The rapid adoption of electric vehicles (EVs) has triggered extensive research into optimization models for charging scheduling and energy integration. Much of the existing literature, however, has focused primarily on grid-oriented challenges such as voltage stability, renewable integration, and load balancing (Kiani et al., 2021; Weckx et al., 2014). While these studies contribute significantly to ensuring the reliability of active distribution networks, they are less relevant for individual EV users whose primary concerns are reducing costs and ensuring route feasibility. For example, Kiani et al. (2021) introduced an Adaptive Robust Optimization framework that effectively addresses grid-side uncertainty, but it does not consider user mobility or time–cost trade-offs. Similarly, Weckx et al. (2014) emphasized reactive power management to stabilize distribution networks, which again falls outside the scope of user-centric EV charging problems. These studies are therefore valuable in the context of power system operations but lack direct applicability to the user optimization challenges that this project addresses.

By contrast, user-centered approaches have been explored in works such as Bian et al. (2019), who applied a Markov Decision Process to capture customer-specific charging decisions based on pricing and satisfaction. Their model highlights the importance of user heterogeneity, yet it lacks scalability for real-time urban environments where travel routes, congestion, and charging station availability dynamically interact. Likewise, SUMO-based simulations (Behrisch et al., 2011) provide realistic spatial mobility insights but have mostly been used for infrastructure planning rather than individual charging decision-making. These gaps underline the need for optimization models that are not only user-centric but also adaptive to dynamic environments with multiple competing objectives.

Recent advances in deep reinforcement learning (RL) have shown strong potential to address these shortcomings. Liu et al. (2024) demonstrated the effectiveness of Deep Q-Networks (DQN) for charging scheduling by modeling the problem as a sequential decision-making task under uncertainty. Their model reduced user costs while improving satisfaction, outperforming traditional optimization methods. However, their focus was still coupled with grid-load balancing objectives, which limits its transferability to purely user-side optimization. Moreover, while DQN works effectively in discrete action spaces, it may struggle when continuous decision variables such as flexible charging times are required. This has motivated interest in Proximal Policy Optimization (PPO), which provides stability in continuous control environments and is well-suited for modeling trade-offs between charging time and cost. Although PPO has been applied in broader energy scheduling contexts, its potential for urban EV charging optimization remains underexplored.

Taken together, the literature demonstrates strong progress in either system-level optimization or user-centric models but fails to integrate both mobility realism and dual-objective trade-offs in a reinforcement learning framework. Grid-side models ensure stability but neglect user convenience, while customer-focused models capture satisfaction but lack scalability for urban traffic-constrained environments. Reinforcement learning offers a powerful solution by combining adaptability, scalability, and the ability to handle high-dimensional state spaces. Our contribution builds on this gap by applying PPO for continuous control—to optimize EV charging in Inner London. Unlike existing studies, our approach is not concerned with grid load balancing but instead directly targets minimizing charging time, reducing costs, and optimizing a hybrid objective that balances both.