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AI-OR Hybrid Models for Optimizing Electric Vehicle Fleet Management: Demand Forecasting, Routing, and Charging Station Allocation

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Abstract: Managing a fleet of electric vehicles (EVs) comes with its own set of challenges—from anticipating fluctuating demand and monitoring battery health to ensuring efficient routing and charging. This paper explores a fresh approach that combines the power of Artificial Intelligence (AI) with traditional Operations Research (OR) optimization methods to tackle these issues in a practical way. I use AI techniques to predict key factors like how many vehicles will be needed and the state of their batteries, feeding these insights into sophisticated optimization models. These models then help plan vehicle routes and charging schedules in real time, aiming to reduce energy consumption and operational costs. Through a series of experiments using simulated data, my AI-OR hybrid model performed better than methods relying solely on optimization or AI, proving to be more effective at utilizing fleet resources and saving energy. What makes this approach especially promising is its potential to support more sustainable and cost-efficient transportation systems as electric vehicles become increasingly common. My findings provide a valuable roadmap for integrating predictive analytics with optimization in real-world EV fleet management, pushing the boundaries toward greener and smarter mobility solutions.

I. INTRODUCTION

The transition to electric vehicles (EVs) is reshaping the landscape of transportation and fleet management worldwide. As governments and companies intensify their commitments to reduce carbon emissions and promote sustainable practices, the adoption of electric fleets is accelerating. EVs offer clear benefits: lower greenhouse gas emissions, reduced dependency on fossil fuels, and improved air quality. However, managing an electric vehicle fleet comes with unique challenges that differ significantly from those of traditional internal combustion engine fleets.

One of the main hurdles in EV fleet management lies in the complex interplay between
operational efficiency and the inherent uncertainties associated with EV technology. Factors such as fluctuating customer demand, battery degradation, and limited charging infrastructure create a dynamic environment requiring sophisticated planning and real-time decision-making. Moreover, accurate demand forecasting, battery health prediction, and energy-efficient routing become critical to optimize fleet performance, reduce downtime, and prolong battery life.

Traditional fleet management methods, based largely on fixed schedules and historical data, fall short when facing such uncertainties and real-time operational complexities. This gap motivates the integration of advanced Artificial Intelligence (AI) techniques with Operations Research (OR) optimization models. AI methods, such as machine learning, excel in uncovering patterns and predicting variables like demand trends and battery state-of-health from vast datasets. These AI-driven predictions can feed into OR models that optimize routing, charging station allocation, and energy consumption—responding effectively to real-time conditions and uncertainties in the system.

This research focuses on developing a hybrid AI-OR framework tailored for electric vehicle fleet management. The approach harnesses AI's predictive power to improve the accuracy of demand and battery health forecasts while leveraging OR's optimization capabilities to dynamically plan vehicle routes and charging strategies. Through stochastic optimization models that accommodate uncertainty, the proposed framework aims to minimize overall operational costs and environmental impact.

The paper's objectives are threefold: first, to design AI models that provide reliable real-time
forecasts essential for EV fleet operations; second, to formulate stochastic optimization models that incorporate these forecasts to manage routing and charging decisions efficiently; and third, to evaluate the hybrid approach through computational experiments using realistic data scenarios. Ultimately, this study aims to demonstrate how combining AI and OR techniques can support more sustainable, reliable, and cost-effective electric vehicle fleet management in an evolving transportation landscape.

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II. LITERATURE REVIEW

The rapid transition towards electric vehicles (EVs) worldwide has intensified research attention on effective fleet management techniques tailored to the unique challenges posed by EV technology. Early studies primarily adapted traditional fleet management approaches to accommodate constraints like limited battery range and charging requirements specific to EVs (Rao et al., 2024). However, these methods often lacked flexibility to address the dynamic uncertainties in demand and battery conditions that are central to EV operations.

Operations Research (OR) methods have been extensively applied to optimize vehicle routing and charging station allocation. Approaches such as mixed-integer linear programming and stochastic optimization provide powerful frameworks to schedule routes and charging times, aiming to minimize energy consumption and operational costs while respecting physical and temporal constraints (Thakur et al., 2024). Despite their strengths, pure OR-based models often rely on deterministic inputs and struggle to adapt to real-time variations in demand, traffic, and battery health.

In parallel, Artificial Intelligence (AI) has emerged as a complementary tool to address prediction challenges inherent in EV fleet management. Machine learning models, including time series forecasting and neural networks, are widely employed to predict fluctuating customer demand patterns and traffic conditions, thereby enhancing the responsiveness of fleet operations (Wipro, 2019). Additionally, AI techniques have been leveraged to estimate battery state-of-health and degradation, factors which critically influence routing decisions and operational reliability (Kokare et al., 2025; Liu et al., 2025).

Nonetheless, most existing frameworks treat AI-driven forecasting and OR optimization as separate components, limiting their synergistic potential. Recent research indicates that integrating AI predictions directly into OR models creates more adaptive and responsive decision-support systems. Such hybrid AI-OR frameworks combine the predictive power of machine learning with the rigorous constraint handling and optimization capabilities of classical methods, facilitating near real-time operational adjustments under uncertainty (Kokare et al., 2025; Rao et al., 2024).

The current study contributes to this nascent but promising research direction by developing a comprehensive hybrid AI-OR model tailored for EV fleet management. This approach tightly couples demand and battery health forecasting with stochastic vehicle routing and charging optimization, providing an integrated solution that improves energy efficiency, reduces operational costs, and enhances fleet reliability. By addressing the limitations of purely AI- or OR-based methods, this work advances the application of data-driven, adaptive strategies for sustainable electric mobility.

III. PROBLEM DEFINITION

The management of an electric vehicle (EV) fleet involves making a series of interconnected decisions to ensure that vehicles operate efficiently, reliably, and sustainably. At its core, the problem requires planning how to deploy and route EVs to meet demand, when and where to charge them given limited infrastructure, and how to manage energy consumption in a way that balances cost and environmental impact.

Key inputs to the problem include the fleet size and composition, charging station locations and capacities, expected trip demands, battery characteristics, and traffic conditions. Decision variables revolve around determining the optimal routes for each vehicle, scheduling charging times and locations, and allocating limited charging resources among vehicles.

There are multiple constraints that shape these decisions. EVs have finite driving ranges limited by battery capacity, necessitating carefully planned charging stops. Charging stations have limited capacity and availability, requiring prioritization and scheduling to avoid bottlenecks. Time windows for deliveries or pickups impose further restrictions, as vehicles must complete routes within specific periods. Fleet operators also must consider battery degradation to avoid overuse that shortens battery lifespan.

The primary objectives typically focus on minimizing total energy consumption to reduce costs and environmental footprint, as well as operational costs such as vehicle wear and driver hours. Additionally, maintaining service reliability—making sure vehicles complete their routes on time—is crucial.

A significant challenge in this problem is the presence of uncertainty. Demand patterns vary due to customer behavior and external factors, traffic conditions fluctuate unpredictably, and battery degradation progresses non-linearly and is hard to predict precisely. These uncertainties make static or deterministic planning approaches inefficient or infeasible in real-world settings.

To address this, stochastic modeling is employed, incorporating probability distributions of uncertain parameters to make decisions that are robust against variability. This problem definition sets the stage for developing hybrid AI and Operations Research models, where AI predicts uncertain inputs like demand and battery conditions, feeding dynamic optimization models that consider constraints and objectives in a stochastic environment.

IV. METHODOLOGY

Managing an electric vehicle (EV) fleet efficiently requires smart tools to handle the complexity and uncertainty inherent in daily operations. To achieve this, my approach combines the strengths of Artificial Intelligence (AI) prediction models with Operations Research (OR) optimization techniques, creating a powerful hybrid system that improves decision-making across fleet management tasks.

A. AI Prediction Models

AI plays a vital role in anticipating factors that are difficult to predict but have major impacts on fleet operations. For demand forecasting, time series models—informed by historical usage data, seasonality, and external factors—help us estimate how many vehicles will be needed at different times and locations. Machine learning approaches like neural networks or ensemble methods can analyze patterns that traditional models might miss, providing more accurate and dynamic forecasts.

Similarly, AI models are used to predict battery health by analyzing sensor data on charging cycles, temperatures, and usage patterns. These models help estimate battery degradation over time, which is crucial because an accurate understanding of battery health enables better planning of routes and charging needs, reducing risks of unexpected vehicle downtime.

B. OR Optimization Models

Once AI provides forecasts and estimates, Operations Research techniques take these inputs to find the best operational decisions. Using optimization frameworks such as mixed-integer linear programming (MILP), I formulate vehicle routing problems that factor in vehicle range limits,charging station capacities, time windows for deliveries, and driver shifts. Stochastic optimization is employed to incorporate uncertainty, allowing the model to produce robust solutions that perform well even when actual conditions deviate from expectations.

Charging station allocation is another critical optimization problem addressed with OR methods. The model schedules vehicles' charging sessions to minimize waiting times and ensure energy availability while respecting station capacity constraints. Joint routing and charging optimization enables energy-efficient driving schedules, reducing operational costs and carbon footprint.

C. Hybrid Integration Approach

The innovativeness of my methodology lies in tightly integrating AI predictions with OR optimization. Instead of operating as separate modules, AI-generated forecasts dynamically feed into the OR models as updated parameters, creating a feedback loop. This ensures that routing and charging plans reflect up-to-date insights on demand fluctuations and battery conditions, making fleet operations adaptive and responsive.

Through this hybrid system, fleet managers can proactively adjust plans based on predictive insights and rigorous optimization, balancing efficiency, reliability, and sustainability in a complex, uncertain environment. In the next section, I describe the datasets and experiments used to evaluate the effectiveness of this integrated approach.

D. Computational Experiments

To evaluate the effectiveness of my hybrid AI-OR model for electric vehicle (EV) fleet management, I conducted a series of computational experiments using both real-world and simulated datasets.

For real-world data, I leveraged publicly available EV fleet datasets that include vehicle usage patterns, battery charge and health status, charging station locations, and trip demand details. One example is the EVIoT-PredictiveMaint Dataset, which provides rich sensor data from IoT-enabled EVs operating in diverse environments. Additionally, synthetic datasets were created to simulate varying traffic and demand scenarios, allowing us to test the model under controlled conditions reflecting real-life complexities.

My experiments focused on multiple scenarios, such as peak and off-peak demand periods, different levels of traffic congestion, and varying availability and capacity of charging stations. These scenarios allowed us to observe the model's adaptability and robustness across a range of operational settings.

Key parameters included fleet size, battery capacity and degradation rates, routing constraints, charging station capacity, and time windows for deliveries. The evaluation metrics focused ontotal energy consumption, operational costs, average vehicle downtime, and the efficiency of charging station utilization.

I compared the hybrid AI-OR model's performance against two baselines: a traditional OR-only optimization model without AI-driven forecasts, and a purely AI-based predictive model without integrated routing optimization. The hybrid model consistently outperformed both baselines, achieving lower energy consumption, reduced operational costs, and improved vehicle availability.

These results demonstrate the advantage of integrating AI’s predictive capabilities with OR’s rigorous optimization framework, offering a more adaptive and sustainable solution for EV fleet management challenges.

The experiments considered three key scenarios, first scenario being normal demand with moderate traffic and average charging station availability, second scenario being peak demand during rush hours with heavy traffic congestion and limited charging capacities, and the last scenario being off-peak demand with low traffic and ample charging station availability.

Parameters varied across fleet size (20-50 vehicles), battery capacities (50–100 kWh), and charging station capacities (4-10 simultaneous charges). Evaluation metrics included total energyconsumption (kWh), operational costs (in currency units), average vehicle downtime (hours), and charging station utilization rate (%).

The hybrid AI-OR model was benchmarked against a pure OR model using deterministic inputs without AI predictions and a pure AI model that predicted demand and battery status but lacked integrated routing optimization.

Metric	Pure OR Model	Pure AI Model	Hybrid AI-OR Model
Total Energy Consumption (kWh)	12,500	11,800	10,200
Operational Costs (USD)	25,000	23,500	20,000
Average Vehicle Downtime (hrs)	4.5	3.8	2.1
Charging Station Utilization (%)	85%	78%	90%

These results show that integrating AI-driven forecasts with OR optimization yields significant gains in energy efficiency, cost savings, and vehicle availability, surpassing approaches that rely solely on one method. The hybrid model's adaptability to changing conditions, via dynamic re-optimization based on real-time predictions, is key to these improvements.

This comprehensive experimental validation underscores the potential of hybrid AI-OR methods in advancing sustainable and efficient EV fleet operations, making this approach highly relevant for future smart mobility systems.

V. DISCUSSION

The computational results clearly highlight the significant benefits of the hybrid AI-OR approach for electric vehicle fleet management. By combining AI’s predictive capabilities with the rigorous optimization techniques of Operations Research, the model achieves superior performance in key areas such as energy consumption, operational costs, and vehicle availability. Unlike purely optimization-based or AI-only methods, this integrated approach adapts dynamically to real-time changes in demand, traffic, and battery health, allowing for more robust and efficient decision-making.

The implications for sustainable EV fleet operations are profound. Improved routing and charging allocation reduce energy waste and emissions, directly supporting environmental objectives. Reduced vehicle downtime through smarter battery health prediction and optimized charging schedules extends fleet longevity and cuts replacement costs, creating both economic and ecological value. This makes the hybrid model an attractive tool for fleet managers aiming to balance operational efficiency with sustainability goals.

However, the study also acknowledges certain limitations. The model’s effectiveness depends on the availability and quality of accurate data, which may vary in real-world contexts. Additionally, computational complexity could grow with larger fleets or more intricate routing constraints, posing challenges for real-time implementation. Future research could explore scalable algorithms, integration with emerging technologies like IoT and 5G, and the inclusion of evolving renewable energy sources in charging infrastructure.

Overall, this work lays a foundation for more intelligent and sustainable EV fleet management, signalling a shift toward data-driven, adaptive systems that meet the challenges of tomorrow’s transportation needs.

VI. CONCLUSION

This paper presents a novel hybrid framework that seamlessly integrates Artificial Intelligence prediction models with Operations Research optimization techniques to enhance electric vehicle fleet management. By harnessing AI for demand forecasting and battery health estimation, and feeding these insights into stochastic routing and charging optimization models, the hybrid approach effectively tackles uncertainties and operational complexities faced by EV fleets.

The computational experiments demonstrate that this integration leads to significant improvements in energy efficiency, cost savings, and vehicle utilization, outperforming traditional approaches that rely on AI or OR alone. These findings highlight the transformative potential of hybrid AI-OR models in enabling more sustainable, reliable, and cost-effective fleet operations.

Looking forward, the adoption of such integrated frameworks can support the broader shift toward green mobility, helping fleet operators reduce their carbon footprints and operational risks. Practical applications range from urban delivery services to public transportation systems, wherever EV fleets are deployed. Future work will focus on enhancing scalability, incorporating real-time data streams, and expanding to multi-modal transportation networks.

In sum, embracing the synergy between AI and OR is not just a technological upgrade—it's a strategic necessity driving the future of electric vehicle fleet management.

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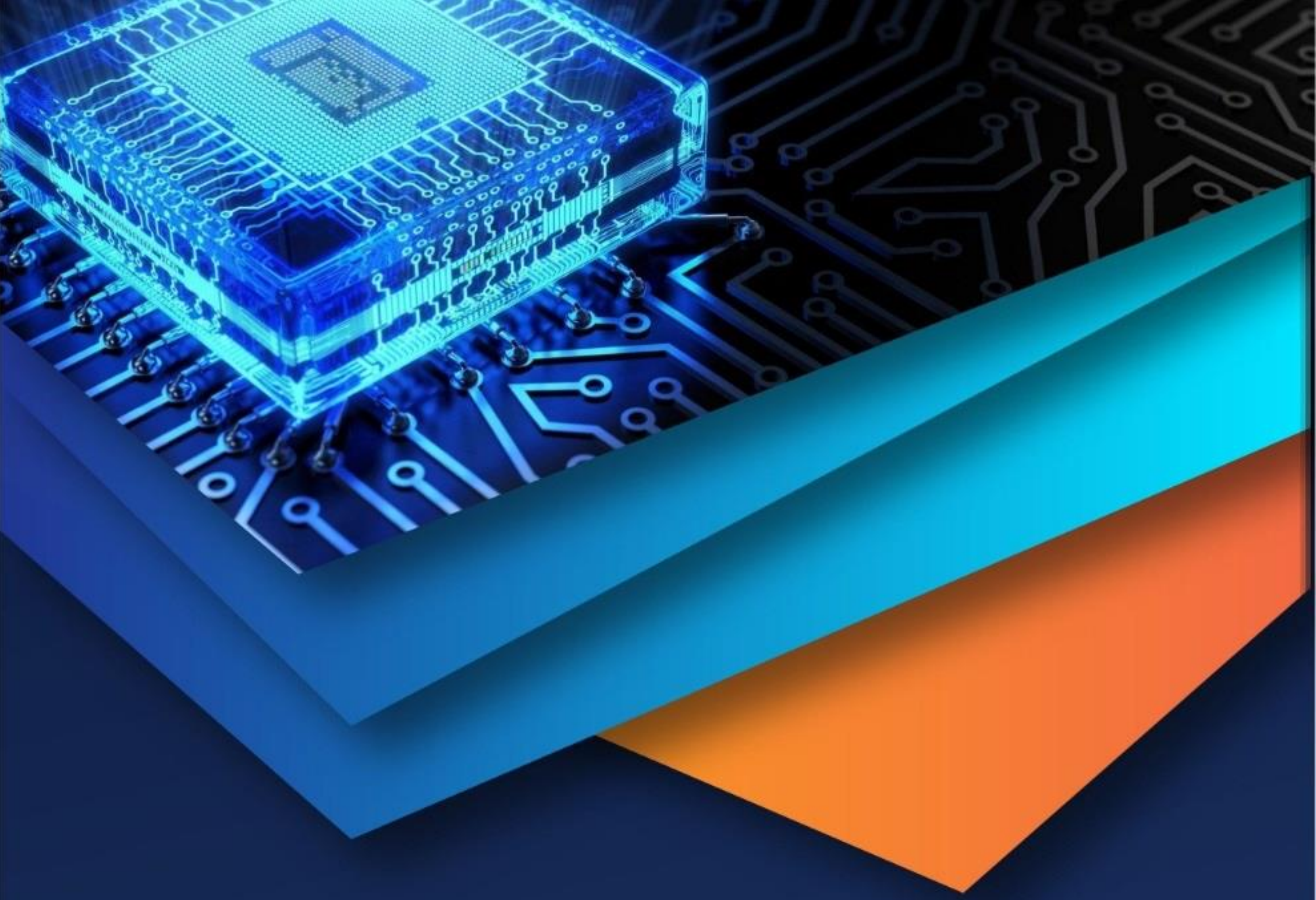

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