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Smart Charging of Electric Vehicle Fleets: Modeling, Algorithm Development, and Grid Impact Analysis, with Emphasis on Fleets of Transit and Heavy-Duty Freight Vehicles

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Smart Charging of Electric Vehicle Fleets

Modeling, Algorithm Development, and Grid Impact Analysis, with Emphasis on Fleets of Transit and Heavy-Duty Freight Vehicles

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16. Abstract

High charging loads associated with fleets of commercial electric vehicles (EVs) are expected to significantly stress electric power distribution networks, leading to high costs seen by fleet operators. To address these challenges, this report presents a highly flexible smart charging (SC) algorithm for managing EV fleets that arrive and depart from a common depot on a schedule. The algorithm features (i) primary consideration of multiple fleet operator preferences (e.g. minimizing cost, using carbon-free energy), (ii) secondary consideration of grid impact that leverages the existence of multiple optimal (or near-optimal) ways to satisfy fleet operator preferences, and (iii) automatic detection and handling of infeasibility due to large energy demands (characteristic of fleet charging). Provided in this document are two numerical impact assessment studies in which the SC algorithm is shown to be superior to conventional rapid charging, and conventional 'smart' charging solutions on the market. These studies utilize a set of synthetic, but realistic fleet charging requirements, a physics-based model of a real feeder and one year of real, hourly load data for that feeder. The first numerical study shows that the proposed SC algorithm can lead to significant (up to 44%, but scenario-dependent) reductions in a fleet operator's annual electricity bill. The second numerical study shows that significant transformer overloading and voltage drop issues can be associated with conventional fleet charging methods, and that the proposed SC algorithm eliminates these issues, thereby enabling higher EV penetration levels and offsetting infrastructure upgrades.

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Smart Charging of Electric Vehicle Fleets: Modeling, Algorithm Development, and Grid Impact Analysis, with Emphasis on Fleets of Transit and Heavy-Duty Freight Vehicles

A National Center for Sustainable Transportation Research Report

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Smart Charging of Electric Vehicle Fleets: Modeling, Algorithm Development, and Grid Impact Analysis, with Emphasis on Fleets of Transit and Heavy-Duty Freight Vehicles

Executive Summary

High charging loads associated with fleets of commercial electric vehicles (EVs) are expected to significantly stress electric power distribution networks, leading to high costs seen by fleet operators. To address these challenges, we present a highly flexible smart charging (SC) algorithm for managing EV fleets that arrive and depart from a common depot on a schedule. Our algorithm features (i) primary consideration of multiple fleet operator preferences (e.g. minimizing cost, using carbon-free energy), (ii) secondary consideration of grid impact that leverages the existence of multiple optimal (or near-optimal) ways to satisfy fleet operator preferences, and (iii) automatic detection and handling of infeasibility due to large energy demands (characteristic of fleet charging). Provided in this document are two numerical impact assessment studies in which our SC algorithm is shown to be superior to conventional rapid charging, and conventional 'smart' charging solutions on the market. Our studies utilize a set of synthetic, but realistic fleet charging requirements, a physics-based model of a real feeder and one year of real, hourly load data for that feeder. Our first numerical study shows that our proposed SC algorithm can lead to significant (up to 44%, but scenario-dependent) reductions in a fleet operator's annual electricity bill. Our second numerical study shows that significant transformer overloading and voltage drop issues can be associated with conventional fleet charging methods, and that our proposed SC algorithm eliminates these issues, thereby enabling higher EV penetration levels and offsetting infrastructure upgrades.

1. Document Summary

The most-recent quarterly project report (submitted 7/10/2024) listed five project objectives: (i) problem formulation, (ii) develop proficiency with methods and tools, (iii) define case studies for analysis, (iv) grid impact analysis and algorithm refinement, and (v) writing. Each of §3 – 5 is dedicated to deliverables derived from the five project objectives. §3 describes the problem formulation, §4 defines our case studies, and §5 presents the results of a fleet operator impact assessment and a grid impact assessment. The excluded project objectives (developing proficiency with methods and tools and writing) are illustrated in the presentation of this report and subsequent results. Final comments are provided in §6, followed by a list of references and data summary.

2. Deliverable 1: Problem Formulation

Formulate the smart charging problem for fleets of medium and heavy-duty vehicles with scheduled arrivals and departures, accounting for (i) interests of the fleet operator (e.g., minimizing costs, and/or maximizing renewable energy consumption), (ii) requirements of the fleet operator (charge requirements, fleet operating schedule), (iii) grid impact considerations. Mathematically pose the optimization-based problem formulations.

In this section, we provide a brief motivation and summary of our contributions to the smart charging problem for electric vehicle fleets and 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.

2.1 Motivation and Literature Review

Electrification of commercial vehicle fleets is being driven by reduced cost of ownership, increasing environmental awareness, regulatory pressures, tax incentives, and positive customer response [1,2]. BloombergNEF projects that by 2040, electric vehicles (EVs) will constitute 80% (resp. 60%, 30%, 20%) of all sales globally in the bus (resp. light commercial, medium commercial, heavy commercial) segment [3]. It is expected that EV fleets will charge overnight at a *depot*, at least until public charging infrastructure is expanded [4]. For medium and heavy-duty EVs, depending on depot charging infrastructure, peak charging load can range from tens to hundreds of kilowatts per EV. Overnight charging loads are therefore expected to significantly stress power distribution networks, resulting in reduced power quality and overloaded transformers [5,6]. To combat this, nearly all utility companies penalize peak power draw by levying *demand charges* on commercial energy customers [7–11]. Demand charges can constitute 30–70% of a customer's total bill [11].

One potential solution to these challenges is to control the EV charging load through smart charging (SC). Fleet EVs will typically remain plugged in all night, but will only charge actively for a fraction of this time. By distributing charging activity overnight, as we will show, SC can realize benefits for the fleet operator *and* the grid operator, thereby enabling higher EV penetration levels and offsetting infrastructure upgrades. SC algorithms use optimization to distribute EV charging activity over time and formally represent the benefits seen by grid and/or fleet operators.

Unscheduled Fleets: Several fleet charging scenarios (e.g., public EV parking lots, workplace charging) are characterized by unscheduled EV arrivals/departures. Representative works on this topic can be found in [12–21]. A common theme among these studies is to ensure that the aggregator's total power limit is obeyed, which (often) means that requests for charge are partially satisfied. Of these works, [12–14] adopt probabilistic problem formulations wherein EV arrival/departure times are treated as random variables and satisfaction of a total power constraint is sought with high probability. Studies [15–21] adopt deterministic problem formulations wherein a finite amount of available power is re-allocated among fleet EVs at each time by employing heuristic methods, optimization, or model-predictive control (MPC). Here, fairness concepts (see [18–20]) often guide the allocation of power.

Scheduled Fleets: In this body of work and herein, optimization is used to determine a charging profile for each EV in a fleet. Representative studies from this body of work include [22–36], while reviews may be found in [37,38]. Fleet charging problems involve three (not necessarily distinct) stakeholders: individual EV owners, aggregators, and power utilities. If considering all stakeholders in an SC problem, EV owner-imposed charging demands, aggregator-imposed operational limits, and utility-imposed operational limits must always be satisfied (by imposing constraints). In addition, the objective function may favor any stakeholder (or combination thereof). Objective functions in [22–24,28–30,36] all aim to minimize aggregator operating cost; each study considers different cost components (e.g., energy charges, demand charges, revenues from grid services, battery degradation, various inconveniences). Other strategies in this body of work include (i) flattening the aggregator's total load profile [26,27,33], (ii) flattening a grid-level total load profile through aggregator-utility cooperation [31,32,34], and (iii) balancing of grid and aggregator concerns through multi-objective optimization [25].

Impact Assessment: Impact assessment refers to the demonstration of a charging strategy's benefits; relevant methods are found in the SC literature, and in [39–42], which treat grid impact assessment of conventional charging. Of the reviewed studies, only [15,16,23–25,27,32,33] reveal computational advantages (e.g., parallelizability, runtime) of their solutions or perform experimental impact assessments. In the remaining studies (and herein), impact assessments are done in simulation via case studies. Researchers agree that a case study demonstrating the benefits of SC to *non-utility aggregators* (e.g., operators of fleets, parking lots, or workplace charging) should utilize the following information: (i) EV arrival/departure times, (ii) EV energy needs, (iii) non-EV load profile(s) at charging location(s), (iv) total power budget(s) at charging location(s), and (v) any other information that guides decision-making (e.g., price signals). Case studies considering grid impacts should *additionally* utilize: (vi) a circuit model of a distribution network (feeder) and (vii) non-EV load profile(s) at all nodes in the feeder. Constructing realistic case studies for impact assessment is crucial (unless solely focusing on computational benefits). Due to limited data, researchers often source necessary information separately and combine it speculatively. A lack of agreed-upon best practices for doing so leads to simulation results that vary in fidelity, interpretability, and generalizability. For further discussion on this topic, we refer readers to [37,43–45].

2.2 Contributions

Contributions to SC Algorithm Design: Our fleet SC problem formulation is more comprehensive and flexible than those in the reviewed literature. Our algorithm features a multi-objective representation of the aggregator/fleet operator that allows interests to be divided over fleet vehicles. It also allows for the fleet operator's interests to change day-to-day. This contrasts with the typical profit-oriented representation in literature. Our algorithm also features automatic detection of infeasibility, and fairly allocates (limited) available power/energy among fleet vehicles if needed. This contrasts with the typical assumption that total power is always a limiting factor. Additionally, our representation of fairness is comprehensive, and captures most fairness metrics as special cases. Finally, our algorithm utilizes the two-stage methodology developed in [43] to address grid-level issues while bounding the compromise (including at zero) on fleet operator's benefits. This contrasts with both single-objective and multi-objective approaches in the literature.

Contributions to Fleet Operator Impact Assessment: Our work presents a high-fidelity assessment of fleet operator impact. We study electrified parcel delivery fleets (an emerging area, see [2]), and use mobility data from conventional parcel delivery fleets to obtain fleet size and arrival/departure information. Furthermore, we disclose how this mobility data is pre-processed before use in SC studies; this crucial step is often omitted or undisclosed in the literature. We use a real distribution feeder and associated load data from [44], and consider several (justified) placements of the fleet within this feeder to explore the effect of non-EV load and grid limits. We therefore speculate only with respect to the choice of EVs in use, leading to meaningful, representative assessment results.

Contributions to Grid Impact Assessment: Our work also presents a high-fidelity grid impact assessment. We use feeder and load data from [44], eliminating the need for a *great deal* of speculation in case study formulation, leading (again) to meaningful, representative assessment results. Our analysis uses standard grid impact metrics (see [46]), but also presents voltage sensitivity results which do not appear in the literature.

Table 1. Nomenclature.

Symbol(s)	Units	Interpretation
N	-	vehicles in EV fleet
n	-	vehicle index: $n = 1, 2, \dots, N$
T	-	integer length of time horizon
t	-	time index: $\mathrm{t} = 1, 2, \dots, T$
$t_{n,\,\mathrm{arr}}$	-	time EV n arrives at depot
$t_{n,dep}$	-	time EV n departs from depot
Δ	h	time step
$\pi[t]$	$\$/\mathrm{kWh}$	price of electricity at time t
$m[t]$	-	grid energy mix at time t
$\hat{P}^C[t]$	kW	estimated non-EV load at time t
$P^G[t]$	kW	power draw from grid at time t
$P^G_{\max}$	kW	$P^G[t] \in [0, P^G_{\max}]$ $(\forall\, t)$
$P^V_n[t]$	kW	power flow into EV n at time t
$P^V_{n,\,\max}$	kW	$P^V_n[t] \in [0, P^V_{n,\,\max}]$ $(\forall\, t)$
$E^V_n[t]$	kWh	energy stored in EV n at time t
$E^V_{n,\,\min}, E^V_{n,\,\max}$	kWh	$E^V_n[t] \in [E^V_{n,\,\min}, E^V_{n,\,\max}]$ $(\forall\, t)$
$E^V_{n,\,\mathrm{arr}}$	kWh	measured value of $E^V_n[t_{n,\,\mathrm{arr}}]$
$E^V_{n,\,\mathrm{dep}}$	kWh	desired value of $E^V_n[t_{n,\,\mathrm{dep}}]$

2.3 Smart Charging Algorithm for Fleets

2.3.1 Overview

The work presented in this report concerns charge planning for commercial EV fleets with scheduled arrivals and departures to/from a central *depot*, where the EVs charge. Examples of such fleets include parcel delivery fleets (e.g., Amazon, FedEx, UPS, USPS), bus fleets (e.g., public transportation, school buses), and refuse-hauling fleets. The SC problem is to determine an optimal charging plan for a fleet over a period of time (i.e., overnight). In principle, this requires determining both (i) a charging profile, and (ii) a parking spot assignment, for each EV, but we focus on the former in this report. The SC algorithm is an optimization-based procedure for solving the SC problem. It is envisioned that the charging plan produced by the SC algorithm will be followed in real-time using command following-capable power converters (e.g., [47]) that interface with the EVs. Table 1 and Figure 1 provide nomenclature and an overview, respectively, supporting the SC approach presented herein.

Let the fleet contain *N* EVs, indexed by *n* = 1,...,*N*. Prior to execution, the SC algorithm is fed an operating schedule, which can be obtained from historical operating data and/or vehicle telematics. This schedule specifies the number of vehicles to charge (*N*), as well as the (i) arrival time $t_{n,\,\mathrm{arr}}$, (ii) departure time $t_{n,dep}$, (iii) energy level upon arrival, $E^V_{n,\,\mathrm{arr}}$, and (iv) required energy level upon departure, $E^V_{n,\,\mathrm{dep}}$, associated with each EV (i.e., for all *n*). The SC algorithm is also fed each EV's availability to charge, denoted by $\mathcal{P}_n \coloneqq \{t\text{: EV } n \text{ plugged in}\}$. Typically (and in this work) EV *n* is plugged in between $t_{n,\,\mathrm{arr}}$ and $t_{n,dep}$; however, our formulation permits other possibilities. Furthermore, the SC algorithm is fed all relevant physical limits ($P^G_{\max}$, $\{P^V_{n,\,\max}\}$, $\{E^V_{n,\,\min}\}$, and $\{E^V_{n,\,\max}\}$), as well as three time-varying signals: (i) *π*[*t*], a utility-provided time-of-use (TOU) price signal; (ii) *m*[*t*], a utility-provided signal indicating the fraction of power generated from renewable sources (with *m*[*t*] ∈ [0,1]; see [48]); and (iii) $\hat{P}^C[t]$, an estimate of the commercial entity's non-EV charging load at the depot (i.e., heating and cooling, lighting, etc.).

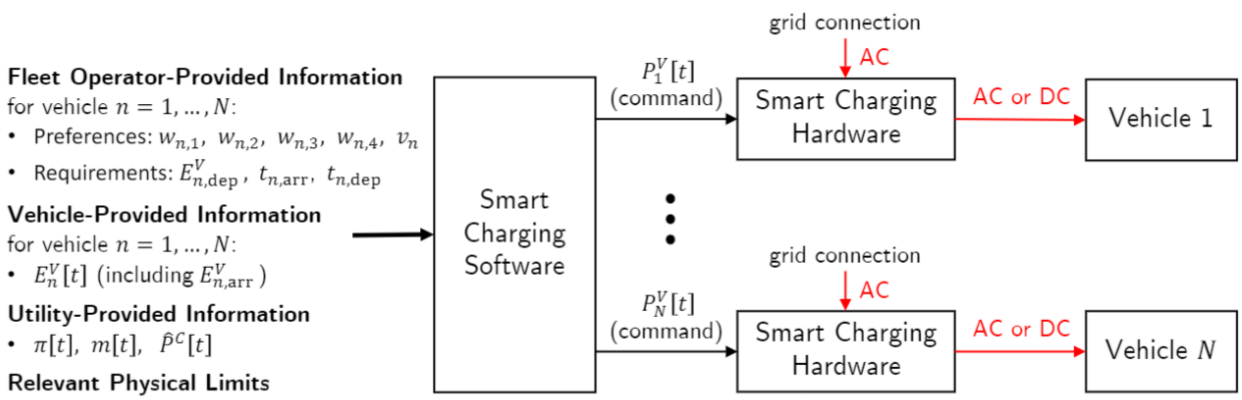

Figure 1. Block diagram representation of a smart charging system for fleets. Black arrows indicate data or information flow and red arrows indicate power flow. This paper emphasizes smart charging algorithms, which would be contained within the Smart Charging Software block.

All three time-varying signals are future projections; they must be specified for all $t = 1, \ldots, T$ before the SC algorithm is executed (prior to *t* = 1). *π*[*t*] will be specified *a priori* in a billing agreement and *m*[*t*] is likely to be published seasonally by a utility company, but $\hat{P}^C[t]$ will require a dedicated estimator. Any such estimator for $\hat{P}^C[t]$ would likely rely on measurements from a dedicated meter; estimation could be performed by averaging historical data (simple) or employing time-series forecasting tools (sophisticated). The SC algorithm plans charging activity on a time grid with *T* grid points and uniform spacing Δ. A typical time grid might span one night due to the use of future projections in the SC algorithm. Grid endpoints are determined by schedule information; *t* = 1 (*t* = *T*) coincides with the earliest (latest) scheduled arrival (departure) of *any* EV to (from) the depot. Time step Δ could be inherited from the time-varying input signals, which are typically discrete-time signals. For each interval $t = 1, \ldots, T-1$, the SC algorithm determines $P^V_n[t]$, the active power flow into EV *n* during interval *t*. The decision vector, or charging profile, associated with EV *n* is

$$\boldsymbol{P}_n^{\boldsymbol{V}} := \left[P_n^V[1] \quad \cdots \quad P_n^V[T-1]\right]' \in \mathbb{R}^{T-1}.$$

All decision variables in the SC problem are collected into

$$\boldsymbol{P}^{\boldsymbol{V}} := [\boldsymbol{P}_1^{\boldsymbol{V}} \quad \cdots \quad \boldsymbol{P}_N^{\boldsymbol{V}}] \in \mathbb{R}^{(T-1)\times N}.$$

Algorithm 1 lists the computations that define our SC algorithm. Our algorithm has two *modes* of operation, Mode 1 and Mode 2, each with an associated convex optimization problem. Mode 1 further consists of two *stages*, Stage 1 and Stage 2, each with an associated convex optimization problem.

As described in this report, the SC algorithm is to be executed one time, prior to initiating any charging activity. However, as discussed in [43,48], the SC algorithm can also be executed time-periodically during charging, using up-to-date input data. Repeated execution can help mitigate uncertainty in input data or deviations from schedule (e.g., changes in electricity price, late arrivals, early departures, extra EVs). The SC algorithm can also be repeatedly executed to optimize EV parking assignments, which is necessary when different types of charging stations (e.g., Level 2 and DC fast charging) are present at the depot. Since our algorithm relies exclusively on convex optimization, efficient numerical solution methods can be leveraged for implementation [49].

Algorithm 1. Smart Charging for EV Fleets

Enter Mode 1, Stage 1
Specify input parameters of (1) and attempt to solve
if (1) was successfully solved **then**
  Enter Mode 1, Stage 2
  Record optimal objective function value, $J_\star$
  Specify $0 \leq \varepsilon \ll 1$
  Solve (5) to select an optimal or near optimal solution to (1)
else
  Enter Mode 2
  Specify $\{v_n\}$
  Solve (6) to fairly allocate (limited) available energy
end if

2.3.2 Mode 1, Stage 1

Mode 1, Stage 1 considers only the interests of the fleet operator. Optimal charging profiles are determined by solving

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

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

$$J_1(\boldsymbol{P}_n^{V}) = \Delta \sum_{t=1}^{T-1} \pi[t] P_n^{V}[t], \qquad J_2(\boldsymbol{P}_n^{V}) = \Delta \sum_{t=1}^{T-1} (1 - m[t]) P_n^{V}[t]),$$

$$J_3(\boldsymbol{P}_n^{V}) = \sum_{t=1}^{T-1} t\, P_n^{V}[t], \qquad J_4(\boldsymbol{P}_n^{V}) = \sum_{t=1}^{T-1} (P_n^{V}[t])^2\,.$$

The $\{J_i\}$ represent potentially competing interests of the fleet operator. J_1 is EV n's contribution to the fleet operator's energy charges (in \$). J_2 is the amount of non-renewable energy consumed by EV n during charging (in kWh). J_3 (J_4) encourages rapid (slow) charging of EV n to minimize charging time (battery degradation) (units not meaningful).

Fleet operator-defined weights $\{w_{n,i}\}$ encode the relative importance of the $\{J_i\}$ on a per-vehicle basis. For (1) to be meaningful, the $\{w_{n,i}\}$ should all be non-negative. Fleet-level objectives can be achieved by choosing a common set of four weights for each vehicle. For example, to minimize the fleet operator's energy charges, choose $w_{n,1} = 1$ and $w_{n,2} = w_{n,3} = w_{n,4} = 0$ for all n. The weights can also be used to partition the fleet. For example, suppose that EVs belonging to a 'critical' subset of the fleet, $\mathcal{C} \in \{1, \dots, N\}$, must be charged rapidly. This could be achieved by setting $w_{n,3} = 1$ and $w_{n,1} = w_{n,2} = w_{n,4} = 0$ for $n \in \mathcal{C}$. The remaining EVs could be charged at minimum cost by setting $w_{n,1} = 1$ and $w_{n,2} = w_{n,3} = w_{n,4} = 0$ for $n \notin \mathcal{C}$.

Power balance and battery dynamics are enforced through the following equality constraints at $t = 1, \dots, T-1$:

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

$$E_n^{V}[t+1] = E_n^{V}[t] + \Delta P_n^{V}[t] \quad \forall n \tag{2b}$$

Physical limits on power and energy are enforced through the following inequality constraints at $t = 1, \dots, T-1$:

$$0 \le P^{G}[t] \le P_{\max}^{G} \tag{3a}$$

$$0 \le P_n^{V}[t] \le P_{n,\ \text{ub}}^{V} \tag{3b}$$

$$E_{n,\,\min}^{V} \le E_n^{V}[t] \le E_{n,\,\max}^{V} \tag{3c}$$

In (3a), $P^G_{\max}$ represents a maximum draw from the grid; its value could be chosen based on a circuit breaker rating, a transformer rating, and/or a desire to cap demand charges. Constraint (3b) captures both an EV's availability to charge, as well as power flow limits during charging. Here, $P^V_{n,\text{ ub}} = P^V_{n,\text{ max}}$ fort $\in \mathcal{P}_n$, $P^V_{n,\text{ ub}}[t] = 0$ for $t \notin \mathcal{P}_n$, and $P^V_{n,\text{ max}}$ represents the power flow rating of a charging point or an EV's onboard charger. Finally, note that power flow into the grid ($P^G[t] < 0$) and discharging of EVs ($P^V_n[t] < 0$) are both disallowed in this study to limit scope. Boundary conditions are that

$$E^V_n\left[t_{n,\text{ arr}}\right] = E^V_{n,\text{ arr}}, \text{ which is measured } \forall n, \tag{4a}$$

$$E^V_n\left[t_{n,\text{ dep}}\right] = E^V_{n,\text{ dep}}\text{ , which is specified } \forall n, \tag{4b}$$

Where $E^V_{n,\text{ arr}} \in \left[E^V_{n,\text{ min}}, E^V_{n,\text{ max}}\right], E^V_{n,\text{ dep}} \in \left[E^V_{n,\text{ min}}, E^V_{n,\text{ max}}\right]$ and $E^V_{n,\text{ arr}} < E^V_{n,\text{ dep}}$ if EV n needs to be charged.

2.3.3 Mode 1, Stage 2

If (1) is feasible, the SC algorithm records the optimal objective function value $J_{\star}$and proceeds to Mode 1, Stage 2. Problem (1) can admit multiple optimal solutions. When the fleet operator is interested in minimizing energy charges, the set of optimal solutions $\mathcal{S}_0 = \{\boldsymbol{P^V}: J(\boldsymbol{P^V}) = J_*\}$ is particularly rich – its elements exhibit a wide variety of temporal behaviors. Choosing among these multiple optimal solutions in a disciplined manner can give rise to *simultaneous* benefits for both fleet and grid operators, as shown in [43] and later in this report. Even if $\mathcal{S}_0$ is not rich, the superset $\mathcal{S}_\varepsilon = \{\boldsymbol{P^V}: J(\boldsymbol{P^V}) \leq (1+\varepsilon)J_* \text{ and } 0 \leq \varepsilon \ll 1\}$ can be. Here, ε is a small relaxation parameter, so $\mathcal{S}_\varepsilon$ is referred to as the set of near-optimal solutions to (1). Choosing $\varepsilon > 0$ introduces a slight increase in cost to the fleet operator, but allows for simultaneous benefits to be realized for fleet and grid operators in a wider range of SC scenarios. This logic is formalized in the Mode 1, Stage 2 optimization problem, which is to

$$\underset{\boldsymbol{P^V}}{\text{minimize}} \sum_{t=1}^{T-1} (P^G[t])^2\,, \tag{5}$$

subject to constraints (2), (3), and (4), and the extra constraint

$$J(\boldsymbol{P^V}) \leq (1+\varepsilon)J_*.$$

Note that (5) is feasible if and only if (1) is feasible. The solution to (5) is not unique, but every solution of (5) is an optimal (a near-optimal) solution of (1) if $\varepsilon = 0$ ($\varepsilon > 0$) which has the virtue of low grid impact, as measured by the peak value of $P^G[t]$. Extensions of (5) can include multiple constraints of the above form, if desired, to accommodate partitioned fleets or differently encode fleet operator benefit(s).

2.3.4 Mode 2

Mode 2 is entered when (1) is infeasible. There are two detectable conditions under which (1) is infeasible: (i) at least one EV requests more energy, $E^V_{n,\text{ dep}} - E^V_{n,\text{ arr}}$, than can be delivered by its charging system within its availability period, or (ii) the combined demands of all EVs cannot be met without exceeding the total power limit for at least one time interval. In fleet charging, scenario (ii) is more common than scenario (i). Overcoming either scenario requires that energy requirements are relaxed. Therefore, the objective in Mode 2 is to charge the fleet ‘as much as possible’; i.e., to

$$\underset{\boldsymbol{P}^V}{\text{minimize}} \sum_{n=1}^{N} v_n \left(E_{n,\ \text{dep}}^V - E_n^V[t_{n,\text{dep}}] \right)^2 \tag{6}$$

subject to constraints (2), (3), and (4a) (but not (4b)). Non-negative weights $\{v_n\}$ govern the allocation of available energy; possible settings for the $\{v_n\}$ include:

1. Choose $v_n = 1$ for all *n* to minimize the sum of squared deviations in *energy* across the fleet.
2. Choose $v_n = \left(E_{n,\ \max}^V\right)^{-2}$ for all *n* to minimize the sum of squared deviations in *state-of-charge* across the fleet.
3. Choose v_n to be proportional (or inversely proportional) to the plug-in duration (i.e., $|\mathcal{P}_n|$) of EV *n* (for all *n*).
4. Choose v_n to be proportional to the profit or revenue generated by operating EV *n* (for all *n*).
5. Choose $v_n = 0$ to ignore EV *n*’s request for energy.

The solution to (6) is not unique, but every solution of (6) leads to (i) total demand profile $P^G[t]$ being largely flat, with $P^G[t] = P_{\max}^G$ for most time intervals (which benefits both fleet and grid operators); and (ii) a controlled distribution of undercharging errors $\{E_{n,\ \text{dep}}^V - E_n^V[t_{n,\text{dep}}]\}$ across EVs. Property (ii) is clear from (6); property (i) follows from the fact that in Mode 2, energy delivered to the fleet is maximized by prolonged operation at the total power limit $P^G[t] = P_{\max}^G$

3. Deliverable 2: Define Case Studies for Analysis

Define scenarios under which to evaluate the grid impact of the proposed smart charging strategies.

By design, both fleet and grid operators are positively impacted by use of our SC algorithm. The remainder of this report is dedicated to assessing the practical extent of these benefits through two numerical studies. Both studies consider the placement of a single, electrified fleet at various locations within a power distribution network, or feeder, and subsequent charging (smart or otherwise) of that fleet. Study design is described in this section and results are provided in §5.

3.1 Day Ahead, Cost-Minimizing Smart Charging

Our impact assessments emphasize the common case of minimizing the fleet operator's charging cost. However, we note that our SC algorithm provides fleet operators with great flexibility in specifying charging preferences and is designed to always benefit both fleet and grid operators.

As stated in §3.1, commercial electricity customers (including commercial fleet operators) typically pay two load-dependent charges, *energy charges* and *demand charges*. Energy charges are typically assessed using piecewise-constant TOU price signals (i.e., $\pi[t]$; units of \$/kWh) which have two or three price levels: (i) a low price for 'off-peak' times of the *day*, (ii) a high price for 'on-peak' times, and sometimes (iii) a medium price for 'shoulder' times which are neither on-peak nor off-peak [11]. Demand charges are typically assessed by multiplying a scalar (units of \$/kW) by the peak power drawn over an *entire billing period* (usually one month). A truly cost-minimizing SC strategy would minimize the sum of both load-dependent charges. However, such an SC problem must be posed over an entire billing period, which is impractical considering input data requirements. Day-ahead planning is more practical, but necessitates a greedy handling of demand charges (if any). A naïve approach to demand charge mitigation is to charge as slow as possible every day, but this is not the optimal solution to the monthly SC problem (under a well-designed TOU price signal). Therefore, we propose executing our SC algorithm with $w_{n,1} = 1$ and $w_{n,2} = w_{n,3} = w_{n,4} = 0$ for all n; this is the definition of SC used in the following impact analyses. Assuming Mode 1 executes (nearly always true in our experiments), our two-stage approach automatically spreads charging out as much as possible while giving preference to 'off-peak' times. Parameter ε controls the extent of this preference, but our analyses use $\varepsilon = 0$; i.e., daily peak power is minimized while ensuring that daily energy charges are truly minimal. Mode 2 is initialized with $\nu_n = 1$ for all n (though rarely invoked).

Our numerical studies consider a feeder located in Iowa, so a billing plan from MidAmerican Energy (a major utility company in Iowa) is also used. The 'GDT' plan of [7] defines a price signal ($\pi[t]$) for energy charges and a demand charge.

3.2 Determination of Fleet Charging Requirements

Our case studies consider an electrified fleet of parcel delivery vehicles in light of recent trends [2]. At this time, charging session data is not publicly available for electrified delivery fleets. However, real, anonymized mobility data for conventional parcel delivery fleets is available in [50]. We process this mobility dataset to obtain fleet charging requirements. Each record in [50] corresponds to one trip made by one vehicle; vehicle-specific information, start time, end time, and distance traveled (among other quantities) are available for each trip. Vehicles make multiple trips per day, and trip data is recorded for multiple vehicles over multiple days. For our study, we consider only Class 3 and Class 5 (as defined in [51]) parcel delivery vehicles. We replace conventional Class 3 (Class 5) with the low (high) payload configuration of the Arrival Van, which has an on-board Level 2 charger rated at 11 kW and a battery capacity of 139 kWh (89 kWh). This vehicle was selected because UPS, a major parcel delivery company in the United States, announced a partnership with Arrival and ordered 10,000 electric delivery vans in 2020 [2]. Further processing is performed as follows:

1. For each vehicle on each day:
   (a) Determine the total distance traveled across all trips.
   (b) Determine the start time (end time) of the first (last) trip, which represents departure from (arrival at) the depot. Charge planning occurs on a discretized time grid, so round this time down (up) to the nearest grid point to ensure that charging ends before departure (begins after arrival). In this work, time grid points are separated by $\Delta = 1$ h (spacing inherited from load data in [44]).
   (c) Determine energy consumption from total distance traveled. For Class 3 (Class 5) vehicles, use an efficiency parameter of 0.659 kWh/mi (0.597 kWh/mi) corresponding to the Arrival Van's low (high) payload configuration.

2. For each day *d*:
   (a) As expected, vehicles tend to arrive at the depot in the evenings and depart in the mornings. Identify vehicles that must charge overnight, beginning on day *d*. All such vehicles arrive at the depot on day *d* and must depart on day *d* + 1. Vehicles that were not deployed on consecutive days get discarded in this step to avoid speculating on when those vehicles would recharge.
   (b) Discard artifacts of the conventional-to-electric conversion, such as requests for negligible amounts of energy (very few such artifacts were observed).

The original dataset of trips in [50] (made by a single fleet operator over 15 days) was mapped to a record of 12 overnight charging sessions. Arrival times, departure times, and energy needs for each charging session were similar, so data from a representative session was selected for analysis. When more fleet trip/charging data becomes available, it is recommended to repeat the analyses in this report by randomly drawing charging session parameters from a dataset. Until such a time, the approach described herein is a practical alternative.

Arrival times, departure times, and energy needs used in our numerical studies are provided in Table 2. Vehicles 1–7 (8–16) are Class 3, low-payload (Class 5, high-payload) delivery vans. Though all 16 vehicles actually belong to the same fleet, our studies consider two scenarios to capture the effect of varying fleet size: (i) a 'small fleet' scenario in which only vehicles 1–7 are charged overnight and (ii) a 'large fleet' scenario in which all vehicles (1–16) are charged overnight.

3.3 Distribution Feeder Model, Load Data

Our impact assessment studies consider the placement of the fleet of §4.2 at various locations within a distribution feeder, and subsequent charging (smart or otherwise) of that fleet. To this end, we utilize a physics-based feeder model and one year of associated load data; both pieces of information are from [44], and are associated with a real feeder in Iowa. The chosen feeder model is shown in Figure 2. The feeder comprises 240 primary buses (collections of nodes) where customers connect; 53 buses (blue squares) are associated with commercial customers. Each bus has a dedicated secondary transformer which serves multiple customers. One year of hourly-averaged active and reactive power data is provided for each bus. However, this data is aggregated across the customers at each bus for privacy.

Seven of the 53 commercial sites are selected as candidate fleet locations for our impact assessment studies. Selected locations are circled and labeled in Figure 2. Each selected location has three customers associated with it (other locations have up to 17 customers). As shown in Table 3, the selected locations have differing (i) typical active power consumption levels, (ii) transformer ratings, and (iii) capacities for additional load. There is also a small reactive power draw at each location (power factors exceed 0.9 at all times).

Table 2. Fleet charging requirements.

Vehicle ID	Arrival	Departure	Energy Needed
1	7:00 PM	8:00 AM	55.36 kWh
2	8:00 PM	10:00 AM	31.74 kWh
3	8:00 PM	8:00 AM	44.89 kWh
4	8:00 PM	10:00 AM	26.14 kWh
5	10:00 PM	8:00 AM	40.37 kWh
6	11:00 PM	8:00 AM	41.31 kWh
7	12:00 AM	8:00 AM	25.30 kWh
8	7:00 PM	6:00 AM	11.26 kWh
9	7:00 PM	7:00 AM	25.86 kWh
10	7:00 PM	10:00 AM	31.99 kWh
11	8:00 PM	10:00 AM	21.48 kWh
12	8:00 PM	7:00 AM	46.52 kWh
13	8:00 PM	7:00 AM	27.65 kWh
14	10:00 PM	8:00 AM	29.51 kWh
15	11:00 PM	8:00 AM	22.61 kWh
16	12:00 AM	7:00 AM	27.14 kWh

Table 3. Select transformer and load characteristics.

Depot Location	Active Power Draw (Annual Average)	Transformer Rating
1008	9.46 kW	45 kVA
1013	2.49 kW	45 kVA
2003	14.01 kW	75 kVA
2030	8.64 kW	75 kVA
2035	6.87 kW	75 kVA
2052	63.54 kW	225 kVA
3048	2.87 kW	45 kVA

Our seven locations were chosen to reveal a range of outcomes in our impact assessments (see §5). For example, the peak power reduction offered by our SC algorithm is likely of more (less) value at locations with less (more) capacity for additional load. Additionally, the demand charge reduction offered by our SC algorithm is likely of more (less) value at locations with less (more) average active power consumption. In our studies, when SC is performed at a particular location, the SC algorithm is supplied with the associated active power data and transformer rating. The former is utilized as $\hat{P}^C[t]$ (equivalent to assuming perfect estimation of this quantity) while the latter determines $P^G_{\max}$. Our use of aggregated load data is mildly limiting, as three customers are treated as one, at least for electricity billing and metering purposes. It should be noted, however, that this is sometimes the case in buildings/complexes with multiple tenants. Locations with few customers per transformer were intentionally chosen.

3.4 Fleet Operator Impact Assessment

Fleet operator impact assessment is summarized in Algorithm 2. For a given day and fleet size, we consider the use of three strategies to meet the requirements in Table 2:

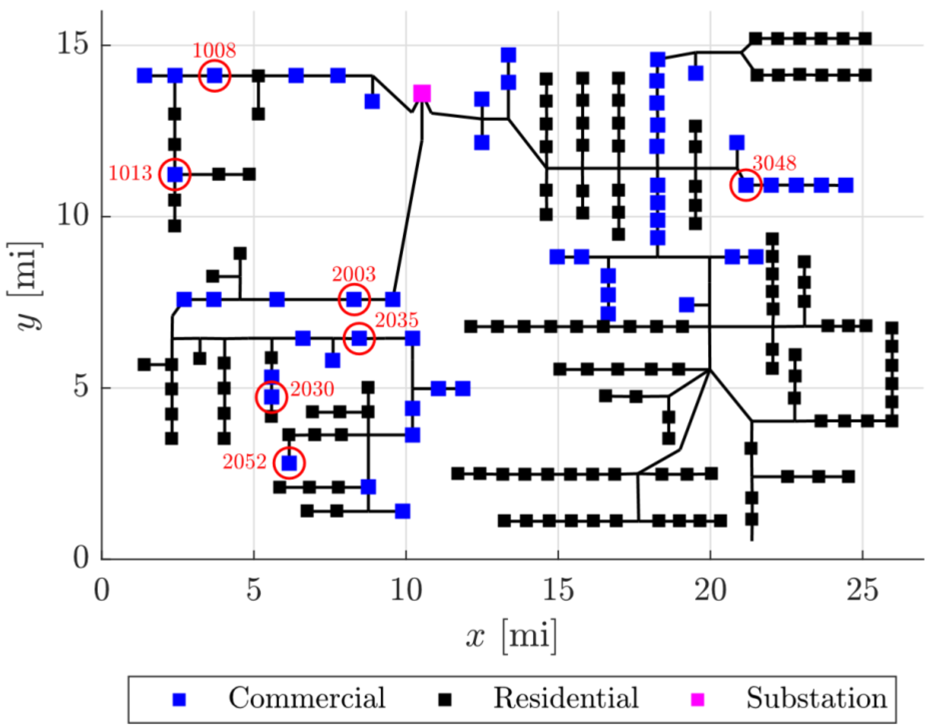

Figure 2. Schematic of the distribution feeder model of [44]. Squares indicate distribution transformers and loads; each load is connected to a dedicated transformer. Locations selected for fleet placement are circled and labeled.

1. *Conventional Rapid Charging (RC)*: Each EV begins charging at maximum power immediately upon plug-in.
2. *Conventional Smart Charging*: Each EV begins charging at maximum power at the earliest, low-cost time possible.
3. *Proposed Smart Charging*: Charging profiles for the fleet are determined by executing Algorithm 1 with $w_{n,1} = 1$, $w_{n,2} = w_{n,3} = w_{n,4} = 0$, and $v_n = 1$ for all n.

Conventional RC and SC represent solutions on the market today [48]. For each charging strategy, we compute the resultant daily (i) energy charge (in $) based on $\pi[t]$ and (ii) peak power. At the end of each month, monthly peak power is used to compute the monthly demand charge. We repeat this daily analysis for an entire year and report the following annual costs for multiple depot locations and fleet sizes:

C_1 : energy charge = sum of daily energy charges ($),

C_2 : demand charge = sum of monthly demand charges ($).

3.5 Grid Impact Assessment

Grid impact assessment is summarized in Algorithm 3. For a given day and fleet size, we consider the use of the three charging strategies of §4.4 to meet the requirements in Table 2; each strategy yields a set of charging profiles. For grid impact analysis, the total load at each depot location is the sum of (i) the baseline commercial load (from [44], not necessarily unity power factor) and (ii) the fleet charging load, which we assume to be unity power factor. Our assumption of unity power factor EV charging is both standard and supported by SAE J2894. The depot's active and reactive power profiles are then fed, one hour at a time (along with active and reactive power profiles of all other loads on the feeder), to OpenDSS, a steady-state circuit equation solver for power distribution systems. For each $t = 1, \dots, T-1$, OpenDSS returns:

- the steady-state active and reactive power flow through each phase of each transmission line,
- the steady-state active and reactive power flow through each phase of each transformer, and
- the voltage magnitude and angle at each node.

Algorithm 2. Fleet Operator Impact Assessment

Initialize electricity billing plan
[7]
for each candidate depot location
do
  for fleet size ∈ {small, large}
    do
    for each charging strategy
    do
      for each day of the year **do**
        Determine fleet charging load (Algorithm 1)
        Update monthly energy charge, peak power
        if end of month **then**
          Calculate monthly demand charge
          Update annual costs C_1 and C_2
        end if
      end for
      Record annual costs in Table 4 or Table 5
    end for
  end for
end for

Additionally, for each $t = 1, \ldots, T-1$, we compute and record the sensitivity of voltage magnitude (i) at the depot and (ii) at any other node, to a marginal increase in active power draw at the depot. Sensitivity is calculated using the standard power flow Jacobian, which is constructed using nodal voltages (returned above), nodal current injections (specified through loads), and the feeder's nodal admittance matrix (part of physics-based model) as described in [52].

According to the inverse function theorem, the power flow Jacobian *J* and its inverse are given by

$$\boldsymbol{J} = \begin{bmatrix} \frac{\partial \boldsymbol{p}}{\partial \boldsymbol{v}} & \frac{\partial \boldsymbol{p}}{\partial \boldsymbol{\theta}} \\ \frac{\partial \boldsymbol{q}}{\partial \boldsymbol{v}} & \frac{\partial \boldsymbol{q}}{\partial \boldsymbol{\theta}} \end{bmatrix} \Leftrightarrow \boldsymbol{J}^{-1} = \begin{bmatrix} \frac{\partial \boldsymbol{v}}{\partial \boldsymbol{p}} & \frac{\partial \boldsymbol{v}}{\partial \boldsymbol{q}} \\ \frac{\partial \boldsymbol{\theta}}{\partial \boldsymbol{p}} & \frac{\partial \boldsymbol{\theta}}{\partial \boldsymbol{q}} \end{bmatrix}$$

where $\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{v},$ and $\boldsymbol{\theta}$ are vectors of nodal active power injections, reactive power injections, voltage magnitudes, and voltage angles respectively. The upper-left block of $-\boldsymbol{J}^{-1}$contains voltage magnitude sensitivities with respect to active power draws (not injections). It is well known that for distribution systems, $\boldsymbol{J}$ can be ill-conditioned [53]. Therefore, instead of $\boldsymbol{J}^{-1}$we utilize the Moore-Penrose pseudoinverse of $\boldsymbol{J}$. This approach can yield approximate sensitivities, as numerical methods for pseudo-inverse computation (e.g., pinv in MATLAB, numpy, and scipy) typically pre-process ill-conditioned matrices by zeroing 'small' singular values. However, use of the pseudo-inverse requires much less computation than the standard alternative, in which $\partial \boldsymbol{v} / \partial \boldsymbol{p}$ is estimated column-wise by perturbing nodal power injections, re-solving the power flow problem, and using a finite-differencing approach with the observed voltage magnitudes.

This information is then summarized; the grid impact of a single overnight fleet charging session is represented by:

- The duration and severity of voltage violations at any node. Violations occur when steady-state voltage magnitudes are not within ±5% of nominal (e.g., 120 V or 240 V) [53].
- The duration and severity of any overloads of any transformer or transmission line. Overloads occur when power flows exceed nominal device ratings.
- The largest voltage sensitivity at each node.

Algorithm 3. Grid Impact Assessment

```
Initialize electricity billing plan [7]
𝒟 ≔ {92 (i.e., ceil(365/4)) distinct, randomly selected days of the year}
for each candidate depot location do
  for fleet size ∈ {small,large} do
    for each charging strategy do
      for each day in D do
        Solve daily power flow problem without EVs (OpenDSS)
        Determine fleet charging load (Algorithm 1)
        Solve daily power flow problem with EVs (OpenDSS)
        Compute impact metrics M_1-M_5 and
      others
      end for
      Average metrics M_1-M_5 over all days
      Record averages M̄_1- M̄_5 in Table 6 or Table 7
    end for
  end for
end for
```

Above, 'duration' refers to the number of one-hour time intervals (not necessarily consecutive) where a violation/overload occurs. In general, violations/overloads can occur; only proposed SC prohibits transformer overloading and no charging strategy considered herein prohibits voltage violations.

In repeating the above daily analysis over multiple days, depot locations, fleet sizes, and charging strategies, *it was observed that there were (i) no transmission line overloads, (ii) no transformer overloads anywhere except at the depot, and (iii) no voltage violations anywhere except at the depot.* It follows that (i) the grid impact of a single EV fleet will be spatially localized, as expected, and that (ii) transformers, rather than transmission lines, are the 'weak links' in our chosen distribution network. Thus, we chose to report only five, meaningful grid impact metrics for each day:

M_1 : duration of transformer overloading (h),

M_2 : average intensity of transformer overloading (per-unit),

M_3 : product of M_1 and M_2 (h, but energy-like quantity),

M_4 : duration of voltage violations (> 5% drop) (h), and

M_5 : voltage sensitivity change: with/without EVs (%).

Note that M_1-M_3 refer to the transformer *at the depot* and M_4-M_5 refer to voltage magnitudes *at the depot*. Also note that M_3 captures the severity of transformer overloading in a single metric; high-intensity or prolonged overloading is detrimental [53]. In §5, we report (for each combination of depot location, fleet size, and charging strategy) $\bar{M}_1$-$\bar{M}_5$, averages of M_1-M_5 taken over ceil(365/4) = 92 distinct, randomly selected days (down-selection limits runtime).

4. Deliverable 3: Impact Assessments

Present results of impact assessments for fleet operators and utility operators.

Table 4. Fleet operator impact assessment results – small fleet scenario.

Depot Location	Conventional Rapid Charging			Conventional Smart Charging			Proposed Smart Charging		
	C_1	C_2	$C_1 + C_2$	C_1	C_2	$C_1 + C_2$	C_1	C_2	$C_1 + C_2$
1008	7,047.99	5,288.28	12,336.26	5,318.47	7,389.29	12,707.76	5,383.00	3,807.53	9,190.53
1013	5,553.36	4,362.23	9,915.59	3,823.85	6,805.31	10,629.16	3,824.01	3,513.64	7,337.65
2003	8,384.41	5,280.41	13,664.82	6,654.90	7,744.59	14,399.49	6,654.90	4,685.02	11,339.92
2030	6,766.45	5,497.72	12,264.17	5,036.94	7,314.93	12,351.87	5,036.94	4,223.67	9,260.61
2035	6,177.26	4,798.22	10,975.48	4,447.75	6,950.45	11,398.20	4,447.75	3,797.66	8,245.40
2052	19,687.77	12,109.91	31,797.68	17,958.26	12,549.14	30,507.40	17,958.26	11,604.14	29,562.40
3048	5,721.31	4,463.91	10,185.22	3,991.80	6,828.28	10,820.09	3,991.80	3,443.38	7,435.18

Table 5. Fleet operator impact assessment results – large fleet scenario.

Depot Location	Conventional Rapid Charging			Conventional Smart Charging			Proposed Smart Charging		
	C_1	C_2	$C_1 + C_2$	C_1	C_2	$C_1 + C_2$	C_1	C_2	$C_1 + C_2$
1008	11,848.23	9,376.87	21,225.09	8,364.99	15,775.00	24,139.99	10,196.54	3,817.80	14,014.34
1013	10,353.60	8,972.18	19,325.78	6,870.37	15,198.98	22,069.35	8,458.66	3,817.80	12,276.46
2003	13,184.66	9,911.50	23,096.16	9,701.42	16,130.14	25,831.56	10,328.57	6,363.00	16,691.57
2030	11,566.69	9,490.22	21,056.92	8,083.45	15,643.98	23,727.44	8,326.38	6,363.00	14,689.38
2035	10,977.50	8,999.79	19,977.29	7,494.26	15,314.16	22,808.43	7,603.46	6,368.59	13,972.05
2052	24,488.02	15,825.09	40,313.10	21,004.78	20,417.31	41,422.08	21,004.78	12,946.74	33,951.52
3048	10,521.56	8,953.53	19,475.08	7,038.32	15,217.76	22,256.08	8,639.90	3,817.80	12,457.70

4.1 Fleet Operator Impact Assessment

Results of executing Algorithm 2 are provided in this section; results for the small (large) fleet scenario are provided in Table 4 (Table 5). For the small fleet scenario, proposed SC outperforms conventional SC (RC) by 3-31% (7-27%) with respect to $C_1 + C_2$. For the large fleet scenario, proposed SC outperforms conventional SC (RC) by 18-44% (16-36%) with respect to $C_1 + C_2$. The proposed SC reduces $C_1 + C_2$ primarily through C_2; this is particularly valuable for large fleets, where peak charging power under conventional schemes is high.

Both conventional and proposed SC respond to TOU pricing and therefore outperform conventional RC with respect to C_1. Note that conventional SC outperforms proposed SC with respect to C_1. This occurs because proposed SC enforces an upper bound on the depot's total demand, whereas conventional strategies do not; enforcing this bound can defer some charging to higher-cost 'peak' hours (while greatly reducing C_2). Note also that conventional RC outperforms conventional SC with respect to C_2. This occurs because conventional SC tends to temporally concentrate charging activity to 'off-peak' hours, whereas charging activity is somewhat distributed in conventional RC due to arrival time variation. Finally, we note that when executing Algorithm 1, energy demand was nearly always feasible, so fleet charging behavior was determined by Mode 1. Mode 2 was very rarely engaged; in these cases, negligible (< 1%) concessions in total fleet energy demand were required to preserve feasibility.

Table 6. Grid impact assessment results – small fleet scenario.

Depot Location	Conventional Rapid Charging					Conventional Smart Charging					Proposed Smart Charging				
	$\bar{M}_1$	$\bar{M}_2$	$\bar{M}_3$	$\bar{M}_4$	$\bar{M}_5$	$\bar{M}_1$	$\bar{M}_2$	$\bar{M}_3$	$\bar{M}_4$	$\bar{M}_5$	$\bar{M}_1$	$\bar{M}_2$	$\bar{M}_3$	$\bar{M}_4$	$\bar{M}_5$
1008	2.989	3.200	11.305	0	2.938	3.065	4.925	15.187	0	5.549	0	0	0	0	2.429
1013	0.391	0.398	0.671	0	3.183	3.000	4.511	13.533	0	5.681	0	0	0	0	2.722
2003	0	0	0	0	1.575	2.000	2.153	4.305	0	2.608	0	0	0	0	1.487
2030	0.054	0.059	0.131	0	1.347	0.326	0.333	0.623	0	2.317	0	0	0	0	1.294
2035	0	0	0	0	1.388	0.065	0.066	0.132	0	2.380	0	0	0	0	1.321
2052	0	0	0	0	0.879	0	0	0	0	1.169	0	0	0	0	0.545
3048	0.826	0.846	1.364	0	3.307	3.000	4.541	13.623	0	5.297	0	0	0	0	2.695

Table 7. Grid impact assessment results – large fleet scenario.

Depot Location	Conventional Rapid Charging					Conventional Smart Charging					Proposed Smart Charging				
	$\bar{M}_1$	$\bar{M}_2$	$\bar{M}_3$	$\bar{M}_4$	$\bar{M}_5$	$\bar{M}_1$	$\bar{M}_2$	$\bar{M}_3$	$\bar{M}_4$	$\bar{M}_5$	$\bar{M}_1$	$\bar{M}_2$	$\bar{M}_3$	$\bar{M}_4$	$\bar{M}_5$
1008	5.978	10.230	61.774	0	9.122	4.000	10.771	43.086	6.000	16.761	0	0	0	0	2.575
1013	5.120	8.750	44.929	0	9.320	3.761	10.114	38.234	6.000	17.064	0	0	0	0	3.230
2003	3.989	4.745	18.941	0	4.846	3.000	5.989	17.966	0	9.264	0	0	0	0	2.800
2030	2.261	2.719	6.513	0	4.519	3.000	5.695	17.084	0	8.854	0	0	0	0	2.996
2035	2.076	2.461	5.237	0	4.584	3.000	5.629	16.888	0	8.880	0	0	0	0	3.166
2052	0	0	0	0	2.998	0.120	0.121	0.121	0	5.940	0	0	0	0	1.872
3048	5.098	8.864	45.295	0.054	9.596	3.989	10.362	41.348	2.000	16.533	0	0	0	0	3.194

4.2 Grid Impact Assessment

Results of executing Algorithm 3 are provided in this section; results for the small (large) fleet scenario are provided in Table 6 (Table 7). For both fleet sizes, proposed SC outperforms conventional SC and RC by 100% with respect to $\bar{M}_1$-$\bar{M}_4$. With respect to $\bar{M}_5$, proposed SC outperforms conventional RC (SC) by 3-39% (42-54%) in the small fleet scenario and by 30-72% (64-85%) in the large fleet scenario.

Both conventional RC and SC lead to significant (and comparable) transformer overloading ($\bar{M}_1$-$\bar{M}_3$) at the depot. This is expected, as both conventional strategies perform high-power charging, differing only in the timing of this activity. Note, however, the varied severity of transformer overloading across depot locations. Due to differing transformer ratings and non-EV loads (see Table 3), the same fleet charging load creates severe overloading at buses 1008, 1013, and 3048; less intense (but substantial) overloading at buses 2003, 2030, and 2035; and no overloading at bus 2052.

Few voltage magnitude violations occurred in our studies ($\bar{M}_4$ is nearly always zero); all recorded violations were due to conventional RC or SC of the large fleet at bus 3048. The value of $\bar{M}_4$= 5/92 ≈ 0.054 associated with conventional RC corresponds to five, isolated one-hour intervals (over 92 days) with 5–9% undervoltage. The value of $\bar{M}_4 = 2$ associated with conventional SC corresponds to two hours of 5–9% undervoltage every day. We also note here that for this feeder, voltage magnitudes at the selected depot locations tend to be 1–2% above nominal before EVs are introduced; this likely helped to reduce the number of undervoltage violations.

5. Summary and Conclusions

5.1 Summary

The deliverables promised in our most recent quarterly project report (submitted 7/10/2024) 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.
- 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.
- Grid and fleet operator impact assessments were performed and detailed to illustrate the performance of our two-stage SC algorithm for EV fleets.

Additionally, the completion of this project has resulted in the submission of two academic papers as work products.

- K. V. Sastry, C. Viteri, D. G. Taylor, and M. J. Leamy, "Two-Stage Smart Charging of Commercial Electric Vehicle Fleets to Benefit Fleet and Grid Operators," *IEEE Transactions on Smart Grid*, 2024. (Submitted, Under Review)
- C. Viteri, K. V. Sastry, D. G. Taylor, and M. J. Leamy, "Electric Vehicle Smart Charging in a Single Residence with Rooftop Solar and Energy Storage," *IECON 2024 – 50th Annual Conference of the IEEE Industrial Electronics Society*, 2024. (Accepted)

5.2 Conclusions

As the medium and heavy-duty (MD/HD) vehicle sectors (e.g., delivery vans, buses) transition to electric vehicles (EVs), large charging loads associated with commercial fleets of such vehicles are expected to significantly stress electric power distribution networks. Electricity pricing is designed to disincentivize this type of loading, leading to high fleet operating costs. To address these challenges, we present a highly flexible smart charging (SC) algorithm for EV fleets that arrive and depart from a common depot on a schedule. Our algorithm features (i) primary consideration of multiple fleet operator preferences (e.g., minimizing cost, using carbon-free energy), (ii) secondary consideration of grid impact that leverages the existence of multiple optimal (or near-optimal) ways to satisfy fleet operator preferences, and (iii) automatic detection and handling of infeasibility due to large energy demands.

We perform two numerical impact assessment studies in which our SC algorithm is compared against conventional rapid charging (RC) and 'SC' solutions on the market. Both studies utilize (i) a physics-based model of a real feeder, (ii) real, hourly load data for that feeder, and (iii) a set of realistic fleet charging requirements that are synthetically generated using operational data from a real fleet of conventional parcel delivery vehicles. Both studies reveal a range of fleet and grid operator benefits by considering various fleet sizes and placements within a feeder. This is important, as fleet sizing and placement are not always free choices; business needs may dictate the size of a fleet and its charging needs, and this load may need to be served at the business' existing location.

In comparison to conventional RC and SC, the proposed SC is shown to (i) provide fleet operators with significant cost savings by targeting both energy charges and (infamous) demand charges, and (ii) significantly reduce sensitivity of voltage magnitude (at the depot) to changes in active power (at the depot). The latter implies that use of the proposed SC (over conventional RC or SC) might allow a fleet operator to operate a larger fleet without degrading their service voltage. It is also shown that significant transformer overload and voltage drop issues can be associated with conventional RC and SC, and that the proposed SC mitigates these issues. The proposed SC achieves this without requiring daily decision-making from the utility, making it a simple means to bring electrified fleets onto existing infrastructure, and to potentially defer expensive infrastructure upgrades.

Finally, we note that the impact assessment methods in this work have decision-support value (independent of the SC algorithm), as existing methods (e.g., those suggested in [54], a guide to fleet electrification) are often crude and inaccurate due to a focus on average (not instantaneous) power. It is noteworthy that application of the methods of [54] to the charging requirements used in our studies leads to the faulty conclusion that no transformer upgrades are needed at the depot, whereas our high-fidelity methods tell a different, more accurate story.

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Data Summary

Data used in case studies was collected from open data catalogs, service plans, and commercial product specifications (e.g., NREL, Pecan Street, vehicle manufacturers, utility operators, and publications), and is cited herein. No data was collected from human or animal subjects. Data generated by the investigators is reported as graphical plots, figures, and tables included in thesis chapters and in published papers.

Products of Research

Data produced by this research is in the form of graphical plots, figures, and tables to be included in thesis chapters and publication of articles in peer-reviewed journals. The specific work products are:

- K. V. Sastry, C. Viteri, D. G. Taylor, and M. J. Leamy, "Two-Stage Smart Charging of Commercial Electric Vehicle Fleets to Benefit Fleet and Grid Operators," *IEEE Transactions on Smart Grid*, 2024. (Submitted, Under Review)
- C. Viteri, K. V. Sastry, D. G. Taylor, and M. J. Leamy, "Electric Vehicle Smart Charging in a Single Residence with Rooftop Solar and Energy Storage," *IECON 2024 – 50th Annual Conference of the IEEE Industrial Electronics Society*, 2024. (Accepted)

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Data produced by this research is in the form of graphical plots, figures, and tables to be included in thesis chapters and publication of articles in peer-reviewed journals. No proprietary data formats were used.

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