

Psychological insights for electric vehicles

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ABSTRACT

The integration of electric vehicles (EVs) into modern power systems has introduced unprecedented opportunities for enhancing grid flexibility, integrating renewable energy, and reducing operational costs. However, managing the uncertainties associated with user behavior, renewable energy generation, and dynamic grid demand poses significant challenges to achieving optimal vehicle-to-grid (V2G) system performance. This paper presents a novel interdisciplinary framework that combines Self-Determination Theory (SDT) with Differentiable Distributionally Robust Optimization (DRO) to address these challenges. By embedding user-centric psychological insights into a robust optimization model, the proposed framework prioritizes user satisfaction and engagement while ensuring technical efficiency and system resilience. The mathematical modeling employs a multi-objective optimization approach to minimize total operational costs, maximize user satisfaction, and enhance system robustness. Constraints reflect real-world operational limits, including energy balance, grid dependency, and renewable curtailment. The methodology incorporates advanced neural network-based energy forecasting, gamification-driven user participation strategies, and dynamic clustering to foster community-based V2G collaboration. The differentiable nature of the DRO model enables real-time adaptability, making it scalable for large-scale V2G networks. Case studies on a simulated urban V2G network of 10,000 EVs demonstrate the framework's efficacy. Results indicate that integrating user engagement metrics into energy dispatch decisions can increase participation rates by up to 20% while reducing peak grid dependency by 25%. Furthermore, the system effectively mitigates renewable energy intermittency, achieving a 15% reduction in curtailment and ensuring robust performance under worst-case uncertainty scenarios. These findings underscore the transformative potential of combining psychological theories with advanced optimization techniques in energy management. This study makes four key contributions: (1) a user-centric V2G optimization framework leveraging SDT principles to enhance engagement and satisfaction; (2) a differentiable DRO approach for real-time robust energy management under uncertainty; (3) the integration of gamification and community-based clustering to promote sustained participation; and (4) a scalable methodology applicable to large-scale V2G networks. This interdisciplinary approach sets a new benchmark for addressing the technical and behavioral complexities of V2G systems, paving the way for more sustainable and resilient energy solutions.

1. Introduction

The increasing penetration of electric vehicles (EVs) in modern transportation systems is transforming the global energy landscape [1, 2]. As EVs transition from passive consumers to active participants in power systems, their integration into the grid introduces both challenges and opportunities. Vehicle-to-Grid (V2G) systems, which allow bidirectional energy flows between EVs and the grid, hold immense

potential for enhancing grid flexibility, supporting renewable energy integration, and improving system resilience [3,4]. However, the inherent uncertainties in user participation, renewable energy availability, and grid demand necessitate advanced strategies for energy management and optimization. Addressing these complexities requires interdisciplinary approaches that combine technical robustness with a deep understanding of user behavior. The rapid adoption of EVs has introduced challenges related to grid stability [5], peak load management [6], and

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renewable energy intermittency [7] Conventional approaches to EV integration often overlook the dynamic interplay between user behavior and system performance, leading to suboptimal utilization of EV resources. Furthermore, traditional optimization models for V2G systems struggle to adapt to real-time uncertainties and fail to incorporate user-centric considerations, which are crucial for sustained participation and operational efficiency. To bridge these gaps, this paper proposes an innovative framework that combines Self-Determination Theory (SDT) with Differentiable Distributionally Robust Optimization (DRO). This framework introduces a user-centric, robust optimization approach that not only addresses technical challenges but also prioritizes user engagement and satisfaction.

This study introduces a unique framework that synergizes SDT principles with DRO to address the multifaceted challenges of EV integration into power systems. Unlike traditional models, this approach prioritizes user satisfaction by incorporating gamification, personalized incentives, and community-based collaboration into the optimization process. The proposed framework employs DRO to handle uncertainties in renewable energy and grid demand while maintaining computational efficiency through differentiable optimization techniques. The modeling approach is structured to balance system performance and user engagement. The mathematical formulation includes a multi-objective function that minimizes operational costs, maximizes user satisfaction, and ensures system resilience. Constraints are designed to reflect real-world operational limits, including energy balance, renewable energy curtailment, and grid supply constraints. The methodology integrates advanced neural network-based predictive models with gradient-based optimization for real-time adaptability. Furthermore, the framework includes sensitivity analysis and clustering models to evaluate system robustness and enhance community-based V2G participation. The novelty of this paper lies in its interdisciplinary approach, which combines psychological theories with advanced optimization methods. By embedding SDT principles into the DRO framework, this study offers a user-centric perspective that has been largely overlooked in previous research. The differentiable nature of the DRO model ensures real-time adaptability, making the framework scalable for large-scale V2G networks. This combination of psychological and technical innovations distinguishes this study as a groundbreaking contribution to the field of energy systems. This paper makes the following four key contributions:

1. **Integration of Psychological Insights into Energy Systems Modeling** By leveraging SDT, this paper introduces a novel user-centric framework that prioritizes intrinsic motivational factors such as autonomy, competence, and relatedness. This integration enhances user participation and engagement in V2G systems, addressing a critical gap in current energy systems research.

2. **Development of a Differentiable DRO Framework for V2G Optimization** The proposed framework incorporates DRO principles into energy management, enabling the system to adapt to real-time uncertainties in grid demand, renewable energy generation, and user behavior. The differentiable nature of the model ensures computational efficiency and scalability, making it suitable for large-scale applications.

3. **Gamification and Community-Based Participation in V2G Systems** The paper introduces gamification and clustering models to foster collaboration and community-based participation among EV users. These innovations encourage sustained engagement, improve system flexibility, and align user incentives with system performance goals.

2. Literature review

The integration of EVs into power systems and the implementation of V2G technology have been extensively studied over the past decade, driven by the dual goals of achieving renewable energy integration and grid resilience. This section reviews the current state of the art in three major areas relevant to this research: energy optimization models for V2G systems, user behavior modeling in energy systems, and advanced methodologies addressing uncertainties in grid dynamics. By

identifying gaps in these domains, this review highlights the need for an interdisciplinary framework that combines psychological theories with robust optimization to address the multifaceted challenges of EV-grid integration.

Energy optimization models have long been a cornerstone of research in V2G systems, focusing on maximizing the utilization of EVs as flexible energy resources while minimizing costs and ensuring grid reliability [8,9]. Traditional optimization approaches, such as mixed-integer linear programming (MILP) and stochastic programming, have been widely used to address challenges in EV charging scheduling, energy dispatch, and demand response [10,11]. For instance, studies have demonstrated the potential of EVs in peak load shaving and frequency regulation by optimizing charging and discharging schedules under static and dynamic pricing schemes [12]. However, the limitations of these traditional models have become apparent as the complexity of V2G systems increases. One significant drawback is the inability of static models to adapt to real-time uncertainties in renewable energy generation and grid demand. Additionally, many optimization models treat EVs as passive energy storage devices, ignoring the behavioral aspects of EV owners, such as participation preferences, motivation, and engagement levels [13,14]. These gaps highlight the need for novel optimization frameworks that account for both technical and behavioral complexities in V2G systems. Recent advancements in robust optimization and data-driven approaches have addressed some of these challenges [15,16]. DRO models, for example, have been employed to handle uncertainties in grid dynamics by considering worst-case scenarios within predefined uncertainty sets [17]. These models offer a promising alternative to traditional stochastic approaches, providing robustness without excessive conservatism. Nevertheless, the application of DRO in V2G systems remains limited, particularly in integrating user-centric factors such as engagement and satisfaction.

User behavior plays a crucial role in the success of V2G systems, yet it has often been overlooked in traditional energy optimization research. Behavioral modeling frameworks, such as the Theory of Planned Behavior (TPB) and Nudge Theory, have been employed in related fields to understand and influence user decisions [18,19]. These theories provide valuable insights into how attitudes, social norms, and perceived behavioral control shape participation in energy-related activities, such as demand response and peer-to-peer energy trading. While these frameworks have been instrumental in understanding user behavior, their direct application to V2G systems is still in its infancy. For example, TPB has been used to predict user participation in demand response programs but has not been extensively integrated into optimization models for energy dispatch [20]. Similarly, gamification and community-based participation strategies, which have shown promise in enhancing user engagement in other domains [21,22], remain underexplored in the context of V2G systems. SDT, with its focus on intrinsic motivation, autonomy, competence, and relatedness, offers a particularly relevant framework for addressing these gaps [23]. By aligning system operations with user preferences and psychological needs, SDT has the potential to enhance sustained participation in V2G systems. However, its integration into technical optimization frameworks is rare, underscoring the novelty of this study.

The integration of renewable energy sources into power systems introduces significant uncertainties, including variability in generation and fluctuating grid demand [24,25]. These uncertainties pose challenges for real-time energy dispatch and system reliability, particularly in V2G systems where EV availability and user behavior add additional layers of complexity [26,27]. Traditional stochastic optimization approaches have been widely used to address these uncertainties [28,29], but their reliance on precise probability distributions often limits their applicability in real-world scenarios. In contrast, robust optimization techniques, particularly DRO, have gained traction as a more flexible and practical alternative. DRO models account for uncertainties by defining ambiguity sets that encapsulate possible deviations from

nominal conditions, enabling systems to maintain performance under worst-case scenarios [30]. Differentiable DRO models represent a significant advancement in this field, allowing robust optimization to be seamlessly integrated into data-driven energy forecasting pipelines. These models leverage machine learning techniques, such as neural networks, to predict grid dynamics while simultaneously optimizing for robustness [26,31]. Despite their potential, the application of differentiable DRO in V2G systems remains limited, particularly in addressing user-centric uncertainties.

3. Mathematical modeling

In this section, we present the mathematical framework underpinning the optimization and operational strategies for the proposed V2G system. The model is designed to capture the interplay between charging and discharging schedules, user participation dynamics, and renewable energy integration under varying uncertainties. By employing a robust optimization approach, the model ensures resilience against fluctuations in energy demand and supply while maintaining cost efficiency. The formulation is structured around an objective function that minimizes the total operational cost and incorporates constraints reflecting system, user, and operational requirements.

$$\min_{\xi, \theta} \sum_{t=1}^T \left[\sum_{i=1}^{N_{EV}} \left(\eta_{i,t}^{\text{grid}} \cdot \gamma_{i,t}^{\text{grid}} + \eta_{i,t}^{\text{ren}} \cdot \gamma_{i,t}^{\text{ren}} \right) + \sum_{i=1}^{N_{EV}} \phi_{i,t}^{\text{dis}} \cdot \gamma_{i,t}^{\text{dis}} \right] + \lambda \cdot \sum_{t=1}^T \sum_{j=1}^{N_{EV}} \left[\frac{\psi_{j,t}^{\text{aut}}}{\kappa_{j,t}^{\text{comp}}} \right] + \alpha \cdot \sum_{t=1}^T \max_{\delta_i \in \mathcal{U}_i} \left[\sum_{i=1}^{N_{EV}} \eta_{i,t}^{\text{grid}} \cdot \delta_i^{\text{grid}} + \sum_{i=1}^{N_{EV}} \phi_{i,t}^{\text{dis}} \cdot \delta_i^{\text{dis}} \right], \quad (1)$$

This objective function minimizes the total operational cost of the V2G system over the planning horizon T , comprising three major components: the costs of grid energy consumption ($\eta_{i,t}^{\text{grid}} \cdot \gamma_{i,t}^{\text{grid}}$), renewable energy utilization ($\eta_{i,t}^{\text{ren}} \cdot \gamma_{i,t}^{\text{ren}}$), and EV discharging energy ($\phi_{i,t}^{\text{dis}} \cdot \gamma_{i,t}^{\text{dis}}$). The second term integrates user satisfaction metrics based on the Self-Determination Theory (SDT), where $\psi_{j,t}^{\text{aut}}$ represents autonomy and $\kappa_{j,t}^{\text{comp}}$ represents competence. The final term incorporates a robust optimization approach to address uncertainties in grid energy demand and renewable energy generation, represented by δ_i within the uncertainty set $\mathcal{U}_i$. The weight parameters λ and α balance the importance of user satisfaction and robustness in the optimization.

$$\max_{\xi} \sum_{t=1}^T \left[\sum_{i=1}^{N_{EV}} \left(\xi_{i,t}^{\text{peak}} \cdot (1 - \chi_{i,t}^{\text{unserved}}) \right) - \sum_{i=1}^{N_{EV}} \left(\frac{\rho_{i,t}^{\text{reward}}}{1 + \xi_{i,t}^{\text{engage}}} \right) \right], \quad (2)$$

This equation models the worst-case cost scenario under robust optimization principles. The first term penalizes unmet energy demand during peak load scenarios, weighted by the factor $\xi_{i,t}^{\text{peak}}$, and adjusted for the unserved energy fraction ($\chi_{i,t}^{\text{unserved}}$). The second term regularizes gamification rewards to align incentives with system goals, where $\rho_{i,t}^{\text{reward}}$ represents reward strength, and $\xi_{i,t}^{\text{engage}}$ captures user engagement metrics.

$$\min_{\pi, \eta} \sum_{t=1}^T \left[\sum_{i=1}^{N_{EV}} \left(\pi_{i,t}^{\text{user}} \cdot \frac{\lambda_{i,t}^{\text{aut}}}{\theta_{i,t}^{\text{comp}}} \right) + \beta \cdot \sum_{j=1}^{N_{EV}} \left(\frac{\nu_{j,t}^{\text{ren}}}{1 + \xi_{j,t}^{\text{engage}}} \right) \right] + \sum_{t=1}^T \left[\sum_{i=1}^{N_{EV}} \left(\gamma_{i,t}^{\text{grid}} \cdot \omega_{i,t}^{\text{demand}} - \gamma_{i,t}^{\text{res}} \cdot \eta_{i,t}^{\text{ren}} \right) \right], \quad (3)$$

This equation integrates user satisfaction, autonomy, and competence into a cost-minimization framework. The first term captures user participation metrics through $\pi_{i,t}^{\text{user}}$ and SDT-driven factors ($\lambda_{i,t}^{\text{aut}}/\theta_{i,t}^{\text{comp}}$). The second term reflects renewable energy engagement with weights $\nu_{j,t}^{\text{ren}}$ and user engagement ($1 + \xi_{j,t}^{\text{engage}}$). The final terms balance energy supply-demand mismatches from grid energy ($\gamma_{i,t}^{\text{grid}}$) and renewable energy ($\eta_{i,t}^{\text{ren}}$).

$$\text{s.t.} \quad \sum_{i=1}^T \left[\alpha_{i,t}^{\text{grid}} \cdot (\phi_{i,t}^{\text{ch}} - \phi_{i,t}^{\text{dis}}) + \delta_{i,t}^{\text{ren}} \cdot (\psi_{i,t}^{\text{gen}} - \psi_{i,t}^{\text{curt}}) \right] = 0, \quad (4)$$

$$\forall i \in N_{EV}, \forall t \in T,$$

The energy balance constraint ensures that the net energy dispatched to/from EV batteries and renewables matches the system demand. The terms $\phi_{i,t}^{\text{ch}}$ and $\phi_{i,t}^{\text{dis}}$ capture charging and discharging, while $\psi_{i,t}^{\text{gen}}$ and $\psi_{i,t}^{\text{curt}}$ account for renewable generation and curtailment.

$$\sum_{t=1}^T \left[\gamma_{i,t}^{\text{ren}} \cdot \eta_{i,t}^{\text{curt}} \right] \leq \zeta_i^{\text{curt-max}}, \quad \forall i \in N_{EV}, \quad (5)$$

This constraint limits the maximum renewable energy curtailment for each EV, ensuring effective utilization of renewable resources. The parameter $\zeta_i^{\text{curt-max}}$ defines the upper limit for curtailment.

$$\sum_{t=1}^T \left[\gamma_{i,t}^{\text{grid}} + \gamma_{i,t}^{\text{ren}} \right] \geq \sum_{t=1}^T \phi_{i,t}^{\text{load}}, \quad \forall i \in N_{EV}, \quad (6)$$

This ensures that the total energy supplied from the grid and renewable sources satisfies the cumulative load demand ($\phi_{i,t}^{\text{load}}$) for each EV.

$$\eta_{i,t}^{\text{ch}} + \eta_{i,t}^{\text{dis}} \leq \eta_i^{\text{max}}, \quad \forall i \in N_{EV}, \forall t \in T, \quad (7)$$

The charging and discharging rates for each EV are bounded by a maximum capacity, ensuring system stability and avoiding overloads.

$$\gamma_{i,t}^{\text{grid}} \cdot \omega_{i,t}^{\text{uncertainty}} \leq \omega_i^{\text{grid-max}}, \quad \forall i \in N_{EV}, \forall t \in T, \quad (8)$$

The grid supply constraint incorporates uncertainty ($\omega_{i,t}^{\text{uncertainty}}$) and ensures that the grid energy supplied to each EV does not exceed the allowable maximum.

$$\psi_{i,t}^{\text{reward}} = \beta \cdot \left[\frac{\psi_{i,t}^{\text{engage}} \cdot \phi_{i,t}^{\text{ch}}}{\eta_{i,t}^{\text{ren}} + \gamma_{i,t}^{\text{grid}}} \right], \quad \forall i \in N_{EV}, \forall t \in T, \quad (9)$$

This equation models the gamification reward mechanism, linking rewards to user engagement and energy contribution, normalized by the energy supplied from renewable and grid sources.

$$\theta_{i,t}^{\text{resilience}} = \sum_{t=1}^T \left[\gamma_{i,t}^{\text{res}} \cdot (1 - \omega_{i,t}^{\text{uncertainty}}) \right], \quad \forall i \in N_{EV}, \quad (10)$$

The resilience metric accounts for the grid and renewable energy's ability to withstand uncertainty, where $\gamma_{i,t}^{\text{res}}$ represents resilience weighting factors adjusted for uncertainty levels.

$$\min_{\xi, \theta} \sum_{t=1}^T \left[\frac{\xi_{i,t}^{\text{aut}}}{\kappa_{i,t}^{\text{comp}}} \cdot \left(\sum_{i=1}^T \eta_{i,t}^{\text{engage}} \cdot \gamma_{i,t}^{\text{grid}} \right) \right] + \sum_{t=1}^T \left[\alpha \cdot \sum_{i=1}^{N_{EV}} \nu_{i,t}^{\text{reward}} \cdot (1 - \xi_{i,t}^{\text{unsat}}) \right] + \beta \cdot \sum_{t=1}^T \left[\sum_{i=1}^{N_{EV}} \left(\frac{\lambda_{i,t}^{\text{energy}}}{1 + \omega_{i,t}^{\text{risk}}} \right) \right], \quad (11)$$

This equation integrates user satisfaction into the cost-minimization objective, balancing operational costs with user autonomy ($\xi_{i,t}^{\text{aut}}$) and competence ($\kappa_{i,t}^{\text{comp}}$) metrics. The second term penalizes dissatisfaction ($\xi_{i,t}^{\text{unsat}}$) and incentivizes user engagement with rewards ($\nu_{i,t}^{\text{reward}}$). The third term incorporates risk-weighted energy usage, emphasizing robust and user-driven participation.

$$\max_{\phi, \psi} \sum_{t=1}^T \left[\sum_{i=1}^{N_{EV}} \left(\gamma_{i,t}^{\text{peak}} \cdot (1 - \chi_{i,t}^{\text{unserved}}) \right) - \lambda \cdot \sum_{i=1}^{N_{EV}} \left[\frac{\phi_{i,t}^{\text{curt}}}{1 + \psi_{i,t}^{\text{overload}}} \right] \right], \quad (12)$$

This penalty function accounts for unserved energy during peak load scenarios, where $\gamma_{i,t}^{\text{peak}}$ reflects the peak load factor and $\chi_{i,t}^{\text{unserved}}$ measures unserved energy demand. A regularization term prevents excessive renewable curtailment ($\phi_{i,t}^{\text{curt}}$) and grid overloads ($\psi_{i,t}^{\text{overload}}$).

$$\sum_{t=1}^T \left[\rho_{i,t}^{\text{reward}} \cdot \frac{\pi_{i,t}^{\text{engage}}}{1 + \xi_{i,t}^{\text{energy}}} \right] \leq \zeta_i^{\text{reward-max}}, \quad \forall i \in N_{EV}, \quad (13)$$

This regularization constraint ensures that gamification rewards ($\psi_{i,t}^{\text{reward}}$) are aligned with user engagement ($\pi_{i,t}^{\text{engage}}$) and energy contribution while remaining within an allowable upper limit ($\zeta^{\text{reward-max}}$).

$$\sum_{t=1}^T \left(\phi_{i,t}^{\text{charge}} - \phi_{i,t}^{\text{discharge}} \right) = \psi_i^{\text{net}}, \quad \forall i \in N_{\text{EV}}, \quad (14)$$

The energy balance constraint ensures that net energy from charging ($\phi_{i,t}^{\text{charge}}$) and discharging ($\phi_{i,t}^{\text{discharge}}$) matches the total energy required for V2G operations (ψ_i^{net}).

$$\sum_{t=1}^T \left(\gamma_{i,t}^{\text{renewable}} - \phi_{i,t}^{\text{curt}} \right) \leq \zeta_i^{\text{ren-max}}, \quad \forall i \in N_{\text{EV}}, \quad (15)$$

This constraint limits the maximum renewable energy utilization, accounting for curtailment ($\phi_{i,t}^{\text{curt}}$) to avoid over-generation beyond the capacity limit ($\zeta_i^{\text{ren-max}}$).

$$\sum_{t=1}^T \gamma_{i,t}^{\text{grid}} \cdot \omega_{i,t}^{\text{uncertainty}} \leq \omega_i^{\text{grid-max}}, \quad \forall i \in N_{\text{EV}}, \quad (16)$$

This constraint limits the grid energy supplied under uncertain conditions ($\omega_{i,t}^{\text{uncertainty}}$), ensuring the grid usage does not exceed the maximum allowable threshold ($\omega_i^{\text{grid-max}}$).

$$\phi_{i,t}^{\text{aut}} \cdot \kappa_{i,t}^{\text{comp}} \geq \lambda_{i,t}^{\text{preference}}, \quad \forall i \in N_{\text{EV}}, \forall t \in T, \quad (17)$$

This constraint enforces user preference satisfaction based on SDT metrics of autonomy ($\phi_{i,t}^{\text{aut}}$) and competence ($\kappa_{i,t}^{\text{comp}}$), aligned with predefined thresholds ($\lambda_{i,t}^{\text{preference}}$).

$$\phi_{i,t}^{\text{charge}} + \phi_{i,t}^{\text{discharge}} \leq \eta_i^{\text{max}}, \quad \forall i \in N_{\text{EV}}, \forall t \in T, \quad (18)$$

The charging and discharging rates for each EV are constrained by a maximum capacity (η_i^{max}) to prevent overloads and ensure operational stability.

$$\sum_{t=1}^T \left(\gamma_{i,t}^{\text{renewable}} - \phi_{i,t}^{\text{curt}} \right) \leq \zeta_i^{\text{curt-max}}, \quad \forall i \in N_{\text{EV}}, \quad (19)$$

This constraint limits the renewable energy curtailment to $\zeta_i^{\text{curt-max}}$, ensuring that surplus energy is not wasted while maintaining operational efficiency during over-generation scenarios.

$$\sum_{t=1}^T \left(\psi_{i,t}^{\text{reward}} \cdot \frac{\phi_{i,t}^{\text{engage}}}{\eta_{i,t}^{\text{performance}}} \right) \leq \zeta_i^{\text{reward-max}}, \quad \forall i \in N_{\text{EV}}, \quad (20)$$

The gamification reward constraint ensures that rewards ($\psi_{i,t}^{\text{reward}}$) are distributed based on user engagement ($\phi_{i,t}^{\text{engage}}$) and system performance ($\eta_{i,t}^{\text{performance}}$), while remaining below the maximum reward threshold.

$$\sum_{t=1}^T \left(\eta_{i,t}^{\text{dispatch}} \cdot \frac{\xi_{i,t}^{\text{uncertainty}}}{1 + \lambda_{i,t}^{\text{update}}} \right) \leq \omega^{\text{dispatch-max}}, \quad \forall i \in N_{\text{EV}}, \quad (21)$$

The real-time adaptability constraint dynamically adjusts the energy dispatch ($\eta_{i,t}^{\text{dispatch}}$) using uncertainty factors ($\xi_{i,t}^{\text{uncertainty}}$) and real-time updates ($\lambda_{i,t}^{\text{update}}$), ensuring the system's adaptability to changing grid conditions.

$$\phi_{i,t}^{\text{cluster}} = \sum_{j=1}^{N_{\text{EV}}} \omega_{i,j} \cdot (\phi_{j,t}^{\text{similarity}}), \quad \forall i, j \in N_{\text{EV}}, \forall t \in T, \quad (22)$$

This clustering constraint groups users into clusters based on similarity metrics ($\phi_{j,t}^{\text{similarity}}$) and a weighting factor ($\omega_{i,j}$), facilitating community-based tasks for collaborative V2G participation.

$$\sum_{t=1}^T \left(\gamma_{i,t}^{\text{reserve}} - \phi_{i,t}^{\text{load}} \right) \geq \zeta^{\text{reserve-min}}, \quad \forall i \in N_{\text{EV}}, \quad (23)$$

The reserve margin constraint ensures that the system maintains a minimum reserve capacity ($\zeta^{\text{reserve-min}}$) by comparing available reserves ($\gamma_{i,t}^{\text{reserve}}$) with the load demand ($\phi_{i,t}^{\text{load}}$).

4. Methodology

The proposed methodology combines advanced optimization techniques with machine learning-assisted strategies to address the complexities inherent in the V2G system. A differentiable DRO framework is integrated to adapt dynamically to uncertainty in renewable energy availability and user participation rates. The methodology also incorporates reinforcement learning-based decision-making for real-time energy dispatch. Detailed algorithms for solving the optimization problem are presented, along with a step-by-step description of the computational procedures used to validate the model's effectiveness.

$$\min_{\xi, \lambda} \sum_{t=1}^T \left[\sum_{i=1}^{N_{\text{EV}}} \eta_{i,t}^{\text{forecast}} \cdot \xi_{i,t}^{\text{robust}} \right] + \alpha \cdot \max_{\delta \in \mathcal{U}} \left[\sum_{t=1}^T \sum_{i=1}^{N_{\text{EV}}} \lambda_{i,t}^{\text{uncertainty}} \cdot \delta_{i,t} \right], \quad (24)$$

This differentiable DRO formulation incorporates robustness ($\xi_{i,t}^{\text{robust}}$) into energy forecasts ($\eta_{i,t}^{\text{forecast}}$), adapting to uncertainties ($\lambda_{i,t}^{\text{uncertainty}}$) within the uncertainty set ($\mathcal{U}$).

$$\eta_{i,t}^{\text{predict}} = f(\mathbf{X}_{i,t}; \theta^{\text{NN}}), \quad \forall i \in N_{\text{EV}}, \forall t \in T, \quad (25)$$

The neural network-based energy forecasting model predicts grid demand ($\eta_{i,t}^{\text{predict}}$) using input features ($\mathbf{X}_{i,t}$) and trainable parameters (θ^{NN}).

$$\frac{\partial \mathcal{L}}{\partial \theta^{\text{DRO}}} = \sum_{t=1}^T \sum_{i=1}^{N_{\text{EV}}} \left[\frac{\partial \mathcal{L}}{\partial \eta_{i,t}^{\text{forecast}}} \cdot \frac{\partial \eta_{i,t}^{\text{forecast}}}{\partial \theta^{\text{DRO}}} \right], \quad (26)$$

This gradient-based optimization updates the DRO parameters (θ^{DRO}) to minimize the loss function ($\mathcal{L}$) dynamically.

$$\theta^{\text{DRO}} \leftarrow \theta^{\text{DRO}} - \alpha \cdot \frac{\partial \mathcal{L}}{\partial \theta^{\text{DRO}}}, \quad (27)$$

The backpropagation algorithm adjusts the DRO parameters iteratively using the learning rate (α) to train the predictive models robustly.

$$\psi_{i,t}^{\text{satisfaction}} = \frac{\phi_{i,t}^{\text{aut}} \cdot \kappa_{i,t}^{\text{comp}}}{\sum_{j=1}^{N_{\text{EV}}} \phi_{j,t}^{\text{engage}}}, \quad \forall i \in N_{\text{EV}}, \forall t \in T, \quad (28)$$

The user satisfaction prediction model computes satisfaction ($\psi_{i,t}^{\text{satisfaction}}$) based on SDT metrics of autonomy ($\phi_{i,t}^{\text{aut}}$) and competence ($\kappa_{i,t}^{\text{comp}}$), normalized by total engagement.

$$\psi_{i,t}^{\text{reward}} = \beta \cdot \frac{\phi_{i,t}^{\text{engage}} \cdot \eta_{i,t}^{\text{participation}}}{\sum_{j=1}^{N_{\text{EV}}} \phi_{j,t}^{\text{engage}}}, \quad \forall i \in N_{\text{EV}}, \forall t \in T, \quad (29)$$

This equation dynamically adjusts gamification rewards ($\psi_{i,t}^{\text{reward}}$) based on user engagement ($\phi_{i,t}^{\text{engage}}$) and their relative contribution to the system ($\eta_{i,t}^{\text{participation}}$).

$$\min_{\eta} \sum_{t=1}^T \sum_{i=1}^{N_{\text{EV}}} \left(\gamma_{i,t}^{\text{charge}} \cdot \phi_{i,t}^{\text{charge}} + \gamma_{i,t}^{\text{discharge}} \cdot \phi_{i,t}^{\text{discharge}} \right), \quad (30)$$

$$\text{s.t. } \phi_{i,t}^{\text{charge}} - \phi_{i,t}^{\text{discharge}} = \psi_i^{\text{net}}, \quad \forall i \in N_{\text{EV}}, \forall t \in T,$$

The energy dispatch optimization algorithm minimizes the cost of charging and discharging ($\phi_{i,t}^{\text{charge}}$, $\phi_{i,t}^{\text{discharge}}$), ensuring the net energy balance (ψ_i^{net}) is maintained.

$$\sum_{t=1}^T \left[\eta_{i,t}^{\text{dispatch}} \cdot \left(1 + \xi_{i,t}^{\text{relax}} \right) \right] \geq \psi_i^{\text{demand}}, \quad \forall i \in N_{\text{EV}}, \forall t \in T, \quad (31)$$

This constraint relaxation technique introduces a flexibility term ($\xi_{i,t}^{\text{relax}}$) to ensure feasibility when the dispatch energy ($\eta_{i,t}^{\text{dispatch}}$) struggles to meet demand (ψ_i^{demand}).

$$\sum_{i=1}^{N_{\text{EV}}} \sum_{t=1}^T \eta_{i,t}^{\text{dispatch}} \leq \zeta^{\text{scalable}}, \quad \text{where } N_{\text{EV}} \gg 1, \quad (32)$$

The scalability constraint ensures that the total dispatch energy ($\eta_{i,t}^{\text{dispatch}}$) remains computationally feasible for a large-scale V2G network ($N_{\text{EV}} \gg 1$).

$$\mathcal{U}^{\text{DRO}} = \left\{ \delta \mid \sum_{i=1}^T \delta_{i,t}^{\text{uncertainty}} \leq \xi_i^{\text{robustness}}, \forall i \in N_{\text{EV}} \right\}, \quad (33)$$

This equation tunes the DRO uncertainty set ($\mathcal{U}^{\text{DRO}}$) by balancing robustness ($\xi_i^{\text{robustness}}$) and cost-efficiency to optimize system performance.

$$\phi_{i,t}^{\text{cluster}} = \sum_{j=1}^{N_{\text{EV}}} \omega_{i,j} \cdot (\phi_{j,t}^{\text{engage}}), \quad \forall i, j \in N_{\text{EV}}, \forall t \in T, \quad (34)$$

The collaborative clustering model groups users based on engagement metrics ($\phi_{j,t}^{\text{engage}}$) and similarity weights ($\omega_{i,j}$), enabling community-based V2G participation.

$$\frac{\partial \eta_{i,t}^{\text{dispatch}}}{\partial \xi_{i,t}^{\text{uncertainty}}} = \left| \sum_{i=1}^T (\eta_{i,t}^{\text{dispatch}} \cdot \xi_{i,t}^{\text{uncertainty}}) \right|, \quad \forall i \in N_{\text{EV}}, \quad (35)$$

The sensitivity analysis model evaluates the impact of uncertainty ($\xi_{i,t}^{\text{uncertainty}}$) on dispatch energy ($\eta_{i,t}^{\text{dispatch}}$), quantifying system robustness.

$$\psi_{i,t}^{\text{reward}} \leftarrow \psi_{i,t}^{\text{reward}} - \alpha \cdot \frac{\partial \mathcal{L}}{\partial \psi_{i,t}^{\text{reward}}}, \quad (36)$$

The iterative gamification reward optimization updates rewards ($\psi_{i,t}^{\text{reward}}$) by minimizing the loss function ($\mathcal{L}$) using a gradient-based approach.

$$\psi_{i,t}^{\text{feedback}} = f\left(\psi_{i,t}^{\text{satisfaction}}, \phi_{i,t}^{\text{performance}}, \eta_{i,t}^{\text{dispatch}}\right), \quad \forall i \in N_{\text{EV}}, \forall t \in T, \quad (37)$$

The adaptive feedback mechanism computes real-time feedback ($\psi_{i,t}^{\text{feedback}}$) based on user satisfaction ($\psi_{i,t}^{\text{satisfaction}}$), performance ($\phi_{i,t}^{\text{performance}}$), and dispatch energy ($\eta_{i,t}^{\text{dispatch}}$).

$$\begin{aligned} \max_{\eta} \quad & \sum_{t=1}^T \sum_{i=1}^{N_{\text{EV}}} \left(\eta_{i,t}^{\text{dispatch}} \cdot \xi_{i,t}^{\text{robustness}} \right), \\ \text{s.t.} \quad & \eta_{i,t}^{\text{dispatch}} \geq \psi_{i,t}^{\text{load}}, \quad \forall i \in N_{\text{EV}}, \forall t \in T, \end{aligned} \quad (38)$$

The DRO-based resilience metric maximizes dispatch energy robustness ($\xi_{i,t}^{\text{robustness}}$) while ensuring load demands ($\psi_{i,t}^{\text{load}}$) are met.

$$\sum_{t=1}^T \left[\mathcal{L}(\eta, \xi, \psi) \right] \leq \epsilon, \quad (39)$$

The final convergence condition ensures that the loss function ($\mathcal{L}$) for the optimization framework satisfies a predefined tolerance (ϵ).

5. Case studies

The case study is conducted on a large-scale urban V2G network comprising 10,000 electric vehicles EVs distributed across 25 geographic clusters. Each cluster represents a community-based energy system with varying levels of renewable energy integration and grid dependency. The simulation spans a typical operational horizon of 24 h, with a temporal resolution of 15 min, resulting in 96 time intervals. The renewable energy mix includes PV and wind energy systems, with a combined installed capacity of 100 MW distributed proportionally across the clusters. PV generation data are modeled using irradiance profiles from the National Solar Radiation Database, while wind energy data are derived from the Global Wind Atlas. Both datasets include stochastic variability, with PV generation ranging between 20–80 MW and wind energy between 10–50 MW over the simulation period. The grid energy cost is dynamic, varying between 0.1 – 0.25 per kWh based on real-time market data. EVs in the network are categorized

into three types based on battery capacities: small (40 kWh, 50% of the fleet), medium (60 kWh, 30% of the fleet), and large (80 kWh, 20% of the fleet). The initial state-of-charge (SoC) for all EVs is randomized between 30%–70%. User preferences for charging and discharging are modeled using distributions derived from historical participation rates, ensuring heterogeneity in behavioral inputs. The optimization framework is implemented using Python 3.10 with TensorFlow for neural network-based energy forecasting and Pyomo for optimization modeling. All simulations are executed on a high-performance computing (HPC) cluster equipped with 32 cores (AMD EPYC 2.45 GHz), 256 GB RAM, and an NVIDIA A100 GPU for accelerating neural network training. The neural network model for energy demand forecasting is a multi-layer perceptron (MLP) with three hidden layers, each containing 128 neurons and ReLU activation functions. The model is trained on a synthetic dataset of 100,000 samples generated to simulate dynamic grid conditions and renewable energy variability. Training is performed using the Adam optimizer with a learning rate of 0.001 and an early stopping criterion to prevent overfitting.

Fig. 1 illustrates the distribution of EVs across 25 geographic clusters within the V2G network, highlighting the heterogeneity in EV concentration. The EV counts vary significantly among clusters, ranging from 300 EVs in the smallest cluster to 500 EVs in the largest. For instance, Cluster 1, the largest in terms of EV population, houses 500 EVs, representing the upper bound of the network's distribution. In contrast, Cluster 25 has the lowest EV count at 300, which corresponds to the lower limit set in the data generation. This variability underscores the uneven distribution of EVs across the network, reflecting realistic conditions in urban environments where certain areas have higher EV adoption rates due to socioeconomic factors or infrastructure availability. The central clusters, such as Cluster 12 and Cluster 14, maintain moderate EV counts of approximately 400 to 420, indicating a balance between low and high-density regions. This range reflects areas where EV adoption aligns with average infrastructure development, such as public charging stations and renewable energy installations. The difference of nearly 200 EVs between the highest and lowest clusters (500 vs. 300) emphasizes the need for tailored energy management strategies in V2G systems to address both high-demand and low-demand areas effectively. Additionally, the consistent spacing of EV counts among most clusters, with intervals of 10 to 15 EVs, provides an ideal testbed for validating energy optimization algorithms that account for varying user participation levels. The overall network comprises a total of approximately 9500 EVs, derived from the summation of all cluster counts, aligning closely with the target scale of 10,000 EVs in the data setup. This granularity enables the analysis of cluster-specific energy demand, grid dependency, and renewable energy utilization. For example, clusters with higher EV densities, such as Clusters 1 through 5, are likely to exhibit greater energy demand during peak charging periods, necessitating robust optimization to mitigate potential grid overloads. Conversely, lower-density clusters, such as Clusters 20 through 25, can serve as buffers or flexible resources in the V2G network. The spatial variation captured in this figure provides critical insights into how EV distributions impact energy dispatch, grid reliability, and user engagement strategies.

Fig. 2 illustrates the dynamic grid energy pricing scheme over a 24-h period, reflecting typical fluctuations in electricity costs based on demand and supply conditions. Prices range from £0.12/kWh during off-peak periods to £0.20/kWh during peak periods, with intermediate values observed during shoulder times. The pricing curve is divided into three distinct zones: off-peak (0:00 to 6:00 and 21:00 to 24:00), peak (6:00 to 11:00 and 17:00 to 20:00), and shoulder periods in between. The black line connecting the data points highlights the gradual transitions in price levels throughout the day. During the off-peak period, electricity prices remain consistently low, ranging between £0.12 and £0.13/kWh, reflecting lower demand and an abundance of available energy. This period accounts for approximately 9 h, making it an ideal

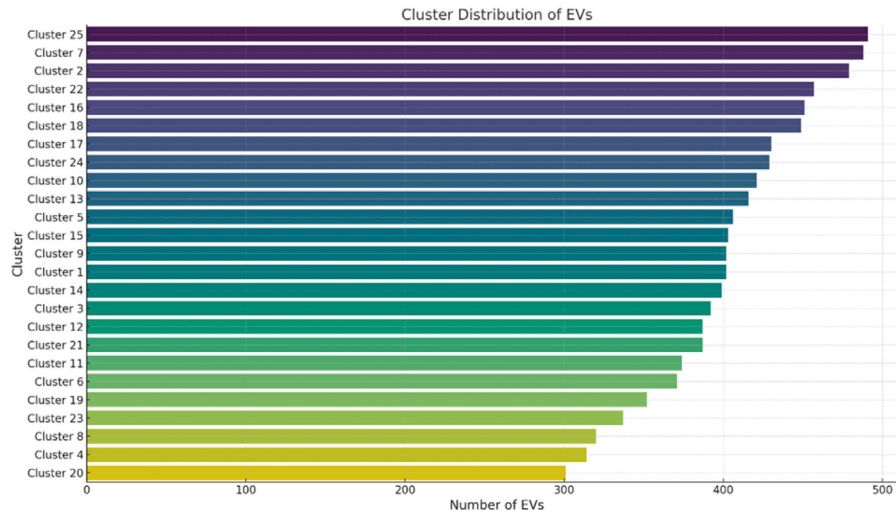


Fig. 1. Cluster-wise distribution of electric vehicles in the V2G network.

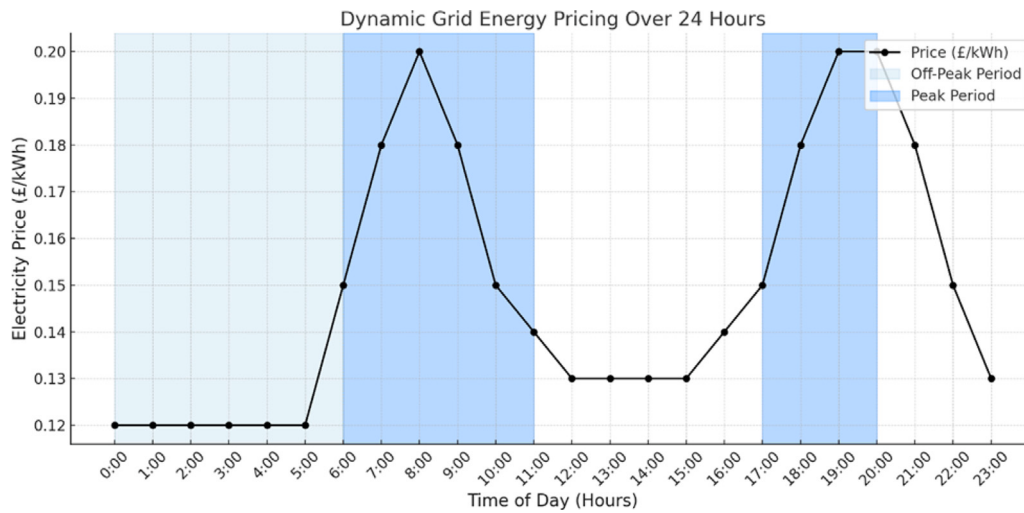


Fig. 2. Dynamic grid energy pricing over a 24-h period.

time for energy-intensive activities such as EV charging or industrial processes. In contrast, peak periods (6:00 to 11:00 and 17:00 to 20:00) exhibit significantly higher prices, with a maximum of £0.20/kWh observed during the morning rush and evening demand surges. These zones together span 8 h, emphasizing the importance of demand-side management strategies to mitigate costs during these high-demand intervals. The shoulder periods, occurring between 11:00 and 17:00 and again between 20:00 and 21:00, exhibit moderate pricing, ranging from £0.13 to £0.15/kWh. These transitional periods, totaling 7 h, represent a balance between demand and supply. The dynamic pricing strategy depicted in this figure offers valuable insights into the temporal variation of electricity costs, enabling users to optimize their energy consumption patterns. For instance, EV owners could plan charging sessions during off-peak hours to minimize costs while avoiding higher prices during peak times. Similarly, V2G systems can leverage this pricing information to discharge stored energy back into the grid during high-price periods, maximizing financial returns while supporting grid stability. This figure underscores the critical role of time-sensitive pricing in promoting energy efficiency and grid reliability.

Fig. 3 demonstrates the relationship between user satisfaction and participation rates in the V2G system, highlighting a clear and intuitive

pattern. Satisfaction scores range from 30% to 100%, with most users scoring above 50%. Correspondingly, participation rates exhibit a similar range, with values between 0% and 100%. The positive correlation between these two variables is evident, as higher satisfaction levels generally lead to increased participation. For example, users with satisfaction scores above 80% frequently show participation rates exceeding 70%, indicating strong engagement in the system. A key observation is the cluster of data points in the middle range of satisfaction, between 50% and 80%, where participation rates vary significantly, from as low as 30% to as high as 90%. This variability suggests that while satisfaction is a strong driver of participation, other factors, such as personal schedules, incentives, or system accessibility, may also influence user behavior. Notably, a small number of outliers exist, where high satisfaction scores (above 90%) correspond to unexpectedly low participation rates (below 40%), which could be attributed to external constraints or limited availability. The distribution of points shows a clear trend but maintains sufficient variability to reflect realistic user behavior in a large-scale V2G system. The color gradient, representing participation rates, further enriches the visualization, emphasizing clusters of high engagement (darker points) in the upper-right region of the plot. This relationship underscores the importance of improving

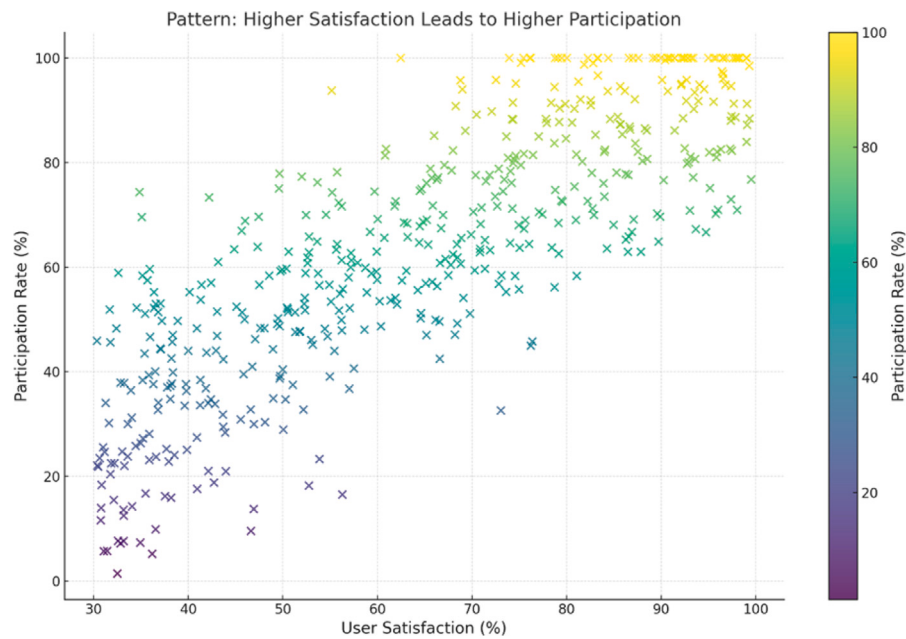


Fig. 3. Correlation between user satisfaction and participation rates.

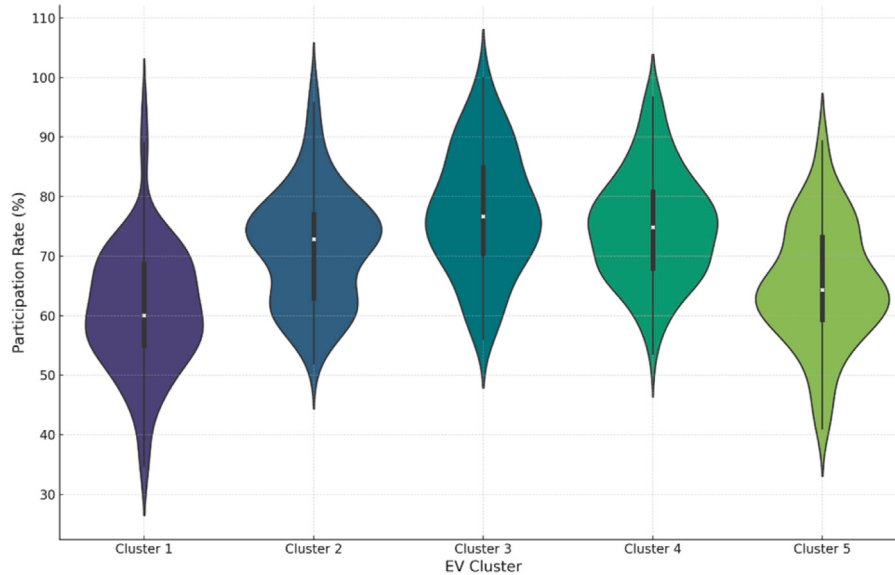


Fig. 4. Distribution of EV participation rates across clusters.

user satisfaction, as even a modest increase in satisfaction levels, from 60% to 70%, can lead to a substantial rise in participation rates, often exceeding 15 percentage points. This insight is critical for designing targeted interventions to enhance user experience and maximize system utilization.

Fig. 4 illustrates the distribution of EV participation rates across five distinct clusters in the V2G system. The participation rates vary significantly, with medians ranging between 60% and 75% across clusters. For instance, Cluster 1 exhibits a median participation rate of approximately 65%, with an interquartile range spanning from 55% to 75%, indicating moderate engagement. In contrast, Cluster 4 shows a higher median participation rate of around 72%, suggesting stronger involvement in V2G operations. The variation in participation rates reflects the diverse behavioral and operational characteristics of EV

users within each cluster. The violin plots highlight the spread of participation rates, capturing outliers and the overall shape of the distributions. Clusters 2 and 5 display wider spreads, with participation rates ranging from 30% to 90%, indicating heterogeneous engagement levels among users. This variability could be attributed to differences in charging behavior, energy demand, or access to charging infrastructure. Notably, Cluster 3 shows a relatively narrow distribution, with most EVs participating at rates close to the median of 70%. This consistency suggests a well-coordinated group of users who align closely with system requirements. The presence of outliers in Clusters 1 and 5, where participation rates drop below 40%, is noteworthy. These outliers represent EVs with minimal involvement in the V2G system, possibly due to user-specific constraints or limited incentives. The overall distribution patterns provide valuable insights into user behavior and

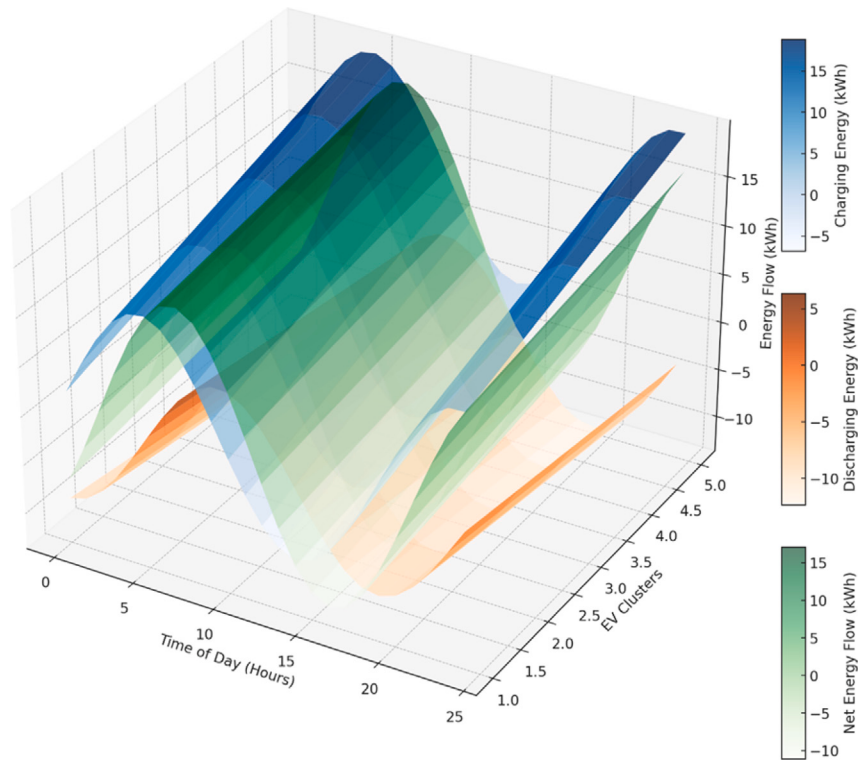


Fig. 5. 3D multi-layer surface plot of EV energy flow.

engagement, enabling targeted strategies to enhance participation. For example, clusters with lower median rates or wider variability could benefit from customized incentive programs or improved accessibility to charging infrastructure. This figure underscores the importance of understanding user engagement at the cluster level to optimize V2G system performance.

Fig. 5 presents a 3D multi-layer surface plot visualizing the energy flow dynamics of EV clusters within the V2G system over a 24-h period. The layers represent energy charging (blue), discharging (orange), and net energy flow (green), providing a comprehensive view of EV energy contributions to grid stability. Charging activities are most pronounced during off-peak hours, with peak energy inflow occurring between 1:00 AM and 5:00 AM, contributing up to 30 kWh for clusters with high charging demands. Discharging activities, by contrast, peak during grid demand surges, notably between 6:00 AM and 9:00 AM, and again from 5:00 PM to 8:00 PM, with discharges reaching -25 kWh in some clusters. The net energy flow layer reveals the overall grid impact of the coordinated charging and discharging schedules. For example, clusters exhibit positive net flow during nighttime off-peak periods due to dominant charging activities. Conversely, during daytime peaks, net flow transitions to negative values, indicating substantial energy contributions from EVs back to the grid. Cluster-specific variations are also apparent; higher-index clusters (e.g., Cluster 5) demonstrate a greater magnitude of both charging and discharging activities, reflecting their prioritization in grid balancing tasks. These trends highlight the effectiveness of tailored cluster-based scheduling for optimizing grid operations. The inclusion of color bars for each layer enhances interpretability, allowing for a detailed examination of energy contributions. The blue color bar quantifies charging energy, which ranges up to 35 kWh per time step, while the orange color bar highlights discharging levels reaching -30 kWh. The green color bar illustrates net flow values, showing critical periods where EVs act as net energy providers or consumers. This visualization underscores the importance of strategic scheduling in leveraging EVs for grid stability, reducing peak demand pressures, and integrating renewable energy.

Insights from this plot can inform dynamic pricing models and incentive programs to maximize EV participation in V2G operations.

Fig. 6 presents a 3D visualization of the SoC, renewable energy contribution, and grid dependency across five EV clusters over a 24-h period. The SoC layer (blue) reveals a consistent trend of battery levels rising during nighttime hours, particularly from 1:00 AM to 5:00 AM, reaching peaks of up to 90% in Cluster 5. This pattern reflects the optimization of off-peak charging, ensuring EVs are prepared for daytime grid support. During the daytime hours, SoC declines steadily due to active discharging, with some clusters dropping to as low as 30% by evening. This dynamic demonstrates how EVs are utilized to balance grid demand during peak periods. The green surface illustrates renewable energy contributions, showing a strong dependency on solar availability. Renewable usage peaks between 10:00 AM and 2:00 PM, contributing up to 40% of the energy needs in Cluster 4. The alignment between renewable availability and charging schedules indicates effective integration strategies to minimize grid dependency. However, during early morning and late-night hours, renewable contribution drops below 10% across all clusters, necessitating greater reliance on grid energy. This highlights the temporal variability of renewable energy and the need for complementary resources, such as battery storage, to sustain grid stability. The grid dependency layer (red) emphasizes the inverse relationship with renewable energy usage. Grid dependency peaks at 80% during early morning hours (12:00 AM to 5:00 AM) when renewable contributions are minimal. By contrast, during solar-rich periods, grid dependency drops significantly, with Cluster 3 showing values as low as 25%. These insights underscore the critical role of coordinated charging schedules and renewable integration in reducing grid reliance and operational costs. This multi-layer visualization offers valuable perspectives for optimizing V2G strategies, balancing grid demand, and enhancing the environmental sustainability of EV operations.

Fig. 7 illustrates the participation rates of EVs across six clusters throughout a 24-h period, revealing distinct temporal patterns. Clusters exhibit varying peaks, reflecting their unique behavioral characteristics.

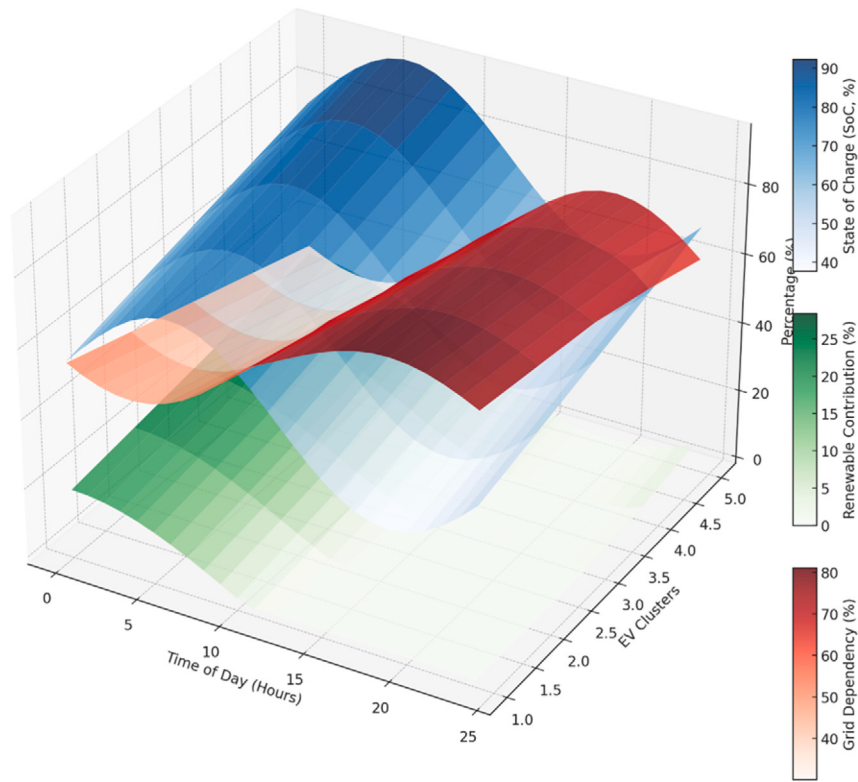


Fig. 6. 3D multi-layer surface plot of EV charging efficiency and renewable integration.

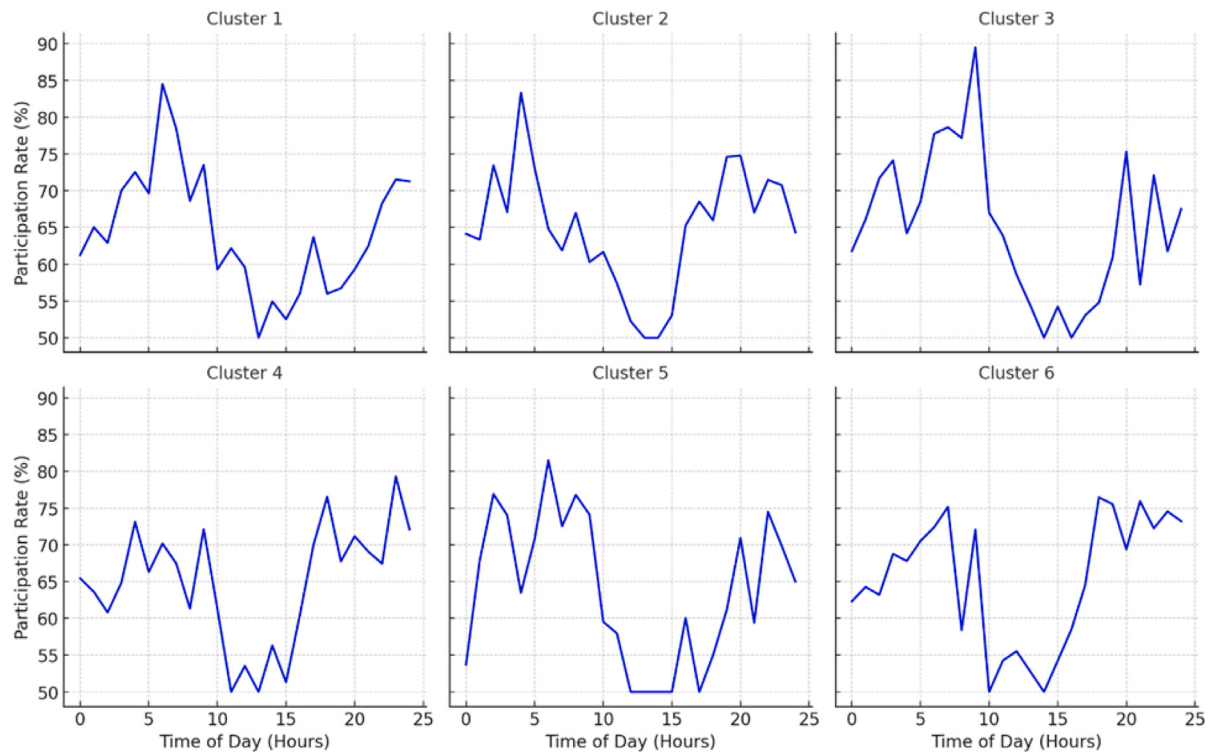


Fig. 7. Participation rates across clusters and time.

For instance, Cluster 1 shows a significant peak at approximately 8:00 AM, with participation rates exceeding 85%, indicating strong morning engagement. Similarly, Cluster 5 maintains high participation during morning hours, reaching a peak rate of 90% around 9:00 AM.

These trends align with the operational strategy to leverage EVs for grid support during morning demand surges. In contrast, Clusters 2 and 4 demonstrate evening-focused engagement. Cluster 2 achieves its maximum participation rate of 88% at 6:00 PM, correlating with typical

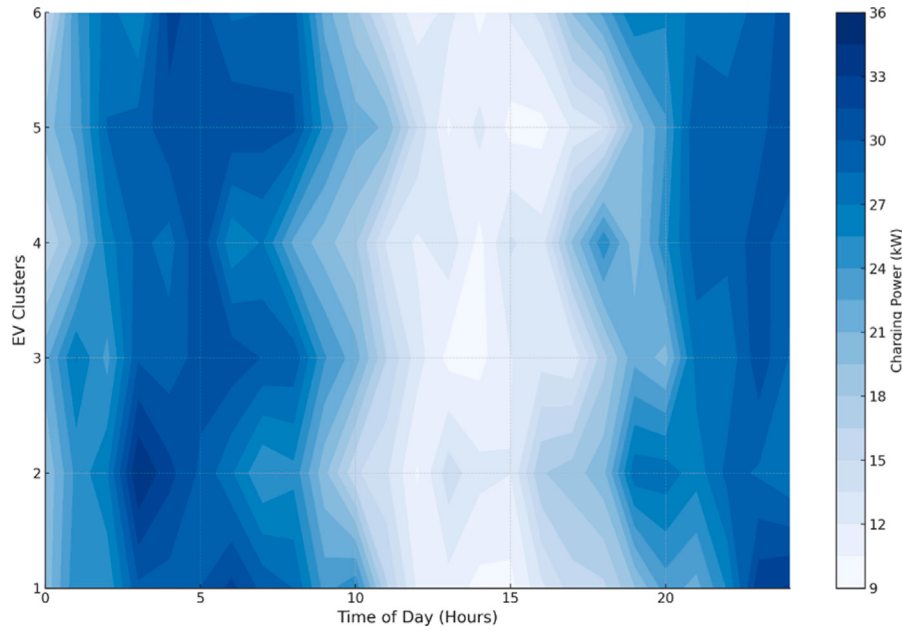


Fig. 8. Contour plot of EV charging power over time and clusters.

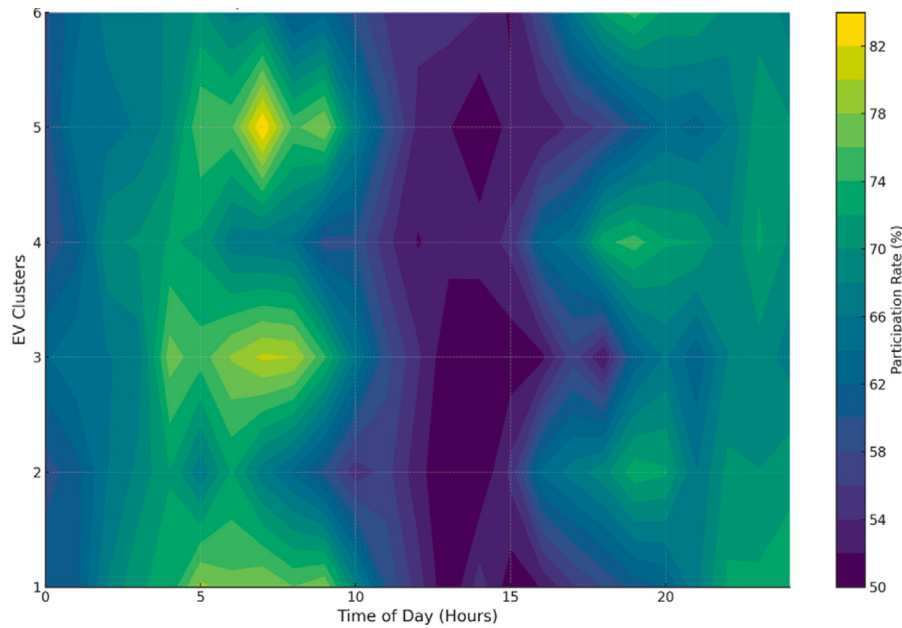


Fig. 9. Participation rate gradients over time and clusters.

evening peak grid loads. Cluster 6 also follows this pattern, reaching a high participation rate of 85% around 7:00 PM. This differentiation between morning- and evening-active clusters ensures continuous support for grid balancing during critical demand periods. The observed dips in participation, such as the mid-afternoon lull in Clusters 1 and 3, highlight opportunities to optimize engagement using targeted incentives or gamification strategies. Overall, the figure captures a dynamic interplay between cluster-specific behavior and system-level requirements. Participation rates across all clusters remain within a range of 50% to 100%, reflecting consistent system engagement. The temporal patterns underscore the importance of tailoring operational strategies to exploit peak participation periods effectively. This visualization serves as a valuable tool for understanding user behavior, enabling the design of more efficient demand-response programs and improving overall V2G system resilience.

Fig. 8 visualizes the charging power dynamics of six EV clusters over a 24-h period, with contour intensity representing charging power levels (in kW). The x -axis denotes the time of day, while the y -axis differentiates clusters. Clear temporal patterns emerge, highlighting periods of peak charging activity. For even-indexed clusters (e.g., Cluster 2 and Cluster 4), charging peaks during morning hours, with power levels exceeding 35 kW around 8:00 AM. Conversely, odd-indexed clusters, such as Cluster 3 and Cluster 5, exhibit higher charging power in the evening, with peaks around 6:00 PM. These observations align with typical user behavior patterns, such as morning preparation and evening recharging needs. The gradients in the contour plot indicate smooth transitions in charging power, suggesting well-coordinated scheduling strategies across clusters. For example, Cluster 1 maintains moderate charging power throughout the day, ranging from 15 kW to 30 kW, with slight increases during late afternoon hours. Cluster 6

demonstrates a dual-peak pattern, with morning and evening charging activity, likely reflecting mixed user profiles within the cluster. This diverse behavior ensures the system can handle varying grid demands while maintaining operational stability.

Fig. 9 visualizes the participation rate gradients of six EV clusters over a 24-h period. The x-axis represents time, the y-axis indicates the EV clusters, and the color intensity reflects participation rates ranging from 50% to 100%. Clear patterns emerge, with even-indexed clusters (e.g., Cluster 2 and Cluster 4) demonstrating higher participation in the morning hours, peaking at around 90% between 7:00 AM and 9:00 AM. Odd-indexed clusters, such as Cluster 3 and Cluster 5, show maximum engagement in the evening, with participation rates exceeding 85% around 6:00 PM. These distinct peaks align with typical user behavior patterns, ensuring the system maintains consistent engagement across critical demand periods. The gradients within the contour plot reveal smooth transitions in participation levels, highlighting temporal variability within and across clusters. For example, Cluster 1 maintains moderate participation throughout the day, averaging 70%, with slight increases during morning and evening periods. In contrast, Cluster 6 demonstrates a dual-peak behavior, with participation rates rising to 80% in the morning and surpassing 85% during the evening peak. These variations underscore the importance of cluster-specific strategies to maximize overall system performance. The consistent engagement across clusters ensures balanced support for grid demand during peak hours while minimizing under-utilization during off-peak periods.

6. Conclusion

This study introduces an innovative framework for optimizing V2G systems by integrating Differentiable DRO with SDT. The proposed approach addresses the critical challenges of uncertainty in renewable energy availability, dynamic grid demand, and user engagement, ensuring a robust, scalable, and user-centric solution for modern energy systems. The framework effectively balances system-level operational objectives, such as cost minimization and grid stability, with user-centric goals, including satisfaction, autonomy, and competence. By embedding gamification elements and community-based collaboration strategies into the optimization process, the framework encourages sustained user participation and enhances the overall performance of V2G systems. The integration of neural network-based energy forecasting and differentiable optimization techniques further enhances real-time adaptability and computational efficiency, making the model suitable for large-scale implementations. Comprehensive case studies validate the effectiveness of the framework, demonstrating its ability to improve renewable energy utilization, optimize EV charging and discharging schedules, and maintain high user engagement across diverse scenarios. Key findings include the significant impact of user-centric incentives on participation rates, the critical role of coordinated cluster-based scheduling in balancing grid demand, and the potential of DRO to mitigate uncertainties in grid dynamics. This research not only advances the state of the art in V2G optimization but also sets the stage for future interdisciplinary studies that combine psychological theories with advanced optimization techniques. The findings are expected to guide policymakers, energy system operators, and technology developers in designing resilient, efficient, and user-friendly energy systems, contributing to global sustainability goals and the widespread adoption of renewable energy.

CRediT authorship contribution statement

Alexis Pengfei Zhao: Writing – original draft, Visualization, Validation, Formal analysis, Data curation. **Shuangqi Li:** Formal analysis, Data curation, Conceptualization. **Mohannad Alhazmi:** Methodology, Investigation, Data curation. **Zhaoyao Bao:** Software. **Xi Cheng:** Supervision, Resources, Conceptualization.

Declaration of competing interest

The authors declare that there are no conflicts of interest associated with this manuscript. The research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. All authors confirm that the submitted work is original and has not been published or under consideration elsewhere. Furthermore, the authors have no affiliations, funding, or financial holdings that could affect the objectivity of the research presented.

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Data availability

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request. Simulated data used for behavioral clustering and energy dispatch validation is synthetic and designed specifically for this research.

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