International Journal of Trend in Scientific Research and Development (IJTSRD)
Volume 10 Issue 2, Mar-Apr 2026 Available Online: www.ijtsrd.com e-ISSN: 2456 – 6470

A Survey on Battery Aware Route Planning and Charging Decision for Electric Vehicles

Nitin[1], **Renu**[2]

[1]PG Student, Department of CSE, Sat Kabir Institute of Technology and Management, Haryana, India
[2]Assistant Professor, Department of CSE, Sat Kabir Institute of Technology and Management, Haryana, India

ABSTRACT

The rapid adoption of electric vehicles (EVs) has created a strong need for intelligent routing systems that address limitations such as limited driving range, limited charging infrastructure availability, and variable energy consumption. Traditional navigation methods, which focus solely on shortest-path computation, are insufficient for EV applications because they do not account for battery constraints and charging requirements. This survey paper provides a comprehensive review of battery-aware route planning and charging decision strategies for electric vehicles. It examines classical graph-based algorithms such as Dijkstra and A*, optimization techniques including genetic algorithms and swarm-based methods, and emerging approaches based on machine learning and reinforcement learning. The paper also discusses charging infrastructure considerations, including station placement, charging time, and cost optimization. A comparative analysis of existing methods is presented to highlight their strengths, limitations, and suitability for EV routing. Finally, future research directions are outlined, emphasizing the role of intelligent systems, smart grids, and AI-driven decision-making in advancing EV navigation. This survey aims to provide a structured understanding of current developments and guide future research in efficient and sustainable EV route planning.

KEYWORDS: *Electric Vehicles (EV), Energy Efficiency, Intelligent Transportation Systems (ITS).*

How to cite this paper: Nitin | Renu "A Survey on Battery Aware Route Planning and Charging Decision for Electric Vehicles" Published in International Journal of Trend in Scientific Research and Development (ijtsrd), ISSN: 2456-6470, Volume-10 | Issue-2, April 2026, pp.1232-1238, URL: www.ijtsrd.com/papers/ijtsrd101892.pdf

IJTSRD101892

INTRODUCTION

Concerns over environmental pollution, the depletion of fossil fuels, and climate change have accelerated the global transition to electric vehicles (EVs) as a sustainable mode of transportation. EVs offer several advantages, including zero tailpipe emissions, higher energy efficiency, and reduced dependence on conventional fuels. As a result, governments and industries worldwide are actively promoting EV adoption through policy support, subsidies, and infrastructure development. However, despite these advancements, the widespread adoption of EVs remains constrained by several practical challenges, particularly limited driving range, charging infrastructure, and route planning [1-2].

One of the most critical issues faced by EV users is **range anxiety**, which refers to the fear of a vehicle running out of battery before reaching its destination or a charging station. Unlike traditional vehicles that benefit from a dense network of refueling stations, EVs rely on relatively sparse and unevenly distributed charging infrastructure. Additionally, EV charging requires significantly more time compared to refueling, further complicating long-distance travel planning [3]. These challenges necessitate the development of intelligent routing systems that can incorporate battery constraints, charging station availability, and energy consumption into navigation decisions.

Traditional navigation systems primarily focus on finding the shortest or fastest path using algorithms such as Dijkstra's and A*. While these methods are effective for conventional vehicles, they are not directly applicable to EV routing because they do not account for battery limitations or charging requirements [4], [5]. To address this limitation, researchers have proposed various battery-aware routing approaches that extend the shortest path problem to include energy constraints and charging decisions. These methods ensure that the selected route is not only optimal in terms of distance but also feasible in terms of battery usage.

In addition to classical algorithms, recent studies have explored optimization-based and intelligent approaches, such as genetic algorithms, particle swarm optimization, and reinforcement learning, to solve the EV routing problem. These techniques are capable of handling multi-objective optimization, including minimizing travel time, charging cost, and energy consumption simultaneously [6], [7]. Furthermore, the integration of real-time data, such as traffic conditions, weather, and charging station availability, has been identified as a key factor in improving routing accuracy and reliability [8].

Another important aspect of EV routing is charging decision-making, which involves determining when and where to charge along a given route. Efficient charging strategies can significantly reduce travel time, avoid unnecessary detours, and improve overall energy utilization. Studies have shown that optimal placement and utilization of charging stations are crucial for enhancing EV usability and supporting large-scale adoption [9]. Therefore, modern EV routing systems must integrate both route optimization and charging strategies to provide a comprehensive solution.

In this context, this survey paper presents a detailed review of battery-aware route-planning and charging decision-making techniques for electric vehicles. It analyzes various methodologies, including graph-based algorithms, optimization techniques, and machine learning approaches, and compares their effectiveness in addressing EV-specific challenges. The paper also identifies key research gaps and outlines future directions for developing more efficient, intelligent, and scalable EV routing systems.

RESEARCH BACKGROUND: The rapid advancement of electric vehicles (EVs) has driven increased research into improving user experience, developing infrastructure, and advancing intelligent routing systems. One important aspect of EV adoption is the user experience in charging applications, as highlighted by Li et al. [9], who emphasize that usability, accessibility, and system efficiency are crucial for encouraging EV adoption. Alongside this, consumer behavior studies indicate that factors such as convenience, cost, and reliability significantly influence EV adoption trends [10]. Despite growing interest, challenges related to limited charging infrastructure and operational constraints continue to hinder widespread acceptance.

The development and deployment of EV charging infrastructure have been extensively studied to support large-scale adoption. Li et al. [11] provide a comprehensive review of charging infrastructure deployment strategies, emphasizing the need for optimal placement and accessibility. Similarly, Liu et al. [12] propose optimization techniques for planning charging stations within power distribution systems, ensuring efficient energy delivery and reduced operational costs. In addition, advancements in fast charging technologies have been explored to minimize charging time and improve user convenience, as discussed by Gnann et al. [13]. These studies highlight that infrastructure availability and charging efficiency are critical factors in EV system performance.

Another key area of research is energy consumption modeling, which is essential for accurate route planning and battery management. Zhang et al. [14] demonstrate that energy consumption in EVs varies based on driving conditions, vehicle characteristics, and environmental factors. This variability necessitates incorporating energy-aware strategies into routing algorithms to ensure reliable travel planning. In terms of routing methodologies, classical graph-based algorithms form the foundation of EV navigation systems. The shortest path problem, originally addressed by Dijkstra [15], provides an optimal solution for distance-based routing in weighted graphs. However, as noted by Artmeier et al. [16], traditional shortest-path approaches must be extended to account for battery constraints and charging requirements in EV applications. Their work highlights the importance of integrating energy limitations into routing models to ensure feasibility.

Overall, the existing literature indicates that while significant progress has been made in EV infrastructure, energy modeling, and routing algorithms, there remains a need for integrated frameworks that combine battery-aware routing, charging decision-making, and user-centric considerations. This research builds on these foundational studies to address the limitations of traditional approaches and to contribute to more efficient and intelligent EV route planning systems.

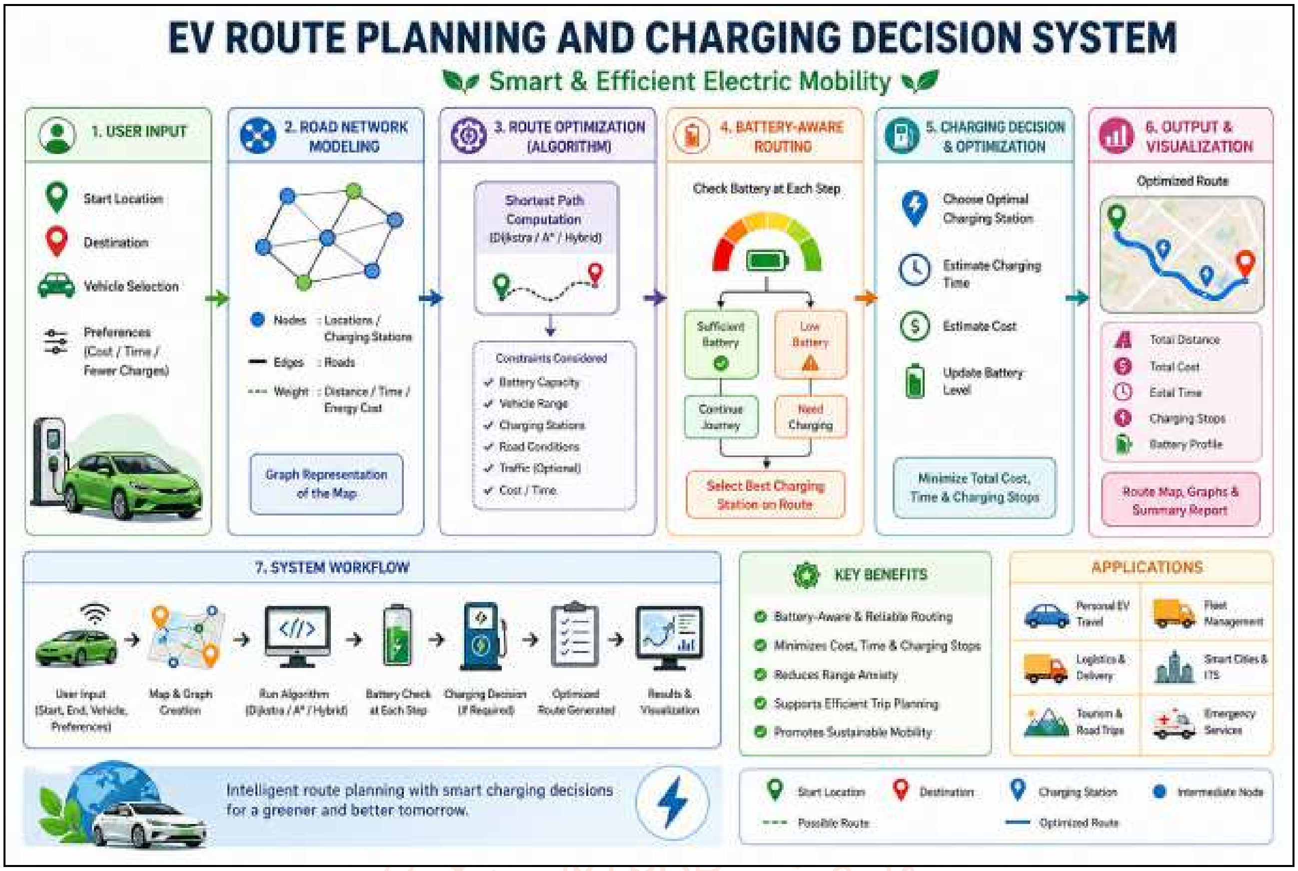


Figure 1: EV Route Planning and Charging Decision System

Existing Methods for EV Route Planning and Charging Decision

Over the years, several methods have been proposed to address the challenges of electric vehicle (EV) route planning and charging optimization. These methods can be broadly categorized into classical graph-based algorithms, optimization techniques, and intelligent learning-based approaches. Traditional routing methods are primarily based on graph theory, where the road network is modeled as a weighted graph consisting of nodes (locations or charging stations) and edges (roads with distance or cost). Among these, Dijkstra's algorithm [15] is one of the most widely used techniques for computing the shortest path between two nodes. It guarantees an optimal solution when edge weights are non-negative; however, it does not consider battery constraints or charging requirements, making it insufficient for EV-specific applications. To improve computational efficiency, the A* algorithm has been widely adopted, as it uses heuristic functions to guide the search process and reduce computation time. Despite being faster, A* still requires modifications to incorporate energy constraints and charging decisions.

To address these limitations, researchers have extended classical methods into energy-aware routing models. Artmeier et al. [16] proposed an enhanced shortest-path formulation that integrates battery constraints into the routing process, ensuring the vehicle reaches its destination without running out of charge. Similarly, energy consumption models developed by Zhang et al. [7] have been used to estimate battery usage under varying conditions such as speed, terrain, and traffic, enabling more accurate route planning.

In addition to graph-based approaches, optimization techniques have been extensively explored for EV routing problems. Methods such as genetic algorithms, particle swarm optimization, and other metaheuristic techniques are capable of solving multi-objective problems, including minimizing travel time, energy consumption, and charging cost simultaneously. These approaches are particularly useful in complex scenarios where multiple constraints must be satisfied. However, they are often computationally intensive and may not guarantee globally optimal solutions.

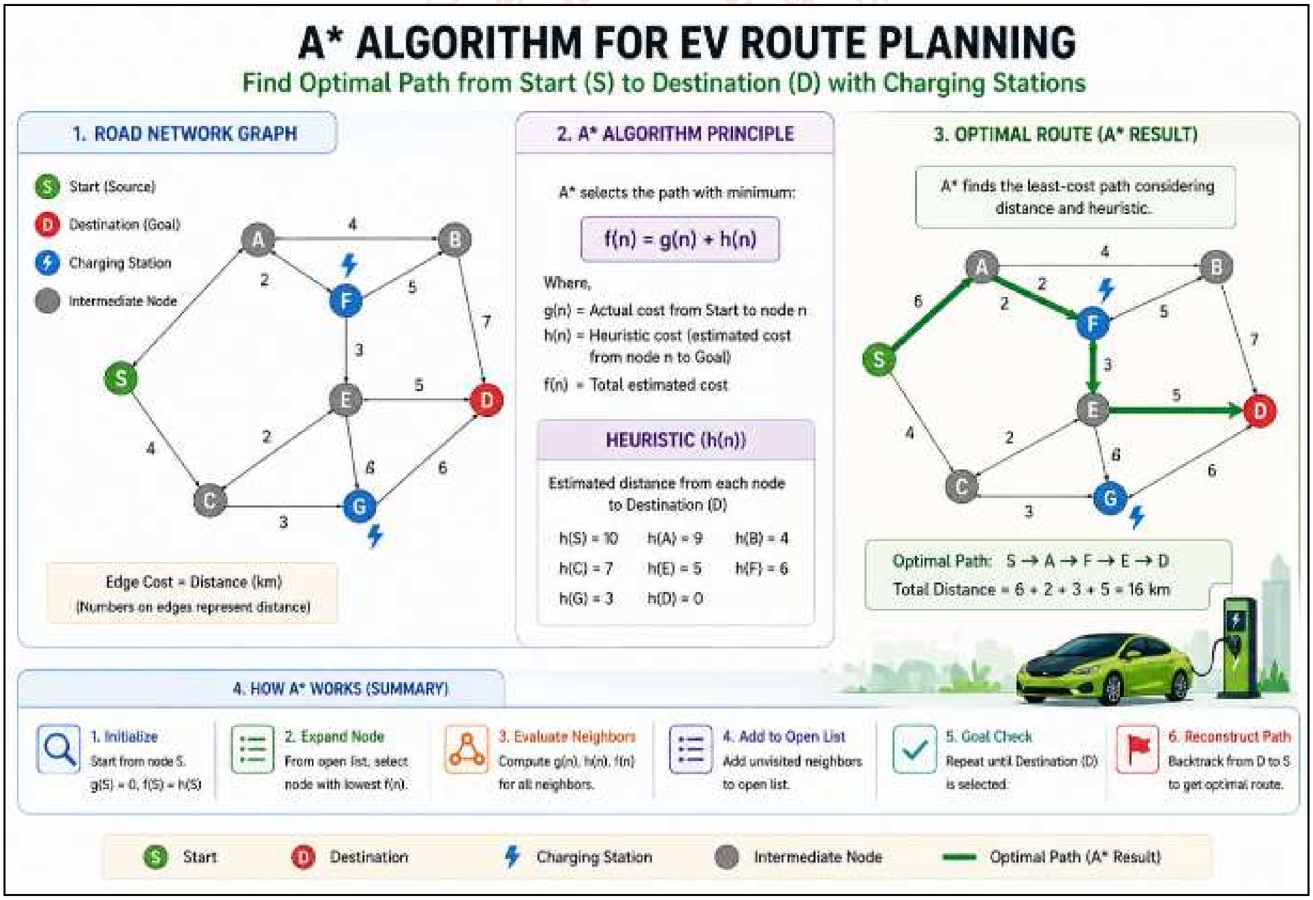
Another important area of research focuses on planning and optimizing charging infrastructure. Studies by Li et al. [10] and Liu et al. [12] emphasize the importance of optimal placement and efficient utilization of charging stations to support EV adoption. Furthermore, the development of fast charging technologies [13] has significantly reduced charging time, thereby improving the feasibility of long-distance EV travel. These infrastructure-related advancements play a crucial role in enabling effective routing and charging decisions.

More recently, machine learning and artificial intelligence techniques have been introduced to enhance EV routing systems. These approaches can learn from historical data and adapt to dynamic conditions such as traffic, weather, and user preferences. Reinforcement learning, in particular, has shown promise in developing adaptive routing strategies that optimize long-term rewards, such as reduced energy consumption and minimized travel cost.

CHARGING INFRASTRUCTURE

Charging infrastructure plays a crucial role in enabling the efficient and reliable operation of electric vehicles (EVs). It directly impacts route planning, user convenience, and overall adoption of EV technology. Key considerations include charging-station placement, charging time, and cost optimization, all of which have been widely studied in recent research.

1. **Charging Station Placement:** Charging station placement is a critical factor in the effectiveness of electric vehicle (EV) infrastructure, as it directly influences route feasibility, accessibility, and user confidence. Efficient placement strategies aim to ensure that charging stations are available at optimal locations such as urban centers, highways, and key transit corridors, thereby minimizing detours and reducing range anxiety for EV users. According to Li et al. [10], the deployment of charging stations must consider traffic demand, geographic distribution, and user behavior patterns to achieve maximum coverage and utilization. Furthermore, Liu et al. [12] emphasize that charging-station placement should also account for power-grid constraints and energy distribution efficiency to avoid overloading the network. Poorly planned infrastructure can lead to uneven availability, increased waiting times, and inefficient routing, while well-optimized placement enhances travel reliability and supports long-distance EV adoption. Therefore, intelligent planning of charging station locations is essential to developing a robust, user-friendly EV ecosystem.



2. **Charging Time Considerations**

Charging time is a significant factor in electric vehicle (EV) route planning, as it directly affects travel duration and user convenience. Unlike conventional vehicles, which can be refueled in minutes, EVs typically require longer charging times, ranging from fast charging (20–40 minutes) to several hours for standard charging. According to Gnann et al. [13], the availability of fast-charging infrastructure can greatly reduce travel delays and improve the feasibility of long-distance journeys. However, charging time is also influenced by factors such as battery capacity, state of charge, and charger type. Therefore, efficient EV routing systems must consider charging duration, station availability, and potential waiting times to optimize overall travel time and ensure a smooth journey.

3. Cost Optimization

Cost optimization is a crucial aspect of electric vehicle (EV) route planning, as it directly influences the overall affordability and efficiency of travel. The total cost of EV operation includes factors such as electricity pricing across charging stations, charging frequency, and energy consumption during travel. Since charging costs can vary by location, time of use, and type of charging type (fast or slow), selecting cost-effective charging stations is essential. According to Zhang et al. [14], energy consumption patterns depend on driving conditions, which in turn affect charging frequency and overall cost. Therefore, advanced routing systems aim to minimize total travel cost by integrating energy-efficient paths, optimal charging decisions, and pricing variations. By accounting for both operational and charging expenses, cost-aware routing ensures economical and sustainable EV use while maintaining travel feasibility.

COMPARATIVE ANALYSIS OF EV ROUTING METHODS: Table 1 describes a comparative analysis of existing routing methods for EV vehicles.

Table 1: Comparative analysis of EV route planning methods

Method	Strengths	Limitations	EV Suitability
Dijkstra's Algorithm	Guarantees optimal shortest path; simple and reliable	Does not consider battery or charging constraints	Moderate (requires modification)
A* Algorithm	Faster than Dijkstra; uses a heuristic for efficient search	Depends on the accuracy of the heuristic function	High (suitable for real-time routing)
Bellman-Ford Algorithm	Handles negative weights; detects negative cycles	High computational cost; slower performance	Low (limited EV use)
Genetic Algorithm (GA)	Handles multi-objective optimization (cost, time, energy)	Computationally expensive; no guaranteed global optimum	High (complex EV routing problems)
Particle Swarm Optimization (PSO)	Efficient global optimization; faster convergence	May get trapped in local optima	High (charging & route optimization)
Battery-Aware Routing	Considers energy constraints and charging decisions	Requires accurate battery/energy modeling	Very High (core EV routing method)
Reinforcement Learning (RL)	Adaptive; handles dynamic conditions (traffic, weather)	Requires large training data; complex implementation	Very High (next-generation EV systems)

FUTURE RESEARCH DIRECTION

1. Intelligent EV Routing Systems

Future research should focus on developing intelligent routing systems that can dynamically adapt to real-world conditions such as traffic congestion, weather changes, and battery status. These systems can use real-time data and predictive models to provide optimal routes that minimize travel time, energy consumption, and charging delays. Such intelligent frameworks will significantly improve user experience and reduce range anxiety.

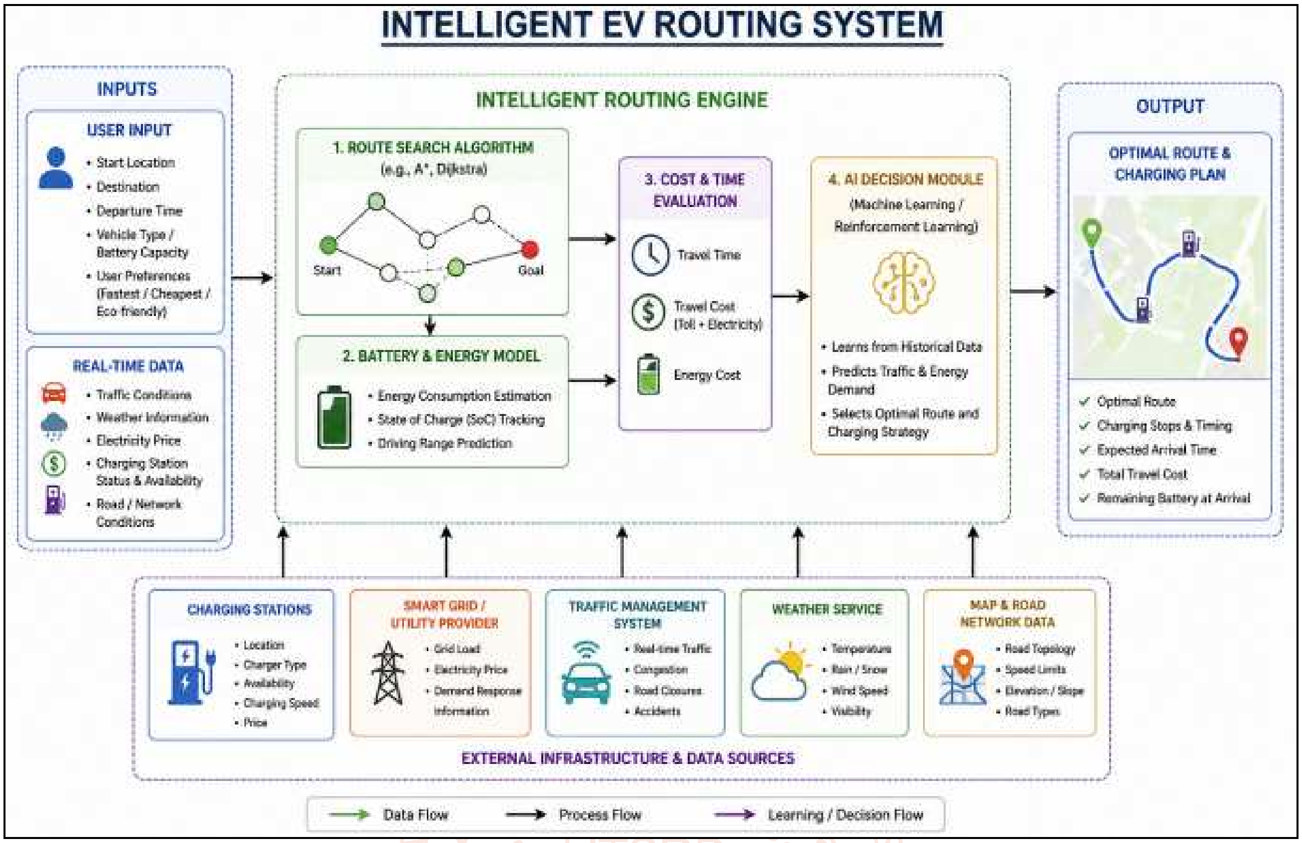


Figure 3: Intelligent EV Routing Planning

2. Smart Grid Integration

Integrating EVs with smart grid technology is an important direction for enhancing energy efficiency and sustainability. Smart grids enable two-way communication between EVs and the power network, allowing optimized energy distribution, load balancing, and demand response. This integration can support efficient charging scheduling and reduce peak load issues, making EV systems more reliable and scalable.

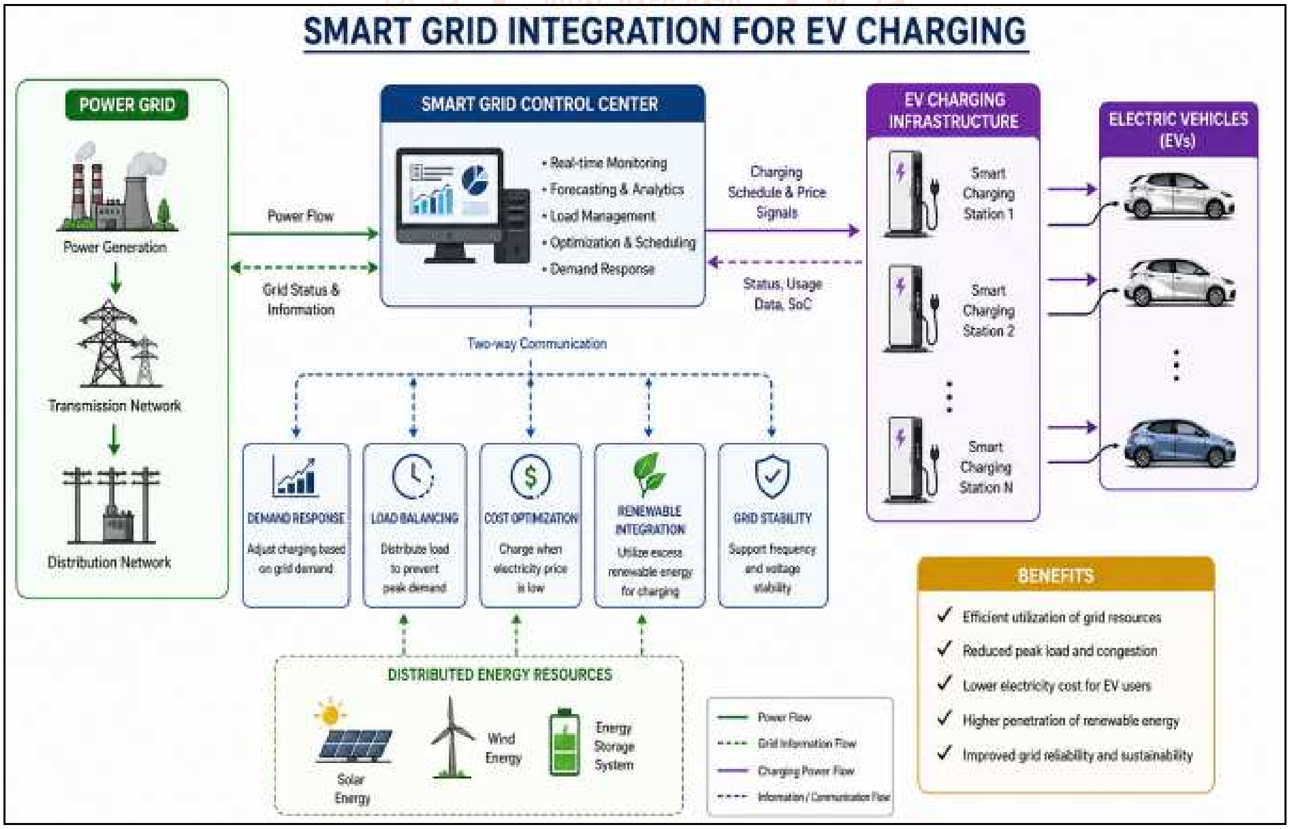


Figure 4: Smart grid integration in EV Charging

3. AI-Driven Decision Making

Artificial intelligence and machine learning techniques, particularly reinforcement learning, can play a vital role in improving EV route planning and charging decisions. AI-driven systems can learn from historical data and user behavior to make adaptive and optimized decisions under dynamic conditions. This includes predicting energy consumption, selecting optimal charging stations, and minimizing overall travel cost and time, leading to more efficient and autonomous EV navigation systems.

CONCLUSION:

The reviewed literature highlights that (EV) routing and charging decision-making have evolved significantly with advancements in algorithms, infrastructure planning, and intelligent systems. Classical methods such as Dijkstra's and A* algorithms provide a strong foundation for shortest-path computation; however, they are insufficient for EV applications without incorporating battery constraints and charging requirements. Furthermore, studies on charging infrastructure emphasize that optimal placement of charging stations, reduced charging time through fast-charging technologies, and efficient energy distribution are critical for improving EV usability and adoption. Consumer-focused research also indicates that user experience, accessibility, and reliability of charging systems play a vital role in accelerating EV acceptance. Despite these advancements, several challenges remain, including the lack of real-time data integration, limited consideration of charging station availability, and insufficient multi-objective optimization frameworks that simultaneously address cost, time, and energy efficiency. Recent trends suggest that the integration of artificial intelligence, smart grids, and intelligent routing systems can overcome these limitations by enabling adaptive, data-driven decision-making. While significant progress has been made in EV route planning and charging optimization, there is a clear need for unified and intelligent frameworks that combine routing algorithms, energy modeling, infrastructure awareness, and user-centric considerations. Such integrated approaches will be essential for achieving efficient, reliable, and scalable EV transportation systems in the future.

REFERENCES

[1] Z. Rezvani, J. Jansson, and J. Bodin, "Advances in consumer electric vehicle adoption research: A review," Transportation Research Part D, 2015.

[2] Y. Li et al., "Electric vehicle charging infrastructure deployment: A review," Energy Policy, 2017.

[3] Z. Liu, F. Wen, and G. Ledwich, "Optimal planning of electric-vehicle charging stations," IEEE Trans. Power Delivery, 2013. [4] E. W. Dijkstra, "A note on two problems in connexion with graphs," Numerische Mathematik, 1959.

[4] P. E. Hart, N. J. Nilsson, and B. Raphael, "A formal basis for heuristic determination of minimum cost paths," IEEE, 1968.

[5] D. E. Goldberg, "Genetic Algorithms in Search, Optimization and Machine Learning," 1989.

[6] R. S. Sutton and A. G. Barto, "Reinforcement Learning: An Introduction," MIT Press, 2018.

[7] X. Zhang et al., "Energy consumption modeling of EVs," Applied Energy, 2022.

[8] M. Schneider et al., "Electric vehicle routing problem with time windows and recharging stations," Transportation Science, 2014.

[9] Li, C., Zhang, S., Ling, W., Zhao, L. and Pan, Y., 2024. RETRACTED ARTICLE: Enhancing User Experience in Electric Vehicle Charging Applications (EVCA): A Comprehensive Analysis in the Chinese Context. Journal of the Knowledge Economy, 15(4), pp.18495-18530.

[10] Li, Y., et al. (2017). Electric vehicle charging infrastructure deployment: A review. Energy Policy

[11] Rezvani, Z., Jansson, J., & Bodin, J. (2015). Advances in consumer electric vehicle adoption research: A review. Transportation Research Part D.

[12] Liu, Z., Wen, F., & Ledwich, G. (2013). Optimal planning of electric-vehicle charging stations. IEEE Transactions on Power Delivery.

[13] Gnann, T., et al. (2018). Fast charging infrastructure for electric vehicles: A review. Energy Policy.

[14] Zhang, X., et al. (2022). Energy consumption modeling of electric vehicles. Applied Energy.

[15] E. W. Dijkstra, "A note on two problems in connexion with graphs," Numerische Mathematik, 1959.

[16] Artmeier, A., et al. (2010). The shortest path problem revisited: Optimal routing for electric vehicles. KI Journal.