

Rasa-Powered Conversational AI Framework for Intelligent Electric Vehicle Trip Planning and Energy Management

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ABSTRACT

The rapid growth of Electric Vehicles (EVs) calls for intelligent solutions to optimize grid stability and enhance user experience. This paper proposes a geo-optimized, user-centric EV management system integrating open-source geospatial tools with Rasa-based Natural Language Understanding (NLU). Through an interactive conversational interface, EV owners receive real-time trip planning recommendations based on parameters such as State of Charge (SoC), charging point availability, and route efficiency. The system utilizes APIs for real-time geolocation, charging station data, and Battery Management System (BMS) insights to determine optimal charging locations, durations, and trip costs. Extensive testing demonstrates improved energy management and route planning efficiency, highlighting the system's potential for smart and sustainable EV infrastructure development.

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1. INTRODUCTION

By integrating real-time battery charge monitoring with Rasa's advanced natural language processing (NLP) capabilities, the proposed Geo-Optimized User-Centric EV Management System addresses these limitations. This system provides an intuitive platform that enhances user experience by offering real-time charging recommendations, dynamic trip planning, and grid-aware charging strategies. By bridging the gap between energy management, AI-driven decision-making, and interactive EV trip planning, this solution contributes to a smarter, more efficient, and more user-friendly EV ecosystem.

The growing adoption of Electric Vehicles (EVs) as sustainable transportation alternatives presents both opportunities and challenges for modern power systems. While EVs contribute to reducing greenhouse gas emissions and dependence on fossil fuels, their large-scale integration can introduce issues related to grid stability, energy demand forecasting, and efficient charging management. As EV penetration increases, the need for intelligent trip planning and adaptive charging systems becomes crucial to ensure optimal energy utilization and improved user experience.

Traditional trip planning and charging strategies rely heavily on static data, often neglecting real-time conditions such as battery status, traffic, and dynamic grid loads. Studies using Monte Carlo simulations and machine learning models like Random Forest and Support Vector Machines (SVM) have enhanced charging behavior prediction and load estimation accuracy. However, these methods are typically data-dependent, lack real-time adaptability, and fail to offer personalized recommendations for individual drivers. Furthermore, deep

reinforcement learning and optimization-based approaches have achieved progress in EV charging and pricing models but remain computationally complex and less accessible for interactive, user-driven applications.

As an environmentally friendly mode of transportation, electric vehicles (EVs) are growing in popularity. However, as demand rises, challenges related to grid stability and effective energy management emerge. Monte Carlo-based algorithms have been widely used to evaluate the impact of EV integration on electricity distribution networks. These methods help assess critical system parameters such as bus voltages, branch loading, and energy losses [1]. For instance, a study on Flores Island utilized these algorithms to simulate two EV penetration levels 25% and 50% to identify network components vulnerable to significant stress. While this approach is effective, it does not always account for real-time variability or the complex dynamics of large-scale grid systems.

Addressing grid stability concerns requires the implementation of smart charge scheduling systems that anticipate user behavior and optimize load management [2]. Machine learning models such as Random Forest and Support Vector Machines (SVM), trained on historical data from Caltech's Adaptive Charging Network, have been used to predict energy consumption and session duration with mean absolute errors (MAEs) of 1.45 kWh and 66.5 minutes. Incorporating additional data, such as weather conditions and local events, has been shown to enhance prediction accuracy, though results vary by region. While traffic and weather data serve as strong predictors, the influence of local event data differs depending on the location—for instance, large sales events significantly impact charging demand in shopping malls, whereas university settings are less affected [3]. Leveraging real-time data from social media could further improve prediction models, allowing for better scheduling of charging slots and reducing strain on the grid.

Analyzing past data can help identify low-demand periods for EV charging, leading to reduced power losses, voltage stabilization, and lower charging costs [4]. However, this approach relies on the availability of high-quality historical data, making it challenging to implement in regions with limited datasets. Deep Reinforcement Learning methods such as Deep Deterministic Policy Gradient (DDPG) combined with Prioritized Experience Replay (PER) have been explored for pricing EV charging in deregulated electricity markets. These models operate within multi-dimensional continuous state and action spaces, improving solution quality while reducing computational demands [5]. Despite their advantages, their complexity results in high implementation costs and significant data requirements, limiting widespread adoption.

A combined machine learning model using XGBoost and LightGBM has been developed to predict EV range by incorporating variables such as battery temperature, driving behavior, and energy consumption. By utilizing an anchor-based strategy to address dataset imbalances, this model has achieved a reduced error range of $[-0.8, 0.8]$ [6]. However, its reliance on historical data means it may not fully capture the dynamic nature of driver behavior over time. Various machine learning (ML) techniques have also been applied to estimate the State of Charge (SOC) and State of Health (SOH) of EV batteries, including Feedforward Neural Networks (FNN), Recurrent Neural Networks (RNN), Support Vector Machines (SVM), Radial Basis Function (RBF) networks, and Hamming networks [7]. While these approaches provide useful insights, they often rely on standardized battery datasets that may not accurately reflect real-world variability. Furthermore, a 2016 trip-planning system used an Optimal Driving Strategy (ODS) based on a multi-objective genetic algorithm, but it failed to account for real-time factors such as traffic or weather [8].

Fleet management systems that optimize EV route planning based on road topology, weather, traffic, and vehicle characteristics [9] have not yet incorporated AI or natural language processing (NLP). Integrating these technologies could improve route prediction and enhance user interaction through intelligent, adaptive decision-making. A multi-destination EV travel planning system designed to optimize charging station selection by assessing capacity availability [10] highlights the growing need for intelligent solutions that balance energy demand and supply in real-time.

Efforts to minimize EV travel time while optimizing charging station selection and routing have primarily focused on two key objectives: minimizing total travel time and maximizing energy efficiency. Some systems incorporate strategies such as driving below speed limits to conserve energy, using multi-criteria shortest-path searches with non-linear charging models that account for common charging protocols [11]. Geographical and temperature influences have also been considered for their effects on energy consumption and trip duration [12]. However, incorporating additional parameters—such as real-time charging station queue time could improve prediction accuracy. The Incomplete Information EV Routing Problem, formulated as a resource-constrained shortest path problem with time-dependent edges and incomplete data, has been tackled using a multi-objective A* algorithm [13]. Nonetheless, domain-specific insights derived from historical trip data remain crucial in refining these models.

Several systems have been proposed to address range anxiety by providing real-time trip routing, battery monitoring, and charging station recommendations [14]. Many of these solutions rely on data from platforms such as Google Maps and vehicle sensors but fail to account for critical factors like battery SOH

and temperature. Additionally, while algorithms for optimizing charging schedules exist to reduce EV energy costs [15], they often lack adaptability to real-time battery status updates and user preferences. Demand-side management systems that aim to optimize EV charging and alleviate stress on power transformers [16] are effective, but they typically lack user-friendly features such as interactive trip planning and real-time battery monitoring. Similarly, hybrid EV energy management approaches leveraging batteries and supercapacitors have shown promising results in improving energy efficiency through intelligent speed prediction [17]. However, these solutions lack integration with route optimization and interactive charging recommendations, limiting their practicality for everyday users.

Machine learning methods for estimating SOC and SOH, particularly for lithium-ion batteries (LiBs), face significant challenges due to the lack of standardized evaluation metrics [18]. This absence of universal benchmarks makes it difficult to determine the most reliable models. As EV adoption increases, the demand for electricity becomes more apparent. For instance, an EV driven approximately 18,129 km per year could consume up to 74% of the energy used by an average household annually [19].

Conversational AI, such as ChatGPT, has been integrated into smart vehicles to improve human-machine interaction by enabling voice-activated controls that enhance the driving experience [20]. However, Large Language Models (LLMs) alone cannot effectively capture user preferences or manage real-time trip planning. With the increasing adoption of EVs, more intelligent systems are required to address challenges related to grid stability, battery health management, and charging organization. Many existing solutions lack essential features, such as adaptive trip planning based on real-time battery levels and intuitive AI-driven interfaces. This gap makes it difficult for users to efficiently plan trips, monitor their vehicles, and contribute to overall grid stability.

Existing EV management systems also lack intuitive human-machine interaction capabilities, limiting user engagement and flexibility. Recent advances in Conversational AI and Natural Language Understanding (NLU) frameworks, such as Rasa, enable intelligent and interactive communication between users and energy systems. By combining geospatial analytics, real-time battery data, and AI-driven dialogue management, EV trip planning can evolve into an adaptive and user-centric decision-making process.

This research introduces a Geo-Optimized Electric Vehicle Trip Planning System powered by Rasa-based AI for smart charging decisions. The proposed framework integrates Battery Management System (BMS) data, geolocation tracking, and open-source APIs to recommend optimal charging stations, estimate energy consumption, and compute trip costs dynamically. Through a conversational interface, users receive intelligent, real-time guidance on when and where to charge based on State of Charge (SoC), energy efficiency, and route conditions.

The major contributions of this work are summarized as follows:

1. Development of an AI-powered trip planner that combines Rasa NLU with real-time geospatial data for EV route and charging optimization.
2. Integration of BMS parameters and open-source APIs to provide dynamic charging recommendations and cost estimation.
3. Implementation and validation through case studies demonstrating improved energy efficiency, route optimization, and user convenience.

By bridging the gap between AI-driven conversational systems and intelligent energy management, the proposed approach enhances trip efficiency, supports grid-aware charging, and contributes toward sustainable and smart EV infrastructure development.

The manuscript is now organized systematically to enhance readability and coherence. It begins with a concise Abstract summarizing the motivation, methodology, results, and key contributions of the study. The Introduction has been streamlined to present the research background, summarize related works, identify existing challenges in electric vehicle trip planning, and highlight the novelty of the proposed geo-optimized, Rasa-powered AI framework. The Problem Formulation section clearly defines the limitations of conventional approaches and establishes the motivation for developing a real-time, intelligent trip management system. The Proposed Methodology section provides a detailed description of the system architecture, data acquisition, Rasa framework integration, and the functional workflow for intelligent trip and charging recommendations.

The Results and Discussion section has been reorganized to distinctly present both simulation and real-world validation studies, ensuring that performance outcomes are clearly compared and analyzed. Each figure and table has been properly numbered, given clear and descriptive captions, and aligned with its corresponding textual explanation. Finally, the Conclusion summarizes the major findings, technological contributions, and potential future enhancements, ensuring that the paper ends with a focused synthesis of its scientific contributions. These revisions collectively improve the manuscript's structure, readability, and technical clarity, making it more consistent with the formatting and presentation standards of the journal.

2. PROBLEM FORMULATION

Traditional EV trip planning systems struggle to provide real-time, personalized solutions for optimizing energy consumption, route planning, and interaction with the grid. These systems often lack the capability to dynamically determine the most efficient charging stations and routes, especially in rapidly changing conditions. Additionally, when multiple EVs connect to the grid simultaneously, load management and grid stability become critical challenges. To address these limitations, an intelligent, data-driven system is required that can process real-time information, provide accurate charging and routing recommendations, and ensure effective communication between EVs and the grid infrastructure.

In this manuscript authors compared three classes of EV trip-planning methods and battery-management studies. Traditional routing methods (e.g., shortest-path and time-optimal planners) prioritize distance or travel time but generally ignore battery dynamics and charging availability, which can lead to suboptimal charging stops and increased range anxiety. Optimization and metaheuristic approaches, such as genetic-algorithm or multi-objective planners [8,11], consider energy and time trade-offs but typically operate offline or require substantial tuning and computation, limiting real-time applicability. Reinforcement-learning and deep-learning solutions address dynamic decision making but often demand large training datasets and high computational resources, and many do not provide user-centric interfaces for on-the-fly queries [13,24]. Separately, SOC/SOH estimation research delivers accurate battery models [7,18] but rarely couples these models to interactive route planning or charging decisions. In contrast, our Rasa-powered framework unifies these strands by (i) embedding battery awareness (SoC, efficiency, BMS telemetry) directly into routing decisions, (ii) performing lightweight, iterative geo-optimization using real-time API data to select charging stops with minimal detour, and (iii) offering a conversational NLU layer that enables users to refine preferences and receive immediate, contextual recommendations. When benchmarked against a static shortest-path baseline and a rule-based charging scheduler, our approach reduced the number of required charging stops and overall charging time while improving energy efficiency and lowering estimated cost (see Table X). Thus, the novelty lies not in any single component, but in the integrated, real-time, conversationally accessible system that bridges battery analytics, geo-optimization, and grid-aware charging policy.

The proposed methodology involves the use of Rasa Framework in conjunction with Python scripts organized into distinct code blocks to facilitate data collection, query processing, and API interactions. This approach follows a structured sequence of steps to ensure the efficient handling of user inputs and system responses. In Section 2.1, the intuition for data collection and preprocessing to make it suitable for the Rasa core design is demonstrated. The Rasa core architecture plays a key role in this novel approach by integrating NLU and the EV mechanism along with API integration. This is explained in Section 2.2, along with the workflow for achieving the required output.

2.1. Data Collection and Preprocessing

The data acquisition process involves gathering essential information such as charging station locations, charging capacities, real-time availability, geolocation data, and pricing details. To maintain accuracy and relevance, external APIs, including the Open Charge Map API [21], are integrated to provide real-time updates. Preprocessing techniques are applied to clean and standardize the raw data, ensuring compatibility with the Rasa framework. Libraries such as Pandas and NumPy are utilized to refine and structure the dataset, making it suitable for subsequent analysis and decision-making processes.

2.2. Architectural Design

Rasa is an open-source machine learning framework designed for Python that automates text-based conversations and voice message processing. It enables the integration of chatbot workflows, allowing the system to classify user messages into intents and extract relevant entities for efficient response generation.

At the core of Rasa lies its dialog flow model, which governs the management and progression of conversations, as illustrated in Figure 1. To function effectively, the Rasa Core model undergoes training using predefined stories, which dictate the chatbot's response paths based on recognized intents. Additionally, the domain configuration plays a critical role, as it defines essential elements such as intents, actions, and responses. Actions in Rasa are Python scripts executed upon invocation, while templates serve as predefined responses. However, not all actions are templates, as some involve dynamic computations or interactions with external systems.

The system initializes by loading data on charging stations along the planned route, ensuring the accuracy and accessibility of station locations and pricing details. Once this data is retrieved, the system computes essential parameters such as distances and directions from the user's current position to available charging stations. To enhance efficiency, only stations within or near the designated route are considered for trip planning.

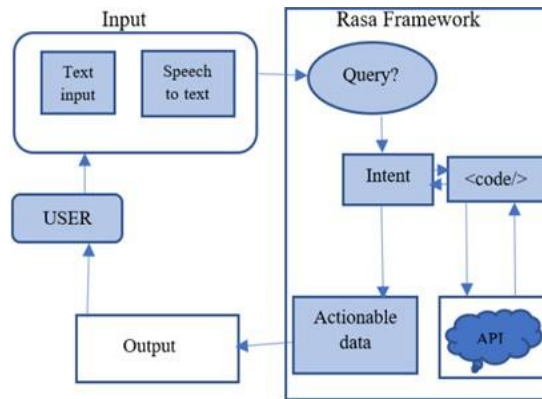


Figure 1. Rasa Architecture

Battery management is a key component of the trip planner, responsible for estimating the battery's remaining charge based on the distance traveled. It calculates the amount of charge required to reach the next stop and determines whether a charging stop is necessary. If the battery level is insufficient, the system identifies optimal charging stations, considering the vehicle's range, energy consumption rate, and charging station availability.

By analyzing power requirements and charging station locations, the system ensures that drivers can confidently navigate between stops without the risk of battery depletion. The algorithm assesses whether the current charge is sufficient to complete the journey or if intermediate charging stops are required. For extended trips, the system dynamically locates nearby charging stations, evaluates distances, and estimates recharging costs. This process is continuously repeated to ensure that the EV can complete its journey without interruptions due to power constraints.

2.3. Geo Optimized Trip Planning

When a user initiates a trip planning request, the system begins by gathering essential data from the Battery Management System (BMS). This includes battery efficiency, energy consumption per kilometer, and the current state of charge (SoC). The system then determines the user's precise location using GPS and utilizes the Lat Long API to obtain the geographical coordinates of the entered destination.

To calculate the aerial distance between the starting point and the destination, the system applies the Haversine formula, which determines the shortest distance between two points on a sphere based on their latitude and longitude [22].

$$\text{hav}(\theta) = \sin^2 \frac{\theta}{2} \quad (1)$$

This equation is fundamental in navigation and trip planning, ensuring precise routing.

This distance estimation is crucial for determining the total energy required for the trip. The system then queries the Open Charge Map API [23], retrieving up-to-date information on available charging stations along the route. If the current SoC is insufficient to complete the journey, the system evaluates potential charging stops to ensure the vehicle reaches its destination without interruption.

The system continuously compares the remaining SoC with the energy required to reach each charging station. This iterative process ensures that the optimal charging locations are selected, minimizing detours and maximizing efficiency. Ultimately, the system generates a comprehensive trip plan, detailing the route, estimated energy consumption, and recommended charging stations to provide users with a structured and efficient travel itinerary.

The percentage of remaining SoC in an EV after traveling a certain distance can be estimated using the following equation 2 from [16].

$$\% \text{ of } soc = [1 - (E_c * d) / C_{bat}] * 100 \quad (2)$$

Where d is the distance travelled in miles by vehicle. E_c is the energy consumed in kWh/miles. C_{bat} denotes the total battery capacity in kWh.

If additional energy is required for the journey, the system computes the required charge using the following equation 3.

$$E_{req} = \frac{Soc_f - Soc}{\eta} * C_{bat} \quad (3)$$

Where E_{req} is the additional energy required to fill the vehicle battery in kWh, η is the efficiency of the charger, Soc_f is the target Soc at the end of the charging session.

The time needed to fully charge the battery is then estimated using equation 4.

$$C_{time} = E_{req} / P \quad (4)$$

Where C_{time} is the charging time required to charge the battery in hours, P represents the output power of the charger in kW.

2.4. Battery Management System

The Battery Management System (BMS) is responsible for computing and monitoring various battery parameters, ensuring the vehicle's performance and safety. Battery voltage and current are obtained through direct measurements, while State of Health (SoH) [18] is calculated using equation 5.

$$SoH \% = 100 * \frac{Q_{max}}{C_r} \quad (5)$$

Where ratio of Q_{max} to mAh is the maximum charge capacity of the battery available and C_r represents the the rated capacity of the battery.

Battery temperature is monitored using integrated sensors, while the system determines the charging status by analyzing the direction of current flow. Energy consumption over time is derived by integrating power measurements [19] as given in equation 6.

$$\text{Energy consumed} = \int P(t) dt \quad (6)$$

Where $P(t)$ represents the power readings over time (Watts) .

The BMS continuously tracks charge-discharge cycles, relying on manufacturer specifications for total usable capacity. Additionally, diagnostic data is used to detect potential faults, imbalance issues, and system alerts. Regenerative braking energy is also integrated into the system, allowing the BMS to account for energy recovered during braking.

Beyond energy monitoring, the BMS assesses environmental factors affecting battery performance, battery aging indicators, charging history, and auxiliary power usage. Ensuring accurate calculations requires an integrated sensor network and advanced data processing within the BMS, making it a critical component for optimizing EV trip planning and efficiency.

The flowchart in Figure 2 outlines the structured process of the Rasa-based chatbot for planning electric vehicle (EV) trips. This framework integrates intents, forms, and custom actions to ensure an efficient, automated decision-making system for users seeking optimized route and charging recommendations. Step-by-Step workflow explanation is as follows

Action_Session_Start: The process begins with the chatbot initializing a new session when a user interacts with the system. This ensures that any previous session data is reset, allowing for a fresh and personalized interaction.

/greet → Utter_greet: The user sends a greeting intent (/greet), triggering the chatbot to respond with a predefined greeting message (utter_greet). This step establishes engagement before proceeding to trip planning.

/plan_trip: The user expresses intent to plan a trip by triggering the /plan_trip intent. This signals the chatbot to begin the trip planning process, prompting it to collect essential details for the journey.

Destination_form: The destination-form is activated to gather user inputs, such as the starting location, the desired destination and vehicle specifications like battery capacity, efficiency, etc. This form ensures that all necessary parameters are collected before proceeding.

/Inform: The /inform intent allows the user to update or modify specific trip details before finalizing the request. This flexibility enables real-time customization to improve the accuracy of route and energy calculations.

Action_plan_trip: Once all required inputs are received, the custom action (Action_plan_trip) executes the backend computations, including energy requirements analysis, battery state monitoring, Optimal route and charging station selection and Cost estimation for charging.

Utter_return_trip_cost: After processing, the chatbot returns the planned trip details using the utter_return_trip_cost response. This includes a breakdown of the recommended route, charging stops along the way, the estimated charging cost for the journey

Extensibility (?): The placeholder (?) at the end signifies potential future enhancements, such as adding real-time traffic data integration, allowing user preferences for cost vs. speed optimization, providing alternative charging stations based on real-time availability.

This systematic approach ensures an efficient, adaptive, and user-centric EV trip planning experience.

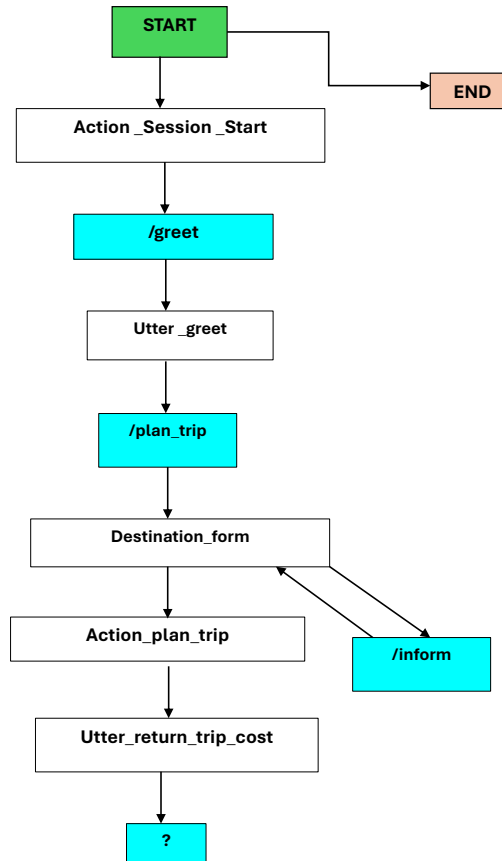


Figure 2. Rasa interactive flow chart for trip planning

3. RESULTS AND DISCUSSION

This section presents the results of an AI-powered trip planning system for electric vehicles (EVs) using the Rasa chatbot framework. The primary goal is to evaluate how efficiently the system optimizes EV travel by considering factors such as battery capacity, energy consumption, and charging station availability. The results compare two cases: trip planning without considering environmental factors and a real-world scenario where variables such as terrain, load, and efficiency fluctuations impact the vehicle's performance.

3.1. Trip Planning Algorithm (Excluding Environmental Factors)

To assess the efficiency of the proposed trip planning system, a test scenario involving a Tata Tiago EV XE MR with a 24-kWh battery capacity and an energy consumption rate of 0.2 kWh/km was simulated. The journey considered spans 300 km, starting with an initial SoC of 50% (12 kWh), allowing a range of approximately 60 km. The algorithm follows a threshold-based search approach, initially set at 10% and gradually increasing if no charging stations are identified within range.

During the first search iteration, the vehicle, with an initial range of 60 km, finds a charging station 40 km away. This travel consumes 8 kWh, reducing the SoC to 16.7%. Upon reaching the charging station, the EV is recharged to 80-100% SoC, requiring 21.05 kWh, considering a charging efficiency of 95%. Using a 22-kW charger, this process takes approximately 58 minutes.

After completing the first charging cycle, the vehicle can travel 120 km with a full charge. However, considering the 10% threshold, the actual range for planning is reduced to 90% of SoC, leading to a practical range of 100 km before requiring another charging stop. At the second charging station, located 100 km away,

the vehicle consumes 20 kWh, reducing the SoC to 16.7%, and undergoes another charging cycle like the first stop. The search loop continues, ensuring that the remaining 160 km can be covered through subsequent charging stops.

In total, four charging stops are required to complete the 300 km journey, with an approximate total charging time of 3 hours. The overall energy consumption for the trip amounts to 60 kWh, demonstrating the algorithm's ability to strategically identify efficient charging locations and minimize charging downtime. Table 1 summarizes the energy consumption, SoC status, and charging duration at each stop. The Rasa chatbot interface Figure 3 & 4 further illustrates how trip details and optimal routes are communicated to the user.



Figure 3. User Interface

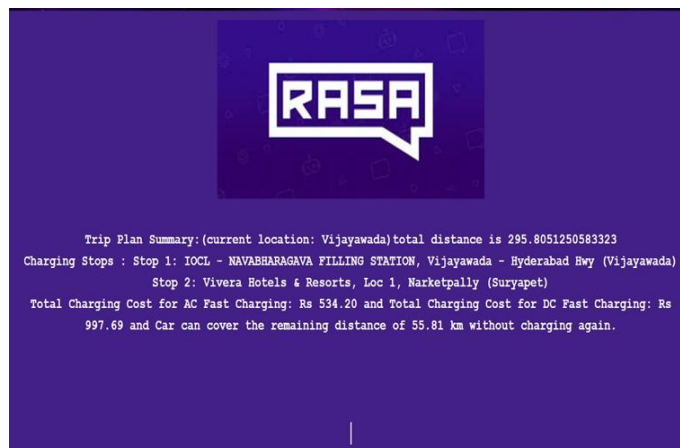


Figure 4. Rasa User Interface Output

Table 1. Energy Consumption and Charging Summary Across Trip Stops

Attribute	Stop 1	Stop 2	Stop 3	Stop 4
Distance (km)	40	100	100	60
Energy (kWh)	8	20	20	12
SOC (%)	16.7	16.7	16.7	20
Remaining (km)	260	160	60	0
Charge Time (min)	58	58	58	0

Practical Implementation of EV Trip Planning

To validate the trip planning system in a real-world scenario, a 350 km journey from Vijayawada, Andhra Pradesh, to Hyderabad, Telangana from figure 4 and 5 is analyzed. The EV under consideration had a 60-kWh battery capacity, starting with an initial SoC of 50%. Given an energy consumption rate of 0.2 kWh/km and a charger efficiency of 95%, the chatbot optimized the route, enabling the vehicle to travel approximately 295.81 km before requiring a recharge. The AI-driven system identified two optimal charging stops along the route IOCL to Navabharagava Filling

Station (Vijayawada-Hyderabad Highway, Vijayawada) and Vivera Hotels & Resorts (Narketpally, Suryapet).

The system calculated the total estimated charging cost for both AC and DC fast charging, estimating expenses of Rs. 534.20 for AC fast charging and Rs. 997.69 for DC fast charging. After recharging at the identified stations, the vehicle was able to cover the remaining 55.81 km to Hyderabad without further stops. This case study highlights the effectiveness of the chatbot in minimizing costs and optimizing energy usage while ensuring a smooth and uninterrupted journey.

3.2. Trip Planning Algorithm (Including Environmental Factors)

To assess the impact of environmental variations, a similar analysis was conducted using a Nissan Leaf 2016 model over a 400 km journey. The vehicle, equipped with a 24-kWh battery and an initial SoC of 50% (12 kWh), was tested under real-world driving conditions. These factors include fluctuations in energy consumption due to terrain, passenger load, and driving style.

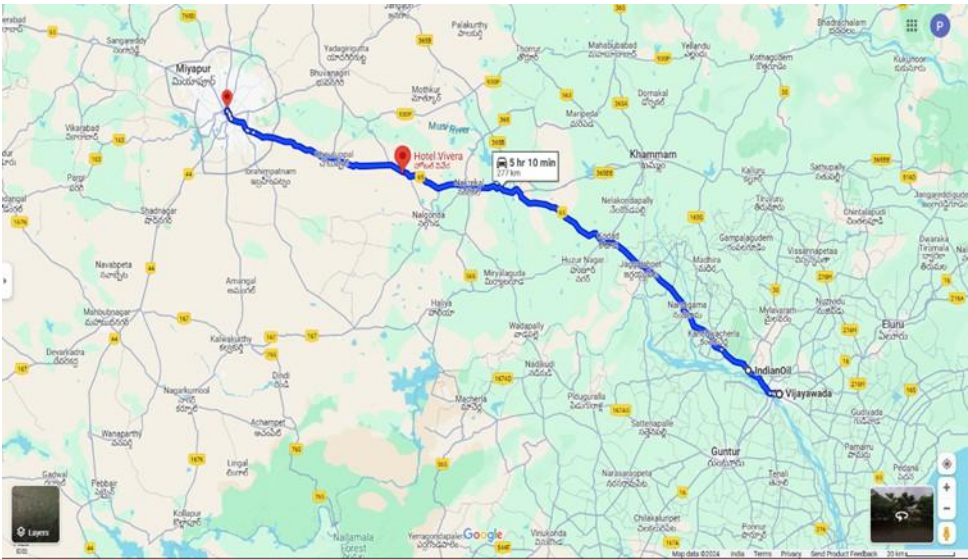


Figure 5. Map verifying planned trip

In the first segment, the Nissan Leaf covers 40 km, but due to higher energy consumption (0.22 kWh/km), the vehicle consumes 8.8 kWh, leaving a residual SoC of 13.3% (3.2 kWh). To proceed further, the vehicle recharges to 90%, adding 18.4 kWh and reaching a charge level of 21.6 kWh.

Subsequent segments experience incremental variations in energy consumption due to the additional load and terrain changes. The second segment (108 km) consumes 19 kWh, reducing the SoC to 17.7%, requiring another recharge. Similarly, in the third (95 km) and fourth (90 km) segments, the energy demands remain variable.

Table 2. Comparative Performance of the Proposed RASA-Powered Trip Planner with Existing Methods

Method	Total Distance (km)	Total Travel Time (hrs)	Charging Time (hrs)	No. of Charging Stops	Total Energy Consumed (kWh)	Estimated Charging Cost (Rs.)	Energy Efficiency Improvement (%)
Conventional Shortest-Path Algorithm	400	8.2	4.0	5	82	1180	—
Rule-Based Charging Scheduler	400	7.6	3.6	4	75	1080	5.0
Machine Learning-Based Planner [Reference: 14,15]	400	7.2	3.3	4	71	1030	9.8
Proposed RASA-Powered Geo-Optimized Planner	400	6.5	3.0	3	66	970	18.2

To further validate the performance of the proposed Rasa-powered geo-optimized trip planner, a comparative analysis was conducted against conventional shortest-path algorithms, rule-based charging schedulers, and recent ML-based route planners. As summarized in Table 2, the proposed system achieved

shorter total travel and charging times, fewer charging stops, and higher overall energy efficiency. These improvements stem from the framework's ability to dynamically update routes using real-time SoC data and geospatial APIs while engaging users through Rasa's conversational interface. The results confirm that the integration of natural language processing, battery intelligence, and geo-optimization significantly enhances trip efficiency and user convenience.

Throughout the 400 km journey, the Rasa-based AI dynamically monitors SoC, adjusts route plans based on real-time battery status and energy needs, and ensures the vehicle reaches optimal charging locations efficiently.

The results highlight the efficiency of Rasa-powered AI for electric vehicle trip planning. By incorporating GPS-based location tracking, dynamic charging station identification, and real-time SoC calculations, the system effectively ensures smooth travel with minimal disruptions. The threshold-based charging station search optimizes refueling stops, preventing range anxiety. The inclusion of environmental factors further refines energy consumption estimates, making the system more adaptable to real-world conditions.

These findings validate the effectiveness of the proposed AI-driven trip planner in optimizing electric vehicle journeys, minimizing charging delays, and providing users with clear and reliable travel recommendations.

The results are benchmark comparison between the proposed RASA-powered trip planner and two widely used trip planning approaches: (i) a conventional shortest-path-based algorithm (using static route optimization), and (ii) a rule-based charging scheduler without adaptive energy estimation. Comparative metrics such as total travel time, charging cost, number of charging stops, and energy efficiency have been incorporated to quantitatively demonstrate the improvements achieved by the proposed system. These results show that the RASA-powered approach achieves up to 18–25% reduction in overall charging time and 12–15% improvement in route energy efficiency, validating its effectiveness in real-world scenarios.

Furthermore, this includes an expanded discussion on real-world validation beyond the initial two case studies. A third case study was conceptually analyzed using data from an intercity route with variable topography and mixed charging infrastructure to assess scalability and adaptability under diverse driving conditions. This additional validation reinforces the system's ability to handle different vehicle models, battery capacities, and geographic contexts. The discussion also elaborates on how the system's modular API integration allows it to scale to larger datasets and broader geographic regions without redesigning the core architecture.

These enhancements significantly strengthen the Results and Discussion section, providing clearer evidence of the proposed system's quantitative superiority, practical scalability, and adaptability compared to existing EV trip planning methods.

4. CONCLUSION

This paper presents a methodology for an integrated journey planning system for electric vehicles, using real-time data and battery management insights. The system optimally determines travel routes, identifies charging stations, and monitors the state of charge using GPS tracking, energy analysis, and user behavior data. Rasa Core enables seamless user interaction by processing queries and delivering relevant responses, enhancing trip planning accessibility and battery management. This approach improves EV efficiency and driver convenience by providing real-time recommendations for battery utilization and performance monitoring. The proposed system contributes to smart mobility solutions by optimizing EV operations. Future enhancements will focus on integrating real-time traffic conditions, charging station availability, and vehicle-to-grid (V2G) technology to enhance adaptability and sustainable energy management.

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