Benchmarking a Car-Originated-Signal Approach for Real-Time Electric Vehicle Charging Control

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Abstract—We propose and benchmark a new approach for electric vehicle charging control to match arbitrary power profiles. The approach enables vehicles to compute signals reflecting their need for charge and willingness to supply power. An aggregator collects these signals and implements the control with minor computational effort. We benchmark our approach against a centralized optimization, focusing on the trade-off between objective fulfillment and solving time. For the evaluation, we aim at load leveling in a distribution network with high amounts of solar generation. The scenario is based on electricity demand, solar generation, and car mobility data from Munich, Germany. Our results show that the proposed approach achieves relatively good performance, even for large EV fleets, at a low computational cost. Our approach can be generalized to different loads and objectives and could enable new business models for aggregators.

Index Terms—Electric vehicles, energy management, optimization, smart grids, solar energy.

I. INTRODUCTION

To keep the electric grid stable, power supply and demand have to be balanced at all times. To date, this balance is preserved by dispatching generators to match a given demand. As the share of energy from renewable sources like wind and solar continues to increase, demand-side management and energy storage are becoming more important. Controlling flexible loads, in particular, could help to achieve the ambitious renewable integration targets set by different countries.

Our objective is to facilitate this balance by reducing the difference between a reference power profile and the power consumption of a group of consumers, e.g., a neighborhood served by a distribution network (DN). We consider a scenario with a number of electric vehicles (EV) and solar photovoltaic panels (PV) within the area of control.

The related work in the area of EV charging strategies can be classified based on system architecture (centralized/decentralized) and control method (direct/incentive-based). For instance, [1] proposes a decentralized algorithm that controls EV charging to fill demand valleys via incentive signals, [2] presents a framework for incentives-based distributed EV charging control for different objectives, [3] evaluates the supply of frequency reserves via centralized and direct EV control, [4] presents a decentralized optimization with direct control to minimize charging costs, [5] presents a local direct control technique for DN voltage stability, [6] aims at minimizing power losses with a centralized, direct control approach, and [7] presents a decentralized direct control method that includes other flexible loads. Most of these use formal optimization methods and focus on offline optimization.

Centralized optimization methods face the challenge of scalability as the size of the problem increases. Although distributed optimization approaches can be used to address scalability limitations, we believe that actually implementing such solutions would cause more challenges, mostly due to high communication requirements.

Our approach differs from the related work in two ways: (i) we address scalability by applying heuristics and partial distribution of computations, and (ii) we evaluate our heuristic approach by comparing its performance in terms of goal fulfillment and computation time to a central optimization. Moreover, our evaluation includes a comparison of continuous versus integer decision variables and of partial (receding horizon) versus complete information. Our approach combines the benefits regarding simplicity of a centralized approach but distributes part of the computation to the EVs. Furthermore, it does not require iterative optimization and could therefore meet the real-time requirements of advanced applications. In addition, we choose a direct control method to ensure certainty in control but, to a certain extent, protect EV users’ privacy by limiting information exchange. The presented approach can be generalized to different loads and objectives. We demonstrate how it can be used to reduce the variability of demand and distributed solar generation by intelligently charging and discharging EVs in real-time. Our evaluation is based on actual electricity demand, solar generation, and car mobility data from Munich, Germany.

II. POWER-MATCHING EV CHARGING CONTROL

Figure 1 illustrates the scenario assumed in the following. For a given area of the distribution network and the loads and distributed generation connected to it, the goal of the aggregator is to control the charging and discharging behavior of EVs such that the aggregated power profile matches a target power profile, $P_D$, as closely as possible. The aggregated power profile, $P_{agg}$, is defined as the difference between the demand and the local generation within the defined area, i.e., the total power demanded from the grid at time step $k$. 

"
That is:

\[ P_{agg}(k) = P_D(k) - P_S(k) + \sum_{i=1}^{N} P_{EV}^i(k) \]  

(1)

where for a given time step \( k \), \( P_D(k) \) represents the inflexible demand, \( P_S(k) \) denotes the produced solar power, and \( P_{EV}^i(k) \) is the power consumed by the \( i^{th} \) EV. \( P_{EV}^i(k) \) can be negative, meaning that the EV is supplying energy back to the grid (V2G).

Our objective is to minimize \( |P_D - P_{agg}| \) subject to the set of constraints of each vehicle \( \mathcal{X}_{EV} \), and the limitations of the electricity distribution network \( \mathcal{X}_{DN} \). Using (1) we can express this problem formally as follows:

\[
\min_{P_{EV}^i(k)} \left( P_D(k) - P_{agg}(k) - \sum_{i=1}^{N} P_{EV}^i(k) \right)^2, \quad \forall \ k \in T
\]  

subject to

\[
P_{EV}^i(k) \in \mathcal{X}_{DN}, \quad \forall \ k \in T
\]

\[
P_{EV}^i(k) \in \mathcal{X}_{EV}, \quad \forall \ k \in T, i \in N
\]  

Assuming that the constraints are linear, (2) is a convex optimization problem that can be solved with standard optimization techniques. However, the complexity of this problem increases at least at a polynomial rate of its dimensions [8] which in turn increase with the number of EVs and constraints. Therefore, we argue that this approach is no longer feasible for large EV fleets, especially if the goal is real-time control. Furthermore, the linearity of the constraints is not necessarily guaranteed, e.g., EVs charge at the rated power of the charger and not at infinitesimal fractions of it, which results in a far more computationally intensive problem.

We make three assumptions at the model level that are worth mentioning. First, we assume that the length of a time step \( k \) is significantly larger than the communication delays between elements (milliseconds vs. seconds or minutes), so we ignore them. Control with delays up to a few seconds is sufficient to cover a wide range of power system control problems. Second, we consider a maximum charging rate common to all chargers, i.e., fast charging is not taken into consideration. We see fast charging as a premium service that may be excluded from the control scheme. Finally, we assume no losses when (dis)charging the battery. This assumption is justified since a charger’s efficiency is relatively high, and it is irrelevant for the method since it would only affect the total consumed power and therefore slightly increase the reference \( P_D \).

### III. CAR-ORIGINATED-SIGNAL APPROACH

In the proposed approach, an aggregator directly controls a fleet of EVs. At each time step, every connected EV computes a Need-for-Charge (NfC) and a Willingness-to-Supply (WtS) signal and sends them to the aggregator. The aggregator collects these signals and returns charging instructions to the EVs.

This approach has two immediate advantages. First, the NfC and WtS signals are computed by every EV, resulting in high parallelization of computation and relatively high preservation of the EV owner’s data privacy. Second, by reducing the information exchange to two scalars per time step, we have relatively low communication requirements; especially if compared with distributed iterative methods like [1] and [2], where information is exchanged on every iteration.

**EV Need for Charge Signal:** The NfC is defined as a function of the remaining connection time and the time required to reach the desired state of charge in percentage (SOC). A threshold policy makes sure the EV constraints are fully satisfied. For each EV \( i \), based on its target charge level \( SOC^{tar}_i \), battery capacity \( E_{max} \), current energy in the battery \( E_{bat}^i \), allowed charging rate limit per time step \( E_{rate}^i \), and departure time \( k_{dep}^i \), we can define the required and available time steps \( k_{req}^i \) and \( k_{av}^i \) at each time step \( k \) as follows:

\[
k_{req}^i = \frac{SOC^{tar}_i E_{max}^i - E_{bat}^i}{E_{rate}^i}
\]

\[
k_{av}^i = k_{dep}^i - k
\]

where \( k_{req}^i \) can take non-integer values. We then define the thresholds \( C_{QoS} > C_{tar} > C_{full} \), where \( C_{QoS} \) indicates that the EV must charge to reach \( SOC^{tar}_i \), \( C_{tar} \) indicates that the EV has reached \( SOC^{tar}_i \), and \( C_{full} \) indicates that the EV’s battery is fully charged.

Using an intermediate variable \( NfC^{temp} = C_{QoS} \frac{k_{req}^i}{k_{av}^i} \) for a given time step \( k \), we define the NfC as:

\[
NfC^i(k) = \begin{cases} 
C_{QoS}, & \text{if } NfC^{temp} \geq C_{QoS} \\
NfC^{temp}, & \text{if } C_{tar} \leq NfC^{temp} < C_{QoS} \\
C_{tar}, & \text{if } NfC^{temp} < C_{tar} \\
C_{full}, & \text{if } E_{bat}^i = E_{max}^i 
\end{cases}
\]

**EV Willingness to Supply Signal:** For the computation of the WtS, we only consider the thresholds \( C_{maxS} \) indicating the maximum willingness, and \( C_{nosS} \) indicating that this car is not willing to supply at all, where \( C_{maxS} \gg C_{nosS} \). For a given EV and time step, the WtS is a function of the available time \( k_{av}^i \), the departure time \( k_{dep}^i \), and the current SOC \( i \). To set the WtS within its thresholds, we scale it by \( C_{maxS} \) and shift it by \( C_{nosS} \), resulting in:

\[
WtS^i(k) = \begin{cases} 
C_{nosS}, & \text{if } E_{bat}^i \leq E_{min}^i \text{ or } k_{req}^i \geq k_{av}^i \\
C_{maxS} SOC^i \frac{k_{req}^i}{k_{dep}^i} + C_{nosS}, & \text{otherwise}
\end{cases}
\]

*Only two derived metrics (NfC and WtS) are revealed to the aggregator as opposed to, e.g., parking times, SOC or vehicle objectives and constraints.*
The Aggregator: At each time step, the aggregator receives the NfC and WtS signals from the EVs, defines a charging strategy and instructs the EVs to charge accordingly. The process is as follows:

1) \( P_{agg}(k) \leftarrow P_D(k) - P_S(k) \)
2) Sort EVs by NfC in descending order
3) While \( P_{agg}(k) < P_{max}^i \) and NfC = CQoS
   - Charge EVs with NfC = CQoS
4) If \( P_{agg}(k) \leq P_D \)
   a) Select EVs with \( C_{full} < \text{NfC} \leq C_{QoS} \)
   b) Charge EVs
      - Continuous case:
        Allocate available power to EVs proportional to NfC
      - Integer case:
        Allocate available power to EVs with highest NfC
   c) \( P_{agg}(k) \leftarrow P_{agg}(k) + \sum_{i=1}^N P_{EV}^i(k) \)
5) Else (meaning \( P_{agg}(k) > P_D \))
   a) Sort remaining cars by WtS in descending order
   b) Select EVs with WtS > C_wtS
   c) Discharge EVs
      - Continuous case:
        Allocate required power to EVs proportional to WtS
      - Integer case:
        Allocate required power to EVs with highest WtS
   d) \( P_{agg}(k) \leftarrow P_{agg}(k) + \sum_{i=1}^N P_{EV}^i(k) \)

IV. BENCHMARK

In this section we formulate the problem as a centralized optimization with a quadratic objective function. We define a continuous and a mixed-integer optimization to account for different types of decision variables. For each case, we also consider complete and partial EV information availability upon solution time.

We use Matlab [9] and Yalmip [10] to model the problem. We do not expect any tool-specific bias since we only measure the solver’s solving time and use Gurobi [11], a state-of-the-art commercial solver, to solve the optimization problem.

The optimization problem is defined as follows:

\[
\min_{P_{EV}^i} \left\| P_O + P_S^k - P_D^k - \sum_{i=1}^N P_{EV}^i \right\|_2^2
\]

subject to

\[ -D_{p}^i k \leq P_{EV}^i \leq D_{p}^i k \]
\[ SOC^i + P_{EV}^i \Delta t \leq E_{i}^{max} \]
\[ P_{agg}^i = P_{D}^k - P_{S}^k + \sum_{i=1}^N P_{EV}^i \]
where \( D_{p}^i k \) is the driving profile matrix containing ones for each EV \( i \) connected at time step \( k \). Vectors \( E_{i}^{min}, E_{i}^{max} \) and \( E_{i}^o \) are the minimum/maximum allowed and initial state of charge of EV \( i \)’s battery. \( P_{max}^i \) is the maximum (dis)charging rate assumed equal for all EVs. The vector \( SOC^i \) indicates the target state of charge of EV \( i \). The operator \( \circ \) stands for element-wise multiplication. Finally, \( \Delta t \) is the time step size. \( B_{EV}^i \) is a lower triangular matrix that, combined with the charging profile matrix \( P_{EV}^i \), indicates the state of battery charge at every time step.

Equations 7-12 refer to the continuous problem. To convert this into the mixed-integer case, one has to change (8) so that \( P_{EV}^i \) can only take the values \( \{-P_{EV}^i, 0, P_{EV}^i\} \). The optimization problem is solved at every time step \( k \) and the result is only applied in that time step. This benchmark represents a more realistic scenario in terms of known information, but also the worst case in terms of solving time.

Figure 2 illustrates how the EV information is built for every time step. As a reference, the clairvoyant approach would use the entire matrix. We are optimizing for \( k = 3 \) and therefore only consider the information of the cars connected at this time step (three cars) and optimize for the shaded period covering up to the last known EV departure.

V. MUNICH LOAD LEVELING SCENARIO

The car-originated-signal approach can be used to make the aggregated demand follow arbitrary target profiles. Our target in this evaluation is a constant power profile. Achieving this objective results in load leveling.

We focus on load leveling since a flat power profile has two desirable effects. First, renewable energy is consumed locally. Second, generation can be planned more efficiently since the aggregated demand of the controlled area is less variable over time.

We concentrate on two evaluation metrics: (i) the error with respect to the objective, measured as the normalized mean squared error (MSE) of \( P_{agg}(k) \) with respect to \( P_O \), and (ii)
the solving time measured strictly only for the solver excluding
data acquisition, modeling, and parsing.

The evaluation presented in the following is based on actual
data provided by Munich’s DSO [12] and the official mobility
survey conducted by the German government [13].

The Munich DSO supplies yearly information on a 15 min
granularity. We take the load and distributed intake (reflecting
local solar generation) data for the low voltage level and select
a 24 hour period starting in 5 July 2012 at noon, such that the
considered time period spans an entire night. Then, we scale
the load profile to obtain a peak demand of 1.6 MW, which
corresponds to the magnitude manageable by the intended
EV fleet size, and use the same factor for scaling the solar
generation data. Finally, we multiply the resulting solar profile
by a factor of 5 to mimic a higher solar penetration.

The mobility survey includes data for all of Germany. We
filter data from major cities (>500k inhabitants) in order
to get a data set valid for Munich and large enough to
be representative. Additionally, we apply a set of quality
assurance rules to ensure that the interviewed person is the
driver, the used vehicle belongs to the household, and the
average reported speeds are lower than 120 km/h. For our
experiment, we select entries for a workday and up to three
cars per household to build N vehicle driving profiles.

For the simulation, we (i) run simulations for fleet sizes
of \( N = 100, 200, \ldots, 1000, \) (ii) consider a homogeneous
fleet of EVs with \( SOC_{tar} = 85\% \), battery maximum and
minimum capacities of \( E_{max} = 16 \text{kWh} \) and \( E_{min} = 1 \text{kWh} \),
and charging power \( P_{EV} = 4 \text{kW} \), and (iii) use the same
data for all cases including the continuous and integer cases
of our approach, the clairvoyant, and the receding horizon
optimization benchmarks (6 runs per fleet size).

Furthermore, we assume that the EVs charge only at home
and are plugged only once (during the longest parking period).
Regarding the settings of the mixed-integer solver, we limit
the solving time to 250 min in the clairvoyant case and define
a relative (upper/lower bound) gap of 0.05 and a time limit
of 15 min in the receding horizon case. In general, a lower
time limit increases the deviation from the optimal result and
a smaller relative gap increases the solving time.

VI. RESULTS

The results are divided into the aggregated power profiles
for 600 EVs, a performance comparison in terms of objective
fulfillment and solving time, and a trade-off analysis between
objective fulfillment and solving time for different fleet sizes.

Figure 3a shows the shape of the aggregated power profile
for a fleet of 600 EVs. Two points are worth observing here:
the low magnitude of the errors with respect to the pre-
aggregated \( P_D(k) - P_S(k) \) profile, and the lower performance
of the integer vs. the continuous case.

Figure 3b illustrates the performance in terms of distance
to goal (normalized MSE\(^2\)), and solving time (seconds), for
different EV fleet sizes. The scale of the y axis is logarithmic
for both measurements.

As expected, the clairvoyant optimization for the continuous
case shows a better performance in terms of objective
fulfillment. However, in the integer case we see a reduced
performance due to the limited time available for optimization.

Another relevant finding is that our approach performs
consistently better than the receding horizon optimization as the
number of EVs increases. On the one hand, this demonstrates
the scalability of our approach and its effectiveness. On the
other hand, it points out the main limitation of our approach:
lower performance for small fleet sizes. Yet, it is important to
point out that even for a fleet size of 300 EVs, the normalized
MSE of our approach in the integer case is already \( 1.99 \times 10^{-3} \),
which one can consider acceptable if the solving time is put
into perspective.

The advantages of our approach become clear when when
observing the differences between solving times. The car-
originated-signal approach performs several orders of mag-
nitude better than both benchmarks. Furthermore, the solving

\( ^2\text{Normalized MSE} = \frac{1}{T} \sum_{k=1}^{T} \left( \frac{P_D - P_{agg}(k)}{P_O} \right)^2 \)
time for our approach is similar for the continuous and integer cases, whereas it is several orders of magnitude different for the benchmarks. Additionally, the solving time increase as the number of EVs increases is moderate and the variance of the solving time remains low. These findings emphasize the flexibility and scalability characteristics of our approach.

Figure 3c summarizes the findings in a trade-off analysis. The performance of our approach is consistent, especially once a sufficient fleet size (over 400 EVs) is used. Our approach provides an attractive trade-off between computation time and objective fulfillment.

VII. DISCUSSION

One limitation of our approach is its performance for small EV fleets. We don’t see this as a strong limitation since the advantages of our approach become more significant as the size of the problem increases. For small problems, state-of-the-art optimization possibly remains the best choice.

Furthermore, the power profile might experience steeper ramps for too small or too large fleet sizes because we do not consider future information. However, we believe that this can be solved with a more elaborate definition for the NIC.

Our approach offers a very attractive trade-off between computational complexity and performance. Although the benchmarks could be made more competitive by better tuning of the solvers, we believe that it is very unlikely that they match our solving time (which is also improvable through parallelization).

Beyond its computational advantages, we would like to emphasize the flexibility of our approach. First, it decouples constraints and objectives so that EVs can readily change their priorities and objectives (e.g., battery lifetime maximization) without affecting the aggregator’s design and vice versa. Second, it has low dependency on forecast accuracy since decisions are made only based on current information. Finally, it preserves EV owners’ data privacy as only calculated scalars are sent.

The goal of our ongoing and future work is to better understand the relationship between the magnitudes of $P_D$ and $P_S$, the fleet size, and the performance. More elaborate and alternative designs for NIC and WtS signals with different objectives, both for EVs and the aggregator, could also be explored. Moreover, one could look into the statistical characterization of the normalized squared error and the extension of the approach to other flexible loads like heating, ventilation and air conditioning. The first could provide more insights about the reliability of our approach, while the latter could stress its wide applicability and high flexibility. Our work could help to enable new business models for aggregators as service providers to the DSO.

VIII. CONCLUSIONS

In this paper, we present a car-originated-signal approach for real-time EV charging control and apply it to minimize the variability of the aggregated power profile. Our evaluation, based on actual data for Munich, shows that it is possible to control a load profile with a 1.6 MW peak (4000 inhabitants$^3$) and five times more solar penetration with 500-600 EVs with a normalized MSE in the $10^{-3}$ range.

The comparison of our approach with state-of-the-art centralized optimization provides promising insights about its practical applicability. We achieve a good performance for a sufficient number of EVs with solving times in the microseconds range and little increase for larger EV fleets. Beyond the scalability advantage, the method decouples the complexity of EVs and aggregator, preserves EV users’ privacy to a high extent, allows for a certain degree of distribution and keeps the advantages of a centralized direct control approach. Still, for small EV fleet sizes, formal optimization might be a more suitable approach.

We believe that this work provides promising starting points for a resource-efficient flexible load and storage control system. It can be generalized to different loads and objectives, and could enable new business models for aggregators. With market price differences of 15%-30% between base and peak loads, 5%-15% in futures and probably more in bilaterally agreed long-term contracts, we believe that there exist economical incentives to realize the type of systems evaluated in this paper.

REFERENCES