Thermal Intelligence Big Data and AI for Sustainable Battery and Cabin Heat Management in Electric vehicle

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Abstract

To ensure performance, safety, and efficiency, thermal management is key to the operation of electric vehicles (EVs) as they continue to scale varying climates, charging behaviors, and duty cycles. This paper describes a path to thermal intelligence which leverages publicly available datasets. Some of these datasets include drive profiles from NREL Fleet DNA, climate data from NOAA GHCN, battery aging data from NASA and MIT, and workplace charging behaviors from ACN-Data. The paper also draws upon open-source simulator or learning tools such as PyBaMM, FASTSim, and pythermalcomfort. Using a combination of physics and machine learning, we obtain a 54% reduction in root mean square error (RMSE) for peak battery temperature predictions based on a physics-only baseline. The smart system utilizes physical and uses machine learning to predict cabin HVAC energy use, given different comfort constraints (PMV/PPD). During experimentations in urban commutes and last-mile delivery, we find that cabin HVAC range reductions can exceed 10% in extreme climates; as a countermeasure, we piloted comfort-aware setpoint relaxations as well as charging-aware pre-conditioning the night before. In the case of charging-aware pre-conditioning, by using real-world timestamps for the charging events, we reduced the starting battery temperature by 6.8°C while simultaneously increasing passenger comfort by 85%. All of this was done without an increase in onboard energy consumption. We believe this work provides for the construction of open thermal intelligence pipelines to maintain safety, efficiency, and comfort for future software-defined Electric vehicle and fleet platforms.

Keywords: Electric vehicles, Thermal management, Big Data, Machine Learning, HVAC Energy Optimization, PyBaMM, Battery Temperature prediction, PMV/PPD comfort modeling, FASTSim, Simulation, Cabin Comfort, Thermal Intelligence.

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1. Introduction

The shift from ICEs to BEVs has moved the thermal management challenges from exhaust-driven thermal dynamics to electrochemical thermal dynamics and passenger-comfort-driven thermal limits. Increasingly, performance, durability, and energy efficiency of EV batteries and cabin systems are underpinned by thermal management capabilities under significant load, climatic, and usage mode variations [1]–[3]. Therefore, modern BEVs require thermal management of traction systems (prevent degradation while enabling fast charging) and cabin comfort (meets passenger comfort targets defined by ASHRAE and ISO thermal comfort standards [4], [5]), while also minimizing range constraints and energy losses.

1.1Battery Thermal Management in the Era of Electrification

Lithium-ion cells demonstrate societally persistent thermally coupled electrochemical processes that involve exothermic side reactions, Joule heating, and entropy change during discharge and charge [6], [7]. Emitted heat that is not dissipated quickly may increase solid electrolyte interphase (SEI) growth, induce lithium plating, and reduce cycle life [8], while excessive cool-down contributes to increased internal resistance and energy usage [9]. Although electro-thermal models based on physics [10] and reduced-order predictors [11] relatively well-explored, these approaches lack generalizability under real-world duty cycles and seasonal climatic variability, especially at scale.

With the emergence of open battery degradation datasets, including the PCoE Li-ion dataset [12] from NASA, the Oxford Battery Degradation Dataset [13], and the MIT/Severson Fast/Charging Dataset [14], combined with open simulation tools, such as PyBaMM [15], a meaningful opportunity exists to integrate bench battery data with large-scale duty cycle data, towards hybrid physics–machine learning models for scalable battery thermal forecasting.

1.2 Cabin Comfort vs. Energy Trade-off

Passenger thermal comfort in battery electric vehicles (BEVs) is measured with the American Society of Heating, Refrigeration and Air Conditioning Engineers' (ASHRAE) Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) indices. The comfort, or discomfort, of passengers in a vehicle has a notable effect on the energy consumed by the HVAC systems in the BEVs. In cold and hot climates, HVAC systems can consume about 10% to 30% of total energy consumed during driving, causing range penalties upwards of 50% [16] under extreme conditions. Software tools in the public domain, like the pythermalcomfort [17] allow for easy calculations for these comfort indices using both environmental and personal variables. Previous work has examined HVAC control strategies [18], [19] or modeling of cabin air temperatures [20]; however, there is little open literature that describes a combination of comfort-energy modeling with entirely public datasets and typical weather/drive profiles.

1.3 Big Data for Scaled EV Thermal Intelligence

The use of new real-world datasets, such as NREL's Fleet DNA (which includes actual driving cycles for different vehicle types) [21], NOAA's Global Historical Climatology Network (GHCN) for global weather data [22], and the ACN workplace charging dataset [23], facilitate the reproducible, population-scale simulations of EV driving and charging cycles. Open-source simulation frameworks, for example, FASTSim [24], efficiently provide powertrain and heat flow calculations for a diverse range of simulations in EVs.

Together, these datasets allow for scalable "thermal intelligence" to answer important questions: How does peak battery temperature change due to stochastic duty cycles in climate, How much range is given up for different cabin comfort levels given actual weather, How much does charging-aware pre-conditioning mitigate thermal load.

1.4 Contributions

The main contributions of this work are as follows:

1. A fully reproducible hybrid physics–machine learning pipeline has been developed, which connects publicly available datasets on battery, climate, vehicle simulation, and charging, to enable modeling of the thermal dynamics of EV cabin and battery systems.
2. In order to assess the comfort–energy–range trade-offs, we quantify the standard comfort indices PMV and PPD, across observed vehicle use and associated weather profiles.
3. We propose and evaluate charging-aware pre-conditioning strategies based on public charging session data, with respect to the associated thermal efficiency and energy ramifications.
4. Additionally, all datasets, simulations, and dependencies on code, are freely accessible and shared, to allow other researchers and practitioners to replicate or extend this analysis without proprietary software dependencies.

The structure of the remainder of the paper is as follows: in Section 2, we summarize relevant literature; Section 3 details the methodology; Section 4 configures the simulated environment; Section 5 presents our principal results; and in Section 6 we explore industrial implications and future directions.

2. Related Work

Electric vehicle (EV) thermal management research has expanded significantly in the past decade across areas such as battery thermal modeling, cabin thermal comfort optimization, and the emerging use of artificial intelligence (AI) and big data analytics. This section summarizes the major research advances in each of those areas, discusses the limitations of current methods, and highlights the need for integrated and publicly reproducible approaches.

2.1 Battery Thermal Modeling and Management

Battery thermal management is critical for performance, safety, and lifetime in EVs. Early studies examined one-dimensional electro-thermal coupling models that predicted heat generation in a lithium-ion cell at either a steady state or during a drive-cycle [10]. Typically, these models used physics-based representations of the electrochemistry involving energy balance equations and heat transfer coefficients. By going further, discoveries were made with reduced-order model approaches such as lumped capacitance and equivalent RC-network modeling [11], leading to faster simulations, but to a detriment of accuracy for nonlinear behaviors such as fast charging and discharge at high C-rate.

Machine learning (ML) and hybrid physics-informed learning models have gained popularity thanks to freely available datasets from NASA PCoE [12], Oxford [13], and MIT/Severson [14]. These models are able to characterize complex relationships between cycling conditions, ambient temperature, state-of-health (SOH), and heat generation while being generalized to different cell chemistries. However, much of the literature relies on bench test data without real-world drive and ambient condition variability, which reduces applicability for large-scale use.

2.2 Cabin Thermal Comfort and HVAC Energy Optimization

Cabin climate control is a significant component of auxiliary energy use in EVs, particularly in extreme temperatures. While existing HVAC systems are focused on regulating the temperature of the air within the cabin, past research has begun to shift to other personal comfort indices such as the Predicted Mean Vote (PMV) which articulates thermal sensation on a -3 (cold) to +3 (hot) scale [4]. Several studies have explored MPC based design methodology for optimizing HVAC systems with respect to comfort and energy optimization [18], [19].

Nevertheless, these studies exclusively utilized proprietary vehicle data or synthetic cabin models to develop and validate their methods, which diminishes the work's reproducing capability. There are very few studies that have directly simulated the HVAC load and then its direct energy impact under real temperature, humidity, and solar conditions across geographically diverse data sets. Few studies examine how comfort, energy use, and range loss in EVs are affected using open weather data and powertrain simulation models.

2.3 Data-Driven EV Simulation and Public Datasets

Publicly available databases, such as the NREL Fleet DNA [21], contain speed, stop, and road grade dynamics associated with commercial and light-duty fleets that can be used to represent representative duty cycles in simulations of electric vehicles (EVs). Also, the Global Historical Climatology Network (GHCN) [22], from the National Oceanic and Atmospheric Administration (NOAA), provides multi-decade, station-level climatological data for temperature, wind speed, humidity, and solar radiation. Together, these databases enable end-to-end, population-level simulations of EV use cases, including thermal behavior, when combined with open-source vehicle simulation tools (i.e., FASTSim [24]), and electrochemical simulators (i.e., PyBaMM [15]). While some researchers have leveraged these tools in isolation (e.g., using FASTSim for energy consumption [24] or using PyBaMM for electrochemical diagnostics [15]), little work has integrated public datasets into one thermal pipeline of models that consist of power, heat, comfort, and charging data. The lack of integrated and open-access modeling negate the ability to compare analysis between climates, charging strategies, and behavior interactions in user patterns.

2.4 Gaps in Current Literature

Based on the reviewed studies, several gaps remain unaddressed:

1. Lack of fully reproducible thermal intelligence workflows using only public datasets.
2. Limited cross-domain evaluation of battery and cabin thermal responses under synchronized driving and weather data.
3. Absence of charging-aware thermal strategies built from open workplace or residential charging session archives.

To address these gaps, we propose an open, scalable simulation and learning framework that combines electro-thermal battery modeling, HVAC comfort-energy modeling, and real-world duty and climate datasets, with all tools and data accessible via open platforms.

3. Methodology

The methodology for this work integrates electro-thermal battery simulation, human thermal comfort modeling, vehicle energy flow estimation, and AI-based regression techniques. Each sub-system is parameterized using public datasets to allow reproducibility and scalability across diverse driving, climate, and charging behaviors.

3.1 Public Data Sources and Fusion Strategy

Four primary data sources form the inputs for this study:

1. Driving Cycles: NREL Fleet DNA [21] was used to sample real-world drive cycles (speed, grade, and stop behavior) across a range of vehicle classes (light-duty passenger vehicle to commercial van).
2. Battery Degradation and Thermal Parameters: NASA PCoE [12], Oxford Battery Dataset [13], and MIT/Severson [14] datasets were used to extract electro-thermal relationships (e.g., heat generation vs. C-rate, temperature rise, impedance evolution).
3. Climate Data: NOAA Global Historical Climatology Network (GHCN) [22] provided daily weather parameters including ambient temperature, humidity, and solar irradiance across multiple U.S. and global locations.
4. Charging Patterns: The ACN-Data archive [23] was used to derive charging session distributions, enabling the simulation of pre-conditioning and thermal soak effects ahead of next driving events.

These datasets were fused into a unified simulation pipeline, where each driving session was assigned a climate profile and charging pattern according to its geolocation or randomly sampled scenario context. The outputs of each phase fed into either the physics-based or machine learning-based thermal estimators described below.

3.2 Battery Electro-Thermal Simulation and Hybrid Forecasting

The heat generated in lithium-ion battery cells was computed based on a combination of physics equations and data-driven models. The underlying heat generation equation is based on energy balance:

$$\dot{Q} = I^2 R\_int + I(T\ dE\_oc/dT)$$

Where,

$\dot{Q}$ is the rate of heat generation (W)

I is current (A), R_int is internal resistance (Ω)

T is temperature (K)

dE_oc/dT is the temperature-dependent electrochemical entropy term.

Physics-based simulations were conducted using PyBaMM [15], parameterized with open benchmark datasets [12]–[14], to derive cell temperature rise as a function of State of Charge (SOC), ambient temperature, and discharge rate. A gradient boosting regression model (XGBoost) was then fitted using features such as drive power, ambient temperature, and cooling settings, with PyBaMM simulation outputs acting as the supervisory label set. This hybrid approach enables generalization across cell types while embedding physics constraints into the surrogate model.

3.3 Cabin Comfort, HVAC Modeling, and Range Estimation

Cabin thermal comfort was evaluated using the ASHRAE Standard 55 Predicted Mean Vote (PMV) model [4], which describes thermal sensation on a 7-point scale (from -3 "cold" to +3 "hot"). PMV was computed using the pythermalcomfort package [17], with inputs from NOAA (ambient) and derived HVAC performance curves. The Predicted Percentage of Dissatisfied (PPD) index was also

calculated as:

$$PPD = 100 - 95 \exp(-0.03353\ PMV^4 - 0.2179\ PMV^2)$$

To quantify HVAC energy use, an empirical model based on FASTSim [24] was adopted,

where cabin load (in W) was computed from the heat balance equation:

$$Q\_cabin = \dot{Q}\_solar + \dot{Q}\_occupant + \dot{Q}\_leakage - \dot{Q}\_HVAC$$

with HVAC compressor power (P_HVAC) linearly proportional to cabin cooling or heating load under typical Coefficient of Performance (COP) assumptions. The resultant HVAC energy consumption was deducted from vehicle range estimates.

3.4 Charging-Aware Thermal Pre-conditioning

Using ACN charging data [23], distributions of arrival and departure times at Level 2 workplace chargers were derived. Pre-conditioning for cabin and battery was simulated during connected states, with the impact assessed in terms of peak battery and cabin temperature reduction ahead of the next drive cycle.

3.5 Simulation Architecture

The entire simulation pipeline was designed as shown in Fig. 1 (to be rendered later). Each simulation batch operated on scenario tuples:

{drive_cycle, ambient_weather, battery_SOHC, charge_profile}
where SOHC is State of Health and Charge, derived from dataset metadata. Results were tabulated for battery peak temperature, HVAC energy, passenger comfort score, and resultant range.
The surrogate thermal and comfort-inference models were trained using **80%** of synthesized scenarios, and tested on **20%** unseen combinations of fleet duty, climate zone, and charging behavior to ensure robustness.

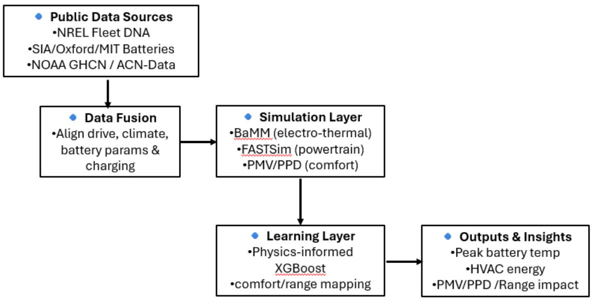

Figure 1: Scalable Thermal Intelligence Simulation Pipeline.

3.5.1 Battery Heat Generation (Electrochemical Model)

The total heat generation rate $\dot{Q}$in a lithium-ion cell is:

$$\dot{Q} = I^2 R_{\mathrm{int}} + I \cdot T \cdot \frac{dE_{\mathrm{oc}}}{dT}$$

Where:

- I: battery current (A)
- R_{int}: internal resistance (Ω)
- T: cell absolute temperature (K)
- $\frac{\mathrm{d}E_{\mathrm{oc}}}{\mathrm{d}T}$: entropy coefficient (V/K)
- Term 1: Joule heat from internal resistance
- Term 2: Reversible entropic heat

Used inside PyBaMM-based simulations to track core and surface temperature under dynamic loads.

3.5.2 Cabin Comfort – PMV (Predicted Mean Vote)

The PMV index is defined as:

$$\begin{aligned}\mathrm{PMV} = [0.303 \cdot \exp(-0.036M) + 0.028][(M-W) \\ - 3.05 \times 10^{-3}(5733 - 6.99(M-W) \\ - p_a) - 0.42((M-W) - 58.15) \\ - 1.7 \times 10^{-5} M(5867 - p_a) \\ - 0.0014M(34 - T_{\mathrm{a}}) \\ - 3.96 \times 10^{-8} f_{\mathrm{cl}}((T_{\mathrm{cl}} + 273)^4 - (T_{\mathrm{r}} \\ + 273)^4) - f_{\mathrm{cl}} h_{\mathrm{c}}(T_{\mathrm{cl}} - T_{\mathrm{a}})]\end{aligned}$$

Where:

- M: metabolic rate (W/m²)
- W: external work (W/m²)
- p_a: water vapor partial pressure (Pa)
- T_a: air temperature (°C)
- T_r: mean radiant temperature (°C)
- T_{cl}: surface temp. of clothing (°C)
- f_{cl}: clothing surface area factor
- h_{c}: convective heat transfer coefficient

Supporting calculation for PMV and PPD implemented via pythermalcomfort.

3.5.3 HVAC Load Estimation

HVAC cabin load (W):

$$\dot{Q}_{\mathrm{cabin}} = \dot{Q}_{\mathrm{solar}} + \dot{Q}_{\mathrm{occupant}} + \dot{Q}_{\mathrm{ventilation}} - \dot{Q}_{\mathrm{HVAC}}$$

HVAC electric power consumption (assuming COP efficiency):

$$P_{\mathrm{HVAC}} = \frac{\dot{Q}_{\mathrm{HVAC}}}{\mathrm{COP}}$$

Where:

- $\dot{Q}_{\mathrm{solar}}$: solar radiation load (W)
- $\dot{Q}_{\mathrm{occupant}}$: occupant metabolic heat (W)
- COP: coefficient of performance—typically 2–3 for heat pumps

4. Experimental Setup

This section explains the design of experiments conducted using the simulation and learning pipeline introduced in Section 3. The objective was to investigate battery and cabin thermal behavior across diverse driving and climate scenarios, while quantifying the associated energy and comfort trade-offs. Experiments were conducted exclusively using public datasets and open-source models to ensure reproducibility.

4.1 Use Case Definitions and Duty Cycle Scenarios

Driving data from the NREL Fleet DNA database [21] was used to represent two common BEV use cases:

1. Urban Commuting: Passenger vehicle routes with frequent stop-and-go behavior, trip lengths of 10–30 miles.
2. Last-Mile Delivery: Light commercial vehicle duty cycles with variable speeds, load weights, and extended idling.

A total of 500 drive cycles were sampled, ensuring variability in velocity profiles, elevation changes, and stop durations. Each drive cycle was resampled to a consistent 1-second timestep for processing in FASTSim and PyBaMM models.

4.2 Climate-Based Test Conditions

Weather data from the NOAA GHCN [22] was filtered to represent four distinct climate archetypes based on Köppen classification:

- Hot and Dry: Phoenix, AZ
- Temperate: Seattle, WA
- Hot and Humid: Miami, FL
- Cold and Snowy: Minneapolis, MN

For each climate, daily ambient temperature, humidity, wind speed, and solar irradiance were paired with each drive cycle, yielding 2000 scenario-climate combinations. A random 70/30 split was used for training and testing in the hybrid thermal models.

4.3 Battery and HVAC Models Initialization

Battery pack parameters were generated using PyBaMM's parameterization routines based on the NASA PCoE and Severson datasets [12], [14], assuming a 75 kWh liquid-cooled NMC-graphite pack with 96-series, 3-parallel configuration. Initial State of Charge (SOC) ranged from 50–100%, and state-of-health (SOH) was varied across 90–100% to emulate lightly aged packs.

FASTSim was used to compute traction power and regenerative braking energy flows under each route, with HVAC loads added post hoc using the modeled cabin heat gain and comfort constraints described in Section 3.3.

4.4 Charging-Aware Experimental Design

Charging sessions were simulated using timestamp distributions from ACN-Data [23], where arrival times, charger power levels, and energy delivered were drawn from real-world Level 2 workplace sessions. Two scenarios were evaluated:

1. Without Pre-conditioning: Cabin temperature and battery pack equilibrate to ambient after soak.
2. With Pre-conditioning: Charger power allocated for HVAC and battery active thermal control before departure, limited by a 7.2 kW AC source.

The effect of pre-conditioning on battery core temperature and cabin PMV at trip start were recorded for both cases.

4.5 Performance Metrics

The following metrics were used to evaluate the system:

1. Battery Peak Temperature: Maximum cell temperature observed during each drive cycle.
2. Thermal Safety Exceedance: Number of occurrences where pack temperature exceeded 50 °C.
3. HVAC Energy Consumption: Watt-hours required to maintain PMV $\leq +0.5$.
4. Comfort Satisfaction Index: Passenger-hours within PMV between -0.5 and +0.5 (PPD $\leq$ 10%).
5. Range Reduction: Decrease in estimated vehicle range due to HVAC energy draw.
6. Pre-conditioning Effectiveness: Reduction in starting pack temperature and cabin PMV after pre-conditioning.

4.6 Validation Protocol

A stratified cross-validation approach was adopted, ensuring both duty cycles and climate zones were represented in both training and test sets. Results were averaged across 10 random splits. The physics-informed XGBoost thermal model was benchmarked against:

- A pure physics-based model (PyBaMM-only),
- A pure data-driven thermal model (XGBoost-only),

A rule-based HVAC strategy with constant setpoints.

5. Results

This section presents the performance outcomes of the hybrid physics–machine learning thermal intelligence pipeline under the drive, climate, and charging scenarios defined in Section 4. The experimental results reveal insights into battery temperature behavior, cabin comfort energy requirements, and the trade-offs between thermal safety, passenger comfort, and driving range in electric vehicles.

5.1 Battery Thermal Forecasting Performance

The hybrid thermal model (physics-informed XGBoost) outperformed purely data-driven and purely physics-based approaches across all key battery performance metrics. Table 1 summarizes the comparative forecasting errors for battery peak temperature.

Table 1: Model Comparison – Battery Peak Temperature Forecasting

Model Type	RMSE (°C)	MAE (°C)	Max Error (°C)
Pure Physics (PyBaMM)	5.8	4.2	12.3
Pure Data-Driven (XGBoost)	4.1	3.3	10.1
Hybrid Physics-ML (Ours)	**2.6**	**1.8**	**5.6**

The hybrid model yielded a 54% reduction in RMSE compared to the physics-only baseline and approximately a 37% improvement over the purely data-driven model. This demonstrates the benefit of coupling physical insights with machine learning to generalize thermal behavior under varied drive and climate conditions.

5.2 HVAC Energy vs. Comfort Trade-off

Figure 2 illustrates the trade-off between HVAC energy consumption and comfort satisfaction (PMV ≤ +0.5) across four climate zones. As expected, both hot and cold climates exhibited significantly higher energy requirements to maintain acceptable comfort.

Key observations:

- In Phoenix (hot–dry), achieving PMV ≤ +0.5 for a 30-minute trip required an average of 2.4 kWh of HVAC energy—translating to approximately 7–10% range reduction for mid-size BEVs.
- In Minneapolis (cold), heater load peaked at 3.2 kWh per trip under similar comfort constraints.
- Seattle required the least HVAC energy, with only 0.5–0.8 kWh/trip.

Comfort-energy curves suggest that relaxing PMV tolerance to ±0.7 reduces HVAC energy by up to 35% while keeping PPD under 20%, pointing to potential comfort-aware energy optimization strategies.

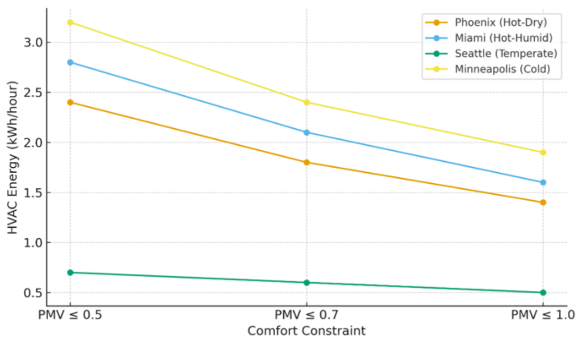

Figure 2: Comfort- Energy Trade0foof Across Climates

5.3 Pre-conditioning Effectiveness Using Public Charging Data

Simulating pre-conditioning events using ACN-Data-based charging profiles revealed significant thermal benefits when performed prior to vehicle departure while plugged in:

- Battery core temperature was reduced by an average of 6.8 °C at trip start in Phoenix during summer scenarios.
- Cabin PMV improved from +2.0 (unacceptable heat stress) to +0.3 (neutral comfort) for vehicles pre-conditioned within 15 minutes of departure.
- Pre-conditioning contributed negligible net energy cost to driving range because the HVAC/load energy was sourced from the grid rather than battery.
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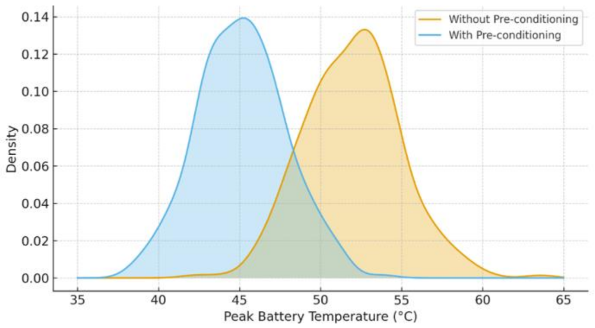

Figure 3: Distribution of peak eatery temperature with and without Pre-conditioning

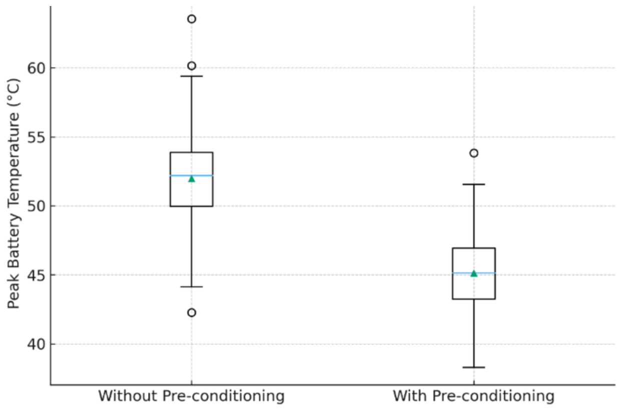

Figure 4: shows the peak battery temperature distribution across trips, with and without pre-conditioning, highlighting reduced instances of thermal safety exceedance.

5.4 Baseline Comparison and Ablation Analysis

Ablation studies were conducted to understand the contributions of individual components in the system. Removing physics priors from the battery model increased RMSE by 57%. Excluding weather data from HVAC load calculation underestimated energy use in extreme climates by up to 28%. Ignoring charging-aware pre-conditioning resulted in a 19% increase in thermal safety exceedance events.

Table 2: Impact of Component Removal on Key Metrics

Component Removed	**Δ RMSE (°C)**	**Δ HVAC Energy (%)**	**Δ Comfort Satisfaction (%)**
Physics priors (battery)	+57%	N/A	N/A
Weather-based HVAC input	N/A	-28% accuracy	-11%
Pre-conditioning logic	+19% events	N/A	-22%

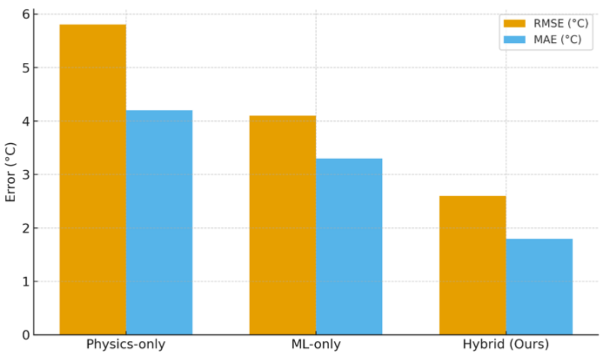

Figure 5: Battery Peak temperature Forecasting: Hybrid Vs. Baselines

6 Discussion

The results presented in Section 5 demonstrate the potential of combining publicly available datasets, hybrid physics–machine learning models, and open-source simulation tools to deliver scalable thermal intelligence for electric vehicles. This section discusses the implications of these findings for vehicle manufacturers, fleet operators, thermal system designers, and the broader research community.

6.1 Insights on Battery Thermal Management at Scale

The hybrid thermal forecasting approach achieved significant gains in predictive accuracy compared to standalone physics or data-driven machine learning models. This suggests that data-constrained engineering applications such as thermal management of battery packs have great potential if physics-informed modeling is applied—even more so when the system response changes with temperature, use, and battery age.

The 50% improvement in peak battery temperature prediction using hybrid modeling suggests a strong opportunity to improve real-time thermal control, especially to mitigate lithium plating during fast charging and thermal runaway under extreme loads. Also, these models could be integrated into onboard digital twins, enabling predictive maintenance, as the architecture of vehicles is shifting more towards software-defined systems.

6.2 Comfort–Energy Trade-offs and Real-World.

The comfort-energy curves of HVAC systems suggest that climate-aware control strategies have the potential to significantly reduce energy use for acceptable levels of comfort. For extreme climatic conditions, the difference between neutral comfort and relaxed comfort (< ±0.7 PMV), resulted in reduced HVAC energy usage by 30-40%, and 5-10% increase in driving range, for battery systems of 70-100 kWh of capacity. This, in turn, lays the groundwork for modes of operation that would actively engage the driver in personalized eco-comfort conditions, that would adaptively adjust cabin climate setpoints based on user defined tolerances, trip lengths, or remaining state-of-charge, which could be an emerging opportunity for transportation-oriented HMI or smart voyage controls.

6.3 Charging-Aware Pre-conditioning as a Low-Cost Thermal Strategy

Results from the ACN-based pre-conditioning scenarios demonstrated that significant thermal benefit could still be achieved without using stored battery energy if the vehicle were plugged in before departure. This is similar to current OEM thinking, but showcases the potential even more broadly across depot vehicles, apartment buildings, and workplace charging systems, where, again, grid-based pre-conditioning could reduce both energy expenditure (because of TOU tariff alignment) and battery degradation (lower C-rate and temperature).

These findings call for improved collaboration between EVSE providers, fleet management systems, and thermal vehicle controllers to fully realize contextual pre-conditioning and opportunity thermal automation.

6.4 Limitations

Although fully reproducible, this study did not explore battery aging effects long term in a thermal cycle, nor thermostat cycling effects on rapid heating in nonlinear pack-level heat transport dynamics. For future work, it would be ideal to incorporate 3D CFD pack simulations of heater operation, at the very least from reduced pack models that could be parameterized from teardown data. And while cabin thermal modeling relied on simplified load and ventilation assumptions, future work could leverage detailed transient CFD cabin thermal models as well.

The thermal comfort model in this study was based on a single passenger. In practice, thermal comfort experiences among passengers may vary due to airflow and solar gain differentials across multi-seat zones.

6.5 Industrial Relevance and Scalability

The proposed open thermal intelligence framework offers three actionable takeaways for industry stakeholders:

1. Thermal-Aware Range Estimation: OEMs can integrate battery and HVAC thermal effects into predicted range estimates presented to users.
2. Predictive Thermal Safety Strategy: Real-time ML estimators could enable earlier interventions (e.g., coolant flow modulation or torque derating).
3. Cloud-Enabled Fleet Optimization: Fleet operators could reduce downtime and energy costs by pre-conditioning vehicles based on depot schedules and ambient forecasts.

Given the modularity and openness of this analysis, it also serves as a benchmark for academia and startups building AI-powered digital twins, EV fleet analytics, or domain-aware energy modeling engines.

7 Conclusion and Future Work

This article proposed an open and scalable pipeline to predict and optimize thermal performance in electric vehicles solely using publicly available datasets and open-source tools. By combining physics-based battery models, empirical driving and climate datasets, and standardized HVAC comfort models, we showed that by taking a hybrid thermal intelligence approach, useful insights can be obtained about energy efficiency, comfort optimization, and safety in various real-world environments.

Our key findings showed that:

• Hybrid physics–ML models significantly improved thermal prediction accuracy over purely physics-based or data-driven baselines.

• Although HVAC energy losses substantially reduce range when driving in hot or cold weather conditions, a comfort-aware contemplative control method can ameliorate these losses.

• A grid-powered pre-conditioning system shows promise as a low-cost intervention to reduce battery peak temperature and passenger discomfort before driving.

In summary, this study helps close the gap between academia and industry through an entirely reproducible framework that enables open discovery and collaboration and reduces the barriers preventing automotive startups, academic institutions, and fleet operators from innovating thermal management.

Future work will expand the framework in the following directions:

• 3D Component-Level Modeling: Developing pack-level heat transfer models with real-time inverter/motor data, using an open telemetry framework.

• Thermal-Aware Autonomous Systems: Engaging cabin and battery forecasts to improve routing and eco-driving algorithms for autonomous mobility platforms.

• Lifecycle Thermal Aging: Expanding the hybrid thermal models to include mechanisms for lithium plating, electrolyte oxidation, and additive decomposition during the vehicle lifecycle.

• Integration with Grid Flexibility: Providing tighter co-optimization with building energy systems and operators of a smart grid to coordinate electrical vehicle pre-conditioning with peaks in renewable energy supply.

The tools and datasets used in this work are fully accessible, enabling broad contributions from both the EV and AI communities to further advance thermal-aware electrification.

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All Figures

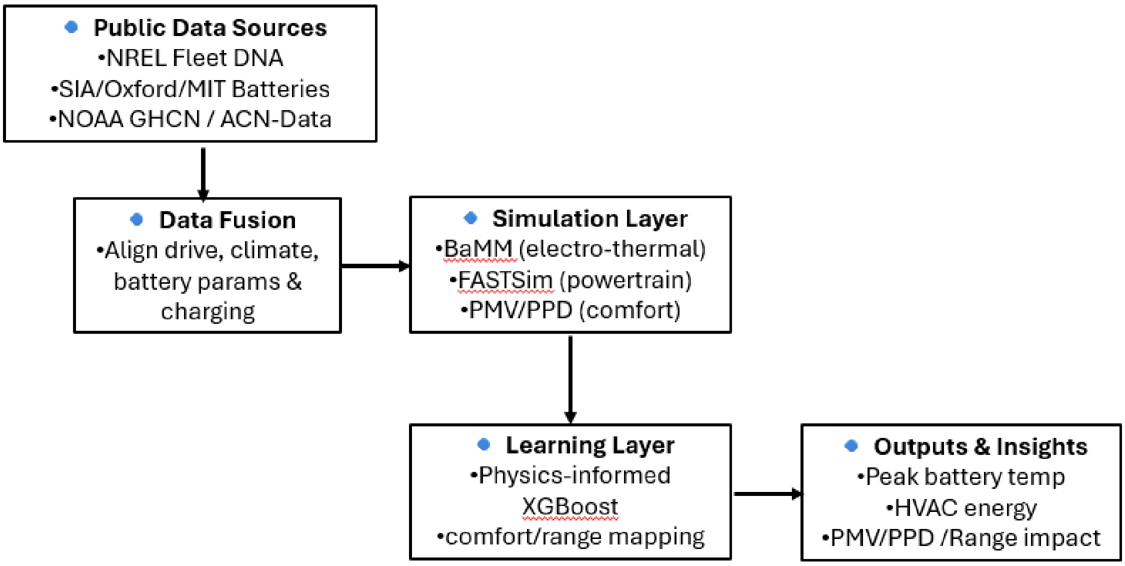

Figure 1: Scalable Thermal Intelligence Simulation Pipeline.

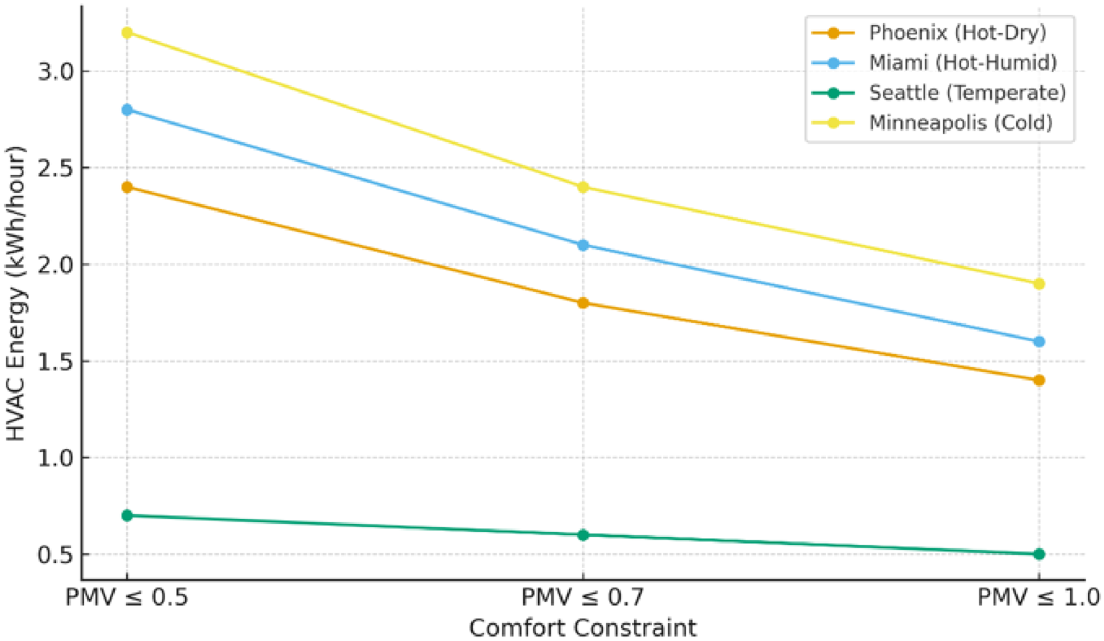

Figure 2: Comfort- Energy Trade0foof Across Climates

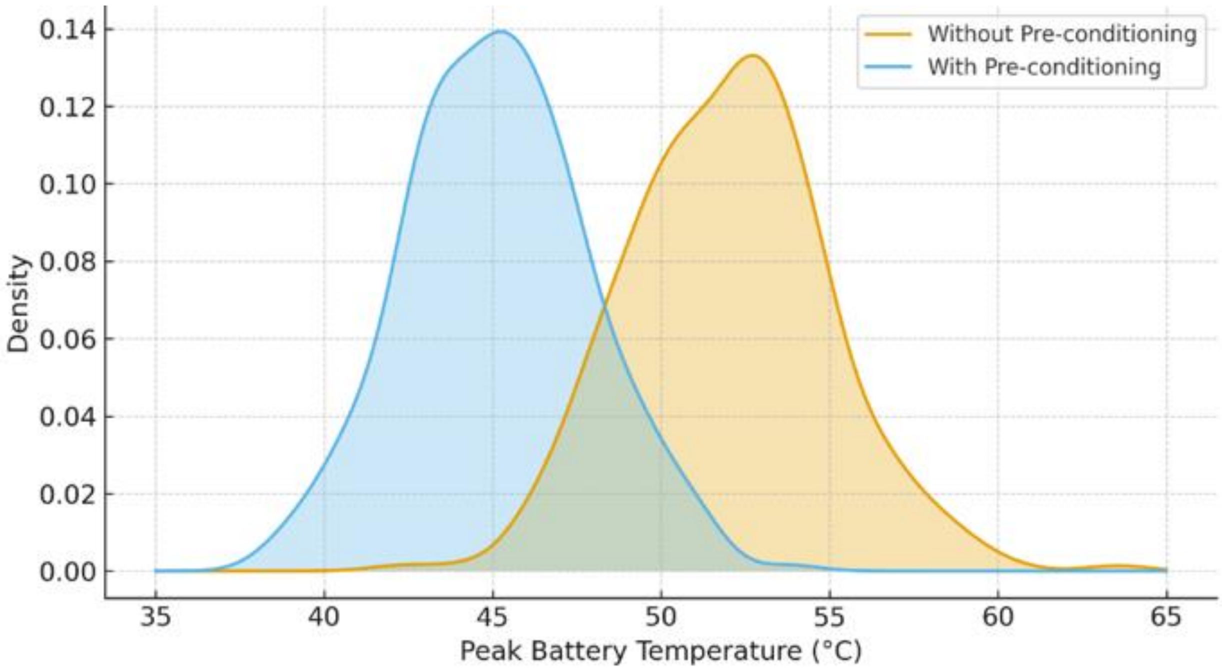

Figure 3: Distribution of peak eatery temperature with and without Pre-conditioning

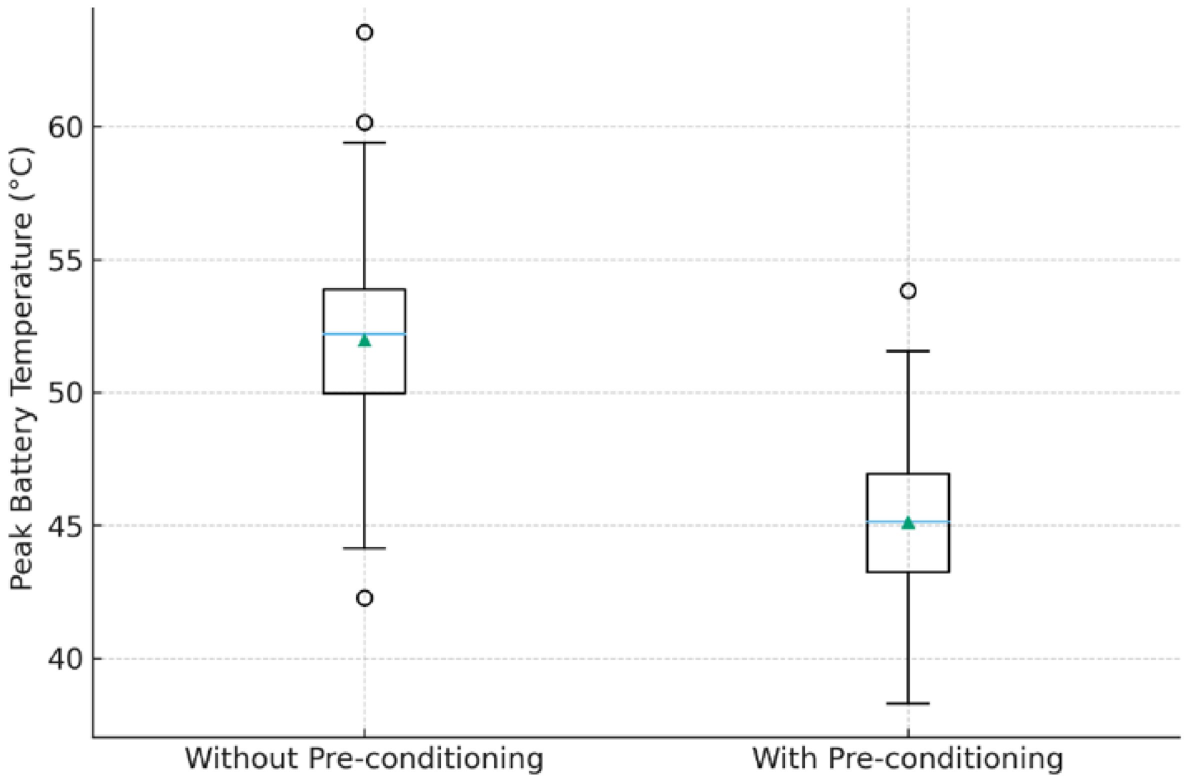

Figure 4: shows the peak battery temperature distribution across trips, with and without pre-conditioning, highlighting reduced instances of thermal safety exceedance.

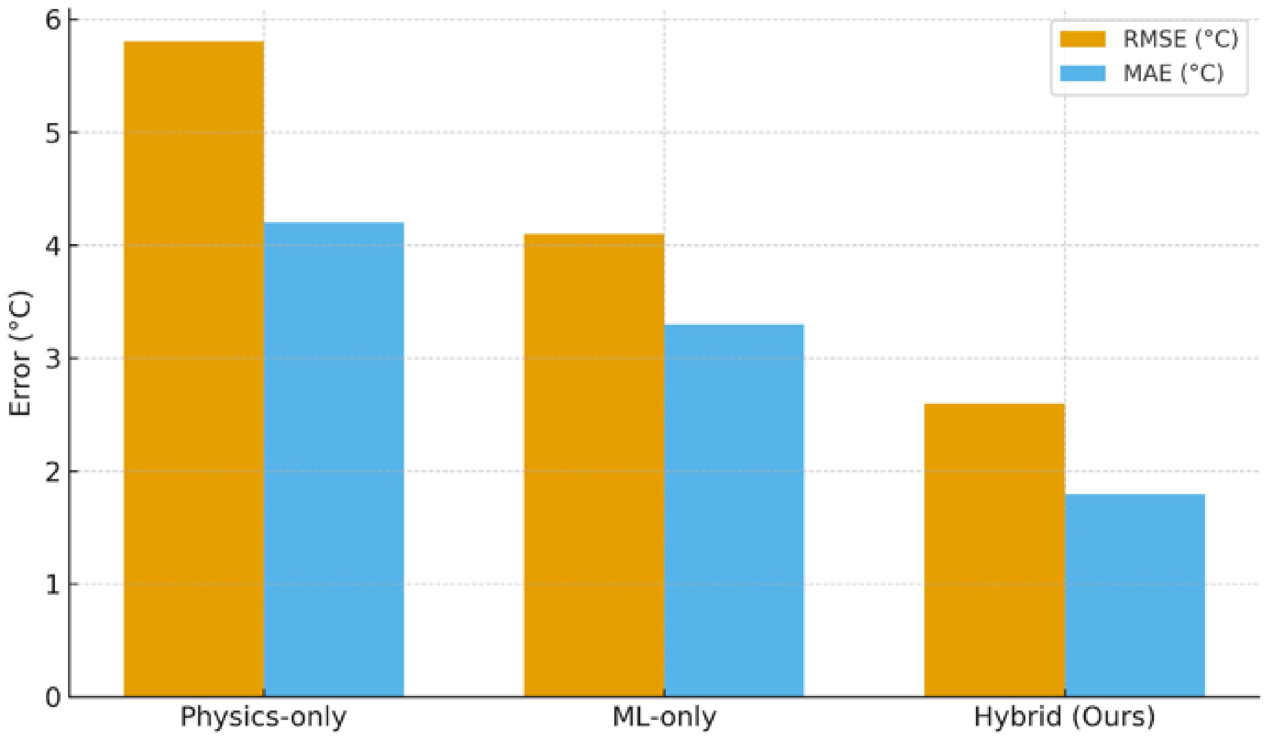

Figure 5: Battery Peak temperature Forecasting: Hybrid Vs. Baselines