Smart Charging of Electric Vehicles: Exploration of Existing Strategies, Modeling, and Grid Impact Analysis Techniques

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A Research Report from the National Center for Sustainable Transportation

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16. Abstract Electrification of the transportation sector provides the means to significantly reduce greenhouse gas emissions from internal combustion engine vehicles (ICEVs). However, for electric vehicles (EVs) to remain a viable alternative to ICEVs, solutions must be developed to meet the associated growth in power demand (for charging) without stressing the power distribution infrastructure. One potential solution to this challenge is to control the EV charging load through smart charging. The objectives of the proposed research effort are to (i) clearly define the smart charging problem, (ii) complete a comprehensive literature review, (iii) develop and document fundamental models needed to analyze EV charging and grid impact, and (iv) develop *mathematical* algorithms for solving the smart-charging problem defined in (i).		

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A National Center for Sustainable Transportation Research Report

June 2023

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TABLE OF CONTENTS

List of Tables

Smart Charging of Electric Vehicles: Exploration of Existing Strategies, Modeling, and Grid Impact Analysis Techniques

1. Document Summary

The most-recent quarterly project report (submitted 4/19/2023) listed five project deliverables. Each of Section 2–6 is dedicated to one of these five deliverables. Final comments are provided in Section 7, followed by an exhaustive list of references.

2. Deliverable I: Problem Definition

Clear definition of the smart charging problem for fleets of medium and heavy-duty vehicles with scheduled arrivals and departures, considering i) fleet operator preferences (including renewable energy consumption), ii) travel demand, and iii) grid implications

2.1. Motivation

Market penetration of light, medium, and heavy-duty electric vehicles (EVs) is rising due to in- creasing environmental awareness, decreasing vehicle costs, regulatory pressures and tax incentives (see Figure 1). Furthermore, no system is currently in place to regulate when EV charging occurs; typically, EV charging either begins moments after the EV is plugged in, or after an owner-specified time delay. In either case, EV charging may be thought of as uncontrolled, since a human deter- mines when charging occurs. Therefore, the increasing market penetration of EVs (more precisely, the corresponding increase in uncontrolled EV charging) is expected to exacerbate the evening surge in power demand, degrade power quality, and overload transformers in distribution networks [1, 2]. The peak power drawn during EV charging depends on the type of vehicle and charging equipment. For medium and heavy-duty EVs, which have larger battery packs than light-duty vehicles, the peak power draw during charging can range from tens to hundreds of kilowatts per vehicle [3]. As the medium and heavy-duty vehicle sectors electrify (delivery vans, buses, etc.), the associated charging loads will be significant, with total power demand expected to approach 1 megawatt, especially in fleet or depot settings [3, 4].

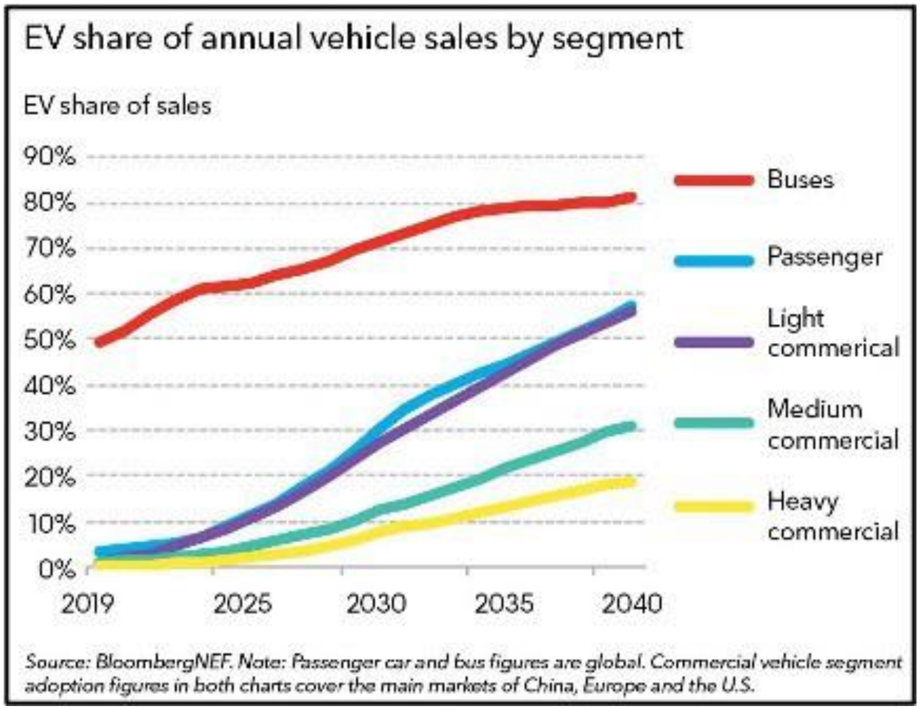

Figure 1. Estimated global market penetration of electric vehicles by segment [5].

At the same time, increasing numbers of renewable energy resources (RESs) are being deployed to reduce dependence on fossil-based energy. This trend will lessen the generation burden on non-renewable generators, but only at times when RESs are generating power. Each type of RES (e.g., wind, hydropower) has a different (characteristic) time-varying power generation profile.

Furthermore, the power generated by RESs is influenced by factors beyond human control (e.g., sunlight intensity, cloud cover, intensity/direction of winds, intensity/direction of water flows), and therefore does not necessarily align (in time) with power demand. As RESs penetration increases, this mismatch between power supply and power demand is expected to worsen, especially when the impact of increasing EV adoption on power demand is considered. For example, in the case of a solar-dominated RES portfolio which mostly generates power around mid-day (as in the State of California), considering EV and RES adoption trends together reveals that an undesirably sharp ramp-up in non-renewable generation will be needed in the afternoon hours to meet the evening demand (see Figure 2) [6].

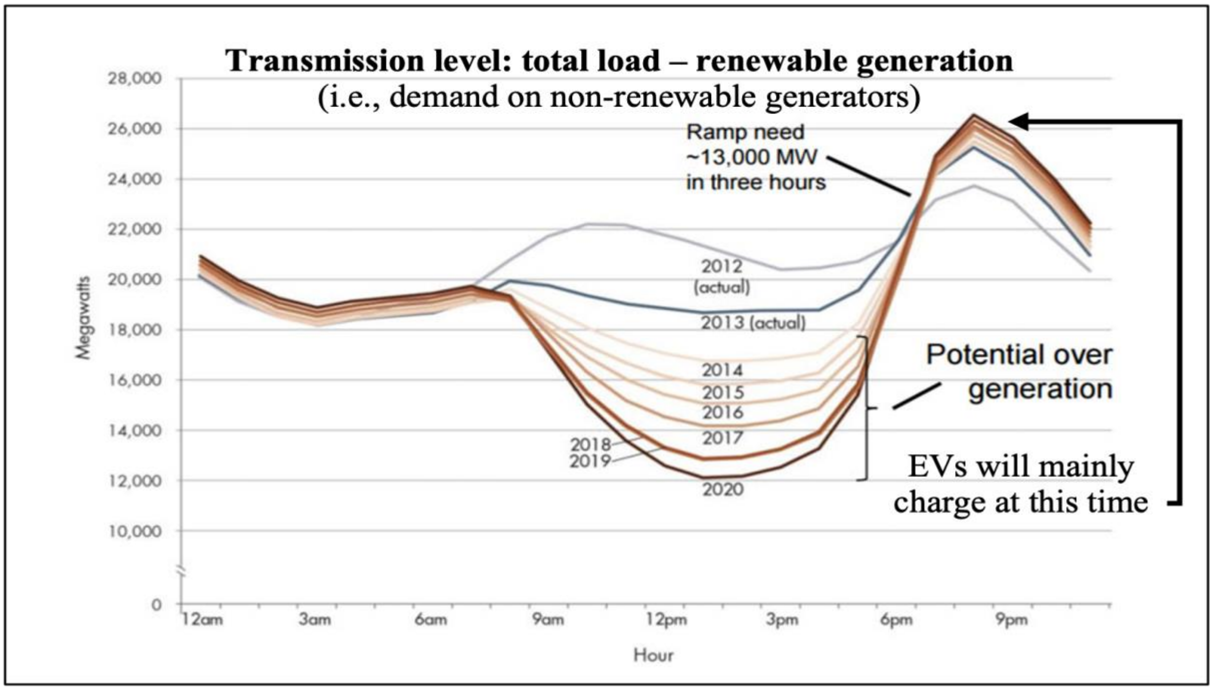

Figure 2. The "duck-curve" phenomenon observed in the State of California, which arises from a combination of increasing solar generation around mid-day and increasing power demand in the evenings [6].

One potential solution to these challenges is to control the EV charging load through smart charging. The term smart charging is not meant to imply that batteries strictly charge—bidirectional power flow may be permitted. According to a 2020 analysis by McKinsey & Company, operators of medium and heavy-duty EV fleets would typically prefer to charge their vehicles overnight, due to large energy requirements (compared to light-duty vehicles) and lower electricity prices in the evening hours [3]. However, most EVs will not be actively charging over the entire night, even though they will remain plugged in. Therefore, there exists an opportunity to distribute charging activity over the entire time that vehicles are plugged in, and doing so can realize benefits for the fleet owner and/or the grid operator. Smart charging algorithms use optimization to distribute EV charging activity over time, and formally represent the benefits seen by fleet owners and/or the grid operator in the form of an optimality criterion.

2.2. Problem Definition (In Words)

The smart charging problem for fleets of medium and heavy-duty vehicles with scheduled arrivals and departures is described in words now, and formulated mathematically later in this document (Section 6). This formulation is applicable, for example, to fleets of package delivery vehicles (i.e., Amazon, FedEx, UPS, USPS), and fleets of buses (i.e., for public transportation or school buses).

All fleet vehicles depart from and arrive at a common depot, or home base, every day. The depot has a number of EV charging stations, where vehicles can plug in to charge. Given the (i) arrival and departure times, (ii) energy requirements, and (iii) physical limitations associated with each fleet vehicle (which must all be satisfied), the smart charging problem is to jointly determine how to "best" charge each EV over a period of time (i.e., overnight). This decision, in general, requires both (i) assigning each EV to a charging station (not all charging stations may be equal), and (ii) determining a charging profile for each EV. A chosen optimality criterion encodes the objective of smart charging, which may be, for example, to (i) minimize the fleet operator's cost of charging, given a rate structure from the utility (e.g., a combination of time-of-use pricing and demand charges), (ii) maximize the fleet operator's dependence on energy produced by carbon-free sources, (iii) minimize total time to charge the fleet by charging rapidly, (iv) minimize (marginal) degradation of the vehicle batteries by charging slowly, or (v) some combination thereof. Additional constraints, such as a cap on the total charging power, must also be considered as appropriate. If the grid operator is to benefit from smart charging, then alternative optimality criteria could be to (i) minimize the total power used to charge the fleet, or (ii) minimize the total power used to charge the fleet and power other loads in the depot (e.g., air conditioning, lighting).

3. Deliverable 2: Literature Review

Critical review of existing i) smart charging strategies in the literature, and ii) commercially available smart charging systems, specifically for fleets of medium and heavy-duty vehicles

3.1. Academic Literature

For the purpose of literature review, a fleet charging problem is any smart charging problem in which charging decisions involving multiple EVs (a fleet) are made jointly by a central decision maker. This decision-maker is often called an *aggregator*, and is not necessarily the same as the owner/operator of the fleet vehicles or the charging stations in use, as shown in Table 1 below.

Table 1. Listing of Fleet Charging Scenarios (Non-Exhaustive)

Aggregator	Scenario Description
EV Owner	EV owner charges multiple personally-owned vehicles at home
Public Charging Network	Multiple EV owners charge at a public AC charging station (e.g., ChargePoint)
Parking Lot Operator	Multiple EV owners charge at a public EV parking lot
Employer	Multiple EV owners who work for a common employer charge at their workplace
Utility	Multiple EV owners charge at a utility-operated DC fast charging station
Utility	EV owners charge at home and are enrolled in a demand response program
Fleet Manager	A business owns a fleet of EVs and charges their fleet in their workplace

3.1.1. Fleets with Unscheduled Arrivals and Departures

The emphasis in this work, and in the majority of the fleet charging literature, is on fleets that have scheduled arrivals and departures to and from their charging location (called a depot or home base). However, there is also a body of work that treats the important problem of managing charging in fleets with unscheduled arrivals and departures, and representative studies from this body of work can be found in [7–9]. One example of a fleet with unscheduled arrivals and departures is a public EV parking lot, perhaps located in a shopping mall. A common theme among these studies is to ensure that the total power demanded by the aggregator (i.e., the parking lot operator) is managed, either by (i) enforcing a hard limit and allocating the finite amount of available power among all vehicles in some fair way, or (ii) creating dynamic pricing strategies in which (a) individual vehicles can pay more for a larger (relative) allocation of power, and (b) prices increase as the total power demand approaches the aggregator's total power limit, so as to disincentivize charging. It is also common to not fully satisfy each vehicle's request for charge in this body of work, as enforcing a total power limit is given priority.

3.1.2. Fleets with Scheduled Arrivals and Departures: Routing Approach

Smart charging is motivated by the fact that spatially and temporally concentrated EV charging activity has undesirable effects on the grid. One class of smart charging studies seeks to address this issue by routing fleet vehicles via various, spatially-distributed charging stations, and incorporating en-route charging sessions into vehicle routes. Representative studies from this body of work can be found in [10–13]. A common theme among these studies is to alter the typical routes taken by route-following vehicles (e.g., trucks, delivery vans, buses) in such a way that the vehicle's charging requirements upon returning to its home base are reduced, while still ensuring that any timing-related constraints are met (e.g., deliveries are on-time, buses arrive/depart from stops on schedule). In this way, the overnight charging needs for the fleet as a whole are reduced.

3.1.3. Fleets with Scheduled Arrivals and Departures: Profile Shaping Approach

The dominant approach taken in the smart charging literature is to intelligently shape the charging profiles of each EV in a fleet. This 'profile shaping' approach is complementary to (rather than an alternative to) the 'routing approach' described in the previous subsection. One reason for this dominance is perhaps due to its applicability in residential EV charging scenarios, where routing approaches might be viewed as inconveniencing individual EV owners. This body of work is most closely related to our work, and is therefore more thoroughly reviewed.

Reviews of the profile shaping literature are available in [14] and [15]. The reviewed studies all determine optimal charging plans for collections of EVs, but differ in their choice of objective function. Fleet charging problems involve three main stakeholders: individual EV owners, the aggregator and the power utility. If considering all stakeholders, EV owner-imposed charging demands, aggregator-imposed operational limits, and power utility-imposed operational limits must always be satisfied (by imposing optimization constraints). However, the objective function can be chosen to favor any stakeholder (or any combination of stakeholders). Smart charging objective functions are classified in [14] and [15] based on their financial or physical nature, and the solution methods required. An alternative classification, adapted from [14] and [15], is given in Table 2. Objective functions favoring the power utility and EV/fleet owners are labeled 'grid-centric' and 'EV/Fleet owner-centric', respectively. We use the acronyms OCSC and GCSC for EV/Fleet Owner-Centric Smart Charging and Grid-Centric Smart Charging, respectively.

The most simple GCSC problem is load profile flattening, where an aggregate power demand curve is maximally flattened over time [16–18]. By embracing a physics-based model of a distribution feeder, [10,15,19–21] emphasize mitigation of the grid-level issues. The dominant approach is to pose smart charging problems (involving multiple EVs) where grid constraints (e.g., bounds on power flows and/or voltage fluctuations) are enforced, and the objective function favors the grid operator (e.g., minimize operating cost or distribution circuit losses, flatten aggregate load profile, maximize a measure of power quality). With additional financial modeling, the cost (or profit) associated with operating the feeder can be minimized (or maximized) [22, 23]. For GCSC in general, EV-owner imposed charging demands enter only through constraints, whereas quantities of interest to the power utility enter in both the objective function and constraints. GCSC directly addresses the grid-level issues which motivate smart charging, but assume the participation of EV/fleet owners who are not explicitly incentivized to do so.

Table 2. Examples of smart charging objective functions

Grid-Centric (GCSC)	EV/Fleet Owner-Centric (OCSC)
Flatten load profile	Maximize charging urgency
Minimize transmission loss	Maximize fairness (among a fleet)
Maximize line utilization	Minimize battery degradation
Maximize profit	Minimize charging costs
Maximize power quality	Maximize profit from grid services

The most simple OCSC problems are utility payment minimization (see [24–27]) and fair charging of multiple EVs (see [28–30]). Fairness is of particular importance in fleet charging problems, since the total power required to charge a fleet of EVs can grow quickly, especially for fleets of medium and heavy-duty vehicles. Thus, total power limits also become relevant very quickly, and it is important to fairly allocate the finite amount of available power among several vehicles. Physics-based distribution feeder models are also employed in [24,25,27] to enforce bounds on power quality metrics. For OCSC in general, power utility-imposed operational limits enter only through constraints (if at all), whereas quantities of interest to EV/fleet owners enter in both the objective function and constraints. OCSC addresses the grid-level issues which motivate smart charging indirectly, if at all. However, EV/fleet owners have clear incentives to participate. Few studies attempt to balance competing desires (such as EV/fleet owner-centric and grid-centric objectives) using multi-objective optimization [31–33], but the selection of parameters that control the trade-off in these approaches is non-trivial.

3.2. Review of Commercially Available Solutions

A fleet operator looking to perform smart charging today has limited options at their disposal. One option is to enroll their fleet in a demand response program that is offered by a grid operator, often in partnership with a vehicle manufacturer [34–36]. In demand response schemes, grid-level issues are mitigated by allowing the grid operator to control the charging of multiple EVs. For further information (and references) on smart charging algorithms of this nature, see [14].

If the fleet operator prefers to retain control over the charging of their vehicles, then they are limited to the “smart” charging features offered by several EV and electric vehicle supply equipment (EVSE) manufacturers. Based on a review of products manufactured by companies listed in Table 3, it appears that these EVs and EVSEs do not rely on optimization methods, but rather on simple, heuristic methods to determine EV charging times. All reviewed products only allow users to delay charging, or to limit when charging can occur (e.g. based on typical two-level TOU signals).

Table 3. "Smart" EVs and EVSEs

EVSE Manufacturers		EV Manufacturers
AMPROAD	Lectron	Audi
Anderson	Mustart	Chrysler Group
BougeRV	Myenergi	Ford
ChargePoint	Ocular	General Motors
Emporia	Smappee	Honda
Enel-x	Splitvolt	Hyundai
EO	Wallbox	Toyota
Fimer	ZJ Beny	Tesla
Grizzel-E		Volvo

4. Deliverable 3: Background on Modeling of EV Charging

Documentation on existing models and model-based analysis methods pertaining to EV charging and grid impact.

It is well-known that most on-board EV battery chargers utilize standard battery charging profiles, with the most common profile being the constant-current-constant-voltage (CC-CV) profile. Other, more sophisticated variants exist, and are discussed in [37], but share the common theme of reducing the charging current once battery state-of-charge (equivalently, stored energy level) reaches a threshold value (which varies in practice, but is around 80%). In smart charging studies, however, it is typical to assume that EV battery charging is a constant-power process. For vehicles that utilize CC-CV charging profiles, this assumption is reasonable during constant-current operation, since battery voltage remains approximately constant, leading to approximately constant-power charging. However, this assumption breaks down when constant-voltage charging is performed. For this reason, it is also common to assume in smart charging studies, that either (i) EVs are charged using DC charging, fed by an off-board, command-following-capable AC/DC power converter that accepts (and tracks) power reference commands (such as the devices designed in [38–43]), or (ii) the on-board battery chargers in EVs are replaced by command-following-capable AC/DC power converters that accept (and track) power reference commands (such as the devices designed in [44–52]). In the presence of these command-following-capable power converters, reference charging profiles produced by smart charging algorithms can be faithfully executed upon in practice.

Grid impact analysis methods are typically model-based, and are discussed in Section 5.

5. Deliverable 4: Background on Analysis of Grid Impact

Documentation on existing datasets, estimation methods, and/or analysis methods pertaining to charging demand, and grid impact.

5.1. Analysis Methods

Reporting and evaluation of grid impact varies greatly across the smart charging literature [14, 15]. Some studies employ physics-based distribution feeder models to assess grid impact using voltage drop or transformer overloading as metrics (e.g., [17, 19, 20, 22–25, 27]) while others do not, instead using aggregate load as a metric (e.g., [10, 16, 18]). For any grid impact metric, computed values will be sensitive to the settings of key parameters, such as EV plug-in time and EV state-of- charge. Since these quantities are linked to human behavior, it is typical to draw them from assumed distributions [10, 16–20, 22–25, 27]. However, in all but one of these studies, key parameter values are randomly drawn one time, and nominal values of grid impact metrics are reported. The exception is in [20], where key parameter values are randomly drawn multiple times (Monte-Carlo style), and distributions of grid impact metrics are reported. Distributions reveal typical values of a grid impact metric, as well as sensitivity to variations in key parameter values, and therefore present a more complete grid impact assessment. This style of analysis is dominant in the literature on unrestricted, conventional charging (not smart charging) [1, 2, 21, 53, 54].

5.1.1. Physics-Based Grid Impact Analysis

The basic requirements for model-based grid impact analysis are (i) a physics-based model of a power distribution circuit (called a feeder), which is typically a three-phase, unbalanced power system; and (ii) a numerical method to solve the circuit equations governing feeder behavior. Ideally, a model of a real feeder would be used. However, models of synthetically generated feeders, called 'test feeders', are typically used in public-facing research, as disclosing actual feeder details can pose a significant security risk. Test feeder models have been made available by multiple institutions, including IEEE, Pacific Northwest National Lab (PNNL), and others [55, 56].

Multiple tools exist for solving the circuit equations associated with a feeder; OpenDSS is a widely popular tool [57]. To evaluate the impact of temporally-varying EV charging loads, the magnitude and spatial locations of all loads, at all times, must be supplied to the solver, which then solves circuit equations. For overnight charging scenarios (more generally, for charging scenarios spanning several hours), it is typical to solve the steady-state circuit equations associated with the feeder (a system of coupled, nonlinear, algebraic equations), using samples of the average EV charging powers at regularly spaced points in time as steady-state load magnitudes (in addition to any non- EV loads). During the solution process, the solver can also account for automatic control actions occurring in the feeder. For example, some feeders contain voltage regulators at pre-specified locations, which are implemented using tap-changing transformers, where the transformer turns ratio is automatically modulated (within physical limits) with the goal of keeping voltage levels to within ±5% of their nominal values

[58]. Some feeders also contain capacitors at pre-specified locations, which get temporarily connected to a node if the current flow in the adjacent transmission lines exceeds a pre-specified threshold value (for a pre-specified amount of time). The solution produced by a steady-state equation solver (like OpenDSS) includes:

- active and reactive power flows through each transmission line (for all phases and all time)
- active and reactive power flows through each transformer (for all phases and all time)
- voltage magnitudes and phases at each node (for all phases and all time)

This solution information can then be processed to yield performance metrics for grid impact analysis. One typically summarizes the reported distributions of power flow and voltage using one or more scalars, since these distributions depend on numerous randomly-assigned parameters that influence how the feeder is loaded (more details in the next sub-subsection). Common summarizing scalar metrics include:

- Worst-case (over all space and time) voltage drop seen by a customer
- Worst-case (over all space and time) overloading of any transformer
- Worst-case (over all space and time) overloading of any transmission line

In general, both power and voltage quality must be ensured within a power distribution system. Several metrics are described in [59] for assessing both power and voltage quality. Metrics related to transient phenomena (e.g., frequency variability, magnitude of short-duration voltage spikes/drops) are appropriate when performing steady-state circuit analysis, and vice-versa.

5.1.2. Monte-Carlo Methods for Physics-Based Grid Impact Analysis

The previous sub-subsection described how to compute grid impact metrics given (i) a fully-specified physics-based distribution feeder model, (ii) a circuit equation solver, and (iii) a specification of the spatial locations and temporal variations in load within a distribution feeder. This constitutes the computations required for one of multiple Monte-Carlo trials in a grid impact assessment simulation. This sub-subsection discusses how to appropriately assign the spatial locations and temporal variations in load across Monte-Carlo trials.

Spatial locations of loads: Suitable connection points for EV charging stations / aggregators should be identified within the feeder. Connections may be single-phase, two-phase, or three-phase, and at a variety of supply voltages (e.g., high-voltage supply if ‘close’ to a substation, low-voltage supply if ‘farther’ from a substation). Connection points may vary or be held constant across trials as appropriate.

EV penetration level: We can reasonably expect that issues caused by unrestricted EV charging will worsen as EV penetration increases. At the same time, we can expect that smart charging is most valuable in these high penetration scenarios. To reveal both of these trends, it is advisable to sweep EV penetration level over a wide range of values. Although higher EV penetration better represents future scenarios, these scenarios are likely representative of the next 20–30 years if recent sales forecasts made by major automakers come to fruition [60, 61].

Definition of charging profiles: Individual EV charging profiles should be determined by considering whether smart charging is present or not, and the particular nature of smart charging being performed (if present). If additional input data is required to perform smart charging, (such as price or grid energy mix signals broadcast by the utility to influence charging behavior), realistic signals should be identified and used.

Individual EV charging profiles are also functions of several human-influenced parameters. To try to generalize grid impact analysis results beyond particular choices of these human-influenced parameters, it is advisable to conduct multiple random trials, randomly setting these human-influenced parameters each time. A non-exhaustive list of human-influenced parameters that deserve consideration is provided below:

- Non-EV loading conditions
- Locations of EVs
- EV battery capacities
- EV energy requirements
- Power flow limits association with EV charging (e.g., what kind of charging station is used?)
- EV arrival and departure times

5.2. Data for Grid Impact Analysis Studies

A grid impact simulation must be informed by several data sources. A real dataset with numerous observations of all required information is not yet available. However, individual datasets are avail- able for some required quantities. The simulation designer must then combine them as appropriate. Some useful datasets for grid impact studies are mentioned below:

- **Test feeder models** are available from multiple institutions, including IEEE, Pacific North- west National Lab (PNNL), and others [55, 56].
- **Non-EV loading data** are available for certain scenarios. For example, repositories of real residential loading profiles are available in [62, 63].
- **Solar generation data** (synthetic) are available via [64]. The grid of the future is expected to be populated with distributed energy resources (like solar panels), so it is advisable to consider the presence of solar panels within distribution feeders when simulating futuristic scenarios.
- **Charging session data** including arrival/departure times, energy consumption, and average power are also available for certain scenarios. For data on light-duty vehicle fleets in Europe, see [65]. For large, anonymized datasets on fleets of commercial vehicles across multiple vocations and weight classes, see [66]. For workplace charging

data collected at a college campus (CalTech), see [67]. Due to the limited availability of critically-important charging session data, it is common practice to augment real data with synthetic data (as described in [68]), or to use entirely synthetic data drawn from assumed probability distributions [14].

- **Vehicle-related parameters** are rarely found in the anonymized charging session datasets mentioned above. While energy transfer can be inferred from the aforementioned datasets, the vehicle state-of-charge upon arrival and vehicle battery capacity cannot be. Since knowledge of these parameters is critical for analyzing many smart charging strategies, it is typical to set these parameters using vehicle-manufacturer-provided information for representative vehicles (e.g., the information found in [69–71]).

6. Deliverable 5: A Smart Charging Algorithm for Fleets

Mathematical algorithms for solving the smart charging problem.

In this section, we disclose a mathematical algorithm for solving a fleet charging optimization problem. We wish to note that this mathematical algorithm is simply a series of calculations that is to be performed, and is independent of any particular computer implementation. We report only the algorithm's essential components briefly, and defer detailed discussion to an upcoming publication.

Based on a review of the published literature and commercially-available smart charging solutions, it was determined that existing smart charging options for fleet operator are...

- ...not comprehensive in their representations of the fleet operator's interests. Therefore, we developed a strategy that captures multiple (competing) interests of fleet operators using a multi-objective representation.
- ...either owner-centric or grid-centric. Therefore, we developed a strategy that is expected to provide simultaneous benefits to both fleet owners and grid operators, making it significantly more attractive for adoption.
- ...varied in their handling of infeasibility. In fleet charging scenarios, especially those involving fleets of medium and heavy-duty vehicles, it is likely that an aggregator operates at or near its maximum power budget. Thus, it is likely that unexpectedly large requests for charge render the aggregator unable to satisfy all charging requests. Therefore, we developed a strategy that detects this infeasibility condition, and adjusts the operating strategy accordingly.

Our strategy is an extension of our prior work in [72–74], which establishes that a similar approach for one vehicle can lead to simultaneous satisfaction of EV/fleet owner and grid operator interests.

6.1. Nomenclature

Important symbols appearing in the mathematical formulation of the fleet charging problem are defined in Table 4 below:

Table 4. Nomenclature

Symbol(s)	Units	Interpretation
N	vehicles	size of EV fleet
n	—	vehicle index: n = 1,2,…,N
T	—	length of time horizon
t	—	time index: t = 1,2,…,T
Δ	h	time step
$\pi[t]$	$/kWh	price of electricity at time t
$m[t]$	—	grid energy mix at time t
$b[t]$	—	monotonically-increasing function of t
$\hat{P}^C[t]$	kW	estimated non-EV load (commercial load) at time t
$P^G[t]$	kW	power draw from grid at time t
$P^G_{\min}$, $P^G_{\max}$	kW	limits: $P^G\ [t] \in [P^G_{\min}, P^G_{\max}]\ (\forall t)$
$P^V_n[t]$	kW	power flow into EV n at time t
$\boldsymbol{P}^{\boldsymbol{V}}_n$	kW	charging profile for EV n: $\boldsymbol{P}^{\boldsymbol{V}}_n = [P^V_n[1] \cdots P^V_n[T-1]]'$
$P^V_{n,\min}$, $P^V_{n,\max}$	kW	limits: $P^V_n[t] \in \left[P^V_{n,\min}, P^V_{n,\max}\right]$(for all n and t)
$E^V_n[t]$	kWh	energy stored in EV n at time t
$E^V_{n,\min}$, $E^V_{n,\max}$	kWh	limits: $E^V_n[t] \in \left[E^V_{n,\min}, E^V_{n,\max}\right]$ (for all n and t)

6.2. Mathematical Formulation

Our strategy consists of two modes, Mode 1 and 2, and Mode 1 further consists of two stages, Stage 1 and 2. The nominal mode of operation is Mode 1, whereas Mode 2 is entered only upon automatic detection of infeasibility, which is likely in fleet charging scenarios, especially those involving fleets of medium and heavy-duty vehicles.

6.2.1. Mode 1, Stage 1

In Stage 1, optimal EV charging profiles for the fleet vehicles are determined by considering only the fleet owner's perspective. The optimization problem solved in Stage 1 is

$$\underset{\boldsymbol{P}^{\boldsymbol{V}}_1,\dots,\boldsymbol{P}^{\boldsymbol{V}}_N}{\text{minimize}}\ J\left(\boldsymbol{P}^{\boldsymbol{V}}_1,\dots,\boldsymbol{P}^{\boldsymbol{V}}_N\right) = \sum_{n=1}^{N}\sum_{i=1}^{4} w_{n,i} J_i\left(\boldsymbol{P}^{\boldsymbol{V}}_n\right), \tag{1}$$

subject to constraints (2), (3), and (4), where,

$$J_1(\boldsymbol{P}_n^{\boldsymbol{V}}) = \Delta \sum_{t=1}^{T-1} \pi[t] P_n^V[t],$$

$$J_2(\boldsymbol{P}_n^{\boldsymbol{V}}) = \Delta \sum_{t=1}^{T-1} (1 - m[t]) P_n^V[t],$$

$$J_3(\boldsymbol{P}_n^{\boldsymbol{V}}) = \sum_{t=1}^{T-1} b[t] (P_n^V[t])^2,$$

$$J_4(\boldsymbol{P}_n^{\boldsymbol{V}}) = \sum_{t=1}^{T-1} (P_n^V[t])^2.$$

As in [72] and [73], performance functionals $\{J_i\}_{i=1}^4$ represent various (potentially competing) interests of the fleet owner, and user-defined weights $\{w_{n,i}\}$ encode the relative importance of the $\{J_i\}_{i=1}^4$ to each vehicle. J_1 represents the EV n's contribution to the fleet owner's electricity bill in dollars. J_2 represents the amount of non-renewable energy consumed by EV n during charging in kWh. Note that if $m[t]$ is not published by the utility, then term J_2 may simply be omitted by setting $w_{n,2} = 0$ for all n. J_3 (J_4) encourages rapid (slow) charging to minimize charging time (battery degradation), but does not have physically meaningful units. In order for (1) to be meaningful, the $\{w_{n,i}\}$ should all be non-negative. Furthermore, since J_3 and J_4 are in clear competition, it is advisable to select $w_{n,3}$ and $w_{n,4}$ in a complementary manner if rate control is desired (e.g., $w_{n,3} = \theta_n$ and $w_{n,4} = 1 - \theta_n$, where $\theta_n \in [0,1]$).

The equality constraints enforced at $t = 1, \ldots, T-1$ are:

$P^G[t] = \sum_{n=1}^{N} P_n^V[t] + \hat{P}^C[t]$ and (2a)

$E_n^V[t+1] = E_n^V[t] + \Delta P_n^V[t].$ (2b)

Note that (2a) is simply a power balance equation for the fleet depot, which has N EVs charging, and a non-EV load. Equation (2b), which holds for all $n = 1, \ldots, N$, describes the battery dynamics associated with an EV.

The inequality constraints enforced at $t = 1, \ldots, T-1$ are

$P_{\min}^G \leq P^G[t] \leq P_{\max}^G,$ (3a)

$P_{n,\mathrm{lb}}^V[t] \leq P_n^V[t] \leq P_{n,\mathrm{ub}}^V[t]$, and (3b)

$E_{n,\min}^V \leq E_n^V[t] \leq E_{n,\max}^V,$ (3c)

where, using the definition $\mathcal{P}_n[t] := \{t\text{: EV } n \text{ plugged in}\}$,

$$P^V_{n,\mathrm{lb}}[t] := \begin{cases} P^V_{n,\min} & ,t \in \mathcal{P}_n \\ 0 & ,t \notin \mathcal{P}_n, \end{cases} \text{ and } P^V_{n,\mathrm{ub}}[t] := \begin{cases} P^V_{n,\max} & ,t \in \mathcal{P}_n \\ 0 & ,t \notin \mathcal{P}_n. \end{cases}$$

Equation (3a) simply bounds power draw from the grid on both sides. Equations (3b) and (3c), which hold for all $n = 1, \dots, N$, bound the power flow into and energy stored in EV n, accounting for power flow limitations of the EV and charging station, plug-in status of the EV, and finite capacity of the EV battery.

Boundary conditions at $t = 1$ and $t = T$ are that

$E^V_n[1]$ is known/measured, and (4a)

$E^V_n[T]$ is specified. (4b)

Note that (4a) amounts to knowing the energy stored in the EV's battery pack at the time it plugs in to charge, and (4b) is a statement of each EV's charging requirements.

6.2.2. Mode 1, Stage 2

If (1) in Mode 1, Stage 1 is feasible, then the algorithm proceeds to Mode 1, Stage 2. If not, the algorithm proceeds to Mode 2, described in the next sub-subsection.

It is often the case that (1) admits multiple optimal or near-optimal solutions, especially when the fleet owner is interested in price minimization or renewable energy maximization. In these cases, choosing among these multiple optimal or near-optimal solutions in a disciplined manner (done in Stage 2) can give rise to simultaneous benefits for both the fleet owner and the grid operator. The optimization problem solved in Stage 2 is:

$$\underset{\boldsymbol{P}^V_1,\dots,\boldsymbol{P}^V_N}{\text{minimize}}\ g\left(\boldsymbol{P}^V_1, \dots, \boldsymbol{P}^V_N\right) \tag{5}$$

subject to (2), (3), (4), and $J\left(\boldsymbol{P}^V_1, \dots, \boldsymbol{P}^V_N\right) \leq (1+\varepsilon)J_*$,

where J_* is the value of Stage 1 objective function when evaluated at an optimal solution to (1), ε is a *relaxation parameter* (with $0 \leq \varepsilon \ll 1$) and $g : \mathbb{R}^{N(T-1)} \to \mathbb{R}$ is a *selection criterion.* ε bounds the level of suboptimality accepted in Stage 2, if any; ε is the maximum-allowable increase in the objective from Stage 1.

Selection criterion g may be chosen in many ways—some choices may benefit the EV/fleet owner, others may benefit the utility (and others may benefit neither). Since only the perspective of the fleet owners was considered in Stage 1, choosing g to benefit the utility can lead to smart charging strategies that benefit fleet owners while also reducing the need for capital investments in infrastructure updates.

6.2.3. Mode 2

If (1) in Mode 1, Stage 1 is feasible, then the algorithm proceeds to Mode 1, Stage 2, described in the previous sub-subsection. If not, the algorithm proceeds to Mode 2. The optimization problem solved in Mode 2 is:

$$\underset{\boldsymbol{P}_1^V,\ldots,\boldsymbol{P}_N^V}{\text{minimize}} \sum_{n=1}^{N} v_n \big(E_n^V[T] - E_{n,\text{des}}^V\big)^2 \tag{6}$$

subject to (2), (3), and (4a),

where $E_{n,\text{des}}^V$ is the desired value of $E_n^V[T]$ (provided when specifying (4b)), and where the decision variables influence $E_n^V[T]$ according to (2b).

The goal in Mode 2 is to charge all vehicles in a fair manner. Since Mode 2 is only entered when Mode 1, Stage 1 is infeasible (charging requests are too large), the mode serves to fairly allocate a finite amount of available power/energy among the fleet vehicles. Weights $\{v_n\}$ control the definition of fairness. Possible settings for the $\{v_n\}$ include:

- Choosing $v_n = 1$ gives the objective function of (6) an interpretation of minimizing the sum of squared deviations in *energy.*
- Choosing $v_n = (E_{n,\max}^V)^{-2}$ gives the objective function of (6) an interpretation of minimizing the sum of squared deviations in *state-of-charge*.
- Choosing v_n to be proportional (or inversely proportional) to $|\mathcal{P}_n|$ gives preference to vehicles based on their plug-in durations.
- Choosing v_n to be proportional to the profit or revenue generated by operating EV n gives preference to vehicles based on financial considerations.

6.2.4. Summary of Smart Charging Algorithm

Algorithm 1 Two-Stage Smart Charging for Fleets

Enter Mode 1, Stage 1
Specify input parameters of (1)
Attempt to solve (1) numerically
if (1) was successfully solved **then**
    Enter Mode 1, Stage 2
    Record optimal objective function value, J_*; specify $0 \leq \varepsilon \ll 1$ and $g\colon \mathbb{R}^{N(T-1)} \to \mathbb{R}$
    Solve (5) numerically to obtain the *best* (near optimal solution to (1), as measured by g
else
    Enter Mode 2
    Specify $\{v_n\}$
    Solve (6) numerically to obtain the most fair allocation of available power/energy
end if

7. Summary and Future Work

The deliverables promised in our most-recent quarterly project report (submitted 4/19/2023) have been successfully completed.

- The smart charging problem was clearly defined for fleets of electrified vehicles with scheduled arrivals and departures, considering i) fleet operator preferences (including renewable energy consumption), ii) travel demand, and iii) grid implications.
- An extensive, critical review of existing i) smart charging strategies in the literature, and ii) commercially available smart charging systems was performed, with particular emphasis on fleets of medium and heavy-duty vehicles with scheduled arrivals and departures.
- Detailed documentation was prepared on existing models and model-based analysis methods pertaining to EV charging and grid impact, as well as existing datasets, estimation methods, and/or analysis methods pertaining to charging demand and grid impact assessment.
- Based on identified gaps in the reviewed literature, a *mathematical* algorithm was developed for managing the charging of an electrified fleet (with particular consideration of medium and heavy-duty vehicles). Our algorithm consists of two modes, Mode 1 and 2, and Mode 1 further consists of two stages, Stage 1 and 2. The nominal mode of operation is Mode 1, whereas Mode 2 is entered only upon automatic detection of infeasibility, which is likely in fleet charging scenarios, especially those involving fleets of medium and heavy-duty vehicles. In Mode 1, our algorithm can produce a charging strategy that realizes simultaneous benefits to the fleet owner and the grid operator, making it particularly attractive in comparison to existing strategies (which favor one party or the other).

Future work in this direction can include: (i) collecting input data required to construct case study analyses of the grid impacts of employing the proposed algorithm in various fleet charging settings, (ii) performing aforementioned case study analyses of grid impact to reveal the efficacy of the proposed algorithm by leveraging the case study design recommendations herein, and (iii) further refining the smart charging algorithm developed herein based on case study observations.

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9. Data Summary

Products of Research

The aim of this project was to collect, organize, and describe background information to support future smart charging research. As such, data produced is qualitative, and takes the form of references and accompanying discussion text. The provided references point to relevant academic publications, descriptions of commercial products, and open data catalogs.

Data Format and Content

Data produced is in the form of references and accompanying discussion text. All data produced is included in this report. There are no supplemental files to describe.

Data Access and Sharing

Data produced will be publicly available via this report. Much of the data collected during this project also appears in thesis chapters and publications, which will be made publicly available via SMARTech (https://smartech.gatech.edu/). The mission of SMARTech is to collect, curate, preserve, and provide access to digital content of enduring value to the Institute, including Georgia Tech scholarship and research.

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