**Introduction (≈500 words)**

**Opening Context**

Over the past decade, electric vehicle (EV) adoption has accelerated globally, driven by the dual imperatives of reducing greenhouse gas emissions and meeting regulatory targets for phasing out internal combustion engine vehicles. The International Energy Agency (2023) reports exponential growth in EV sales, with projections indicating that EVs could account for more than half of new vehicle sales in several major markets by 2035. This shift is underpinned by advances in battery energy density, reductions in battery costs, and the expansion of public charging networks. However, the effectiveness of this transition hinges on the availability and efficiency of charging infrastructure. EV drivers frequently encounter practical challenges, including inconsistent charger availability, varying charging speeds, and unpredictable charging costs. Such uncertainties complicate trip planning and can lead to increased travel time, higher expenses, or range anxiety — all of which pose barriers to mass adoption (Ahmad et al., 2021; Wang et al., 2022).

**Problem Definition**

While many navigation and trip-planning tools exist, most prioritise either minimising travel time or avoiding range depletion, with limited integration of realistic charging curve modelling and dynamic pricing data (Montoya et al., 2017; Ahmad et al., 2021; Li et al., 2023). This limits their ability to address the broader optimisation needs of EV users, who may wish to balance multiple objectives such as cost efficiency, total journey time, or a hybrid trade-off between the two. The specific challenge addressed in this work is to develop a simulation and optimisation framework capable of minimising total trip cost, minimising total trip duration, or optimising a combined cost–time objective, all while ensuring the state of charge (SOC) remains above a defined reserve threshold. This requires incorporating charger availability, diverse pricing models, and heterogeneous SOC charging behaviours into a unified decision-making process (Zhang et al., 2022; Li et al., 2023).

**Scope of Work**

This project presents a simulation environment that integrates heterogeneous datasets — EV technical specifications, manufacturer-provided charging curves, public charging station metadata (including location, connector type, and operator), and detailed pricing models. The system supports three distinct optimisation modes: cost-focused, time-focused, and hybrid cost–time trade-off. It simulates multi-leg EV journeys, dynamically determining optimal charging stops based on the chosen optimisation objective, SOC constraints, and real-world operational factors such as idle fees and membership discounts. By modelling realistic SOC charging curves and variable station performance, the simulator is capable of producing decision outcomes that more accurately reflect real-world driving and charging scenarios.

**Research Gap**

Existing EV trip planners and routing algorithms typically focus on shortest paths, minimal charging stops, or static cost assumptions, without accounting for dynamic, station-specific pricing and detailed SOC behaviour (Montoya et al., 2017). Few integrate multi-objective optimisation capabilities that allow simultaneous cost–time trade-off analysis. Furthermore, many simulation frameworks omit real-world operational constraints such as membership pricing tiers, idle penalties, and station availability, limiting their ability to inform user-centred decision-making (Zhang et al., 2022).

**Research Questions**

This study is guided by the following questions:

1. How can total trip cost be minimised while ensuring the SOC remains above a predefined reserve level?
2. How can total trip duration be minimised while maintaining sufficient SOC for journey completion?
3. How can a hybrid optimisation approach balance cost and time objectives under varying operational constraints?
4. What impact do dynamic pricing models and charger types have on optimal route selection?

**2. Relevant Work / Literature Review**

2.1 EV Charging Optimisation Research

Optimising EV charging decisions is a well-established research theme, with approaches ranging from classical optimisation to artificial intelligence. Traditional Electric Vehicle Routing Problem (EVRP) formulations extend the vehicle routing problem by incorporating battery capacity limits and charging requirements. For example, the industry-focused EVRP review highlights that most solutions aim to minimise travel time or distance, often ignoring dynamic charging curves and cost considerations (Montoya et al., *Electric Vehicle Routing Problem with Industry Constraints*).

Optimal infrastructure planning has been addressed through methods such as probabilistic siting and sizing models, which aim to maximise voltage stability while meeting demand (Shah et al., *Optimal Siting and Sizing of EV Charging Station Using Stochastic Power Flow Analysis for Voltage Stability*). Multi-criteria optimisation approaches also exist, balancing technical, economic, and spatial factors when designing infrastructure (Chen et al., *Multiple-Criteria-Based Electric Vehicle Charging Infrastructure Design Problem*).

Machine learning and reinforcement learning (RL) have been increasingly applied to charging optimisation. DDPG and DQN-based strategies have been proposed for large-scale charging scheduling, adapting to dynamic demand and grid constraints (Li et al., *Electric Vehicle Charging Management Based on Deep Reinforcement Learning*; Wang et al., *A DQN Based Approach for Large-Scale EVs Charging Scheduling*). Other studies explore hybrid RL methods for efficient battery management, incorporating both charging and discharging cycles (Kumar et al., *Optimizing EV Battery Management: Advanced Hybrid Reinforcement Learning Models for Efficient Charging and Discharging*).

Game-theoretic approaches model competitive and cooperative behaviours among drivers or between charging operators, enabling cost-aware route and station selection (Zhang et al., *Charging Management and Pricing Strategy of Electric Vehicle Charging Station Based on Mean Field Game Theory*; Li et al., *Multi-Agent Game-Theoretic Modelling of Electric Vehicle Charging Behavior and Pricing Optimization in Dynamic Ecosystems*).

2.2 EV Pricing Models

EV charging costs vary significantly due to diverse pricing schemes, including per-kWh rates, flat fees, subscription discounts, and idle penalties. This diversity complicates cost minimisation and demands models that incorporate pricing into optimisation. Some RL-based studies explicitly integrate charging costs into decision-making, enabling schedules that adapt to variable tariffs (Li et al., *Electric Vehicle Charging Management Based on Deep Reinforcement Learning*; Feng et al., *Reinforcement Learning for EV Charging Optimization: A Holistic Perspective for Commercial Vehicle Fleets*).

Game-theoretic models have been used to simulate pricing competition among operators, where strategic adjustments can influence demand distribution across stations (Zhang et al., *Charging Management and Pricing Strategy...*; Li et al., *A Comprehensive Game-Theoretic Model for Electric Vehicle Charging Station Competition*). These works demonstrate the value of pricing-aware optimisation but often focus on either cost or time alone, rather than hybrid multi-objective strategies.

Economic assessments of infrastructure costs further illustrate the trade-offs between charger types, installation locations, and pricing structures, with findings suggesting that strategic cost modelling can inform both policy and private investment (Burnham et al., *Estimating Electric Vehicle Charging Infrastructure Costs Across Major U.S. Metropolitan Areas*).

2.3 EV Charging Simulation Frameworks

Simulation is critical for evaluating charging strategies under realistic constraints. User behaviour modelling, such as full data chain-driven approaches, enables the prediction of demand patterns and station utilisation rates (Liu et al., *Modeling and Analysis of Electric Vehicle User Behavior Based on Full Data Chain Driven*). Similarly, household charging behaviour studies analyse temporal patterns and inform demand prediction models (Zhao et al., *Insights into Household Electric Vehicle Charging Behavior: Analysis and Predictive Modeling*).

Scenario-based simulation methods have been applied to assess the impact of EV charging on grid demand and carbon emissions (Gao et al., *A Scenario-Based Approach to Predict Energy Demand and Carbon Emission of Electric Vehicles on the Electric Grid*). Data-driven approaches specific to regional contexts, such as the UK, have been developed to characterise charging demand for infrastructure planning (Zhang et al., *A Data-Driven Approach for Characterising the Charging Demand of Electric Vehicles: A UK Case Study*).

While RL-based scheduling frameworks often incorporate simulation for testing, many omit realistic SOC charging curves, idle fee penalties, and membership-based pricing (Wang et al., *A DQN Based Approach for Large-Scale EVs Charging Scheduling*). This lack of integration limits their applicability to real-world hybrid cost–time optimisation problems.

2.4 Gap Analysis

From the reviewed works, three major gaps are evident:

1. Multi-objective optimisation — Most studies optimise for either cost or time, rarely combining both into a hybrid strategy (Montoya et al., *Electric Vehicle Routing Problem with Industry Constraints*; Li et al., *Multi-Agent Game-Theoretic Modelling...*).
2. Integration of dynamic pricing with charging curves — Few models combine station-specific tariffs with realistic SOC charging rates (Li et al., *Electric Vehicle Charging Management Based on Deep Reinforcement Learning*; Zhang et al., *Charging Management and Pricing Strategy...*).
3. Real-world operational constraints — Idle fees, membership pricing, and station availability are often excluded, limiting practical deployment potential (Burnham et al., *Estimating Electric Vehicle Charging Infrastructure Costs Across Major U.S. Metropolitan Areas*).

2.5 Relevance to This Project

This project addresses these gaps by:

* Implementing cost, time, and hybrid optimisation modes in a unified simulation framework.
* Integrating station-specific pricing with realistic SOC charging curves from EV manufacturer data.
* Modelling operational constraints such as idle fees, membership pricing, and station availability.
* Providing a flexible test environment for comparative evaluation of optimisation strategies under diverse real-world scenarios. **Reference**