Literature Review

The increasing adoption of electric vehicles (EVs) and renewable energy sources (RESs) is redefining the operation and structure of power systems. As the modern grid transitions toward decentralized, clean energy integration, it faces challenges of variability, uncertainty, and bidirectional power flow. These factors necessitate advanced optimization techniques that align system-level efficiency with user-centric performance.  
  
Active Distribution Networks (ADNs) are becoming the foundation for managing this complexity. They incorporate distributed energy resources (DERs) such as rooftop solar, battery storage, and flexible loads like EVs. However, their operation is complicated by uncertainties in energy supply and demand, market prices, and consumer behavior. Kiani et al. (2021) proposed an Adaptive Robust Optimization (ARO) model that deals with these uncertainties by focusing on worst-case scenarios. Unlike stochastic methods that rely on probability distributions and scenario analysis, ARO avoids computationally expensive simulations and provides high reliability for real-time applications.  
  
Electric vehicle integration introduces additional complexity due to its dynamic charging behavior. From a user’s standpoint, charging decisions are influenced by energy costs, battery levels, waiting time, and mobility needs. Bian et al. (2019) proposed a Markov Decision Process (MDP) framework to optimize user-specific charging strategies, accounting for dynamic pricing, driving habits, and user satisfaction. This complements grid-focused studies by emphasizing the importance of integrating behavioral aspects into EV charging models.  
  
Despite advances in active power control, reactive power remains an underutilized capability in EV and inverter-based DER systems. Reactive power plays a vital role in maintaining voltage stability, especially in distribution systems with high renewable penetration. Weckx et al. (2014) demonstrated that coordinated control of local and centralized inverters could stabilize voltage fluctuations. Building on this, Kiani et al. (2021) explicitly integrated reactive power constraints into their ARO model, offering a more comprehensive approach to voltage control in uncertain grid environments.  
  
Beyond optimization frameworks, simulation tools are vital in evaluating grid-EV interactions under realistic mobility scenarios. One of the most robust tools in this space is SUMO (Simulation of Urban Mobility). SUMO is an open-source, microscopic traffic simulator widely used for modeling urban traffic flows and EV charging patterns. It enables researchers to analyze real-time EV movements, charging station demand, and congestion impacts under various traffic and policy scenarios (Behrisch et al., 2011). When integrated with power system models, SUMO provides spatial and temporal granularity for charging demand, which enhances the accuracy of load forecasting and infrastructure planning.  
  
Heterogeneity in EV user behavior further complicates system design. As Bian et al. (2019) highlighted, users vary in their charging times, willingness to participate in vehicle-to-grid (V2G) schemes, and sensitivity to electricity pricing. Without tailored economic incentives and intelligent scheduling, customer engagement in smart charging will remain low. Therefore, aligning optimization goals with customer interests is critical for wide-scale adoption of grid-friendly EV charging.  
  
To reduce computational delays in solving power flow problems, several studies emphasize the importance of linearizing nonlinear equations. Kiani et al. (2021) adopted standard linearization techniques to transform the AC optimal power flow (AC-OPF) problem into a linear programming (LP) model. This reformulation significantly speeds up execution time, making the model viable for day-ahead scheduling and real-time decision-making.  
  
Both technical and behavioral strategies converge under the umbrella of multi-objective optimization. Kiani et al. (2021) implemented an ε-constraint method to minimize both the cost of operations and voltage deviation. On the other hand, Bian et al. (2019) focused on maximizing customer satisfaction while minimizing energy costs. This duality underlines the necessity of hybrid frameworks that incorporate system stability, economic efficiency, and user behavior.

# Research Gaps and Contributions

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| Research Gap | Addressed By |
| Overreliance on stochastic models with large scenario sets | Kiani et al. (2021) introduced ARO, avoiding dependence on probability distributions |
| Limited focus on reactive power control in EV optimization | Integrated reactive power in ADN operation using inverter-based control (Kiani et al., 2021) |
| Neglect of user-centric modeling in EV charging optimization | Bian et al. (2019) provided a customer-focused approach using MDP |
| Absence of spatial mobility insights in charging models | SUMO offers location-based traffic simulation to inform infrastructure planning |
| Lack of alignment between grid objectives and user incentives | Bian et al. (2019) emphasized behavioral modeling and incentive compatibility |
| Inefficiency in solving non-linear OPF for real-time application | Kiani et al. (2021) applied linearization techniques to reduce computational burden |

# Incorporating DQN and PPO in EV Optimization

Recent advancements in deep reinforcement learning have introduced powerful algorithms like Deep Q-Network (DQN) into EV charging optimization. DQN combines Q-learning with deep neural networks, enabling it to manage complex, high-dimensional environments such as EV-grid interactions. Liu et al. (2024) developed a DQN-based charging scheduling system that dynamically balances grid load, reduces user cost, and improves satisfaction. By modeling the problem as a Markov Decision Process (MDP), their DQN model was able to consider state variables such as tariff levels, EV demand, and grid load to make discrete charging decisions over time.  
  
The reward function in their model combined grid overload penalties, cost minimization, and satisfaction rates. The system achieved a 10.29% reduction in charging cost and a 5.2% increase in user satisfaction compared to unoptimized strategies. Notably, the model used techniques such as experience replay and target networks to stabilize learning. These capabilities are critical for achieving real-time scalability and convergence in dynamic energy systems【40†Research\_on\_Reinforcement\_Learning-based\_Optimization\_Algorithm\_for\_Electric\_Vehicle\_Charging\_Scheduling.pdf†L1-L5】.

Proximal Policy Optimization (PPO), another deep reinforcement learning technique, is also gaining traction for its stability and performance in continuous control settings. (Details will be added after extracting from the second paper.)

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