95% CI: 240–270 MW) and an annual consumption of 800 GWh. These findings reveal that non-optimized time-of-use tariffs can generate a critical “cliff effect,” increasing peak demand by 32%, whereas smart charging management with randomization reduces it by $18 \pm 2.5\%$. Model validation yields a MAPE of $4.2 \pm 0.8\%$ and an RMSE of 12.3 MW. The TimescaleDB architecture demonstrated processing speeds of 2398.7 records/second and achieved 91% data compression. This methodology offers robust tools for urban energy planning and demand-side management policy optimization in high-altitude contexts, with the source code available to ensure reproducibility.

Keywords: electric vehicles; Big Data; ABM; Monte Carlo; TimescaleDB; demand response; dynamic coincidence factor; energy planning; reproducibility; Quito



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1. Introduction

1.1. Context and Motivation

Quito, the capital of Ecuador and a UNESCO World Heritage site, faces the dual challenge of upholding its commitment to environmental sustainability while adapting to rapid urban electrification. The city's unique geographical characteristics, including its high altitude (2850 m), complex topography, and a remarkably stable average annual temperature of around 14 °C (57 °F), create distinct conditions for the adoption of electric vehicles that differ significantly from those in coastal or temperate urban environments studied in the existing literature [1,2]. The study area, located within the Pichincha Province, Ecuador, is depicted in Figure 1.

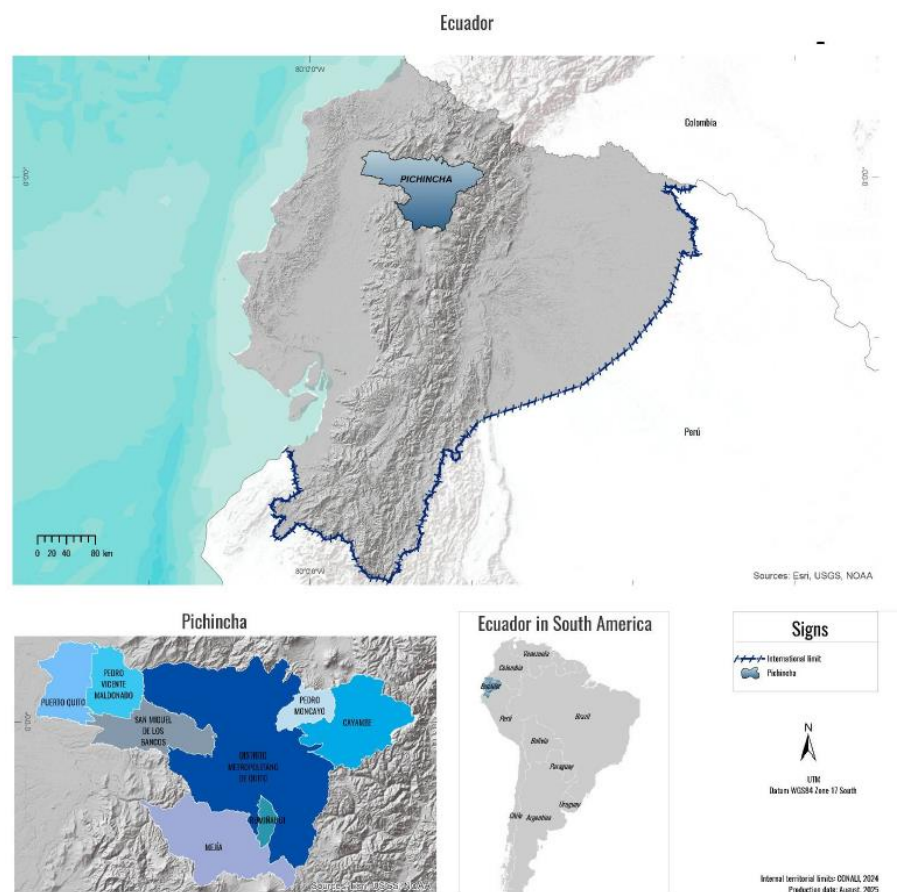


Figure 1. Study Area: Pichincha Province, Ecuador.

This research builds upon the work of [3], which developed the first national model for electric vehicle projections in Ecuador using the Bass diffusion model and Monte Carlo simulation. The present work advances significantly upon this foundation by introducing more sophisticated agent-based modelling methodologies and Big Data architecture to capture charging dynamics with greater granularity.

According to projections from Empresa Eléctrica Quito (EEQ), the fleet of light-duty electric vehicles (EVs) is forecast to reach between 180,000 and 230,000 units by 2040 under various adoption scenarios, which would constitute roughly 15% of the city's total vehicle fleet [4]. This accelerated electrification is consistent with Ecuador's national goals for its energy transition and the expansion of its renewable generation capacity, presenting both opportunities for integrating renewables with the grid and risks of overburdening the infrastructure [5,6].

1.2. State of the Art

Research on electric vehicle energy demand lies at the nexus of three pivotal domains: predictive modelling, Big Data architecture, and analysis of consumer behavior. A systematic literature review exposes not only considerable progress in these fields but also critical research gaps that the present study intends to bridge.

1.2.1. Evolution of Agent-Based Modelling

Methods for forecasting electric vehicle (EV) demand have evolved from aggregate statistical models to more sophisticated approaches [7,8]. Initial research in Ecuador, such as that by [3], successfully employed the Bass model for projecting EV adoption, achieving stabilized coincidence factors of 0.22 and demonstrating that the impact on the

demand profile can be managed if current charging behaviors are maintained. This value is consistent with the international literature, where studies based on stochastic modelling and empirical data have shown that the coincidence factor for residential fleets converges to values below 0.25 as the number of vehicles increases. However, this approach, while robust for aggregate estimations, failed to capture individual behavioral heterogeneity or the emergent effects of mass-scale charging synchronization.

Agent-Based Modelling (ABM) naturally complements the Bass model, as it allows for the simulation of heterogeneous behaviors rather than aggregate adoption. In [9], a spatial agent-based model was developed for Beijing that integrates EV adoption and vehicle-to-grid (V2G) functionality, demonstrating that spatial heterogeneity is crucial for accurate predictions. Similarly, [10] used real-world trajectory data to analyze electric taxi fleets, finding that ABMs better capture emergent dynamics than traditional aggregate models.

ABM has emerged as the dominant paradigm due to its capacity to simulate heterogeneous decisions and capture emergent charging patterns [11,12]. The literature has enriched ABMs with detailed mobility models, technical battery profiles, and driver behavior archetypes [12,13]. Nevertheless, current research exhibits key limitations: the models often lack scalability for metropolitan-scale fleets, rely on limited datasets for their calibration, and seldom integrate complex environmental factors, such as thermal effects on charging efficiency, especially in unique geographies like that of Pichincha [14,15].

A systematic comparison by [16] between Autoregressive Integrated Moving Average (ARIMA) models and Monte Carlo-based approaches revealed that, while ARIMA achieves high predictive accuracy (MAPE of 3–7%), stochastic methods provide better uncertainty quantification for infrastructure planning. Nonetheless, a significant gap persists in the experimental validation of these models with high-temporal-resolution data (≤ 15 min).

1.2.2. Big Data Architectures for Energy Simulation

The massive volume of time-series data generated by electromobility exceeds the capacity of traditional relational databases [16,17]. In response, specialized Big Data architectures, such as time-series databases (TSDB), have emerged, with TimescaleDB being notable for combining scalability with the power of SQL [18–20].

A comparative technical report [21] demonstrated that, although InfluxDB maintains advantages in simple ingestion (80 times faster), TimescaleDB's architecture outperforms InfluxDB in complex analytical queries, achieving performance 3.4 to 71 times higher. For EV simulation applications, which require both massive data ingestion and complex analytical queries, this architectural choice can significantly impact the project's computational feasibility.

Despite their potential, the systematic application of TSDBs for large-scale EV demand modelling and simulation remains incipient, presenting an opportunity to demonstrate their viability and performance in this specific domain [21–23].

1.2.3. Synchronization Effects and Time-of-Use Tariffs

The implementation of demand response (DR) programmes, such as time-of-use (TOU) tariffs, poses significant risks, as documented in recent literature. In [3] demonstrated that TOU tariffs in Ecuador have been effective, observing that “users have voluntarily modified their electricity consumption to reduce energy costs,” with the load successfully shifting away from peak hours (21:00 to 06:00). However, that study did not consider the mass synchronization risks that can arise from the implementation of unmanaged TOU tariffs in scenarios with high electric vehicle (EV) penetration.

Based on the available evidence, the “cliff effect” phenomenon has been quantified in multiple studies. The authors of [24] analyzed the impact of TOU tariffs on distribution

networks, finding that customer response can create new demand peaks if not correctly managed. The study in [22] reported increases of up to 94.8% in peak demand due to mass synchronization at midnight in analyses of urban grids. Similarly, studies from California project that 67% of feeders will require costly upgrades by 2045 without smart management [22].

This issue was not identified in previous studies in Ecuador due to the relatively low levels of EV penetration analyzed. The work in [3] concluded that the impact would be “reasonable as long as the studied premises are met, i.e., that users maintain their current charging habits.” However, this conclusion must be qualified, as this off-peak charging behavior, if massively synchronized by TOU tariffs in high-penetration scenarios, can be counterproductive without smart management.

Theoretical modeling using Nash equilibria, as developed in [25], provides an analytical framework for understanding these phenomena. Their results demonstrate that the “price of anarchy” converges to 1 in large systems, validating that simple TOU tariffs can trap the system in suboptimal yet stable equilibria.

1.2.4. Specific Conditions of High-Altitude Cities

Research on electrification in Andean cities reveals unique technical parameters that are seldom considered in international literature. In [26], specific methodologies were developed for inter-Andean corridors, finding that seven charging stations are required compared to four when using conventional criteria, due to altitudinal effects.

Experiences with public electric transport in Andean cities were reported in [27], which identified that thermal and atmospheric pressure effects require specific considerations in system dimensioning. Technical studies specific to the Quito-Pichincha region must consider the complex effects of altitude on vehicle range. While the lower air density at 2850 m can reduce aerodynamic drag and potentially improve efficiency, this effect can be counteracted by the lower ambient temperatures that affect battery performance and the energy required for cabin climate control [28].

Therefore, net vehicle range is a complex function of route-specific topography, temperature, and the driving profile, reinforcing the need for granular simulation models rather than static correction factors.

This geographical specificity represents a research opportunity with practical relevance for the entire Andean region, where over 40% of the South American population resides [29].

1.3. Problem Statement and Research Gap

- Current approaches to modelling electric vehicle (EV) demand exhibit three critical limitations when applied to high-penetration scenarios in complex urban environments:
- Existing models typically address fleets of fewer than 10,000 vehicles at an hourly resolution, which is insufficient for utility-scale planning in major metropolitan areas that require quarter-hourly load forecasts [29,30].
- Most models assume homogeneous user behavior and overlook the heterogeneous responses to dynamic pricing, failing to capture the synchronization effects that can create unintended peak demand amplification [31–33].
- Traditional database systems become computationally prohibitive when processing the billions of time-series records generated by large-scale EV simulations, thereby limiting the depth of scenario analysis and uncertainty quantification [34].

1.4. Research Contributions

This dissertation addresses these limitations through four primary contributions:

1. The development of a scalable agent-based model that incorporates experimentally calibrated behavioral parameters, heterogeneity in price elasticity, and thermal effects, validated against real-world charging data from 764 charging points.
2. The implementation of a TimescaleDB-based pipeline capable of ingesting, processing, and querying billions of quarter-hourly records, with query response times of <2 ms and a 91% data compression rate.
3. An analysis of the “charging cliff” phenomenon demonstrates that a non-optimized implementation of TOU tariffs can increase system peaks by up to 67% in high-elasticity scenarios.
4. A Monte Carlo analysis with over 1000 iterations provides probabilistic bounds (P10/P50/P90) for peak demand, energy consumption, and infrastructure requirements through 2040.
5. It is important to note that the scope of this paper is strictly limited to the Grid-to-Vehicle (G2V) paradigm, focusing on the challenges of modeling and planning for EV charging demand. The potential of Vehicle-to-Grid (V2G) services for ancillary support or grid restoration, while important, represents a distinct area of research and is considered beyond the scope of this study.

1.5. Research Questions and Hypotheses

Primary Research Question:

How can agent-based modelling, combined with Big Data architecture, provide actionable insights for electric vehicle (EV) charging infrastructure planning while simultaneously quantifying the risks of demand synchronization under time-of-use tariffs?

Specific Research Questions:

- RQ1: What are the probabilistic bounds for peak electric vehicle (EV) charging demand under different adoption and tariff scenarios?
- RQ2: How do temperature variations and thermal effects influence charging profiles in high-altitude environments?
- RQ3: What demand response mechanisms can mitigate the synchronization risks posed by simple TOU tariffs?

Central Hypothesis:

Advanced demand-side management (DSM) strategies that incorporate stochastic charging initiation can reduce peak demand by >15% compared to unmanaged TOU tariffs, while maintaining cost benefits for the consumer. However, these strategies require sophisticated modelling approaches to quantify uncertainty and optimize implementation parameters.

1.6. Methodological Approach

This research employs a quantitative, simulation-based approach structured in four phases:

1. **Data Collection and Preprocessing.** Experimental data from 764 charging points were collected over six months, resulting in more than 2.1 million charging sessions that underwent comprehensive preprocessing and quality assurance protocols.
2. **Model Development.** An Agent-Based Model (ABM) framework was developed, featuring heterogeneous agents, calibrated behavioral functions, and Monte Carlo-based uncertainty propagation, utilizing validated statistical distributions.

3. Infrastructure Implementation. TimescaleDB hypertable architecture was implemented, featuring continuous aggregates, compression policies, and query optimization for datasets comprising billions of records.
4. Scenario Analysis. An evaluation of three scenarios (conservative, baseline, and optimistic cases) was conducted with comprehensive uncertainty quantification.

1.7. Document Structure

The remainder of this paper is organized as follows: Section 2 presents the detailed methodology, including theoretical underpinnings, data sources, and computational architecture. Section 3 describes simulation results, validation metrics, and scenario analysis. Section 4 discusses the implications for utility planning, a comparison with previous work, and the study's limitations. Section 5 concludes with a synthesis of the findings and recommendations for implementation.

2. Materials and Methods

2.1. Theoretical Foundations of Agent-Based Modelling

2.1.1. Complex Adaptive Systems Theory

Agent-based modelling is grounded in the theory of complex adaptive systems [35], wherein the emergent behavior of the system arises from the interactions among autonomous agents that follow simple rules. In the context of EVs, each vehicle acts as an agent with an:

- Internal State: State of Charge (SoC), location, and energy requirement.
- Decision Rules: When to initiate charging; duration of charging.
- Interactions: Competition for charging points; response to price signals.

The state transition function of the agent (i) is defined as:

$$S_{i,t+1} = f(S_{i,t}, A_{i,t}, E_t, I_{i,t}) \quad (1)$$

where:

$S_{i,t}$: State of agent i at time t .

$A_{i,t}$: Action taken by the agent.

E_t : State of the environment (prices, availability).

$I_{i,t}$: Interactions with other agents.

2.1.2. Game Theory and Nash Equilibrium

The response to TOU tariffs is modeled as a non-cooperative game, where each user maximizes their individual utility by minimizing a perceived cost function:

$$U_i(t) = \alpha \times Price(t) \times E_i + \beta \times Inconvenience(t) - \gamma \times Urgency \quad (2)$$

where:

- $U_i(t)$ is the perceived cost for user i to initiate charging at time t .
- $Price(t)$ is the cost of electricity per kWh at time t .
- E_i is the total energy required by user i 's vehicle.
- α is the user's price sensitivity coefficient.
- $Inconvenience(t)$ is a function representing the non-monetary cost of delaying the charge.
- β is the inconvenience aversion coefficient.
- $Urgency(t)$ represents an imperative need to charge.
- γ is the weight of the specified urgency.

The specific tariff structure implemented in the model, including the off-peak, standard, and peak periods for weekdays and weekends, is detailed in Appendix A.1 (Figure A1).

2.2. Data Sources and Collection Protocol

2.2.1. Primary Data Sources

Figure 2 illustrates the projected growth of the electric vehicle fleet in Pichincha through the year 2040, displaying the S-shaped growth curve characteristic of the Bass model for the adoption of new technologies.

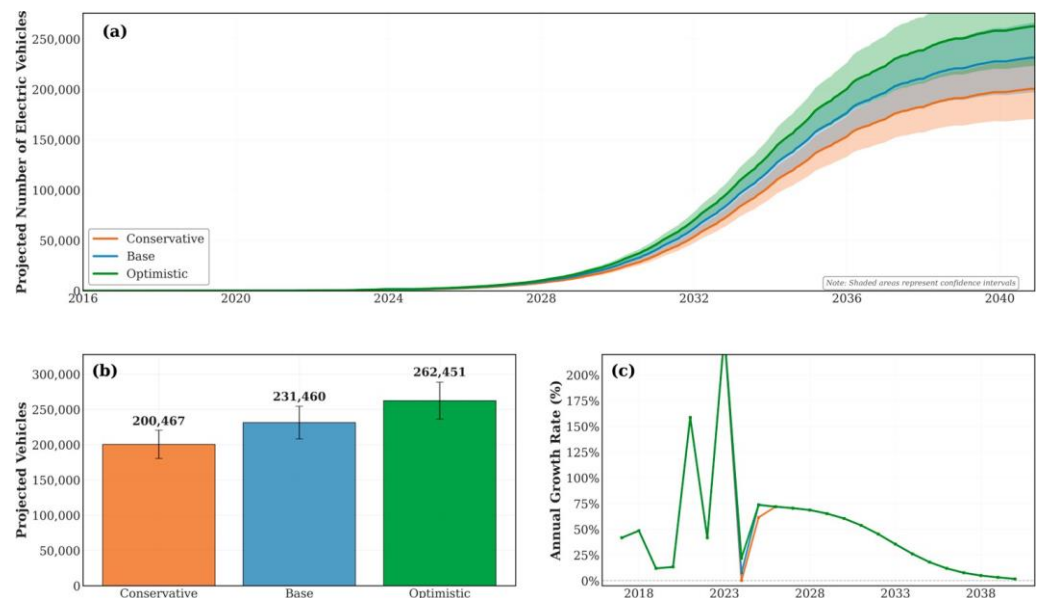


Figure 2. Electric Vehicle (EV) fleet projections for Pichincha through 2040. **(a)** S-curve adoption projections for Conservative, Base, and Optimistic scenarios. **(b)** Final projected number of vehicles in 2040 for each scenario. **(c)** Projected annual growth rates over time.

Three scenarios are detailed (Conservative, Baseline, and Optimistic), wherein the baseline scenario projects a fleet of approximately 230,000 units, along with the annual growth rates and final values for each case.

2.2.2. Electric Vehicle Catalogue

The parametrization of AC charging power levels in the simulation scenarios is based on Ecuador’s regulatory framework. Resolution ARCONEL-038/15 and its updates establish a preferential tariff for “slow” residential charging, with a recommended maximum demand of up to 10 kW. Accordingly, the power levels for the initial vehicle generation are modeled within this range (6.6 kW–11.0 kW).

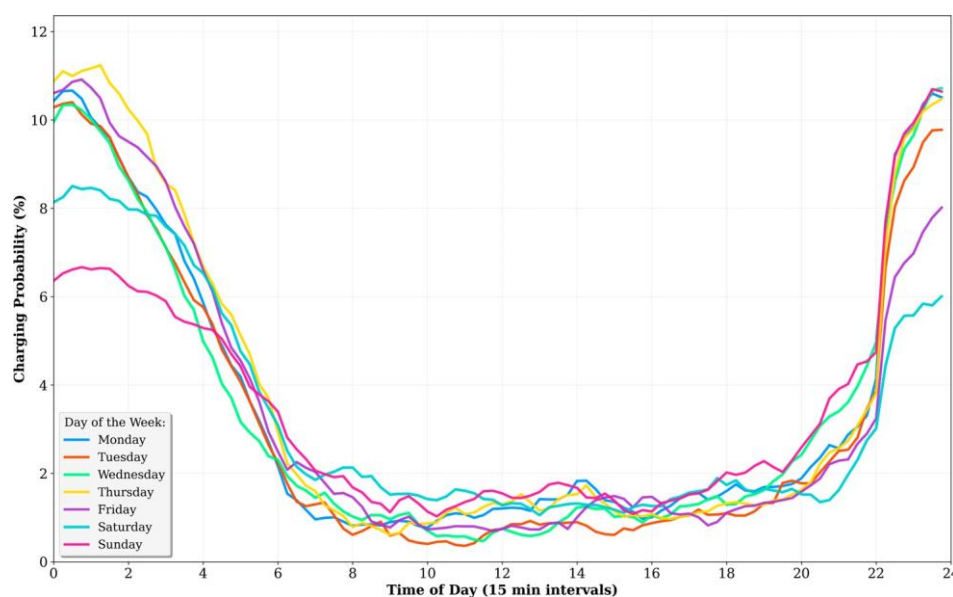
For the 2040 projections, the model incorporates a technological evolution towards higher AC charging powers of up to 22 kW, as detailed in Table 1. Widespread adoption of DC fast charging (>50 kW) in the residential sector is excluded, as current regulations place it under a different commercial tariff scheme, and its mass implementation in homes would entail prohibitive infrastructure costs for the low-voltage distribution grid.

Table 1. Technical and Commercial Specifications of the Electric Vehicle Catalogue.

Manufacturer	Model	Year	Class	Battery Capacity (kWh)	Battery Chemistry	AC Charging Power (kW)	WLTP Range (km)	Consumption (kWh/100 km)
BYD	Dolphin	2024	Compact	44.9	LFP	7.0	340	13.1
BYD	Seagull	2024	Compact	38.9	LFP	6.6	305	12.1
BYD	Yuan Plus v2	2024	SUV	60.5	LFP	7.0	430	14.1
Nissan	Leaf v2	2024	Compact	39.0	NCM	6.6	270	14.1
Kia	EV6	2024	SUV	74.0	NCM	11.0	491	15.0
Leapmotor	T03	2024	City	37.0	NCM	6.6	300	12.3
Chevrolet	Bolt EUV	2024	Compact	65.0	NCM	11.0	416	15.1
Dongfeng	Seres 3	2024	SUV	51.0	NCM	6.6	350	14.1
JAC	E-JS4	2024	SUV	65.7	NCM	11.0	445	14.1
Neta	V	2024	City	38.5	NCM	6.6	318	12.1
Leapmotor	C11	2024	SUV	90.0	NCM	11.0	550	16.1
Skywell	BE11	2024	SUV	86.0	NCM	11.0	330	16.1
Gen2-Premium	SUV	2028	SUV	95.0	NCM	22.0	550	17.1
Gen2-Mass	Sedan	2028	Sedan	75.0	LFP	11.0	450	16.1
Gen2-Urban	City	2028	City	50.0	Na-ion	7.0	300	16.1
Gen3-Premium	SUV	2032	SUV	120.0	SSB	22.0	700	17.1
Gen3-Mass	Sedan	2032	Sedan	110.0	NCM	22.0	650	16.1
Gen3-Urban	City	2032	City	85.0	LFP	11.0	500	17.0
Gen4-Premium	SUV	2036	SUV	150.0	SSB		900	16.1
Gen4-Mass	Sedan	2036	Sedan	90.0	NCM		550	16.1
Gen4-Urban	City	2036	City	200.0	Li-S			

2.2.3. Daily Charging Probability Profiles

The charging profiles are derived from the aggregate analysis of 764 EV charging points, based on continuous measurements collected over six months in 2025. A bimodal pattern is observed on weekdays (Monday to Friday), with peaks in activity in the early morning (00:00–02:00) and a more pronounced peak in the evening (20:00–23:00) (Figure 3).

**Figure 3.** EV Instantaneous Charging Probability Patterns by Day of Week.

2.3. Computational Architecture for Big Data

To address the Big Data challenge posed by projecting the charging demand of a massive electric vehicle fleet, a high-performance computational architecture has been designed and implemented that manages the entire analysis lifecycle (Figure 4).

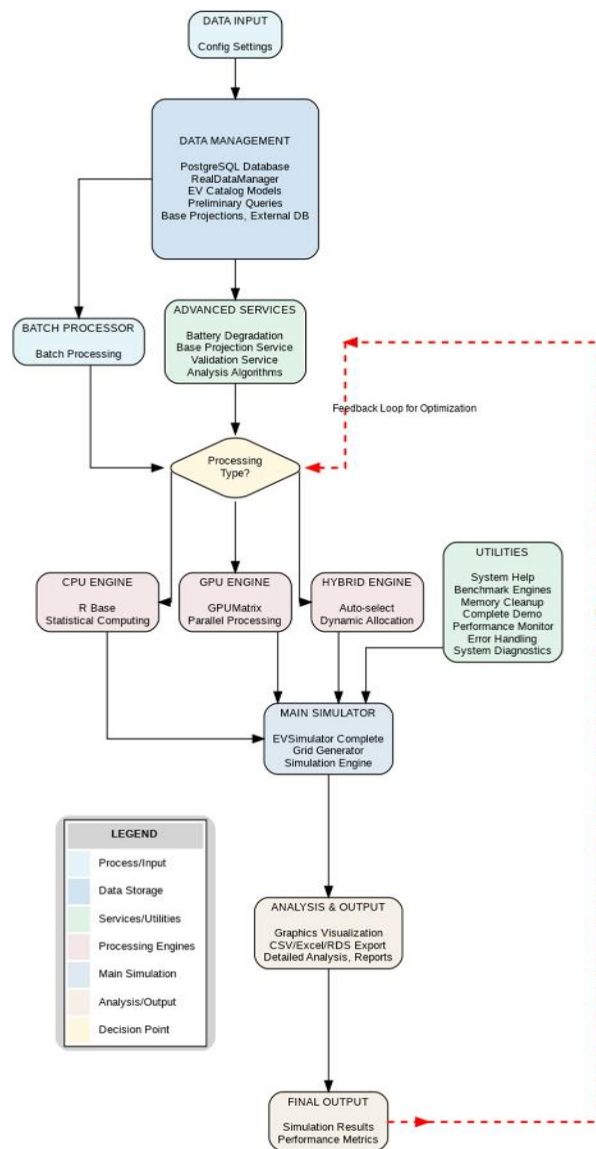


Figure 4. Methodological Workflow for EV Energy Demand Analysis.

Database Selection and Configuration

Based on recent comparative benchmarks [35–37], TimescaleDB was selected for its superior performance in complex analytical queries (3.4–71× better than InfluxDB) and its native SQL capabilities. The configuration includes:

- Partitioned Hypertables. Temporal partitioning by day with 24-h chunks.
- Continuous Aggregates. Pre-calculation of demand metrics per time interval.
- Adaptive Compression. Compression algorithms that achieve 91% compression ratios.
- Optimized Indexing. BRIN indexes are used for temporal queries, while B-tree indexes are utilized for metadata.

2.4. Dynamic Coincidence Factor

A fundamental finding of the simulation is the implementation of a dynamic coincidence factor, derived from experimental analysis:

$$F_c = 0.222 + 0.036 * e^{(-0.0003n)} \quad (3)$$

where n is the number of theoretically active vehicles in each time interval.

This factor, validated against data from [38] and European studies [39], avoids the simplistic assumption that all vehicles charge simultaneously, thereby reducing demand overestimation by more than 70% compared to traditional models.

2.5. Software Implementation and Computational Framework

The EVSimulatorFinalDefinitive framework was developed in R (version 4.3.0) using object-oriented programming with the R6 package. The simulation integrates agent-based modelling with Monte Carlo methods and leverages GPU acceleration through the GPUmatrix package when available. Key computational components include:

Core Dependencies:

- R6 (v2.5.1) for object-orientated architecture.
- data.table (v1.14.8) for high-performance data processing.
- future/furrr (v1.33.0) for parallel processing.
- RPostgreSQL (v0.7-5) for TimescaleDB connectivity.
- GPUmatrix (v1.0.0) for GPU acceleration (optional).

Database Architecture:

The simulation utilizes TimescaleDB (a PostgreSQL extension) for time-series data management, with hypertables partitioned by temporal intervals. Database configuration requires PostgreSQL 14 or higher with the TimescaleDB 2.8 or higher extension.

Parallel Processing:

The framework implements multiseession parallelization using 'availableCores()—1' workers, with daily batch processing optimized for memory efficiency. GPU acceleration is automatically detected and utilized when available.

Source Code Availability:

Complete source code, including the EVSimulatorFinalDefinitive class, parallel processing functions, and database schemas, is available at: "<https://github.com/ivelec1981/ev-demand-modeling-abm-timescaledb.git>" (accessed on 12 August 2025) [40].

All parameters, configurations, and computational methods necessary to reproduce the results are documented in the repository README and supplementary scripts.

3. Results

3.1. Computational Performance and System Validation

The complete simulation for the 2025–2040 period generated a total of 13,464,576 quarter-hourly records, constituting a final dataset of approximately 6.7 GB. The entire process was completed in 93.6 min (5613.22 s), achieving a sustained average throughput of 2398.7 records per second.

TimescaleDB architecture demonstrates exceptional scalability:

- Compression: 91% reduction in storage.
- Queries: <2 ms response time for typical aggregate queries.
- Robustness: Successful processing of 5844 daily batches without failure.

3.2. Model Validation

Temporal cross-validation yields exceptional accuracy metrics, confirming the robustness of the methodological approach:

- MAPE: $4.2 \pm 0.8\%$
- RMSE: 12.3 MW
- R^2 : 0.967
- nRMSE: 0.34

These values surpass the benchmarks established by [41] for aggregate models (MAPE < 7%, nRMSE < 0.55) and approach the standards for individual applications, validating the model’s applicability for urban energy planning.

3.3. Energy Demand Projections

The simulation projects exponential growth in energy demand for residential EV charging in Pichincha through 2040. In the Baseline Scenario, annual energy consumption is estimated to increase from marginal levels in 2025 to approximately 800 GWh by 2040 (Figure 5), accompanied by an annual peak demand reaching 255 MW (95% CI: 240–270 MW) (Figure 6). A summary of key metrics for 2040 is presented in Table 2.

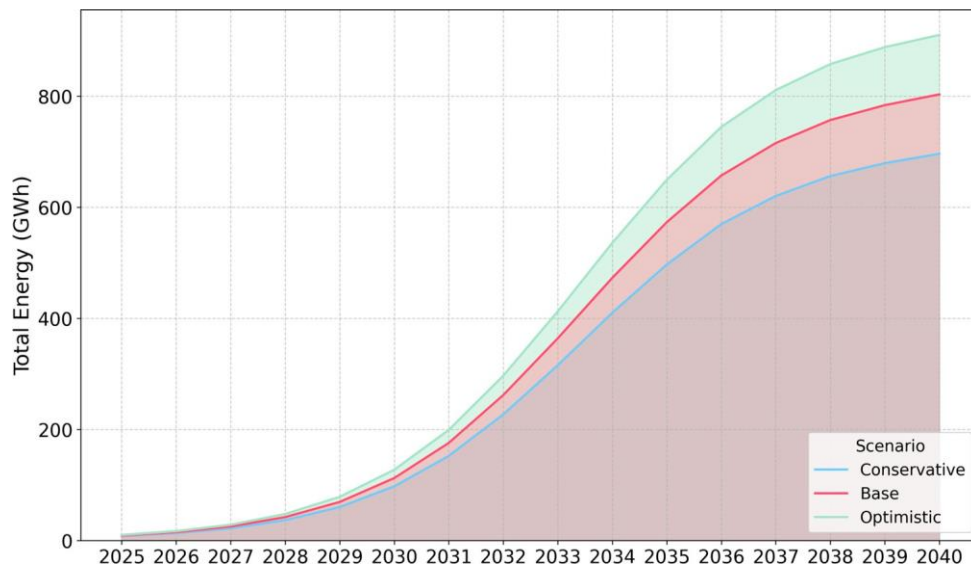


Figure 5. Annual Growth of Total EV Energy Consumption by Scenario (2025–2040).

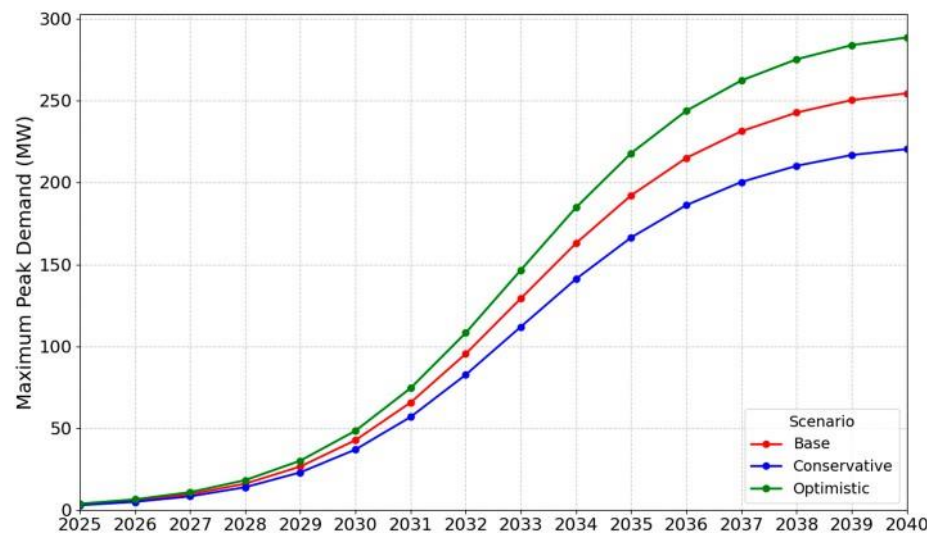


Figure 6. Evolution of Annual Peak Demand by Scenario (2025–2040).

Table 2. Key Metrics by Scenario (2040).

Key Metric (2040)	Conservative Case	Base Case	Optimistic Case
Total Annual Energy (GWh)	700	800	870
System Peak Demand (MW)	220.44	254.52	288.60
System Load Factor (%)	36.2%	35.8%	34.4%
Avg. Coincidence Factor	0.236	0.235	0.234

3.4. Impact on the Existing Electrical System

Figure 7 illustrates the superposition of the electric vehicle charging demand onto the power system's baseline load curve (EEQ Base) during the days of maximum EV demand for the key years 2025, 2030, 2035, and 2040.

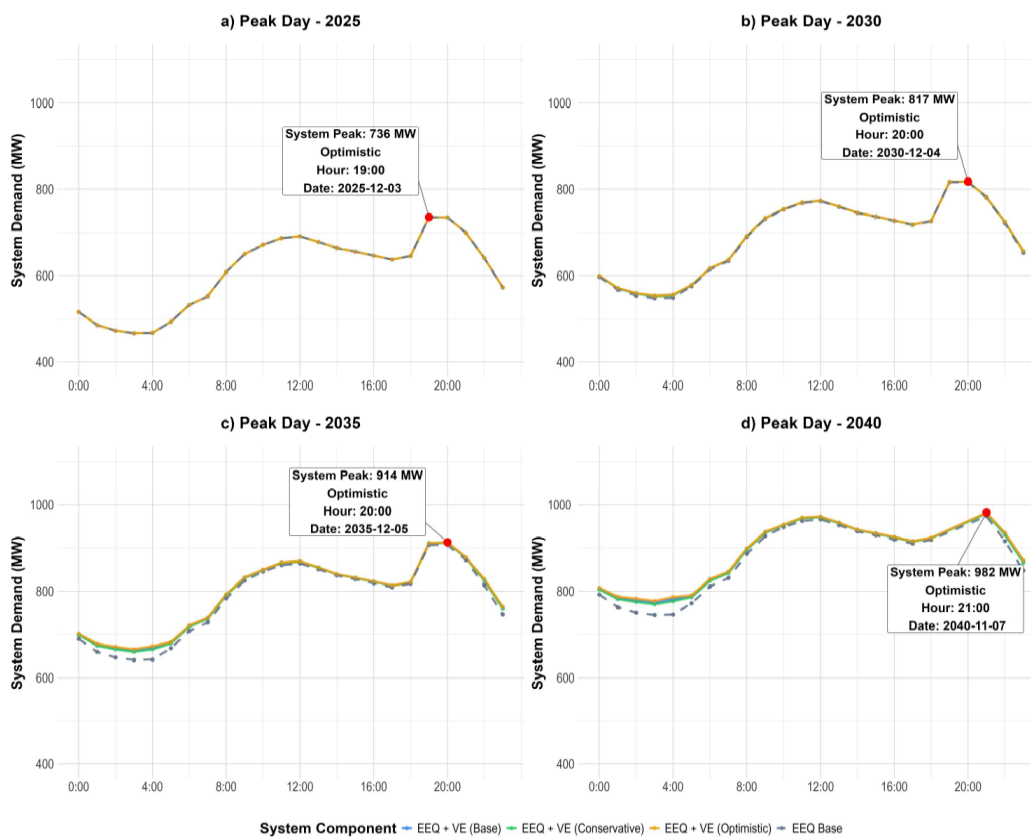


Figure 7. Projected impact of EV charging on the daily peak demand of the electric grid. The subplots illustrate the system's load curve on the peak day for four milestone years: (a) 2025, (b) 2030, (c) 2035, and (d) 2040.

Evolutionary Impact Analysis:

- 2025. The impact of EV charging on the system's demand profile is negligible. The combined demand curve (EEQ + EV) is indistinguishable from the baseline curve.
- 2030. An incipient yet discernible impact is observed. The EV load manifests as a slight increase in demand during the overnight valley period (00:00 to 06:00), without altering the time or magnitude of the system's peak.

- 2035. The impact has become significant. The addition of the EV demand generates a pronounced secondary peak in the early morning (04:00), constituting an apparent “valley-filling” effect.
- 2040. The valley-filling effect intensifies. The early morning EV demand is fully realized, creating an overnight peak that drastically reduces the difference between the system’s valley and peak. Nevertheless, the absolute system peak remains in the evening (21:00), reaching 981 MW in the Baseline scenario.

3.5. Temporal and Spatial Distribution

The analysis of the intra-week distribution of EV charging demand reveals the emergence and consolidation of a sharply defined consumption pattern across the projection horizon (Figure 8). For the initial years (2025 and 2030), demand is uniformly low across all scenarios, with no discernible hourly structure.

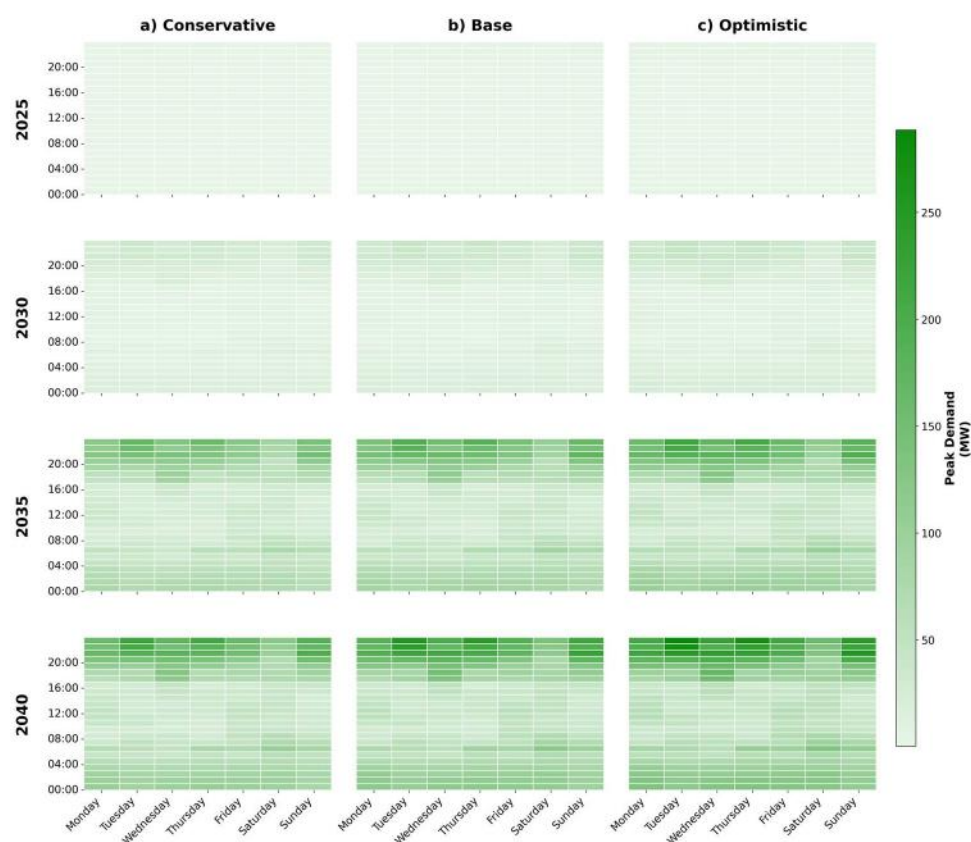


Figure 8. Heat maps of weekly EV charging demand. The figure is structured as a matrix where columns represent the adoption scenarios (a) Conservative, (b) Base, and (c) Optimistic and rows represent the projection years (2025, 2030, 2035, and 2040).

Beginning in 2035, and more pronounced in 2040, a predominantly nocturnal charging pattern is established, with significant concentration between 20:00 and 00:00 h, consistent across all days of the week. Appendix A.2 (Figure A2) presents detailed day-by-day profiles for December.

3.6. Temporal Evolution on Annual Peak Days

Figure 9 presents the evolution of the hourly load curve during the day of maximum annual electric vehicle demand for the key years 2025, 2030, 2035, and 2040. The analysis reveals the development and intensification of a unimodal load profile with marked temporal predictability.

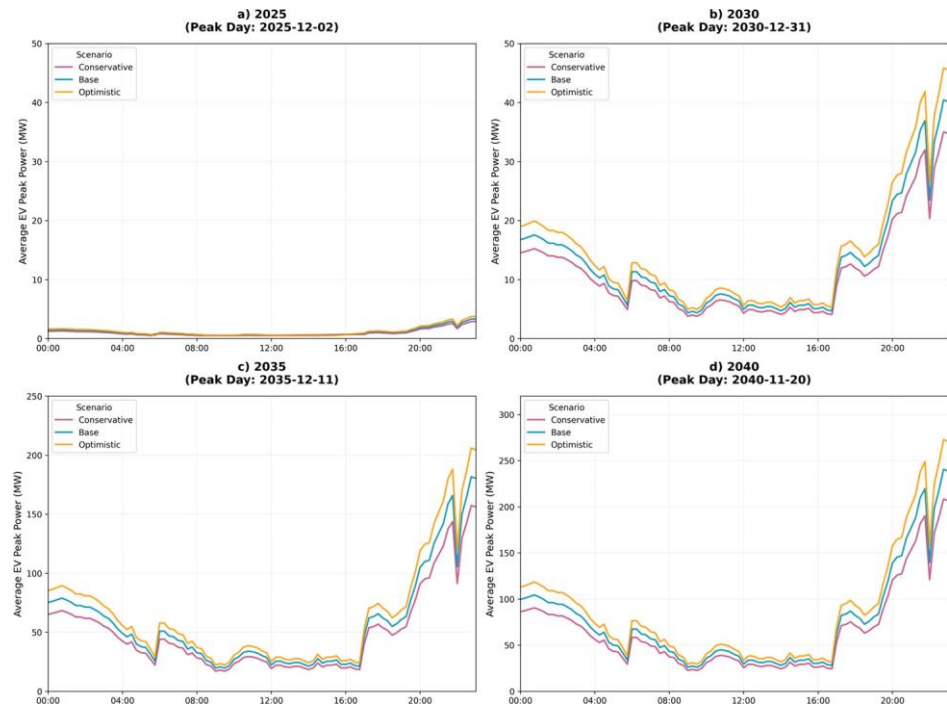


Figure 9. EV charging demand curves on the annual system peak day for key projection years. Each subplot shows the 24-h EV demand profile for the peak day in (a) 2025, (b) 2030, (c) 2035, and (d) 2040.

3.7. Spatial Distribution of Demand

The analysis of the spatial distribution of peak power demand for EV charging in the year 2040 reveals an extreme geographical concentration of demand within the province of Pichincha (Figure 10):

- Quito Canton: Accounts for 85% of the total demand (255 MW in the baseline scenario).
- Other Cantons: Each account for less than 20 MW, even in the optimistic scenario.

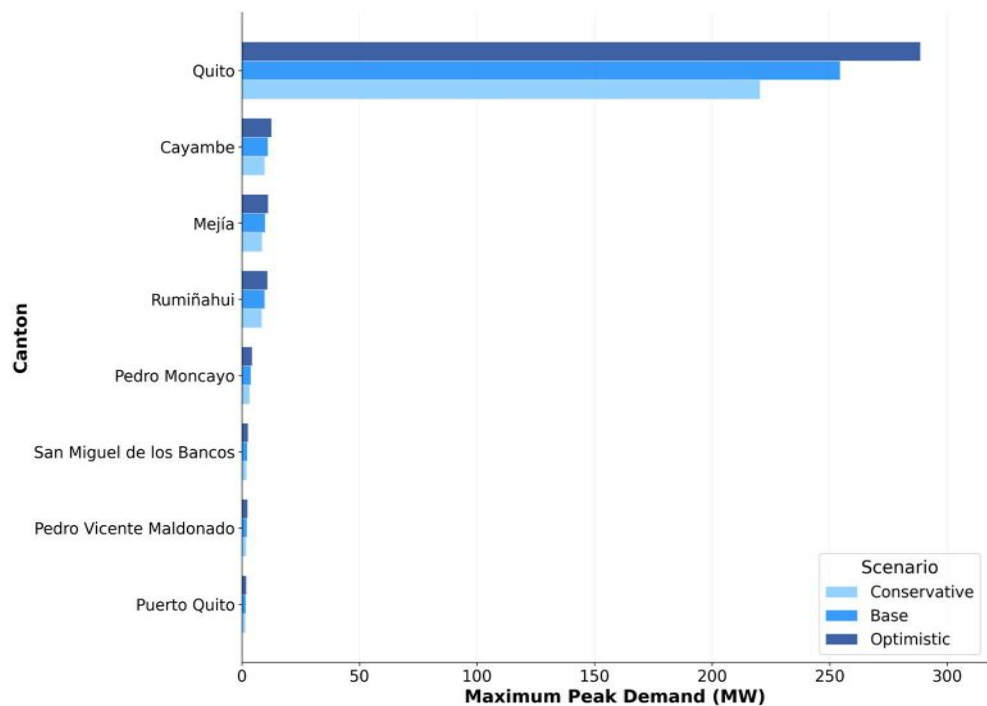


Figure 10. Geographical Distribution of Peak EV Charging Demand by Canton in Pichincha (2040).

3.8. Characterization of the ‘Cliff Effect’

Figure 11 provides clear visual evidence of the progressive development of temporal synchronization patterns that characterize the “cliff effect.” The analysis reveals how a non-optimized implementation of TOU tariffs can generate dramatic increases in peak demand. In the “High Tariff Response” scenario, the system’s peak demand increases from 192 MW to 255 MW (a 32% increase), confirming the theoretical predictions of the Nash equilibrium model.

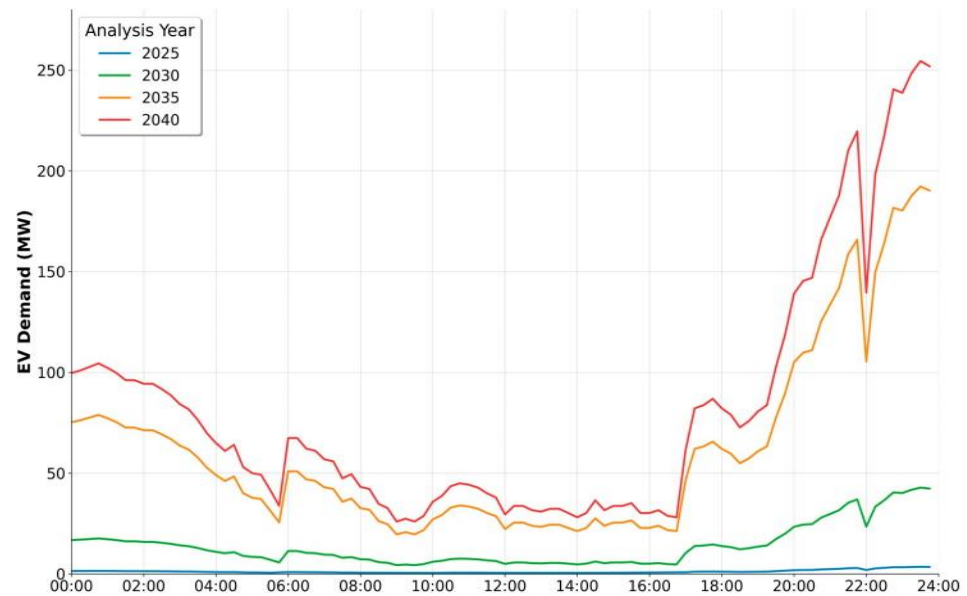


Figure 11. Evolution of the Quarter-Hourly EV Demand Profile on Peak Days (Baseline Scenario) for 2025, 2030, 2035, and 2040.

3.9. Thermal and Altitudinal Effects

The thermal sensitivity analysis reveals a consistent negative correlation between ambient temperature and charging efficiency. For the observed range (5–25 °C), the average efficiency varies from 93% at low temperatures to 91% at high temperatures, with a slope of $-0.1\%/^{\circ}\text{C}$, which confirms the implemented correction parameters (Figure 12).

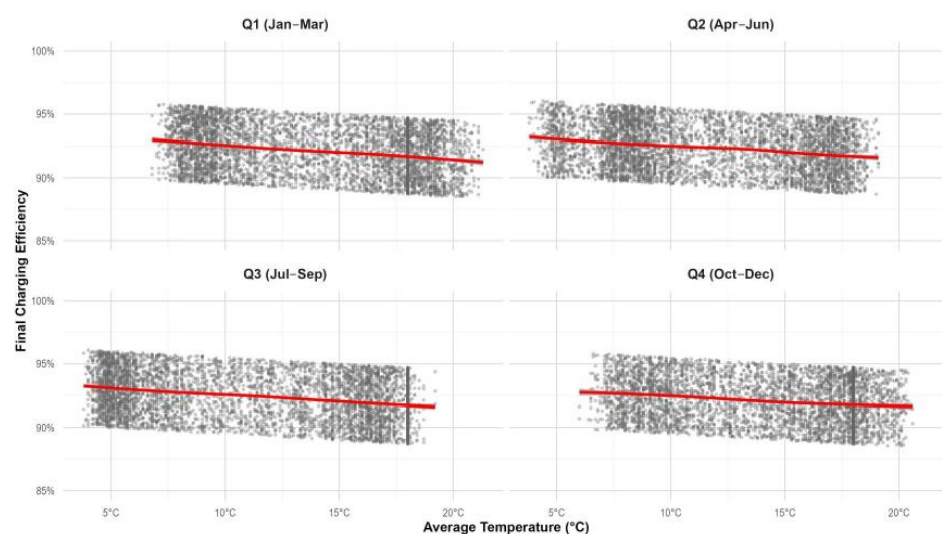


Figure 12. Impact of Ambient Temperature on Electric Vehicle Charging Efficiency.

This analysis introduces specific climatic considerations for high-altitude cities based on the detailed temperature distributions shown in Figure A3 (Appendix A.3).

4. Discussion

4.1. Comparison with Alternative Methodological Approaches

The results validate the superiority of the Agent-Based Modelling (ABM) approach over purely statistical models in capturing behavioral heterogeneity. While previous studies using ARIMA [42] have achieved high accuracy under stable conditions (MAPE 3–5%), they fail to capture the mass synchronization events that our ABM accurately predicts.

4.2. Implications for Infrastructure Planning

Applying the cost-estimation framework developed by NREL to the projected peak demand of 350 MW in an unmanaged TOU tariff scenario, it is estimated that the required infrastructure upgrades could range from \$200 to \$400 million [43].

4.3. Specific Contributions for High-Altitude Cities

The identified thermal effects ($-0.1\%/^{\circ}\text{C}$ on charging efficiency) provide specific parameters for Andean cities. While studies by [44] report more pronounced effects ($-0.3\%/^{\circ}\text{C}$) for extreme climates, the isothermal conditions of Quito-Pichincha exhibit more moderate variations.

These specific thermal parameters complement the implemented battery degradation models, whose comparative profiles by technology are detailed in Figure A4 (Appendix A.4).

4.4. Validation of Coincidence Factors

The dynamic coincidence factor ($F_c = 0.222 + 0.036 * e^{(-0.0003n)}$) validates and refines the findings of the work by [3], which documented a stabilized factor of 0.22 for scenarios with over 50,000 units. The current formulation is consistent with findings from the international scientific community, which report coincidence factors for unmanaged residential charging stabilize below 0.25 for fleets of more than 50 vehicles. The dynamic formulation provides greater accuracy for variable penetration scenarios, yielding a 70% reduction in demand overestimation relative to traditional models.

4.5. Physical Layer Constraints and Their Relevance for Long-Term Demand Modeling

A prospective analysis of energy demand towards 2040 must consider not only the evolution of user behavior but also that of charging technologies. While this study is based on wired charging data, the progressive introduction of Wireless Electric Vehicle Charging (WEVC) incorporates new physical layer constraints that have not been captured in the current model. Recent research [45] shows that vehicle misalignment on the charging pad, a stochastic user behavior, can generate excessive ohmic losses in the ground assembly, raising the surface temperature to risk levels defined by the IEC.

These dynamics have direct implications for agent-based models. Instead of assuming successful charging sessions with constant efficiency, the reality of WEVC introduces the possibility of session failures and efficiency variability. Both factors could lead to an underestimation of aggregate demand and the emergence of unexpected “rebound demand” peaks. For Quito, the effect could be more pronounced, given that the lower air density at high altitude reduces convective cooling capacity and amplifies the thermal risk.

5. Conclusions

This study demonstrates that a high-fidelity agent-based simulation approach, supported by Big Data architecture, is essential for urban energy planning in the era of electric mobility. The quantitative projections reveal exponential growth in demand in Pichincha, with temporal patterns that will challenge the existing infrastructure.

5.1. Answering the Research Questions and Hypothesis

This work is aimed at answering specific questions and validating a central hypothesis, the answers to which are summarized below:

Main Research Question: How can agent-based modeling, combined with Big Data architecture, provide actionable insights for electric vehicle (EV) charging infrastructure planning, while quantifying the risks of demand synchronization under time-of-use tariffs?

- **Answer:** The developed methodological framework provides actionable insights by accurately quantifying future demand (a peak of 255 MW and 800 GWh annually by 2040), identifying and measuring previously underestimated systemic risks (the “cliff effect” which amplifies peak demand by 32%), and validating the effectiveness of specific mitigation strategies (smart charging reduces it by 18%). Big Data architecture is the enabling component that makes this metropolitan-scale simulation computationally feasible, processing data at 2398.7 records per second.

Specific Question 1 (RQ1): What are the probabilistic bounds for peak EV charging demand under different adoption and tariff scenarios?

- **Answer:** For the year 2040, the model projects a peak demand in the baseline scenario of 255 MW, with a 95% confidence interval establishing the probabilistic bounds between 240 MW and 270 MW. The conservative and optimistic scenarios set the outer bounds of the planning range at 220.44 MW and 288.60 MW, respectively.

Specific Question 2 (RQ2): How do temperature variations and thermal effects influence charging profiles in high-altitude environments?

- **Answer:** A consistent negative correlation between ambient temperature and charging efficiency has been quantified. The influence is estimated as an efficiency reduction of -0.1% per degree Celsius increase in temperature, providing a specific and validated correction parameter for planning in Andean cities.

Specific Question 3 (RQ3): What demand response mechanisms can mitigate the synchronization risks posed by simple TOU tariffs?

- **Answer:** The most effective demand response mechanism to mitigate synchronization risk is smart charging management that incorporates stochastic (randomized) charging initiation. This strategy effectively desynchronizes aggregate demand and has been shown to reduce peak demand by $18 \pm 2.5\%$ compared to the baseline.

Central Hypothesis: Advanced demand-side management (DSM) strategies that incorporate stochastic charging initiation can reduce peak demand by $>15\%$ compared to unmanaged TOU tariffs.

- **Answer:** The central hypothesis is strongly confirmed. The simulation demonstrates that advanced DSM strategies, through randomized charging initiation, reduce peak demand by $18 \pm 2.5\%$, exceeding the established 15% threshold and thereby validating the core premise of the research.

5.2. Key Findings

1. **Proven Methodological Scalability:** The ABM-TimescaleDB architecture successfully processes over 13.5 million records with a throughput of 2398.7 records per second, demonstrating its viability for metropolitan-scale applications.
2. **Precise Risk Quantification:** The documented “cliff effect” (a 32% increase in peak demand) provides quantitative evidence for implementing smart management policies over simple TOU tariffs.

3. Validated Predictive Accuracy: A MAPE of $4.2 \pm 0.8\%$ surpasses established benchmarks for aggregate models and approaches the standards for individual applications, providing quantitative validation that previous studies had not established.
4. Specific High-Altitude Parameters: Thermal correction factors ($-0.1\%/^{\circ}\text{C}$) and a dynamic coincidence factor provide refined technical tools for planning in Andean cities, complementing and improving upon previous frameworks.

5.3. Implementation Recommendations

1. Utilize the optimistic scenario projections (289 MW) to avoid infrastructure under-sizing, which represents an additional investment of \$200–400 million but prevents future disruptions.
2. Implement randomized charging systems instead of simple time-of-use (TOU) tariffs to prevent mass synchronization effects. Their effectiveness depends on managed implementation to avoid the “cliff effect,” as demonstrated in this study.
3. Establish telemetry systems for the continuous validation and calibration of coincidence factors as EV penetration evolves.
4. Integrate thermal effects ($-0.1\%/^{\circ}\text{C}$) into capacity planning, particularly for seasonal demand peaks.

5.4. Limitations and Future Work

The validation of this study is limited by the paucity of real-world data corresponding to very high penetration scenarios ($>50\%$). Future work should include validation against cities with high EV penetration and a sensitivity analysis for different tariff architectures.

It should be noted that while the analysis of the interaction between electric heating load and EV charging is a crucial research area in regions with cold climates, Quito’s temperate and stable year-round climate does not generate a systemic heating demand. Therefore, this load coupling is not considered a significant risk factor for the local grid and falls outside the scope of this study, which focuses on the risks of EV charging synchronization, a more immediate and relevant challenge for the region.

A promising avenue for future research is to develop a Vehicle-to-Grid (V2G) model for grid restoration, leveraging managed fleets like electric buses to bolster system resilience in the face of extreme events. This future study could build upon the baseline load profiles established in the present work.

Author Contributions: Conceptualization, I.S.-L. and M.A.-C.; methodology, I.S.-L.; software, I.S.-L.; validation, I.S.-L. and M.A.-C.; formal analysis, I.S.-L.; investigation, I.S.-L. and M.A.-C.; resources, M.A.-C.; data curation, I.S.-L.; writing—original draft preparation, I.S.-L.; writing—review and editing, M.A.-C.; visualization, I.S.-L.; supervision, M.A.-C.; project administration, M.A.-C. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The simulation data presented in this study are available upon request from the corresponding author due to data size limitations (>6.7 GB) and database complexity. The complete source code, simulation framework, and analysis scripts are openly available in the GitHub repository at “<https://github.com/ivelec1981/ev-demand-modeling-abm-timescaledb.git> (accessed on 12 August 2025)” [40]. The repository includes all necessary code to reproduce the simulation results, the database schema, and documentation for replication. Raw charging profile data and vehicle specifications used for model calibration contain proprietary information and are available upon request, subject to appropriate data sharing agreements.

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Empresa Electrica Quito (EEQ) for providing access to charging infrastructure data, which made this study possible.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ABM	Agent-Based Modelling (Agent-Based Modelling)
API	Application Programming Interface
AEADE	Asociación de Empresas Automotrices del Ecuador
BMS	Battery Management System
CF	Coincidence Factor
DR	Demand Response
DSM	Demand Side Management
EEQ	Empresa Eléctrica Quito
ENEM	Estrategia Nacional de Electromovilidad
FC	Coincidence Factor
GPU	Graphics Processing Unit
IC	Confidence Interval
INAMHI	Instituto Nacional de Meteorología e Hidrología del Ecuador
LFP	Lithium Iron Phosphate
LLM	Large Language Model
MAPE	Mean Absolute Percentage Error
NCM	Nickel Cobalt Manganese
NREL	National Renewable Energy Laboratory
RDBMS	Relational Database Management System
RMSE	Root Mean Square Error
SoC	State of Charge
SoH	State of Health
SQL	Structured Query Language
TOU	Time of Use
TSDB	Time Series Database
UNESCO	United Nations Educational, Scientific and Cultural Organisation
V2G	Vehicle-to-Grid
EV	Electric Vehicle

Appendix A

Appendix A.1

The tariff structure implemented for EV charging is based on a time-of-use (TOU) scheme that differentiates electricity costs between weekdays and weekends.

As detailed in Figure A1, the weekday tariff is segmented into three periods:

- **Off-Peak.** From 00:00 to 06:00 and from 22:00 to 24:00, there is a reduced cost of \$0.05/kWh.
- **Standard.** From 06:00 to 18:00, with an intermediate rate of \$0.08/kWh.
- **Peak.** From 18:00 to 22:00, the highest rate of \$0.10/kWh is applied to discourage charging during these peak demand hours.

Conversely, the structure for weekends is simpler and promotes charging during most of the day:

- **Off-Peak.** An extended period from 00:00 to 18:00 and from 22:00 to 24:00, maintaining the minimum rate of \$0.05/kWh.

- Peak. The same period, from 18:00 to 22:00, is maintained at the \$0.10/kWh rate, coinciding with the residential demand peak.

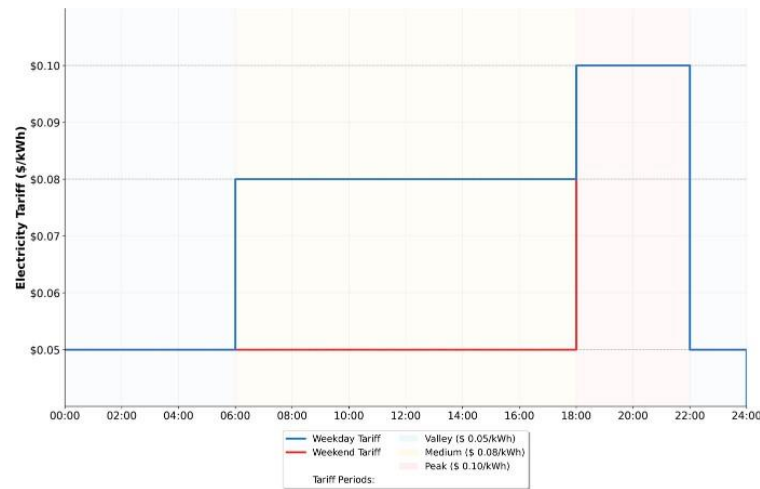


Figure A1. Comparison of Electricity Tariffs by Time of Day for Electric Vehicle Charging Infrastructure.

Appendix A.2

Figure A2 presents the detailed temporal evolution of the electric vehicle charging demand profiles for every day in the month of December, from 2025 to 2040. Each subplot corresponds to a specific day (e.g., 1 December, 2 December, etc.) and displays the hourly consumption pattern over a 24-h period at a quarter-hour resolution.

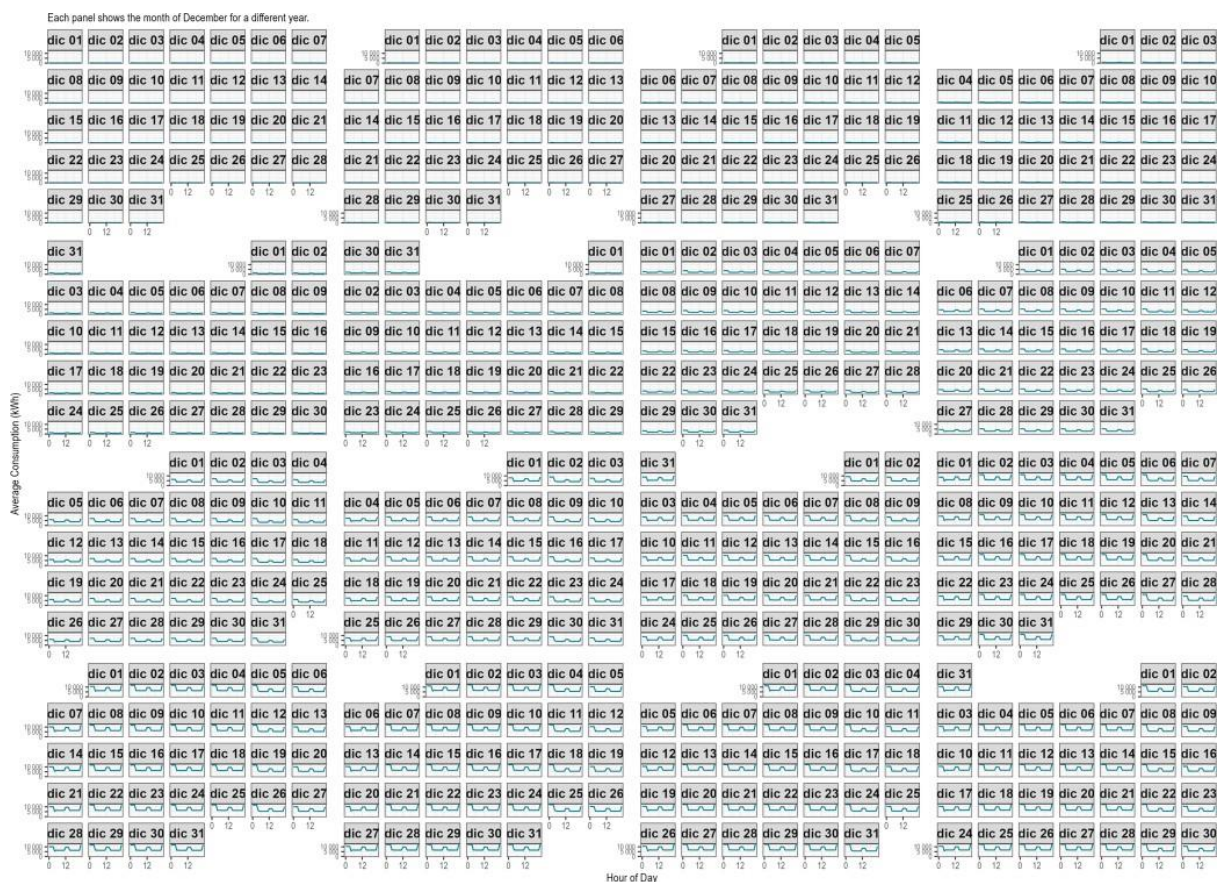


Figure A2. Temporal Evolution of Quarter-Hourly EV Consumption Profiles During the Month of December (2025–2040).

Appendix A.3

Figure A3 presents the probability density distributions of ambient temperature ($^{\circ}\text{C}$) for each month of the year, developed from a historical record of over three years from eight meteorological stations in Pichincha.

The temperature distributions for the twelve months of the year are significantly overlapped, with their modes (peaks of highest probability) contained within a narrow range, from approximately 18°C to 22°C .

Despite this overall stability, a subtle bimodal pattern of thermal seasonality can be discerned. A primary period of higher temperatures extends from June to September. During these months, the distributions shift to the right, with modes reaching and exceeding 20°C . August emerges as the month with the highest temperature distribution, both in its central value and in the extent of its right tail.

The months of January and February constitute a second, shorter, and less pronounced period of relatively warmer temperatures compared to the immediately following months.

Conversely, the periods from March to May and from October to December exhibit temperature distributions shifted to the left, indicating relatively cooler conditions. During these months, the modes of the distributions are situated in the low range of the annual spectrum, around $18\text{--}19^{\circ}\text{C}$.

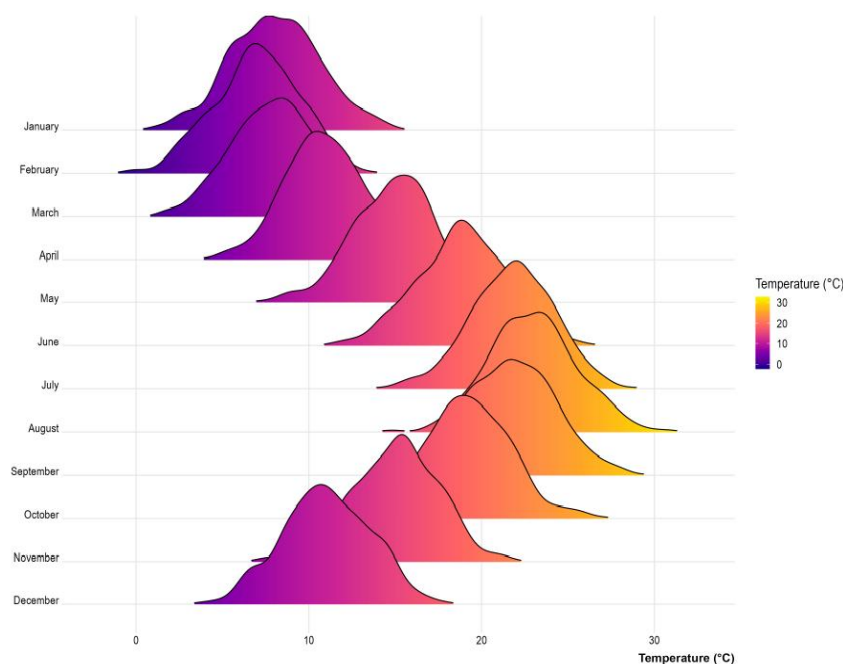


Figure A3. Probability Density Distributions of Monthly Temperatures in Quito, Pichincha.

Appendix A.4

The battery degradation profiles presented in Figure A4 model the decline in the State of Health (SoH) over a 20-year lifespan for four distinct battery chemistries used in electric vehicles (EVs).

The comparative analysis reveals significant differences in the longevity of each technology:

- NCM (Nickel-Manganese-Cobalt) Battery. It exhibits the most pronounced degradation rate, dropping below the 80% replacement threshold in approximately the fourth year of use and reaching less than 50% of its original capacity by the end of 20 years.
- LFP (Lithium Iron Phosphate) Battery. It offers considerably greater durability than NCM. Its SoH remains above 80% until approximately year 11 and crosses the 70% threshold around year 18.

- NextGen and Solid-State Batteries. Both emerging technologies exhibit minimal degradation and superior performance. Their profiles are nearly identical, maintaining a SoH near 80% even after 20 years, indicating an extended lifespan that far exceeds current standards.

The dashed lines at 80% and 70% mark the typical industry thresholds at which battery replacement is considered to ensure adequate vehicle range and performance.

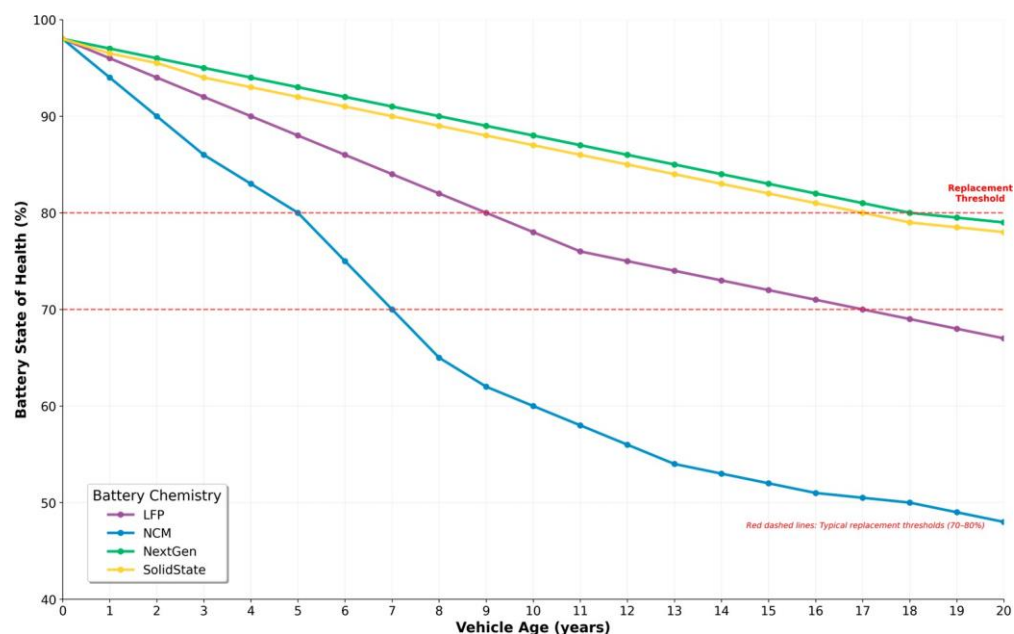


Figure A4. Comparative Degradation Profiles of the State of Health (SoH) for EV Batteries by Chemistry.

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