

EV Trip Planner with Environmental Apis: A Survey on Intelligent Battery Drain Prediction using Weather, Elevation, and Speed Factors

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Abstract

Electric Vehicles (EVs) are rapidly transforming urban mobility; however, accurately predicting real-world battery drain remains a fundamental challenge for route-planning applications. This survey paper synthesizes and extends four state-of-the-art research works that collectively address urban link travel-time estimation from sparse GPS data, hybrid AI-based recommender systems for trip planning, multi-objective tourist itinerary optimization, and stochastic geometry modeling of dynamic EV charging road deployment. We integrate their findings into a unified conceptual framework for an EV Trip Planner that computes real-time battery consumption by coupling three environmental APIs: (1) a weather API whose temperature data modulates lithium-ion chemical efficiency, (2) the Mapbox Elevation API whose terrain gradients drive a physics-based energy model, and (3) highway speed limits that govern aerodynamic drag. Our analysis identifies critical gaps in existing literature — specifically the absence of joint environmental-routing optimization for EVs — and proposes an architecture that addresses these gaps for the Vision Astra EV Academy TechBuild project.

Index Terms — *Electric vehicles, battery drain estimation, route planning, weather API, Mapbox elevation API, GPS-based travel time, hybrid recommender systems, multi-objective optimization, dynamic wireless charging, stochastic geometry.*

I. INTRODUCTION

Electric vehicles (EVs) represent one of the most consequential transitions in personal transportation since the internal combustion engine. According to the International Energy Agency, EV adoption is expected to account for more than 60% of new passenger car sales globally by 2030. Yet one of the persistent concerns for both EV adopters and fleet operators is range anxiety — uncertainty about whether a vehicle will complete a journey without running out of charge. At the core of this anxiety lies a fundamental engineering problem: battery energy consumption is not static. It varies dynamically with temperature, road gradient, vehicle speed, driving behavior, and the availability of regenerative braking opportunities.

Current commercial navigation systems (Google Maps, Apple Maps, Waze) have begun incorporating rudimentary EV range overlays, but these tools largely ignore real-time environmental parameters. They do not account for the fact that at -10°C , a lithium-ion battery may lose up to 40% of its rated capacity, or that a 7% uphill gradient in a city such as San Francisco can triple instantaneous power draw compared to flat terrain. The TechBuild project group of Vision Astra EV

Academy aims to address this gap by designing an EV Trip Planner that fuses three live environmental API streams — weather, elevation, and roadway speed — into a continuous battery-drain model along the planned route.

To anchor this design in the academic literature, this survey paper distills and synthesises four peer-reviewed research contributions that each address a distinct sub-problem of the EV trip-planning challenge. Specifically:

- Ghandeharioun and Kouvelas (2022) [1] address how sparse GPS probe data can be used to estimate per-link urban travel times, which is the foundational problem of inferring road-segment performance from taxi OD data.
- AL Fararni et al. (2021) [2] present a hybrid AI recommender system for tourism that integrates user profiling, content-based filtering, collaborative filtering, and trip-planning optimisation — offering a framework transferable to EV routing.
- Choachaicharoenkul et al. (2022) [3] formulate the multi-objective tourist trip design problem with restaurant selection and compulsory points of interest, providing Pareto-based algorithms directly applicable to EV waypoint planning with charging constraints.
- Nguyen, Kishk, and Alouini (2021) [4] build a stochastic geometry framework for modeling city-wide dynamic wireless EV charging road deployment — directly informing the en-route charging opportunity module of the TechBuild planner.

The remainder of this paper is structured as follows. Section II provides detailed background from each of the four source works. Section III presents an integrated system architecture for the EV Trip Planner. Section IV discusses the battery drain model combining temperature, elevation, and speed signals. Section V analyses multi-objective routing with charging constraints. Section VI evaluates the framework against existing tools, and Section VII concludes with future directions.

II. BACKGROUND AND LITERATURE REVIEW

A. Urban Link Travel-Time Estimation from Sparse GPS Data

The foundational problem of estimating travel times on individual road links — rather than entire origin-to-destination paths — is thoroughly treated by Ghandeharioun and Kouvelas [1], who propose a parametric maximum-likelihood framework built on GPS probe data collected from New York City taxicabs. The authors observe that in most urban GPS datasets the precise trajectory of a trip is unknown; only the origin, destination, and total duration are recorded. Their method applies Yen's k-shortest-path algorithm to infer the most probable route, then distributes observed trip time to individual links through a decomposition scheme.

A particularly important contribution for the TechBuild project is their introduction of progressive spatial correlation. Classical parametric methods assume link travel times are spatially independent, which is demonstrably false — adjacent links share traffic signals, merge conflicts, and queue spillback. The progressive model updates a spatial correlation matrix across iterations based on directional changes in mean travel-time estimates, converging to a more realistic distribution. Experiments on the Manhattan network show that the progressive correlated model consistently achieves lower RMSE and MAPE than uncorrelated and static correlated variants. This directly motivates incorporating link-level travel time uncertainty into battery drain calculations, since a vehicle idling in unexpected congestion consumes energy without distance progress.

Key modelling assumptions from [1] that the TechBuild framework inherits include: Gaussian distributions for link travel times, a quarter-hourly temporal resolution, and exclusion of trips whose inferred path length deviates by more than 50% from the observed distance. The convergence criterion — mean relative parameter change below 1% across all links — serves as a quality gate that the TechBuild planner adopts when pre-computing route speed profiles from historical data.

B. Hybrid AI Recommender Systems for Trip Planning

The work of AL Fararni et al. [2] shifts the perspective from infrastructure estimation to user-centric recommendation. Their hybrid tourism recommender architecture combines three complementary filtering paradigms: content-based filtering (matching attractions to the user's previously visited or rated items), collaborative filtering (exploiting preferences of similar users), and context-aware filtering (incorporating geolocation, time, weather, and device state). The hybrid approach overcomes well-known single-method weaknesses: collaborative filtering struggles with the cold-start problem for new users, content-based filtering over-specialises, and context-aware systems require rich sensor data.

The proposed five-module architecture — visitor profiles, services repository, contextual meta-model, hybrid filtering process, and trip planner — maps naturally onto an EV routing context. In the TechBuild system, 'visitor profiles' become driver profiles capturing charging habits and range preferences; 'services repository' becomes a database of charging stations, fuel prices, and en-route amenities; and the 'contextual meta-model' incorporates real-time battery state-of-charge, ambient temperature, and elevation forecasts drawn from the Mapbox and weather APIs. The hybrid filtering process, augmented with operational research techniques (analogous to variants of the travelling salesman problem), selects the energy-optimal waypoint sequence.

The authors' discussion of big data integration layers — aggregation, recommendation, visualisation, and validation — is directly replicated in the TechBuild stack: a data ingestion layer collects API streams, a computation layer runs the energy model, a mobile/web presentation layer renders battery consumption overlays, and a feedback layer logs actual versus predicted consumption to retrain the model. Their emphasis on NoSQL storage (Cassandra, MongoDB) and distributed file systems (Hadoop HDFS) underpins the scalability requirements of a live EV routing application.

C. Multi-Objective Trip Design with Compulsory Waypoints

Choachaicharoenkul, Coit, and Wattanapongsakorn [3] address the tourist trip design problem (TTDP) as an instance of the Orienteering Problem with Time Windows (OPTW). Their novel variant — MOPTW-RSCP — adds restaurant selection (mandatory lunchtime stop), compulsory points of interest (POIs), and a second objective of minimising total walking distance alongside the standard objective of maximising the satisfaction score of visited attractions. The resulting Pareto front enables trip planners to select knee-point solutions that best balance the two conflicting objectives.

For the EV Trip Planner, the correspondence is direct: charging stations replace restaurants as mandatory waypoints, 'compulsory POIs' become must-visit destinations specified by the driver, and total distance is replaced by total battery energy consumed. The two objectives — maximise driver convenience (minimum detour, minimum total time) and minimise energy consumption — are inherently conflicting because the energy-minimising route (slowest speeds, flattest roads) differs from the time-minimising route. The Pareto-based approach proposed in [3] directly addresses this tension.

The authors propose two algorithms: a branch-and-cut algorithm that is exact but exponentially complex (practical only up to ~15 POIs), and a greedy algorithm that finds near-optimal Pareto fronts in under 1.5 minutes even for 50 POIs. Their RADA knee-point ranking algorithm post-processes the Pareto front to present the top-ranked itineraries to decision makers — a feature the TechBuild planner exposes as 'suggested routes' ranked by a composite driver-preference score. Experimental validation on the Rattanakosin Island (Bangkok) dataset confirms algorithm performance across 24 test cases varying the number of compulsory POIs from zero to three.

D. Stochastic Geometry Modelling of Dynamic EV Charging Deployment

The fourth foundational work, by Nguyen, Kishk, and Alouini [4], addresses a city-planning question that is prerequisite to EV route optimisation: given that a fraction p of roads are equipped with wireless dynamic charging capability, what is the probability that a random trip will pass through at least one charging road, and what is the distribution of the distance from trip origin to the nearest charging road?

The authors model the urban street network as a Manhattan Poisson Line Process (MPLP), a stochastic geometry abstraction that captures the grid-like structure of cities such as New York and Chicago. They derive closed-form probability distributions for both performance metrics across eight sub-events defined by the charging status of source and destination roads and their spatial relationship (parallel or perpendicular). Monte-Carlo simulations on Manhattan ($\lambda = 0.016$ road/m) and western Chicago ($\lambda = 0.006$ road/m) confirm the analytical results.

The key practical finding is that even when only 20% of roads are equipped with dynamic charging, a driver in Manhattan has an 80% chance of encountering a charging road within 500 m of trip origin. This directly informs the TechBuild planner's charging opportunity module: when the route passes through a high- p corridor (e.g., a city-centre arterial), the planner can extend range forecasts by the expected en-route charge accumulated, computed from the trip efficiency metric (fraction of total trip on charging roads) derived from [4].

III. INTEGRATED SYSTEM ARCHITECTURE

Drawing on all four reviewed works, the TechBuild EV Trip Planner is structured as a five-layer pipeline, illustrated conceptually below. Each layer maps to one or more source contributions.

A. Data Ingestion Layer

This layer continuously polls three external APIs and an internal historical datastore. The OpenWeatherMap API provides ambient temperature T ($^{\circ}\text{C}$), wind speed v_w (m/s), and precipitation type at each waypoint along the planned route. The Mapbox Elevation API returns digital elevation model (DEM) values at configurable resolution, enabling computation of grade (%) for every road segment. Speed data are obtained either from the HERE or TomTom traffic APIs or inferred from historical travel-time estimates following the methodology of Ghandeharioun and Kouvelas [1]. Charging-road availability is modelled probabilistically using the MPLP framework of Nguyen et al. [4], parameterised with city-specific road density λ and infrastructure deployment ratio p .

B. Energy Computation Layer

The energy computation layer implements a physics-based model of instantaneous power draw for a reference EV. For a road segment of length d (m), grade θ (degrees), vehicle speed v (m/s), and ambient temperature T ($^{\circ}\text{C}$), the energy consumed E_{seg} (Wh) is:

$$E_{\text{seg}} = [F_{\text{roll}} + F_{\text{grade}} + F_{\text{aero}} + F_{\text{HVAC}}(T)] \times d / (3600 \times \eta_{\text{drivetrain}})$$

where $F_{\text{roll}} = \mu_r \times m \times g \cos \theta$ is rolling resistance ($\mu_r = 0.01$ for typical tyres), $F_{\text{grade}} = m \times g \sin \theta$ is gravitational load on a slope, $F_{\text{aero}} = \frac{1}{2} \times \rho \times C_d \times A \times v^2$ is aerodynamic drag ($\rho =$ air density, $C_d =$ drag coefficient, $A =$ frontal area), and $F_{\text{HVAC}}(T)$ is the temperature-dependent HVAC load. Regenerative braking on downhill segments recovers a fraction η_{regen} of the gravitational potential energy. The temperature correction factor for battery capacity $C(T)$ follows an empirical quadratic model $C(T) = C_{\text{rated}} \times (1 - \alpha \times (T - 25)^2)$ where $\alpha \approx 0.003 / ^{\circ}\text{C}^2$ for standard lithium-ion chemistry, based on published cell characterisation studies.

C. Route Optimisation Layer

Given a set of driver-specified waypoints $W = \{w_1, \dots, w_k\}$, the route optimisation layer solves a variant of the MOPTW-RSCP problem from [3] with two objectives: minimise total energy E_{total} and minimise total travel time T_{total} . Mandatory charging stops are inserted whenever the state-of-charge (SOC) is forecast to fall below a safety threshold (default: 15%). The greedy algorithm from [3] is adapted to handle energy constraints, producing a Pareto front of candidate routes from which the driver selects using the RADA knee-point ranking.

D. Recommendation Layer

Following the hybrid recommender architecture of AL Fararni et al. [2], the recommendation layer constructs a driver profile from historical trips, explicit preferences (e.g., preferred charging networks, maximum detour tolerance), and contextual signals (current battery SOC, time of day, weather severity). Content-based filtering matches route characteristics to the driver's historical behaviour; collaborative filtering surfaces routes preferred by similar drivers in comparable conditions. The combined score re-ranks the Pareto-optimal routes from the optimisation layer.

E. Presentation and Feedback Layer

The presentation layer renders battery consumption as a colour-coded overlay on the Mapbox map (green $\geq 50\%$ SOC, yellow 25–50%, red $< 25\%$), with real-time recalculation as conditions change. After trip completion, actual energy consumption is logged and fed back to retrain the energy model and update the driver profile, progressively improving prediction accuracy — analogous to the validation layer proposed in [2].

IV. BATTERY DRAIN MODEL: ENVIRONMENTAL API INTEGRATION

A. Temperature Effect on Battery Chemistry

Lithium-ion batteries exhibit a well-documented non-linear dependence of available capacity on temperature. At temperatures below 10°C, internal resistance increases substantially, reducing both the usable capacity and the peak power the battery can deliver. This is compounded by cabin heating demands: an EV may consume 3–5 kW for HVAC at –10°C, representing 20–30% of a typical 15–20 kW average road-load. The TechBuild model parameterises HVAC load as $F_{\text{HVAC}}(T) = \max(0, k_{\text{heat}} \times (T_{\text{comfort}} - T))$ for $T < T_{\text{comfort}}$, and $F_{\text{HVAC}}(T) = \max(0, k_{\text{cool}} \times (T - T_{\text{comfort}}))$ for $T > T_{\text{comfort}}$, where $T_{\text{comfort}} = 22^\circ\text{C}$ and k_{heat} , k_{cool} are vehicle-specific coefficients calibrated from manufacturer data.

The weather API integration polls temperature at 15-minute intervals along the planned route, using forecast temperatures for future waypoints. This is consistent with the temporal resolution used in [1], whose quarter-hourly travel-time estimates serve as the speed inputs to the aerodynamic drag term. Precipitation (rain, snow) increases rolling resistance by 15–25% due to tyre-road contact effects, and is modelled as a multiplicative factor on μ_r .

B. Elevation and Grade from the Mapbox Elevation API

The Mapbox Terrain-RGB API provides elevation tiles at up to 5-metre horizontal resolution. The TechBuild layer samples elevation at every 100 m along the planned route polyline, computing instantaneous grade as the finite difference of consecutive elevation samples divided by horizontal distance. Grade values are clipped at $\pm 20\%$ to exclude artefacts from bridge overpass misalignment in the DEM.

Positive grades (uphill) add to the propulsive energy demand; negative grades (downhill) trigger regenerative braking recovery. The net energy over a segment with variable grade profile is computed by numerical integration using a trapezoidal rule applied to the per-sample power estimates. This approach captures the significant asymmetry between climbing and recovery: regenerative efficiency $\eta_{\text{regen}} \approx 0.60\text{--}0.70$ means that climbing an elevation gain ΔH costs significantly more energy than descending the same ΔH recovers.

C. Highway Speed and Aerodynamic Drag

Aerodynamic drag scales as the cube of speed ($\text{power} = F_{\text{aero}} \times v \propto v^3$), making it the dominant energy consumer above 80 km/h. A driver cruising at 120 km/h on a motorway consumes approximately 2.4× the aerodynamic drag energy of the same driver at 80 km/h. The TechBuild planner fetches posted speed limits from the Mapbox Directions API and combines them with real-time traffic speed estimates derived from the travel-time model of Ghandeharioun and Kouvelas [1], using the lower of the two as the effective road-speed input.

For motorway segments, the spatial correlation model from [1] is particularly valuable: travel times on adjacent motorway links are strongly correlated ($\rho \approx 0.7\text{--}0.9$ for consecutive links), so uncertainty in one link propagates predictably to adjacent links. The progressive spatial correlation update in [1] thus allows the energy model to propagate speed uncertainty across motorway corridors, producing confidence intervals on battery consumption that the UI displays as forecast SOC range bands.

V. MULTI-OBJECTIVE ROUTING WITH CHARGING CONSTRAINTS

A. Problem Formulation

The EV routing problem with charging constraints is formulated as a bi-objective optimisation: (i) maximise driver convenience (minimise total travel time T_{total} including waiting at chargers) and (ii) minimise total energy consumption E_{total} . These objectives conflict because slower speeds reduce aerodynamic drag and extend range, but increase journey time. Mandatory charging stops (when $\text{SOC} < \text{SOC}_{\text{min}}$) are modelled as compulsory POIs following the OPCNTW formulation of [3].

Let $G = (V, E)$ be the road network graph where V is the set of nodes (intersections + charging stations + destination waypoints) and E is the set of directed edges (road segments) weighted by travel time t_{ij} and energy cost e_{ij} . A feasible

route $R = (v_0, v_1, \dots, v_n)$ must satisfy: (a) all compulsory waypoints are visited, (b) at least one charging station is visited whenever cumulative energy consumption between consecutive charging visits would reduce SOC below SOC_{min} , and (c) the route begins and ends at the specified origin and destination.

B. Pareto Front Generation

Adopting the greedy Pareto-based algorithm from [3], the TechBuild planner iteratively builds routes by inserting the next best node (greedy by convenience score) and pruning branches that violate energy feasibility. Pareto dominance is tested after each valid route completion: route A dominates route B if A achieves strictly lower E_{total} and T_{total} than B, or equals one objective while strictly bettering the other. The non-dominated solution set constitutes the Pareto front presented to the driver.

For datasets of up to 50 candidate waypoints (consistent with urban trip planning), the greedy algorithm from [3] completes in under 1.5 minutes on commodity hardware, meeting real-time requirements. For longer inter-city trips with hundreds of potential charging stops, a hierarchical decomposition pre-clusters the route into city-scale segments, applies the algorithm within each segment, and stitches the segment Pareto fronts using dynamic programming.

C. Charging Opportunity Integration

Dynamic wireless charging roads, modelled via the stochastic geometry framework of Nguyen et al. [4], introduce a probabilistic energy gain that depends on the route's overlap with the city's charging road network. Given a road segment of length L on a road with charging probability p and linear charging density λ_c , the expected energy recovered is:

$$E_{gain}(L) = P(T_c) \times P_{charger} \times (L / v_{segment})$$

where $P(T_c)$ is the probability of encountering at least one charging road (from Theorem 2 in [4]) and $P_{charger}$ is the rated charging power in Watts. This gain term is subtracted from E_{seg} in the energy model, effectively extending the predicted range on routes that traverse high-density charging corridors. The Pareto front is thus re-computed with charging opportunity gains, producing a shifted Pareto curve that reveals the value of routing through charging-equipped arterials even at slight time cost.

VI. DISCUSSION AND COMPARATIVE ANALYSIS

A. Strengths of the Proposed Framework

The primary strength of the TechBuild EV Trip Planner relative to existing commercial tools is the integration of environmental signal fidelity with multi-objective optimisation. Where Google Maps EV mode applies a single static energy model, the proposed framework dynamically adjusts for temperature (via weather API), slope (via Mapbox elevation), and congestion-modulated speed (via the travel-time model of [1]). The hybrid recommender architecture from [2] further personalises the route to driver behaviour, and the Pareto-ranking mechanism from [3] provides transparent trade-off information rather than a single opaque recommendation.

The stochastic geometry model from [4] enables the planner to reason about charging infrastructure as a probabilistic resource rather than a deterministic point-of-interest database — important in cities where wireless charging deployment is still nascent and may be unreliable.

B. Limitations and Open Challenges

Several limitations remain. First, the energy model assumes a reference vehicle; in practice, C_d , A , and η_{regen} vary across EV models. A vehicle-profile database must be maintained and kept current. Second, the MPLP model of [4] assumes a perfectly grid-like city; irregular urban geometries (common in Indian cities such as Bengaluru, the home city of the TechBuild group) require extension to general Poisson Line Processes. Third, the progressive spatial correlation model of [1] was validated on New York City taxicab data; its transferability to two-wheeler or electric rickshaw datasets in South Asian cities has not been established. Fourth, real-time API latency — particularly for elevation queries at high polyline resolution — may exceed acceptable route-recalculation times.

C. Comparison with Related EV Planning Tools

Feature	Google Maps EV	A Better Route Planner	PlugShare	TechBuild (Proposed)
Temp. Correction	Partial	Yes	No	Full (API)
Elevation Model	Basic	Yes	No	Mapbox (5m res.)
Real-time Traffic	Yes	Partial	No	Yes (GPS model)
Multi-objective Opt.	No	No	No	Yes (Pareto)
Dynamic Charging	No	No	No	Probabilistic
Personalisation	Basic	Basic	No	Hybrid AI

Table I. Feature comparison of EV trip planning tools

VII. CONCLUSION

This survey has demonstrated that the problem of EV trip planning with environmental APIs is not merely a software engineering challenge but a rich interdisciplinary research problem spanning traffic engineering, operations research, AI recommendation systems, and stochastic network theory. By synthesising four peer-reviewed contributions — GPS-based travel-time estimation [1], hybrid AI trip planning [2], multi-objective orienteering optimisation [3], and stochastic geometry EV charging analysis [4] — we have constructed a unified conceptual framework for the Vision Astra EV Academy TechBuild project.

The proposed EV Trip Planner integrates real-time data from three environmental APIs (weather, Mapbox elevation, and traffic speed) into a physics-based energy model that accounts for temperature-induced capacity degradation, elevation-driven grade forces, and velocity-cubed aerodynamic drag. A Pareto-based multi-objective optimiser, adapted from [3], presents drivers with transparent trade-offs between travel time and energy consumption. A hybrid AI recommender layer, inspired by [2], personalises route selection to individual driver profiles. And a probabilistic dynamic charging opportunity module, grounded in the stochastic geometry of [4], extends range forecasts in cities with wireless charging infrastructure.

Future work will focus on extending the MPLP charging model to non-grid urban geometries, validating the energy model on South Asian EV platforms (electric two-wheelers, e-rickshaws), and integrating real-time battery degradation signals to personalise the capacity model to each individual vehicle's ageing state. The TechBuild team aims to deploy a functional prototype on the Bengaluru road network within the 2025–2026 academic year.

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