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# Herding from Uncoordinated Smart Charging of EVs: A Real-Life Demonstration

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***Abstract*—Electric vehicle (EV) adoption is accelerating globally, raising concerns about distribution network stability and the effectiveness of smart charging strategies. While time-of-use based smart charging approaches are widely promoted as a solution to manage network impact and demand, this paper presents empirical evidence that uncoordinated smart charging where EVs self-schedule based on the time-of-use tariff signal or algorithm may lead to unintended consequences, specifically a "herding effect" where EVs collectively create new demand peaks. Through empirical analysis of data from a field trial, this paper demonstrates that at 20–30% EV penetration levels, uncoordinated smart charging creates demand peaks that exceed traditional evening peaks. A localised demand diversification service (LDDS) is proposed in this paper, enabling coordinated, adaptive, and context-aware demand management as a mitigation strategy, and its real-life implementation is demonstrated. The empirical evidence on the herding effect and the proposed LDDS provide actionable insights for network operators and flexibility service providers.**

***Index Terms*—Electric vehicles, smart charging, time-of-use, herding effect, localised demand diversification service.**

## I. Introduction

The global transition to electric vehicles (EVs) is accelerating at an unprecedented pace, primarily driven by growing environmental concerns, technological advancements, and the implementation of supportive governmental policies. The UK's Zero Emission Vehicle Mandate [2] exemplifies the strategic efforts aimed at promoting EV adoption. As a result of similar efforts globally, global EV sales reached 14 million units in 2023, a 35% increase compared to 2022 figures [3]. A significant proportion of this growth is attributed to home-based charging solutions [3]. While this rapid adoption presents opportunities for decarbonising the transport sector, it also introduces considerable challenges for existing electricity distribution networks. These networks must adapt to accommodate the increased and often unpredictable demand. As a result, strategic and innovative solutions are required to ensure continued network reliability and operational stability [4].

Smart charging has emerged as a critical strategy for addressing the challenges associated with increased EV adoption, particularly in terms of grid stability and peak demand management [5]. Unlike conventional charging, where EVs begin drawing power immediately upon being plugged in, smart charging systems enable EVs to shift their charging periods to off-peak hours, helping reduce pressure on the grid. These systems utilise time-of-use (ToU) tariffs, allowing charging to occur when electricity demand is low and tariffs are more favourable [5]. This approach not only supports grid efficiency but also offers financial benefits to EV owners by optimising charging schedules and minimising energy costs. In recognition of these advantages, several governments such as the UK have implemented regulatory measures requiring all public EV charge points to incorporate smart charging capabilities [6].

While the benefits of smart charging are well-documented, less attention has been paid to the potential negative consequences of widespread adoption of uncontrolled smart charging, such as the tendency for independently operating smart chargers to create new, potentially more problematic demand peaks when responding to similar tariff signals, a phenomenon we term the "herding effect". The "herding effect" or "rebound peak" is identified and acknowledged in [7]–[10], warning that identical tariff signals and mass migration of EV charging to low-tariff periods could lead to synchronised charging behaviours and create new network challenges. Despite these theoretical acknowledgments, empirical evidence documenting the actual occurrence and magnitude of the herding effects in real-world networks are limited.

This paper aims to empirically address the following research questions:

1) Can uncoordinated smart EV charging result in a new demand peak?

2) If yes, how prominent is this new peak compared to traditional demand peaks?
3) At what percentage penetration of EVs does this phenomenon become more prominent than the typical evening demand peak?
4) What strategies might effectively mitigate this herding effect?

While previous simulation-based research has theoretically identified the potential for uncoordinated smart charging to create new demand peaks, this paper provides empirical evidence from a real-world trial. This paper quantifies the extent to which uncoordinated smart charging can generate new demand peaks that exceed traditional evening demand peaks, thereby providing critical real-world context lacking in prior theoretical analyses. Furthermore, a Localised Demand Diversification Service (LDDS) concept is proposed to mitigate the herding effects, addressing a gap in the literature regarding adaptive pricing mechanisms that consider historic demand and real-time local network conditions.

The rest of the paper is structured as follows: Section II describes the trial design and system architecture; Section III presents the results; Section IV proposes the LDDS; and Section V concludes the paper.

## II. Trial Design And System Architecture

This study is part of the Demand Diversification Service (DDS) project led by Scottish and Southern Electricity Networks (SSEN), which evaluates the impact of dynamic price signals and coordinated smart charging of low-carbon technologies, including EVs, storage heaters, and heat pumps, on the residential energy demand and distribution network performance. Although the broader project encompasses multiple technologies, this paper focuses specifically on EVs. The objective is to evaluate the potential impacts on the distribution network if smart charging operates without coordination with network conditions, even when price signals incentivise off-peak charging.

### A. Participant Recruitment and Infrastructure

A total of 96 households with electric vehicles were recruited from the Energy Systems Catapult (ESC) Living Lab to participate in the trial. Each participating home was equipped with a smart charging system capable of receiving price signals and logging back real-time demand data from EV charging events.

The system architecture, depicted in Fig. 1, describes the flow of signals and data among three main actors: the Energy Supplier (ES), for instance Octopus Go; the Aggregator, represented by ev.energy; and the participating EV homes. The consumers' individual ESs define a dynamic retail tariff structure designed to encourage EV charging during off-peak hours. Typically (e.g., Octopus Go), today this specifies between 23:30 and 05:30 at the lowest prices. In contrast, charging during peak hours (05:30–23:30) is discouraged by setting substantially higher rates.

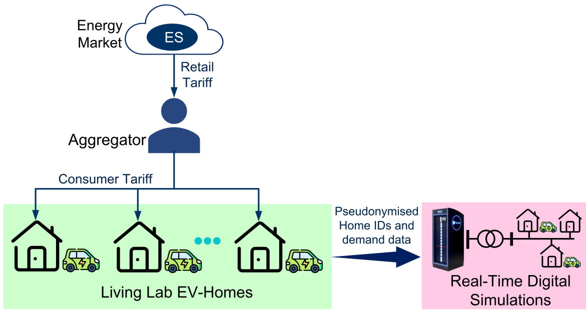


Fig. 1. System architecture for uncoordinated EV smart charging based solely on retail tariff structure from the energy supplier (ES), without feedback on network loading conditions.

The Aggregator's role was to optimise the individual EV charging events, aligning them with off-peak retail tariff windows, thereby reducing EV charging costs for the consumers and shifting aggregate demand away from traditional peak periods, benefiting the grid.

### B. Real-Time Digital Simulations

As illustrated in Fig. 1, the Aggregator issued charging commands or consumer tariff-based incentives to homes based on the optimised retail tariff structure from the ES. Real-life operational data from each home were collected, with home identifiers pseudonymised. This data was used to drive realistic and real-time digital network simulations to evaluate the broader impact of uncoordinated smart charging across modelled distribution networks. This data exchange leveraged an already established Whole Energy System Accelerator (WESA) platform developed by PNDC and Energy Systems Catapult [11].

Two network configurations were modelled during the simulations: a semi-urban topology consisting of 120 households and an urban topology with 205 households. Details of these configurations are provided in [12]. To introduce sensitivity, varying transformer sizes were used to simulate different loading conditions: 100 kVA and 315 kVA for heavily loaded semi-urban and urban networks, and 315 kVA and 500 kVA for lightly loaded ones. The WESA platform was then used to map the geographically spread households to the respective network configuration. The simulations measured transformer loading, voltage levels, and voltage imbalance (VI). The latter was determined according to the IEEE 141–1993 standard [13] as follows:

$$\mathrm{VI}(t) = \frac{\max\left(\Delta V_1(t), \Delta V_2(t), \Delta V_3(t)\right)}{\overline{V}(t)} \times 100 \quad (1)$$

$$\overline{V}(t) = \frac{V_1(t) + V_2(t) + V_3(t)}{3} \quad (2)$$

where $\Delta V_i(t) = |V_i(t) - \overline{V}(t)|$ for $i = 1, 2, 3$, $V_1(t), V_2(t), V_3(t)$ are the voltages of the three phases at a given time $t$ and $\overline{V}(t)$ is the average voltage across all three phases.

To evaluate when the herding effects began to significantly impact network performance, the simulations were run across multiple EV penetration levels, ranging from 10% to 80% of the total homes in the network. Each penetration level was simulated under three spatial distribution assumptions: EVs concentrated near the transformer, located far from the transformer, and randomly distributed throughout the network. The non-EV homes were assigned a consistent base load across all scenarios to isolate the effects attributable to EV charging.

### C. Evaluation Metrics

Each scenario was analysed in terms of the magnitude and timing of new demand peaks, transformer loading, and voltage patterns. The results were compared against the characteristics of traditional evening peaks. A "critical point" was defined as the EV penetration level at which the demand peak induced by EV charging exceeded the magnitude of the conventional evening peak.

This methodological framework enabled a robust technical and behavioural assessment under controlled yet realistic conditions. The findings serve as a foundational input for the broader DDS project and can significantly inform future smart charging algorithms and tariffs.

## III. Results and Discussion

### A. Evidence of Herding Effects

Our resultant data confirmed the existence of herding effects from uncoordinated smart charging. Fig. 2(a) illustrates the average daily transformer loading profiles for different EV penetration scenarios compared to the baseline (no EVs). At low penetration levels (10-20%), the impact of smart charging is minimal, with new demand distributed broadly throughout off-peak hours (23:30-05:30). However, as penetration increases to 20% and beyond, a distinct new peak is formed around 01:00 in the morning, coinciding with the lowest period in the tariff structure from the Aggregator.

Between 20% and 30% penetration, this new peak is comparable in magnitude to the traditional evening peak. Beyond 30% penetration, the new peak consistently exceeds the evening peak, and the loading profiles are less diverse due to the simultaneous occurrence of multiple peak charging demands, leading to pronounced and synchronised transformer loading.

Fig. 2(b) shows the relationship between EV penetration and the ratio of the new peak to the evening peak. This relationship appears non-linear, with the ratio increasing more rapidly as penetration exceeds 20%. This finding has significant implications for

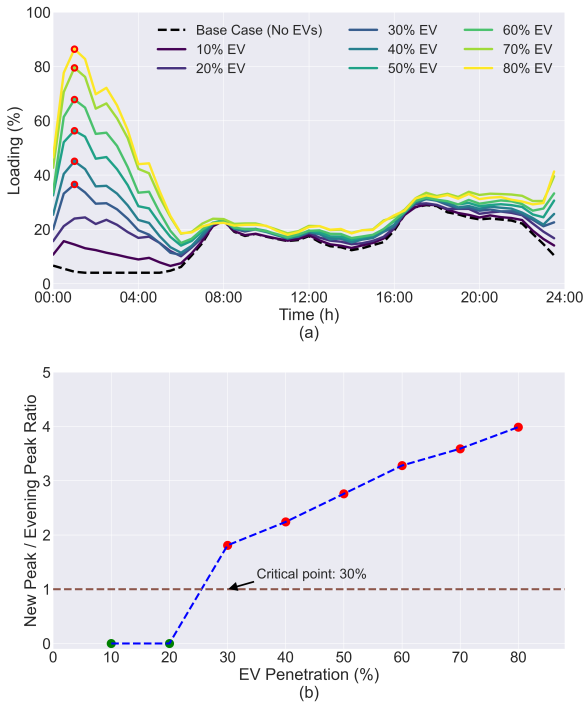


Fig. 2. (a) Average daily transformer loading profiles under different EV penetration levels, and (b) ratio of the new demand peak to the traditional evening peak across varying EV penetration levels, considering a semi-urban network with a 315 kVA transformer and high EV concentration near the transformer.

network planning and management, since distribution network operators typically design their systems to accommodate the traditional evening peak. Our results suggest that at 30% EV penetration (the critical point) with uncoordinated smart charging, networks may face higher new peaks that exceed the traditional evening peak. Beyond 30% penetration and depending on the network loading conditions, the new peak has the potential to unintentionally overload the network assets.

Fig. 3 illustrates that voltage quality declines with increasing EV penetration levels, leading to the emergence of new voltage dips during the morning period along with more pronounced voltage imbalances. These effects can significantly compromise power quality and potentially impact sensitive equipment and highlight the need for voltage regulation strategies or network reinforcement in scenarios involving uncoordinated smart charging and high EV adoption.

### B. Network Sensitivity Analysis

The network sensitivity analysis under different loading conditions reveals that the critical point for herding effects remains consistent across the simulated network configurations. Table I summarises these findings.

The critical point at which the new smart charging peak exceeds the traditional evening peak remains constant at 30% EV penetration across the network topologies. This finding strengthens our overall conclusion that the herding effect emerges at a predictable

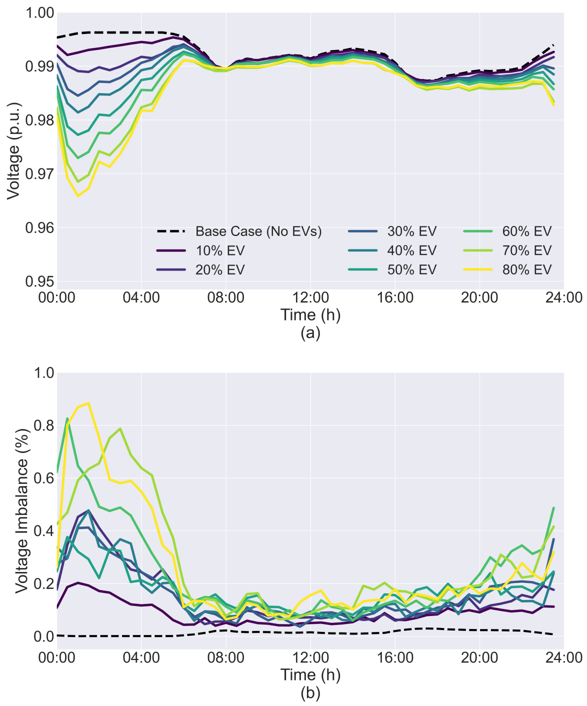


Fig. 3. Average daily transformer voltage quality: (a) phase voltage and (b) voltage imbalance profiles under different EV penetration levels, considering a semi-urban network with a 315 kVA transformer and high EV concentration near the transformer.

penetration level, allowing network operators to anticipate and plan for this phenomenon.

The maximum peak ratio (the ratio of the new smart charging peak to the traditional evening peak) shows limited sensitivity to network configuration, with the semi-urban network topology using a 100 kVA transformer (i.e., heavily loaded network condition) exhibiting a lower value (2.4) compared to the urban network topology (4.0). This suggests that while the threshold at which herding effects emerge is consistent, the severity of these effects may vary based on network characteristics and loading conditions. The analysis determined that the concentration of EVs on the network relative to the transformer (Far, Near, or Random concentration) has a negligible impact on both the critical point and maximum peak ratio. This finding suggests that the herding effect is primarily driven by the temporal synchronisation of charging rather than the spatial distribution of EVs within the network.

## IV. Proposed Localised Demand Diversification Service

Section III has demonstrated that relying solely on supplier tariffs to control EV smart charging without accounting for real-time network conditions can unintentionally introduce new demand peaks and voltage dips during off-peak periods. If left unchecked, these effects can undermine the benefits of demand flexibility and pose risks to network stability.

To address this challenge, a novel LDDS is proposed as part of the DDS project. This service aims

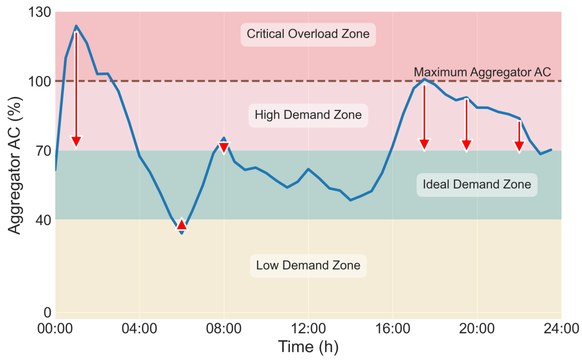


Fig. 4. Illustration of the proposed LDDS pricing mechanism, highlighting four operational zones where Aggregators are rewarded.

to enhance demand diversity and mitigate network stress by actively linking Aggregator incentives to both historical usage patterns and real-time network conditions.

Within the LDDS mechanism, Aggregators are periodically allocated a dynamic capacity band by the Distribution System Operator (DSO), based on their historical aggregate demand data and real-time network conditions. This allocation defines the range within which the Aggregator is expected to maintain its demand. Particularly, the Aggregator's total demand profile is segmented into four operational zones, as illustrated in Fig. 4:

- Low Demand Zone: 0–40% of the allocated capacity (AC)
- Ideal Demand Zone: 40–70% of AC
- High Demand Zone: 70–100% of AC
- Critical Overload Zone: $>$100% of AC.

The LDDS is designed to incentivise Aggregators to maintain their aggregate demand within the ideal demand zone, thereby promoting a more balanced and diversified load profile. Operating within this zone ensures optimised network usage and mitigates herding effects on the distribution network. Conversely, operation outside of the ideal demand zone, especially within the overload or critical zones can incur loss of accrued revenues, while consistent operation within the ideal demand zone is strongly incentivised. Similar in intent to traditional retail tariff mechanisms from ESs, the LDDS approach encourages demand shifting to off-peak hours. However, it goes further by explicitly rewarding Aggregators for improving the diversity of their EV charging profiles, moving demand not only to low-demand periods, but also ensuring it is distributed more evenly over time to align with the ideal demand zone.

Under this service, the DSO compensates Aggregators through three payment components:

1) Flat Payment: A fixed fee is paid for every kWh of demand that remains below the Aggregator-AC.

TABLE I
SENSITIVITY OF THE CRITICAL POINT AND PEAK RATIO TO NETWORK TOPOLOGY AND TRANSFORMER SIZE.

| **Metric** | **Semi-urban network** | | | | | | **Urban network** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 100 kVA | | | 315 kVA | | | 315 kVA | | | 500 kVA | | |
| | **Far** | **Near** | **Random** | **Far** | **Near** | **Random** | **Far** | **Near** | **Random** | **Far** | **Near** | **Random** |
| Critical point (%) | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 30 |
| Max. peak ratio | 2.4 | 2.4 | 2.4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 |

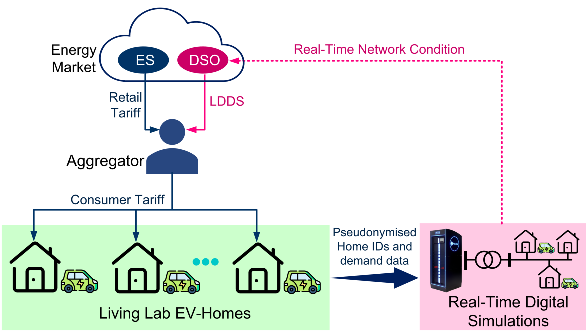


Fig. 5. Implementation architecture of the proposed LDDS pricing mechanism for coordinated smart charging, accounting for real-time network conditions.

2) Capacity Breach Adjustment: If an Aggregator exceeds its allocated capacity for a settlement period, a portion of the payment may be withheld. However, this can be waived in the absence of network congestion or connection issues.
3) Diversification Reward: A variable payment is awarded in proportion to the improvement in the diversification factor, which quantifies the extent to which the aggregator has smoothed or spread its demand profile.

Accordingly, the Aggregator's role becomes one of multi-objective optimisation: to minimise EV charging costs while maintaining the aggregate demand within the ideal demand zone.

Fig. 5 demonstrates the implementation of the LDDS within other parts of the DDS project for coordinated smart charging. In addition to the uncoordinated smart charging setup shown in Fig. 1, the DSO is introduced to coordinate the charging through the LDDS. The LDDS provided by the DSO is influenced by both historical asset-level demand and real-time network conditions, including transformer loading conditions. This integration of real-time and historical data allows for coordinated, adaptive and context-aware demand management that benefits both the Aggregator and the DSO.

## V. CONCLUSION AND FUTURE WORK

This paper has provided empirical evidence that uncoordinated smart charging of EVs can create new demand peaks and voltage dips during off-peak periods. And that, at EV penetration levels above 20-30%, the new demand peaks exceed traditional evening peaks. We have quantified this critical threshold and demonstrated that it remains consistent across the two different network topologies considered, suggesting this could be a universal concern rather than one limited to specific network types. We have also proposed and shown how an LDDS can effectively mitigate these herding effects and implemented while ensuring that Aggregators are properly incentivised. Future work will focus on the real-time implementation of the LDDS to address the challenge of herding effect from uncoordinated smart charging to ensure optimised network utilisation and stability.

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