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*Abstract*—**Driven by governmental policies, particularly in Europe, Electric Vehicles (EVs) are gradually replacing the current fleet. Since they are only used during a small portion of the time for transportation, their batteries can be used for other purposes during the rest of the time. The power grid constantly requires to maintain the balance between electricity production and consumption. Controlling the charge of EVs can avoid the need to invest in grid reinforcement. This research work focuses on flattening the consumption in residential areas, also known as peak shaving, which reduces the need for reactive power plants on the grid. Existing solutions often rely on coordination among vehicles, meaning that they require a communication network between the various consumers in the area (e.g., vehicles, houses). However, such a dedicated communication network is not yet deployed in practice. It would be costly to deploy and operate, and could potentially constitute a privacy breach for consumers. In this paper, we propose a local smart charging solution only relying on information exchanges between each house's smart-meter and its EV's charging station. We compare our local peak shaving to solutions without communication infrastructure, and to an optimal theoretical solution provided by a linear programming solver. Simulation campaign show that our local peak shaving algorithm offers a solution close to the optimum, with advantages in terms of voltage stability, fairness among users and vehicle battery lifetime preservation.**

## I. Introduction

The increasing electrification of transport in the coming years poses new challenges for the electrical grid. Electric Vehicles (EVs) tend to represent a major source of consumption, but they could also become an opportunity for the grid to operate efficiently thanks to their batteries. Peak shaving methods involve smoothing the daily consumption curve to avoid the need for reactive power plants which are either polluting, costly, and/or limited [1]. EVs are going to become more and more common and they have large-capacity batteries, which means unused reactive storage potential that could be used when they are parked.

EV charging must be controlled to avoid overloading the distribution network and to keep voltage deviation within defined limits. But, a control infrastructure (i.e. telecommunication means) is costly to deploy and operate, and may create privacy issues for users. To evaluate the efficiency of a system, it is essential to estimate the potential energy savings, while taking into account operating and deployment costs.

In this paper, our local smart charging method consists of a ready-to-deploy decentralized control solution, based on a control signal sent via a Local Area Network (LAN): from each home smart-meter to the associated EV charging station. The aim is to investigate the achievable performance without having to deploy a large, costly and energy-consuming Wide Area Network (WAN) infrastructure. To evaluate performance, a new Key Performance Indicator (KPI), independent of the studied network, is defined, by comparing to the optimal peak shaving solution. It can be used to determine the performance gains that are still possible, and to evaluate the efficiency of future solutions.

Our proposed local algorithm demonstrates the capacity to concurrently charge 55 vehicles, while ensuring that transformer utilization remains within prescribed thresholds, voltage drop stays above acceptable limits, and charging among EVs remains fair and balanced. Smart grid-related research often uses sensor networks to monitor the power grid [2]. Our focus is to design a solution that balances network performance and user satisfaction, i.e. Quality of Experience (QoE), by ensuring that vehicles are recharged on time, and that user privacy is preserved.

This paper is organized as follows. Section II presents a review of the state of the art, followed in by our case study in III. Next, in Section IV, we present the charging algorithms studied, followed by experimental conditions of the study in V and performance evaluation in VI. We then discuss results and limitations in VII before concluding in last section, by summarizing the main findings and suggesting directions for future research.

## II. Related Work

Given that EVs remain parked 96% of the time [3], their batteries can be efficiently used for the benefit of the electrical grid [4]. Smart charging algorithms, integrated into charging stations, also known as Electric Vehicle Supply Equipments (EVSEs), enable better control of charging power. Indeed, mobile applications provided by Original Equipment Manufacturers (OEMs) for Plug-in Electric Vehicles (PEVs) are often limited, and generally allow only the programming of the charging hours and the desired State of Charge (SoC). Using EV's batteries has an impact on their lifetime. Yet, considering the number of cycles, the depth of discharge and charging powers used in smart charging solutions, and also involving a rising number of EVs, it is possible to mitigate the negative impacts on batteries with high benefits to the power grid [5].

Peak shaving is the most beneficial way to use EVs, however it can be difficult to implement [1], and is often associated in literature with static Battery Energy-Storage

Systems (BESSs) and local generation sources [6]. Peak shaving has been studied for decades [7], and home-scale peak shaving has already been studied using static BESSs and local generation sources [6]. Stationary BESSs are useful when the EV is not available, usually during the day, when there is excess energy production, as with solar panels. However, it requires the user to invest in an expensive self-consumption infrastructure. Using a constraint solver to solve a charging optimization problem for EVs has been proposed in [8]. Yet, it assumes a centralized knowledge of the local conditions (consumption and charging state). Peak shaving algorithms based on a decentralized (aka local or distributed) control architecture [9], as opposed to a centralized (aka direct) control method, present the advantage of not sending personal information to an external entity. It also removes the need for a large communication infrastructure, which has a significant energy impact [10]. In this paper, we use a constraint solver to compute the optimal peak shaving solution on which to base our performance measurements. The proposed solution relates to a control signal, which is the global consumption of the house, measured and transmitted by a smart-meter. The currently available smart-meters connected EVSEs [11] shows the feasibility and ease of deployment of our local solution.

Several indicators can be used to evaluate the performance of peak shaving algorithms. The Peak Shaving Percentage KPI used by [12] seems to be calculated in the same way as the Peak Reduction Percentage described in [13], both being dependent on the network and the dataset employed for method validation. As these data are usually provided by a Distribution Network Operator (DSO) partner, they are not public and do not allow the results to be reproduced. The Cumulative Overcurrent Duration (COD) metric, defined in [14], is network-independent and a reliable indicator of the feasibility and effectiveness of a solution.

Many studies seek to maximize the performance of power grids, often with a centralized approach involving communications from some entities of the network to the central decision point. However, the real impact of communication infrastructures has yet to be assessed, as its deployment involves additional energy costs and also has consequences in terms of quality of service depending on the communication technology (latency, bandwidth, packet loss, etc.). Many studies in the literature rely on pricing schemes for handling the peak shaving issue in a distributed manner [1], [13]. In this paper, we propose an alternative approach that is distributed and does not rely on peak demand pricing.

## III. Case Study

A publicly available consumer behavior survey conducted by Enedis [15], the main DSO in France, guided our case study. We target the charging of EV at home, as this is the practice adopted by 88% of users. The focus is specifically on residential areas made up of individual houses, which represents the majority of users, and on night-time charging, since 66% of EV owners perform this operation between 9pm and 7am, and this number rises to 79% between 5pm and 7am. We assume that consumers have a single-tariff electricity contract, excluding peak/off-peak tariffs, and therefore any financial advantage to delay charging. The survey also reveals that EV users mainly plug into conventional 16-amp sockets (45%) or reinforced 32-amp sockets (34%) [15]. Therefore, we limit the maximum EV charging power to 3.6kW and 7.36kW respectively. EV owners on average start charging their vehicle when it reaches around a third of its capacity [15]. Thus, the starting SoC of EVs is randomly selected between 4 and 50 percent of the EV's capacity.

TABLE I
Electric vehicles home charging frequency [15]

| Frequency of Recharging | Percentage of Users |
|---|---|
| Almost every day | 18% |
| Every 2-3 days | 30% |
| About once a week | 30% |
| Less than once a week | 9% |
| Never or almost never | 13% |

This paper focuses exclusively on fully-electric vehicles, excluding Plug-in Hybrid Electric Vehicles (PHEVs). Fully electric vehicles (referred to as EVs) have higher capacities and can therefore place greater demands on the electrical grid. We use EVs with a battery capacity of 50kWh, slightly less than that of a Renault Zoé, the best-selling EV in France with a total of 163,590 units by the end of 2023 [16]. The DSO's study also indicates that the average daily distance covered by a fully electrical vehicle is around 50 km. For an EV with a battery capacity of 50kWh and a range of 300 km (like the Renault Zoé), this means an average consumption of 166 Wh/km (average being 188 Wh/km according to [17]), representing around 6 days of range. Table I shows that 48% of EV owners recharge more than once a week. The remaining half recharge once a week or less, which is consistent with the calculations of a 6-days autonomy.

Only network losses are taken into account, i.e. losses due to line resistance and iron losses in the transformer. Even if charging losses (mainly due to EV's rectifiers and the imperfect efficiency of chemical reactions in battery cells) are significant, they are not taken into account in this paper, as it is usually omitted in other studies.

We focus on the worst-case scenario in which each house contains an EV and all have to be recharged on the same night. The aim is to observe the behavior of the distribution network when energy demand is at its highest.

## IV. Charging Algorithms

This section presents the different charging algorithms used in this study. We detail two distributed algorithms that operate without charging power control and without communication infrastructure. Then we introduce our proposed distributed algorithm, based on a simple infrastructure and a local control. We compare these approaches to an optimal charging algorithm, representing the maximum achievable level of peak shaving, detailed hereafter.

### A. Optimal peak-shaving algorithm using Constraint Solver

A constraint solver finds solutions to a Mixed Integer Linear Programming (MILP) problem, in which variables are subject to restrictions called constraints. The solver seeks to optimize an objective function by determining the optimal values of these variables, which can be both continuous and discrete. The aim is to maximize or minimize the objective function while respecting the specified constraints.

In our study, our objective function is to minimize the difference between peak and valley grid's consumption values over a period when flexibility is possible, i.e. when EVs are connected to the grid. This is the whole concept of peak shaving strategy. The solver finds an optimal solution to achieve this objective, by adjusting the charging power rates $P_{v,t}^{ev}$ of the 55 vehicles every minute they are connected, representing a total of around 50,000 variables. We use the open-source HiGHS solver for this purpose [18].

The data provided to the solver includes several key parameters related to EVs and household energy consumption. For each EV $v$, the starting and ending times for charging are represented by $Start_v^{ev}$ and $End_v^{ev}$, respectively. The energy stored in the EV at the start time is denoted by $E_{v,Start_v^{ev}}^{stored}$, while $E_v^{max}$ indicates the battery capacity. At the end of the charging period, the desired energy level is specified as $E_v^{desired}$. The charging power is bounded by a minimum power $P_v^{min}$, a maximum power $P_v^{max}$, and a nominal charging power $P_v^{nom}$. For a house $h$, the minimum and maximum grid power levels are $P_h^{min}$ and $P_h^{max}$, respectively, with $P_h^{mean}$ representing the average power drawn during the EV charging period. Additionally, the non-flexible power consumption of the house at any time $t$ is denoted by $P_{h,t}^{baseload}$.

The result of the solver is used to determine several variables, such as the power of EV $v$ at time $t$ ($P_{v,t}^{ev}$), the total power consumption of house $h$ at time $t$ ($P_{h,t}^{house}$), and the total grid power consumption at time $t$ ($P_t^{grid}$). We also obtain the energy stored in EV $v$ at time $t$, represented by $E_{v,t}^{stored}$, and the SoC of the EV, expressed as a percentage, as $SoC_{v,t}$.

To get the amount of energy in a EV $v$ at time $t+1$, we add the charging power $P_{v,t}^{ev}$, divided by $\Delta t$, to the energy stored at time $t$. $\Delta t$ corresponds to the time interval between two instants and must be expressed in hours to obtain a result in Watt-hour.

$$E_{v,t+1}^{stored} = E_{v,t}^{stored} + \frac{P_{v,t}^{ev}}{\Delta t} \quad \forall(v,t) \tag{1}$$

$$SoC_{v,t} = \frac{E_{v,t}^{stored}}{E_v^{max}} \quad \forall(v,t) \tag{2}$$

The total power consumption for a house $h$ at time $t$ is equal to the sum of its baseload power and the power consumption from its EV $v$, if any:

$$P_{h,t}^{house} = P_{h,t}^{baseload} + P_{v,t}^{ev} \quad \forall(h,t) \quad \text{if } v \text{ in } h \tag{3}$$

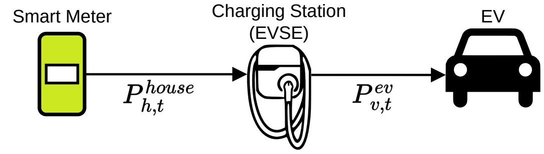


Fig. 1. Representation of a house Local Area Network (LAN)

The objective function minimizes the difference between maximum and minimum power consumption across all distinct time points $(t, t')$:

$$Minimize \quad \max(P_t^{grid}) - \min(P_{t'}^{grid}) \quad \forall(t,t') \tag{4}$$

The EV's charging power must be limited, in our case by the charging socket installed, with a minimum value $P_v^{min}$ equal to the opposite of the maximum value $P_v^{min}$, considering Vehicule to Grid (V2G): $P_v^{min} \leq P_{v,t}^{ev} \leq P_v^{max} \quad \forall(v,t)$. The energy stored in the EV $E_{v,t}^{stored}$ must remain within the limits of its battery capacity $E_v^{max}$: $0 \leq E_{v,t}^{stored} \leq E_v^{max} \quad \forall(v,t)$.

To ensure that users needs are satisfied, we add the constraint that the EV must have reached the desired SoC level $E_v^{desired}$ by the end of its charging session (if possible): $E_{v,End_v^{ev}+1}^{stored} = E_v^{desired} \quad \forall(v)$.

The total power demand of a household $P_{h,t}^{house}$, which includes its non-flexible loads $P_{h,t}^{baseload}$ as well as the EV $P_{v,t}^{ev}$, must not exceed its grid connection power, either for consumption or injection: $P_h^{min} \leq P_{h,t}^{house} \leq P_h^{max} \quad \forall(h,t)$.

### B. Uncontrolled charging algorithm

Uncontrolled charging is currently the most common charging method used by EVs. It is the default method, maintaining constant power throughout the charging process. The EV is charged at its maximum power, reaching the user's desired SoC as soon as possible. Charging power is calculated as follows:

$$P_{v,t}^{ev} = \begin{cases} P_v^{max}, & \text{if } E_{v,t}^{stored} < E_v^{desired} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

### C. Nominal charging algorithm

With the Nominal algorithm, the user provides additional information by specifying the time at which he or she wants to reach the desired SoC. Although this method is still not considered as smart charging since it maintains constant power during the charge, it offers the possibility of spreading the charging over the entire available time window, without the need for external communications.

$$P_{v,t}^{ev} = P_v^{nom} = \frac{E_v^{desired} - E_{v,Start_v^{ev}}^{stored}}{End_v^{ev} - Start_v^{ev}} \tag{6}$$

### D. Local charging algorithm

In our proposed local method, the EVSEs remains constantly connected to the smart-meter, see Figure 1. This gives access to the house's power usage history, enabling to predict the average consumption of other appliances during

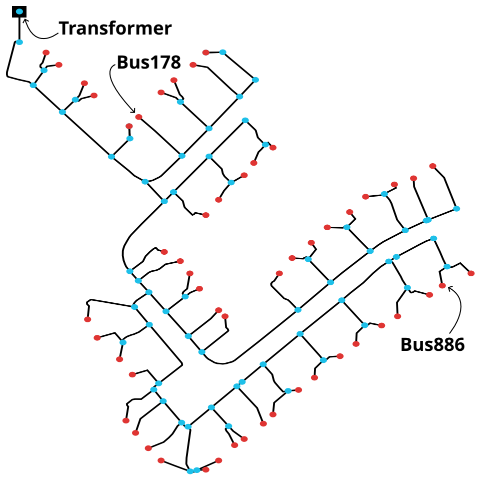

Fig. 2. Representation of the Simplified ELVTF Distribution Network

the charging period. This average is represented by the term $P_h^{mean}$, see equation 7. Charging power is defined as the sum of the vehicle's nominal power $P_v^{nom}$ and the house's average consumption $P_h^{mean}$, minus the instantaneous consumption of other household equipment $P_{h,t}^{baseload}$.

$$P_{v,t}^{ev} = P_v^{nom} + P_h^{mean} - P_{h,t}^{baseload} \tag{7}$$

$$P_h^{mean} = \frac{\sum_{t=Start_v^{ev}}^{End_v^{ev}} P_{h,t}^{baseload}}{End_v^{ev} - Start_v^{ev}} \tag{8}$$

## V. Experimental Conditions

### A. ELVTF Model

The European Low Voltage Test Feeder (ELVTF) model [19] provides consumption data for 100 houses over a 24-hour period with a timestep ($\Delta t$) of 1 min. However, only 55 houses are represented on the distribution network provided by the model. The ELVTF model is represented in Figure 2. It can be seen as a rooted tree graph, whose root is symbolized by a black square representing the MV/LV transformer. The graph's blue nodes correspond to power line junctions, while the red leaves represent individual houses.

### B. Electric Vehicles Modeling

Each one of the 55 EVs is equipped with a 50kWh battery and capable of charging or injecting at a maximum power of 3.6kW, with a standard 16A household socket on a 230V grid voltage. All EVs are equipped with V2G capabilities.

A household with its EV connected can draw a maximum combined power of $P_h^{max}$ + $P_v^{max}$ = 12.6kW (9kW from the grid, through the smart-meter, and an additional 3.6kW from the EV). In the ELVTF dataset, a specific house on Bus178 has a consumption peak of 14.6kW between 22:48 and 22:50. To accommodate such a power demand, this particular household is equipped with a dedicated 32A reinforced charging socket, allowing the EV to inject up to 7.36kW. EVs start charging with a randomly selected capacity between 2kWh and 25kWh, according to a discrete uniform distribution. These initial capacities are derived from the data presented in [15].

Users indicate their desired charging capacity $E_v^{desired}$, ranging from 2/3 to the total capacity of their EV. This selection follows the same discrete uniform distribution as used above. Furthermore, EV connection $Start_v^{ev}$ and disconnection $End_v^{ev}$ times are respectively between 4:10pm and 6:50pm, and between 6:50am and 8:30am the following day, following a uniform discrete distribution.

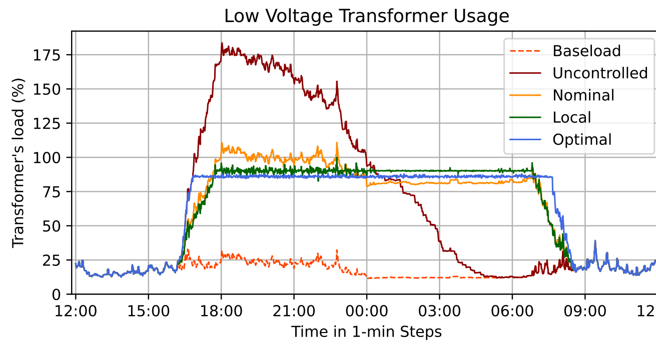

Fig. 3. Low Voltage Transformer Usage over Time

### C. Simulation Framework

PandaPower [20] is an open-source Python library based on pandas and PYPOWER, offering power system modeling, including an optimal Power Flow (OPF) solver and timeseries simulations. It includes an instance of the ELVTF distribution network, but we recreate an equivalent of the reduced ELVTF, as in [21], to improve simulation time and readability. Our simplified version of the distribution network is shown in Figure 2. All houses in the neighborhood are considered with a connection power of 9kW, as it is generally the case in France. A house can therefore draw from or inject into the grid a maximum power of 9kW to -9kW respectively.

Since the distribution network in the ELVTF model seems incomplete, and therefore oversized for a neighborhood of 55 houses, we resize it. The MV/LV transformer capacity is set at 1/3 of the connected power, as they are typically sized in France [22], i.e. 160kW instead of 800kW in the original model. Three-phase lines resistors and reactances are also doubled. All the houses are connected to the same phase. Indeed, it is common on a distribution network to have 55 houses on the same phase and this highlights the worst case scenario targeted by this analysis. This also reduces simulation times.

For readability reasons, we present the results from 12:00pm to 11:59am to focus on one night. To do this, we divide the provided household consumption dataset into two parts at the midpoint (12:00pm), placing the second part first. Consequently, the dataset spans from 12:00pm to 11:59am, allowing us to simulate night time. As the dataset only provides 24 hours of data from midnight to 11:59pm, there is no continuity from 11:59am to 12:00pm. This does not affect the obtained results.

TABLE II
CONSUMPTION PEAK AND OVERLOAD DURATION COMPARISON

| Charging Algorithm | Highest Peak | % to Optimal | COD (min) |
|---|---|---|---|
| Optimal | 140.89kW | - | 0 |
| Uncontrolled | 247.87kW | 75.93% | 419 |
| Nominal | 174.77kW | 24.05% | 146 |
| Local | 160.66kW | 18.83% | 1 |

### D. Reproducibility

To ensure reliable reproducibility of the results, we opt for the ELVTF model due to its open-source nature. However, its perceived incompleteness required modifications. We provide both the modified version and accompanying code for transparency and ease of replication (code available here: https://gitlab.inria.fr/msilard/localpeakshaving).

## VI. PERFORMANCE EVALUATION

### A. Transformer Load

Figure 3 shows the simulation results, where the x-axis represents time from 12:00 PM to the same time the following day, divided into 1440 one-minute intervals. The y-axis shows the percentage of transformer utilization, with the capacity set at 160 kW (100% of capacity).

- **Orange Dashed Curve**: Represents non-flexible loads (e.g., household appliances) beyond our control.
- **Red Curve**: Illustrates the uncontrolled charging scenario, where the transformer experiences a 419-minute Cumulative Overcurrent Duration (COD), with a peak overload of 290.06 kW at 6:02 PM, 81% above capacity. Such conditions would likely cause the transformer to trip in reality.
- **Yellow Curve** Corresponds to the nominal charging algorithm, reaching a peak overload of 175.10 kW (110% of capacity) at 10:46 PM, for a COD of 146 minutes. This pattern mirrors the behavior of non-flexible loads.
- **Green Curve**: Represents the local proposed solution, resulting in a minimal one-minute COD at 10:46 PM, with a peak of 160.66 kW (0.1% over capacity). Due to the simulation's time step limitations, the actual COD could be even shorter, but finer-resolution data is needed for confirmation.
- **Blue Curve**: Depicts the optimal solution computed by the constraint solver, which ensures the transformer's capacity is never exceeded. The peak load is distributed over 14 hours and 49 minutes, from 4:50 PM to 7:39 AM. The performance gain is primarily due to prioritizing EVs that begin charging early and those that finish charging late, following the behavior of the uncontrolled charging scenario.

The results are summarized in Table II.

### B. Fair Sharing

Figure 4 shows the SoC progression for EVs under each charging algorithm, from when they begin charging (bottom left) to when they finish (top right). The clustering of the charging curves indicates the algorithm's fairness across different EVs. Fairness, in this context, ensures that each EV charges at a similar pace, providing equal satisfaction to users by achieving a similar percentage of charge based on their initial and target SoC. Fairness also means that during events like power cuts, no EV is prioritized over others.

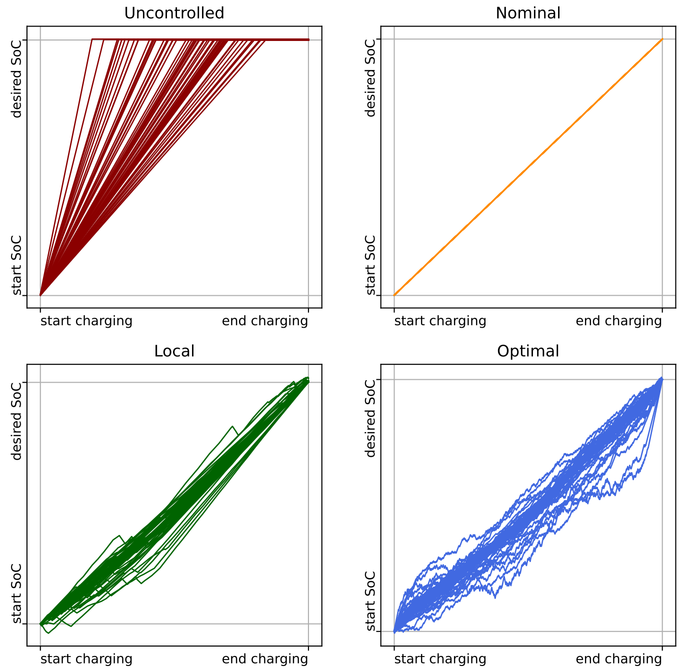


Fig. 4. SoC Evolution of EVs from Initial to Final Charging Time

The nominal algorithm demonstrates perfect fairness due to its strategy of equal treatment and full window charging. Under all algorithms, EVs generally reach the desired SoC by the end of the charging period. However, with uncontrolled charging, EVs often slightly exceed the desired SoC, due to the lack of power adjustment and stopping once the SoC threshold is met or surpassed. In contrast, the nominal and optimal algorithms achieve the desired charging levels with precision.

Our local peak shaving algorithm also shows no significant disparities between EVs, ensuring fairness, and performs closely to the optimal solution.

### C. Voltage Deviation

In a 230V network, the voltage at the house smart-meter needs to remain within ±10% of the designed voltage. The house located at Bus886 is particularly affected due to its distance from the transformer, resulting in higher cable resistance (See Figure 2).

The optimal peak-shaving solution exhibits fluctuations due to the significant power variations at each bus, ranging from -3.6kW to +3.6kW. On the other hand, the local algorithm ensures smoother power variations within houses, contributing to a more stable voltage profile.

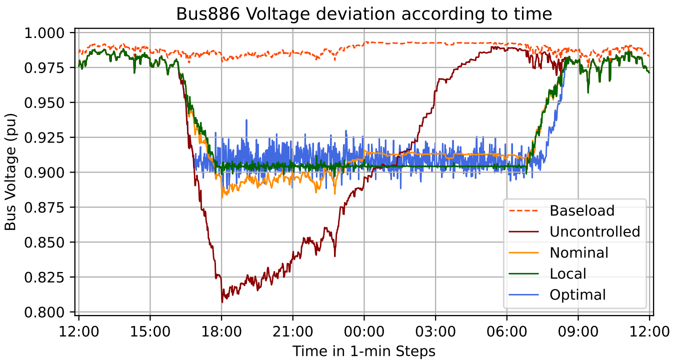


Fig. 5. Voltage Deviation on Bus886 house with largest drop

TABLE III
NETWORK LOSSES AND CURRENT REVERSAL COUNT

| Charging Algorithm | Network Losses | Mean BCR per EV |
|---|---|---|
| Optimal | 150.22kWh | 282 |
| Uncontrolled | 236.14kWh | 0 |
| Nominal | 175.10kWh | 0 |
| Local | 157.90kWh | 4.15 |

The uncontrolled charging algorithm, by contrast, is unable to keep the voltage constantly above the threshold of 0.9 per unit (pu), which can disrupt certain devices operating only in certain voltage ranges.

### *D. Electrical Network Losses*

We measure electrical losses on the network during the 24-hour simulation. Network losses are high with uncontrolled charging, with a total of 236.14kWh. As soon as we switch to solutions that do not overload the transformer too much, the gain among the solutions seems negligible. The local peak shaving obtains 157.90kWh loss, it is 38.38% more efficient than the uncontrolled charging solution and 0.175% more efficient than the nominal one that reaches 175.10kWh. The optimal peak-shaving solution reaches 150.22kWh.

### *E. Batteries Cycles*

The average number of Battery Current Reversal (BCR), which is two times the number of V2G periods performed by an EV, is shown in Table III. The optimal peak-shaving method requires power to be reversed 282 times, which could cause considerable degradation to the EV's battery. By contrast, our approach performs far better with an average of only 2 V2G periods, i.e. 4 power inversions.

## VII. DISCUSSION AND LIMITATIONS

We have to consider whether getting closer to the optimum solution might involve additional costs that could exceed the potential gains.

In particular, to achieve this optimal solution, we need to set up a robust communication network with high reactivity and bidirectional communication (communication between EVs) since implementing this optimal solution requires each EV to adapt every minute depending on the charging of all other EVs. Indeed, EVs arriving first and leaving last need to charge their batteries at full power until the network has reached its optimum consumption value, so this optimization requires communications among the EVs. Furthermore, EVs need to be able to attenuate peaks in consumption by other households, and thus they need to know what flexible power capacity is available at any given time. Deploying such a communication network involves high energy and financial costs, particularly in terms of deployment and maintenance. It is therefore necessary to determine whether the associated gains are justified. Additionally, such an optimal strategy requires to exchange information among houses that may be sensitive (i.e. the electrical consumption of a house is considered as sensitive because it may reveal whether inhabitants are at home or not for instance).

## VIII. CONCLUSIONS AND PERSPECTIVES

Electrical vehicles represent both a challenge and an opportunity for electrical grids in residential areas. Indeed, if uncontrolled when reaching a large number of EVs, their high charging rates may require grid reinforcement or cause voltage fluctuations. Yet, their batteries offer interesting vehicle-to-grid options for peak shaving. We have suggested that a simple and ready-to-deploy local smart charging method is sufficient to achieve efficient peak shaving throughout a residential district. The optimal method is not ideal either for battery life or for voltage fluctuations in the grid.

We plan to extend this work in several directions, the first one being to increase the diversity of considered evaluation conditions. Including users with different electric vehicles, varying electricity contracts and lifestyles (e.g., remote workers or night shifts) and considering weekdays and weekends would better capture the diversity of actual consumption profiles. Testing different electric vehicle penetration rates, especially given France's current 3%, would help to determine when their use could benefit the grid balance. Lastly, it is essential to take large-scale energy consumption into account, to prevent vehicle charging from increasing peak demand and compromising grid balancing efforts at a larger scale.

## ACKNOWLEDGEMENT

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