Article Type: Research and Analysis

Title: Optimizing future cost and emissions of electric delivery vehicles

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Conflict of Interest Statement: The authors declare no conflict of interest.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Keywords:

Electric Vehicles

Greenhouse Gas Emissions

Multi-Objective Optimization

Smart Charging

Last-Mile Delivery

Industrial Ecology

Abstract:

Electrification of delivery vehicles will play an important role in decarbonizing the transportation sector. As electricity generating technologies vary regionally and temporally, where electric vehicles are deployed and when they are charged will determine the greenhouse gas (GHG) emissions and cost consequences of delivery vehicle electrification. We couple a vehicle charging model with a dataset that provides hourly projections of marginal electricity cost and marginal emissions factors across 134 electricity balancing areas in the United States. We calculate the cost and emissions of charging an electric delivery vehicle over a 10-year service life (2021-2030) at different times-of-day and in different locations. Using a multi-objective optimization framework we explore two potential goals – minimizing GHG emissions and minimizing cost – and investigate the tradeoffs between those goals. We show emissions ranging from 136 to 485 g CO_2/mile, and costs ranging from 0.79 to 3.18

cents/mile depending on location and optimization weighting. We demonstrate the impact of charge time-of-day optimization frequency, showing emissions reductions of 19%-62% by choosing the optimal charging time every day, rather than annually. We show that the benefits of electrification are reduced when potential charge times are constrained (e.g., if charging must take place overnight). And we calculate the carbon price needed to align cost-optimized and emissions-optimized charge timing in different regions. Our results highlight the opportunity to reduce cost and emissions by strategically charging at certain times of day and show the importance of accounting for spatial and temporal variability when developing effective carbon reduction strategies.

1. INTRODUCTION

In the United States between 1990 and 2019, greenhouse gas (GHG) emissions due to the transportation sector have increased 24%, more than from any other sector (U.S. Environmental Protection Agency, 2021). Transportation now represents the largest contribution to U.S. GHGs (28% in 2020) and is projected to remain the largest contributor through 2050 (U.S. Energy Information Administration, 2020). Rapid deployment of electric vehicles (EVs) has been identified as a crucial component of decarbonizing the transportation sector (Ambrose et al., 2020; Taptich et al., 2016; Tsakalidis et al., 2020).

Though most research has focused on passenger vehicles, research on and deployment of electrified delivery vehicles is growing (Pelletier et al., 2016). Even before the COVID-19 pandemic, increases in online shopping and just-in-time delivery systems were increasing the use of delivery vehicles (Marmiroli et al., 2020; Morganti & Browne, 2018). Due to their short average route length, low average speed (especially in urban routes), ability to return to a central location each day, and frequent stops and starts (opportunities for regenerative breaking), delivery vehicles are well suited for rapid fleetwide electrification (National Renewable Energy Laboratory, 2019; Quak et al., 2016). This transition has already begun, with multiple delivery companies ordering electric delivery vehicles in the past several years (Arrival Ltd, 2020; FedEX Corp., 2018; Rivian Automotive, 2019), and several automotive companies ramping up production of these vehicles (Daimler AG, 2019; Ford Motor Company, 2020). The benefits of electrified delivery vehicles displacing conventional diesel delivery vehicles include reduced air pollution (CO_2, NO_x, $PM_{2.5}$, PM_{10}) (Giordano et al., 2018; Hawkins et al., 2013; Marmiroli et al., 2020) and potential cost savings (Taefi, 2016). However, the emissions benefits and potential cost savings vary depending on where, when, and how these vehicles are charged (Arvesen et al., 2021; McLaren et al., 2016; Miller et al., 2020; Woody et al., 2021).

To better understand the spatial and temporal variability of the emissions benefits of electrifying delivery vehicles across the United States, we couple a delivery vehicle charging model with an hourly marginal emissions factor (MEF) dataset spanning 134 balancing areas (BAs) through 2030.

The small spatial resolution of the MEF data, combined with the use of projected MEFs over the lifetime of the vehicle fills an important gap in the literature. We include a novel evaluation of how frequently to update vehicle charging-time-of-day to meet operational goals, i.e., cost reduction and emissions reduction. We assess tradeoffs in cost and emissions reductions using a multi-objective optimization framework, highlighting that in some regions cost and emissions goals align, and in other regions a carbon price is needed to achieve alignment. Our results will inform carbon reduction strategies of delivery fleet operators, and deployment and operational practices encouraged by policy makers.

1.1 Literature Review

There are several studies focusing on the life cycle emissions of electrified delivery vehicles in comparison to internal combustion engine vehicle (ICEV) alternatives. Lee et al. (2013) show electric delivery vehicles have 42%-61% lower GHG emissions than diesel alternatives when operated in U.S. urban settings. L. Yang et al. (2018) show that on average electric delivery vehicles operating in China have 69% lower GHG emissions compared to diesel alternatives. Giordano et al. (2018) compare electric and diesel delivery vans in European cities and find that in cities with particularly clean electric grids, an electric delivery vehicle may have life cycle GHG emissions that are only 10% of the emissions of a diesel delivery vehicle. Marmiroli et al. (2020) report similar results – that an electric delivery vehicle has lower GHG emissions than a diesel and a compressed natural gas alternative, comparing across Italian and Norwegian power grids, different vehicle loadings, and different drive cycles. These studies show that the emissions attributable to electric delivery vehicles are lower than the emissions attributable to conventional alternatives. However, these studies do not show the full impact of adopting a new electric delivery vehicle, due to the use of Average Emissions Factors (AEFs) rather than Marginal Emissions Factors (MEFs).

AEFs represent the emissions (mass of pollution per unit of energy generated) from the entire generation mix for a given time and location. MEFs represent the emissions from generators that are added or removed from the generation mix in response to additions to or reductions in demand (Ryan et al., 2016). Thus, while AEFs represent a mixture of all generation sources at a particular place and time, MEFs represent the emissions of whichever single generator is on the margin at a particular place and time. As new demand is added to the grid, generators will not scale up production equally. And as the new demand is met by a single generator, the emissions of that generator can be attributed to the source of the new demand. MEFs should be used to study increased electric vehicle adoption because this represents a new load (i.e., it is not part of the current demand), necessitating a change in the generation mix (Ryan et al., 2016, 2017). As MEFs are typically higher than AEFs, the environmental impact of technologies and policies may be underestimated when AEFs are used (Bigazzi, 2019). Like AEFs, MEFs vary based on location and time (Graff Zivin et al., 2014).

Previous studies of light duty EVs that have used hourly MEFs typically consider specific regions as case studies (Axsen et al., 2011; Kim & Rahimi, 2014; Tu et al., 2020; Weis et al., 2015) or have used large regions, e.g. the eight North American Electric Reliability Council (NERC) regions (Archsmith et al., 2015; Graff Zivin et al., 2014; Tamayao et al., 2015; Yuksel et al., 2016; Yuksel & Michalek, 2015). The smaller EPA eGRID subregions have also been used with MEFs (Tamayao et al., 2015) and AEFs (Wu et al., 2019; F. Yang et al., 2018). These may include county level data for driving conditions and temperature but rely on NERC or eGRID level emission factor aggregations when comparing the emissions of different vehicles (Wu et al., 2019; Yuksel & Michalek, 2015). Additionally, past studies largely use historic MEFs that are calculated by regressing historic emissions on historic generation or consumption (Donti et al., 2019; Siler-Evans et al., 2012). Tamayao et al. (2015) consider multiple MEF data sources, but each one uses historic MEF values. Onat et al. (2015) compare EVs to internal combustion engine vehicles (ICEVs) in each state, using estimated 2020 MEFs, and an alternative scenario in which all charging is accomplished via solar energy. The use of historic MEFs neglects ongoing grid decarbonization over vehicles' lifetimes. To account for ongoing decarbonization, MEFs can instead be calculated using emission and generation outputs from power system optimization models run for future scenarios (Ryan et al., 2016).

Using projections of future costs and emissions, and by accounting for the daily variability each, charging time-of-day can be optimized. Tu et al. (2020) optimize passenger EV charge timing in an Ontario case study with the goal of minimizing GHG emissions, showing EV emissions can be reduced by over 50%. Hoehne and Chester (2016) optimize charge time-of-day each day in the U.S., choosing to charge in the lowest emitting hours of the day, and show GHG emissions up to 31% lower compared to standard pre-timed charging. Dixon et al. (2020) optimize charge timing not only to minimize GHG emissions, but also to absorb excess wind generation that would otherwise be curtailed. Vehicle-to-Grid (V2G) charging may be used to further lower overall emissions (Xu et al., 2020). However, emissions minimization is not the only relevant goal for an electric delivery vehicle that must compete economically with other delivery options (Feng & Figliozzi, 2013).

Multiple studies show that the daily variation in electricity cost and MEFs reveals significant tradeoffs. Kim and Rahimi (2014) project MEFs for Los Angeles in 2020 and 2030 based on planned developments and resource dispatching, showing the highest marginal carbon intensity if EV charging takes place in off-peak hours. McLaren et al. (2016) similarly show higher emissions when charging is restricted to off-peak hours, in low, medium, and high carbon grids across the United States. Weis et al. (2015) show that controlled EV charging in the PJM region leads to lower costs but higher emissions as load is shifted to coal plants. Graff Zivin et al. (2014) use MEFs at the NERC region level to show that emissions are generally highest in the hours that electricity demand and cost are lowest. This presents a clear challenge to fleet operators and policy makers, who would like to minimize costs while reducing emissions. These tradeoffs can be investigated via multi-objective optimization and optimal solutions compared using Pareto frontiers (Brinkel et al., 2020; Maigha & Crow, 2017).

Based on our review of the literature our study fills several important gaps (see table S1):

-We report the first nationwide comparison of EV charging emissions at or below the spatial resolution of electricity balancing authorities (134 regions), rather than NERC regions (8 regions) or EPA eGRID regions (22 regions).

-We report the GHG emissions impact of electric delivery vehicles more appropriately, by using MEFs, and by including projected future changes to the grid.

-We use multi-objective optimization to evaluate the tradeoffs between cost-optimized and emissions-optimized charging.

-We include novel evaluations of optimization frequency and available charging window that offer comparisons between idealized and more realistic time-of-day optimization results.

2. METHODS

2.1 Goal and Scope

Here we assess the spatial and temporal variability in cost and emissions of charging an electric delivery vehicle. We demonstrate the opportunity to lower cost or emissions by optimizing the time-of-day of charging. Finally, we evaluate the tradeoffs between cost and emissions that arise from time-of-day optimization.

Though production phase impacts vary between EVs and ICEVs, we are primarily concerned with the vehicle's use phase. The use phase makes up the majority of a vehicle's total emissions, especially in carbon intensive grids (Ellingsen et al., 2016; Hawkins et al., 2013), and we are comparing the emissions from charging at different times and in different places. The grid's ability to react to changes in demand may also be an important factor in optimizing charge time-of-day. Here we take the perspective of a single delivery vehicle, acknowledging that our results may change when taking the perspective of a delivery fleet or the entire stock of delivery vehicles in a region (Dixon et al., 2020; Onat et al., 2015). Although we are comparing the cost and emissions of different operations for an electric vehicle, a comparison with a conventional delivery vehicle is also warranted, and is included in Supporting Information S1.

2.2 Vehicle Parameters

To calculate the charging emissions of an electric delivery vehicle we begin with a simplified charging profile that assumes one continuous linear charging event per day (i.e., charging at a central depot with no en-route charging, which is typical for electric freight vehicles (Pelletier et al., 2018)). Vehicle parameters are estimated based on current EV battery and charging infrastructure technology (Table 2). We assume a 10-year vehicle lifetime and use a static 55-mile daily route, which is an average value for a delivery van based on the National Renewable Energy Laboratory (NREL) Fleet DNA data (Table 3). With these parameters the vehicle requires 30 kWh of energy each day to complete its route. The average energy consumption of the vehicle is 0.55 kWh/mile, which is similar to the value used by Giordano et al. (2018) to model a light-duty delivery van operated in an urban setting. We use the same energy consumption each day, as Miller et al. (2020) have shown including seasonal variation in grid emissions and fuel intensity results in error of under 1% when compared to using an average value for the entire year.

2.3 Vehicle Charging Emissions and Cost

To estimate spatially-differentiated emissions and costs of EV charging given future changes in the electricity system, we use NREL's Cambium resource (Pieter et al., 2020). Cambium provides marginal emissions factors, cost, generation, and other data for 134 BAs on an hourly basis from 2020-2050. This resource is built on output from a sequence of two models: the Regional Energy Deployment System (ReEDs) (Brown et al., 2019) and PLEXOS (Energy Exemplar, n.d.). ReEDS is a linear optimization capacity planning model that simulates electricity sector investment (i.e., deployment and operation of generation, transmission, and storage) based on energy demand and various system constraints. ReEDS determines how the grid will change for each biennial simulation between 2020-2050 under a variety of future scenarios, and has been used to investigate renewable electricity policy coordination (Bistline et al., 2020), battery storage for peak demand (Frazier et al., 2020), and other topics. Then, within each modeled year, the future generator fleet is dispatched using a unit commitment and economic dispatch (UCED) model in PLEXOS (Energy Exemplar, n.d.). The UCED controls hourly operations of each power plant while minimizing variable costs and enforcing operational constraints (e.g., supply and demand balance and reserve constraints). In short, ReEDS determines optimal investments and retirements in generation and transmission assets, then the UCED model determines optimal hourly operations of those assets. An overview of the system is shown in Figure 1.

In our base case we use the mid-case from NREL's 2020 standard scenarios, which is the business-as-usual scenario. The mid-case takes into account state, regional, and federal policies in place as of June 20, 2020 (Cole et al., 2020), uses NREL's Annual Technology baseline for generation costs, and the Annual Energy Outlook's 2020 reference case for fuel costs and demand growth projections (U.S. Energy Information Administration, 2020). To capture emissions impacts, we use Cambium's Short Run MEFs (SRMEFs), which are calculated using emissions and generation output from the UCED model. Like existing MEF resources, the SRMEF is equal to the emissions rate of the generator that serves a marginal increase in load at that point in time (plus transmission, distribution, and efficiency losses). To validate Cambium data, we compare Cambium's 2020 projected SRMEFs with recent (2018) MEFs obtained from the Climate and Energy Decision Making Center (CEDM) (Azevedo et al., 2021), shown in Supporting Information S2. The Cambium MEFs are generally higher, though the values are reasonably close in most regions.

While structural changes to the grid are incorporated into the model every two years, there is no mechanism to explicitly model and account for the generating capacity, some of it cleaner than the existing grid, that would be added specifically because of the introduction of electric delivery vans. If the intervention (i.e., increased EV charging) leads to the construction of new renewable generators but fossil generators remain on the margin, then this method may not adequately illustrate the true impact of the intervention. Investigating this potential shortcoming is an opportunity for future research.

To calculate cost we use the total marginal end use cost (TMC) from Cambium, which is the sum of energy, capacity, operating reserve, and portfolio (cost to comply with renewable portfolio standards and clean energy standards) costs. Figure S2 shows the hourly MEFs and hourly electricity costs for three different Cambium scenarios (low, mid, and high renewable electricity prices) between 2020-2030. Our results use the mid case, and we show sensitivity analysis to renewable electricity prices using the high and low cases in Supporting Information S1. In each scenario, the low and high daily electricity prices move farther apart over time. In Figure S3 the same trend is shown from 2020-2050. Therefore, the opportunity for cost savings or emissions savings by optimizing charging times is expected to increase over time.

2.4 Multi-Objective Optimization to Minimize Costs and Emissions

As delivery vehicle routes are predictable, schedulable, and repeatable (Tsakalidis et al., 2020), delivery vehicles are well suited to time-of-day charging optimization (Dahmane et al., 2021). We use a multi-objective optimization to select charging times that minimize emissions and/or costs. For input to this optimization, we first quantify charging emissions ($e_{h,d,y}$) and costs ($c_{h,d,y}$) for each potential charging start time *h* (0-23) in each day *d* (1-365) in each year *y* (2021-2030) as:

$$e_{h,d,y} = \sum_{h}^{h+N} MEF_{h,d,y} * \frac{BS * DOD}{N} \quad (1)$$

$$c_{h,d,y} = \sum_{h}^{h+N} TMC_{h,d,y} * \frac{BS * DOD}{N} \quad (2)$$

where *N* is the number of hours for which the battery is charged, *BS* is the battery size, *DOD* is the depth of discharge, *MEF* is the marginal emissions factor, and *TMC* is the total marginal cost. This results in a linear charge profile at a constant charging power of 7.5 kW.

Given these costs and emissions associated with beginning charging in each hour through 2030, our multi-objective optimization decides when to start charging to minimize a weighted combination of costs and emissions. We run our optimization for each BA separately. In deciding when to start charging, we use three optimization frequencies: annually, daily, or decadally. When optimizing annually, our optimization selects one charging start time across days for each year. Its objective function is:

$$\begin{aligned} &\mathit{Emissions\ and\ Cost}\ (\mathit{Annual\ Optimization}) \\ &= \sum_{y=2021}^{2030} \underset{\beta_0,\beta_1,\ldots\beta_h}{Min} \left(\sum_{h=0}^{23} \beta_h \sum_{d=1}^{365} (\alpha * e_{h,d,y} + (1-\alpha) * c_{h,d,y}) \right) \quad (3) \end{aligned}$$

where *h, d,* and *y* index hour of day, day of year, and year, respectively; α is a unitless weighting factor that ranges from zero to one; and β_h is a binary decision variable that represents whether the charging period started in a particular hour:

$$\beta_h = \begin{cases} 1, & \mathit{Charging\ starts\ at\ hour\ h} \\ 0, & \mathit{Charging\ does\ not\ start\ at\ hour\ h} \end{cases} \quad (4)$$

We minimize emissions only when α = 1 and minimize costs only when α = 0. As charging takes place once each day, the charging start time is subject to the constraint:

$$\sum_{h=0}^{23} \beta_h = 1 \quad (5)$$

For the decadal optimization frequency, we optimize the charging start time per equations 1-5 above but only for 2021, and then the same charging start time is used for the remainder of the decade. Thus, the charging time is optimized only once per decade. For the daily frequency, we optimize unique charging start times each day for the entire decade as follows:

$$\begin{aligned} &\mathit{Emissions\ and\ Cost}\ (\mathit{Daily\ Optimization}) \\ &= \sum_{y=2021}^{2030} \sum_{d=1}^{365} \underset{\beta_0,\beta_1,\ldots\beta_h}{Min} \left(\sum_{h=0}^{23} \beta_h (\alpha * e_{h,d,y} + (1-\alpha) * c_{h,d,y}) \right) \quad (6) \end{aligned}$$

While this is probably not a realistic option for a company, as they have various operating constraints and may not be able to change their charging time every day, this does represent an upper bound as to what is possible through charge time-of-day optimization.

Regardless of optimization frequency, our base case assumes that charging can take place at any time throughout the day (i.e., the delivery route is scheduled around the optimal charging time). However, as most delivery vehicles make deliveries during the day, delivery companies would have to make significant operational changes to fully realize the benefits of time-of-day optimization. As an intermediate option, companies may adopt a charge time-of-day optimization framework while limiting charging to nighttime hours. We show such a scenario in section 3.2.3 by constraining h, the hour at which charging starts, to $h = \{0 - 4, 20 - 23\}$. This means that the vehicle must start charging sometime after 8 pm and must be finished charging by 8 am.

2.5 Creating Pareto Frontiers

For each BA and year, our base case (annually optimized charging start times) selects among a potential solution space of 24 possible charging start times. We create a Pareto frontier by finding the set of charging start times for which no improvement can be made for one of the objectives without worsening the other objective. For a convex solution space, the points along the Pareto frontier can be found by varying α. This is shown in Figure 2 by the filled-in points. Each point represents an optimal solution according to a particular weighting of the objectives. Figure 2 also shows the charging start time that corresponds with each of these points.

The Pareto frontier can be used to make operational decisions based on the objectives. In the example shown in Figure 2, if optimizing only for emissions ($\alpha = 1$), then the vehicle should be charged starting at 1 am. If optimizing only for cost ($\alpha = 0$), then the vehicle should be charged starting at 6pm. Different weightings will result in choosing different points along the Pareto frontier. The points not along the frontier are dominated, i.e., at least one of the objectives can be improved upon without any sacrifice of the alternative objective(s). Pareto frontiers for specific BAs, and the insights they offer, are shown in the results section.

3. RESULTS

3.1 Charge Timing

Across the 134 BAs between 2020 and 2030, optimal charging start times when optimizing only for emissions ($\alpha = 1$) are generally in the middle of the night or in the mid-afternoon (Figure 3). Through 2030, optimal start times shift from nighttime to mid-afternoon as the latter becomes more favorable in most BAs. When optimizing charging start times according to cost ($\alpha = 0$), optimal start times fall around 12-1 a.m., though mid-morning (8-10 a.m.) charging becomes favorable in some BAs through 2030.

3.2 Cost and Emissions

The cost and emissions of electric delivery vehicles vary greatly depending on charging time-of-day. Here we show the variation in charging across balancing areas and by optimization frequency, as well as highlighting results from the 20 largest balancing areas (by cumulative energy demand 2021-2030) which together account for approximately 50% of the total US demand. The 20 largest BAs also contain 15 of the 20 largest cities in the U.S., which are likely locations for the first deployment of electric delivery vehicles (See Figure S1 and Table S6).

3.2.1 Regional Variation

Within the 134 BAs, annual emissions-optimized ($\alpha = 1$) charging results in demand-weighted average emissions of 323 g CO_2/mile and demand-weighted average cost of 2.13 cents/mile (with ranges of 136 to 381 g CO_2/mile and 0.83 to 3.18 cents/mile, respectively) (Figure 4a). When just the 20 largest BAs are investigated the average demand-weighted emissions and costs equal 318 g CO_2/mile and 2.09 cents/mile, respectively (with ranges of 238 to 376 g CO_2/mile, and 1.27 to 2.97 cents/mile respectively) (Figure 4b).

Emissions optimized charge timing typically does not align with cost optimized charge timing (Figure 3). When charging times are optimized according to cost rather than emissions ($\alpha = 0$), the overall cost of charging decreases and the charging emissions increase. Within the 134 BAs, annual cost-optimized ($\alpha = 0$) charging results in demand-weighted average emissions of 371 g CO_2/mile and demand-weighted average cost of 1.53 cents/mile (with ranges of 155 to 485g CO_2/mile and 0.79 to 1.87 cents/mile, respectively) (Figure 4a). When just the 20 largest BAs are investigated the average demand-weighted emissions and costs equal 352 g CO_2/mile and 1.55 cents/mile, respectively (with ranges of 247 to 472 g CO_2/mile, and 1.12 to 1.84 cents/mile respectively) (Figure 4b). Switching from annual emissions-optimized ($\alpha = 1$) charge timing to annual cost-optimized ($\alpha = 0$) charge timing results in an 18% increase in demand-weighted average emissions and a 27% decrease in demand-weighted average cost over a vehicle's 10-year lifetime.

3.2.2 Optimization Frequency

In the base case results shown above, the optimal charging start time was chosen for each year of the decade (i.e., optimized annually). In our first alternate scenario, we optimize the charging start time in 2021 then use the same start time through 2030. For regions with relatively stable optimal start times, there is little difference in emissions between the base case and the decadal alternative scenario. However, in other regions the first year may be an outlier in terms of optimal time-of-day. In these regions, failure to update the charging start time each year can result in significantly higher emissions. In this alternative scenario, using α=1 weighting, emissions are between 0% and 47% higher, with a demand weighted average of 8% increase (18 g CO_2/mile), compared to the base case of updating optimal charging times each year. Costs exhibit a 57% decrease to a 60% increase, with a demand-weighted average of 14% decrease (0.25 cents/mile) (Figure 4c).

In our second alternative scenario, as shown in Equation 6, we optimize charging start times daily. Daily optimization approximates an upper limit of what can be accomplished through charge time-of-day optimization. In this alternative scenario, using α=1 weighting, emissions would decrease by between 19% and 62%, with a demand-weighted average of 30% (85 g CO_2/mile). This also results in a change in cost, ranging from a 61% decrease to a 10% increase, with a demand-weighted average of 18% decrease (0.37 cents/mile) (Figure 4d).

When using α=0 weighting, changing the optimization frequency to decadal or daily is much less impactful. Upgrading from decadal to annual optimization decreases demand-weighted costs and emissions by just 0.6% (Figure 4e). Upgrading from annual to daily optimization decreases demand-weighted costs and emissions by just 3% and 0.6%, respectively (Figure 4f). This reflects the fact that there is much less variation in cost optimized start times (see Figure 3).

3.2.3 Limited Nighttime Charging

Delivery companies may be constrained by consumer preferences for delivery timing (e.g., no deliveries in the middle of the night), which would limit the effectiveness of time-of-day based optimization. However, the reduced noise of electric vehicles may eliminate one obstacle to non-standard delivery hours, and within overnight charging windows there remain opportunities for optimizing charge timing. Here we limit the charging window to between 8pm and 8am.

With charging constrained to nighttime, annually emissions optimized (α=1) emissions range from 183 to 427 g CO_2/mile with a demand-weighted average of 344 g CO_2/mile, with emissions increases of 0% to 44% with a 6% demand-weighted average compared to the unrestricted charging scenario. If emissions are optimized daily, emissions range from 124 to 341 g CO_2/mile with a demand-weighted average of 276 CO_2/mile, with emissions increases of 4% to 84% with a demand-weighted average of 16% compared to the unrestricted charging scenario (Figure 5a).

Nighttime charging has a much smaller impact on cost-optimized charging, as nighttime charging is already often the least expensive time to charge (Figure 5b). For both annual and daily cost-optimized (α=0) charging, switching from unrestricted hours to nighttime hours increases cost by less than 5% in each scenario. However, there are certain regions that see cost increases above 50%. Results for each balancing area can be seen in Supporting Information S3.

3.3 Pareto Frontier Analysis

The shape of the Pareto frontier offers valuable information about tradeoffs in individual years and trends over time, with more nuance than exploring just the extreme ($\alpha = 0$ and $\alpha = 1$) scenarios. We show several examples in Figure 6 (full results in Supporting Information S4). Each example in Figure 10 is one of the 20 largest BAs. In BA 58, which covers most of Louisiana, the Pareto frontier is relatively stable through 2030. BA 101, in Florida, shows a rightward shift through 2030. In BA 103, which covers most of Michigan, there is a clear leftward shift in the Pareto frontier through 2030, showing the potential for improved emissions and cost outcomes. Finally, BA 127, covering most of New York, shows no clear trend through 2030. Among the 20 largest BAs through 2030, 10 shift leftwards, 5 shift right, 2 are stable, and 3 show no clear trend. Additionally, as seen in BAs 101 and 127, the Pareto frontier is often represented by a single point. This shows that the emissions minimizing ($\alpha = 1$) and cost minimizing ($\alpha = 0$) charging start times are in fact the same time, and all other points are dominated. The single point frontier shows no tradeoff between cost and emissions optimization.

4. DISCUSSION

Using MEFs that capture future changes in the electricity system, we show the spatial and temporal variability in electric vehicle charging emissions and costs, using electric delivery vehicles as a case study due to the predictable, schedulable, and repeatable nature of their route characteristics and operating procedures. In addition to time and space, emissions also vary with optimization weighting and frequency. Across 134 BAs spanning the contiguous U.S. through 2030, we show charging emissions ranging from 136 to 485 g CO_2/mile depending on charging location and optimization weighting and show a 19%-62% reduction in emissions by optimizing charge timing more frequently. This information yields important insights for the deployment and operation of electric delivery vehicles.

4.1 Cost vs. Emissions Optimization Tradeoffs

Switching from annual emissions-optimized ($\alpha = 1$) charge timing to annual cost-optimized ($\alpha = 0$) charge timing increases emissions by 18% and decreases costs by 27% in terms of demand-weighted averages over the vehicle's 10-year lifetime. There is significant regional variation, with emissions increases as little as 0% or as high as 37%, and cost savings as little as 0% or as high as 55%.

Implementing a carbon price could lead to cost and emissions optimization aligning at the same time of day. By finding the difference in cost and emissions between the $\alpha = 1$ and $\alpha = 0$ optimization weightings, we can determine a price of carbon needed to shift from cost-optimized times to emissions-optimized times. This represents the value needed to shift from the least expensive charging time to the least emitting charging time. The cost ranges from 0 \$/ton CO_2, in BAs in which emissions- and cost-optimized charging already occur at the same time, to over 900 \$/ton CO_2. To shift from cost-optimized charging hours to emissions-optimized charging hours in the regions that collectively make up 50% of the US energy demand would cost 127 \$/ton CO_2, and to shift to emissions-optimized charging hours in the regions that collectively make up 75% of US energy demand would cost 166 \$/ton CO_2 (Figure 7).

Even if a company optimizes for cost, this can have a positive impact on emissions if the cost savings are used to electrify the fleet more rapidly. The carbon prices needed to shift from cost-optimized (α=0) to emissions-optimized (α=1) charging are generally higher than what has been proposed in the U.S. (Deutch, 2019; Maloney, 2019; Whitehouse, 2019), but smaller values could still lead to improvement, shifting to an intermediate α value, and charging at a cleaner (but not the cleanest) time. For regions with a convex Pareto frontier, this may be a more cost-effective method to reduce emissions. To take an extreme example (BA 22 in 2030), shifting from α=0 to α=1 achieves a 25% reduction in emissions with a 149% increase in cost. This 25% reduction in emissions could be incentivized with a carbon price of 173 \$/ton CO_2. However, shifting from α=0 to α=0.57 achieves a 20% reduction in emissions with an 18% increase in cost. This 20% reduction in emissions could be incentivized with a carbon price of only 26 \$/ton CO_2. For both fleet operators and policy makers, using region-specific and year-specific Pareto frontiers, and considering each point rather than only the extremes is integral to determining the most cost-effective emissions reduction strategies.

4.2 Vehicle Deployment and Operations

While previous studies have investigated EV emissions using MEFs at the NERC region level, using data for geographically smaller BAs allows for improved decision making about the most environmentally beneficial deployment locations. There is important variation within NERC regions that is not captured when using emissions data aggregated by NERC region. For example, annual emissions-optimized (α=1) charging emission within the TRE NERC region vary greatly. In BA 63, which includes Dallas and Ft. Worth, charging an additional electric delivery vehicle would result in 238 g CO_2/mile; in BA 61, which covers much of Western Texas, charging an additional vehicle would result in 136 g CO_2/mile. This can occur with cost optimized (α=0) charging as well. Charging an additional vehicle in the WECC NERC region, BA 14 in Eastern Washington State, results in 300 g CO_2/mile, and 440 g CO_2/mile in BA 23 in Northeast Wyoming. As a rule, one should use the smallest area for which data are available and reliable.

Comparing emissions and cost results with α=1 and α=0 weighting can be used to identify regions in which deployment is favorable and emissions reductions are most cost-effective. In Figure 8, Texas and New England remain the least emitting locations to deploy a vehicle, regardless of the optimization weighting. With α=1 weighting, Colorado has similar emissions as much of the Midwest, but accomplishes those emissions at a much higher cost.

Many of the cases presented here are extreme situations: finding the least emitting time to charge, finding the least expensive time to charge, and optimizing times daily. In practice, these objectives will be weighed against operational constraints, such as delivery schedules (Goeke & Schneider, 2015), charging availability, power constraints at the fleet depot (Jahic et al., 2019), driver scheduling, and battery preservation (Schoch et al., 2018), and may be modified by new capabilities such as vehicle to grid services (Zhao et al., 2016) and vehicle automation (Luo et al., 2020). Furthermore, our cost optimization only accounts for the energy used by a single vehicle. A commercial fleet with multiple vehicles may be subject to demand charges based on peak power requirements of the charging depot, in addition to energy consumption charges. Scaling up this model to the fleet level may introduce tradeoffs between charging at times when energy is the least expensive and limiting the peak power consumption of the fleet depot. This would also impact the tradeoffs between private and environmental costs, potentially increasing the cost to charge at low emitting times. However, if some of these operational constraints can be managed, new operating procedures such as nighttime deliveries (charging during the day) can yield significant emissions reductions in many regions.

Even with all of these constraints, there is room for improvement in both cost and emissions simply by avoiding the most costly and highest emitting hours. Critically, this should be done using the most spatially and temporally specific data available for both cost and MEFs. The time-of-day optimization should be done as frequently as is possible, with as wide of a charging window as possible, considering the operational constraints of the fleet. Seasonal, monthly, or weekly optimizations would lower cost and emissions over annually optimizing charge time-of-day, particularly when emissions are weighted heavily in the optimization. This may be accomplished through advances in smart charging (Cheng et al., 2018).

5. CONCLUSIONS

Using predicted MEFs, charge timing can be optimized to meet various operational goals, including emissions reductions and cost reductions. Using data at the BA level allows for greater insight into regional emissions variation and using projected emissions accounts for ongoing grid decarbonization efforts.

Of course, GHG emissions are not the only factor considered when determining optimal deployment locations and charging practices. Other environmental benefits, such as reduced local air pollution and noise pollution should also be considered, which means dense urban areas are prime candidates for deployment. Deploying in locations that are or have been most harmed by local air pollution from diesel vehicles is also an important opportunity for environmental justice (Nguyen & Marshall, 2018). Operating capability is another critical factor. Though an electric van results in lower GHG emissions than its diesel alternative, the advantages of EVs over diesel vehicles are most fully realized in settings with low average speeds and frequent stops and starts, so limiting deployment to settings with those route characteristics is beneficial. Finally, the availability of charging infrastructure, and the capacity of the grid to meet the increased electricity demand also need to be considered.

Optimizing charging timing more frequently can further reduce cost and emissions. Regardless of the optimization weighting or the optimization frequency, the variability of electric vehicle charging emissions in both time and space creates an opportunity for significant reductions in emissions by deployment of vehicles in strategic locations and charging vehicles at specific times. Delivery companies should account for regional variation and expected changes to the grid over time when developing carbon reduction policies and goals. These strategies can work alongside other transportation decarbonization efforts including improving material efficiency (Wolfram et al., 2021) and reducing vehicle miles traveled (Milovanoff et al., 2020). The opportunity for cost and emissions savings is expected to increase over time, as the hourly variation in cost and emissions throughout the day are expected to increase. However, there remain significant tradeoffs between cost and emissions in many regions. Understanding these tradeoffs, as well as improvements in the specificity of emissions data in time and space, will help elucidate the benefits of electrification, yield cost-effective carbon reduction strategies, and accelerate the decarbonization pathways for electric delivery vehicles.

ACKNOWLEDGMENTS

The authors thank the Responsible Battery Coalition (RBC) leadership, partners, and members for their contributions on this project.

FUNDING INFORMATION

This work was supported by the Responsible Battery Coalition (RBC). The findings and views expressed are those of the authors and not necessarily those of the sponsors.

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Figure Legends

Figure 1. Overview of the NREL Cambium model, and the outputs that are used in the vehicle charging model: marginal emissions factors (MEFs) and total marginal cost (TMC)

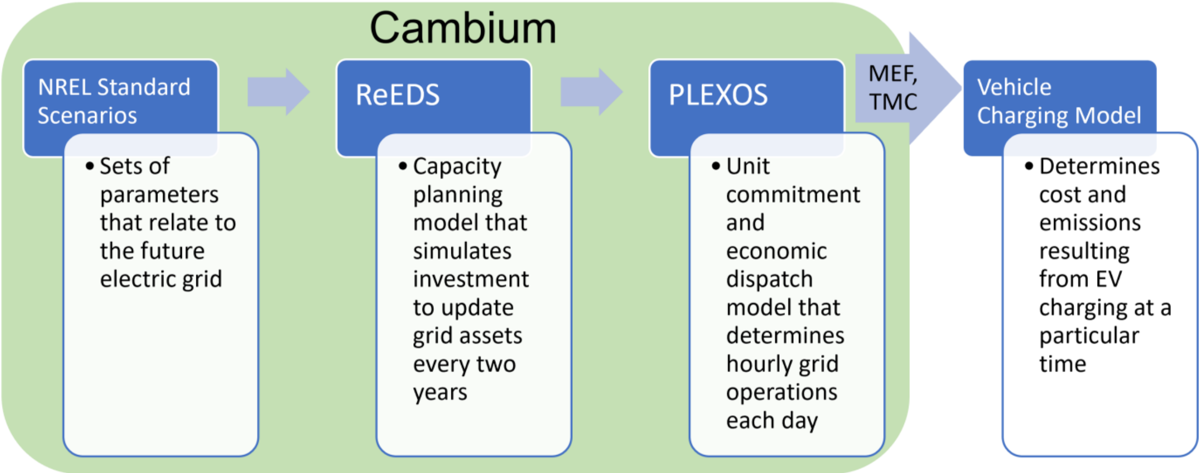

Figure 2. For a representative region and year, a solution space is shown by 24 points representing each potential charging start time, and a Pareto frontier is shown by the filled in points

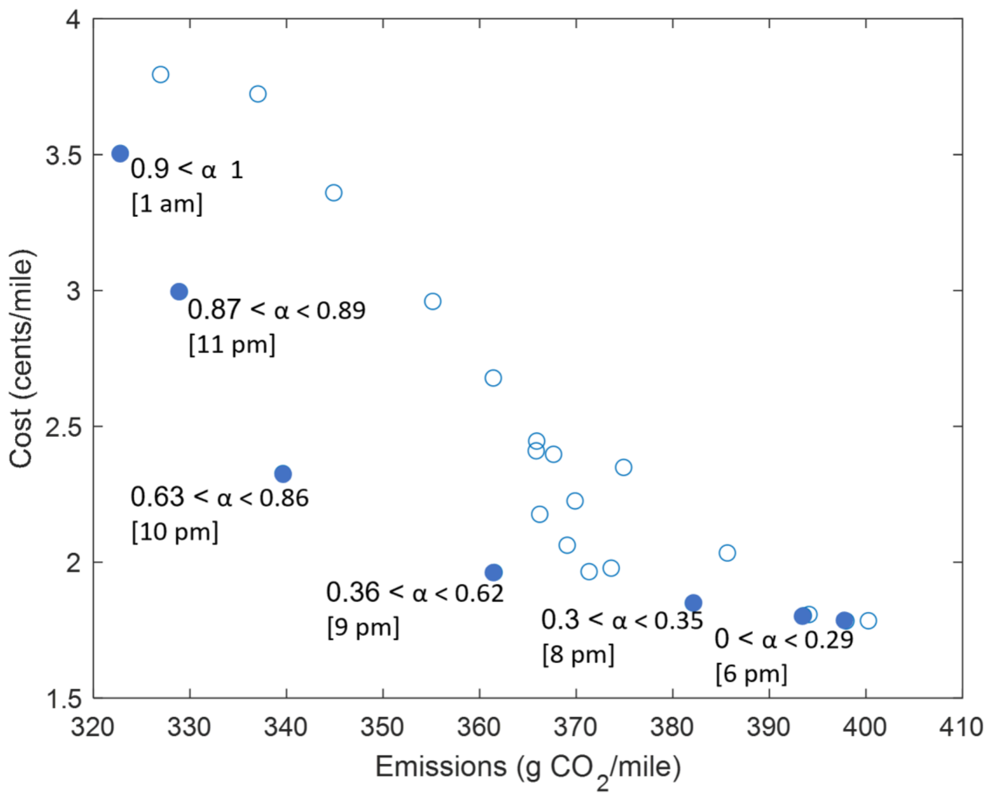

Figure 3. Frequency of annually optimized charging start times from 2020 to 2030 across the 134 balancing areas, yielding 1,340 unique year-balancing authority data points. Optimized by emissions (α = 1) or cost (α = 0). Underlying data available in Supporting Information S5.

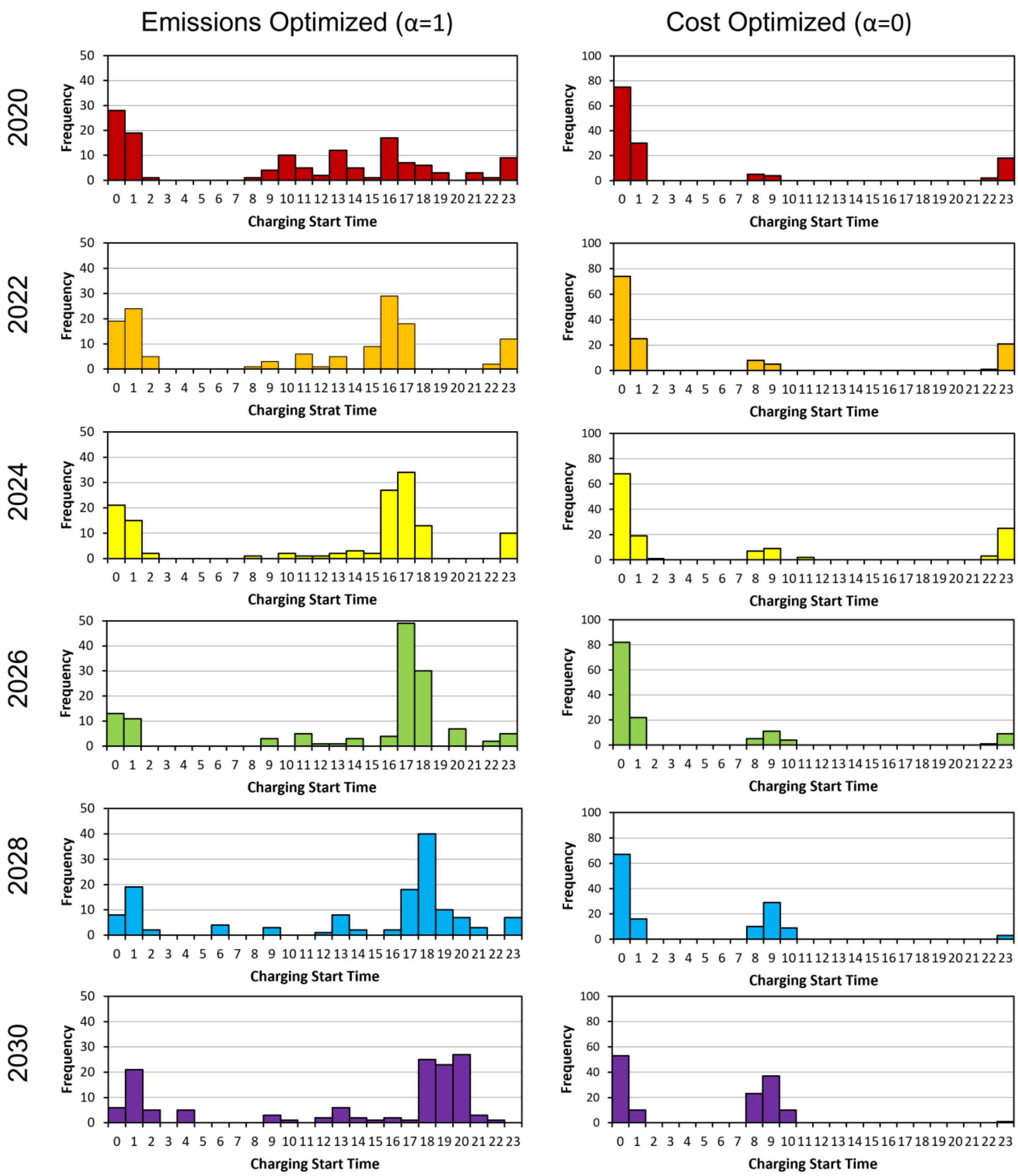

Figure 4. Comparison of emissions and costs of charging for (α=1) and (α=0) weighting in a) all 134 balancing areas and b) the largest 20 balancing areas. Percentage change in emissions and cost for each balancing area with c) and d) emissions optimized (α =1) charging, and e) and f) cost optimized (α =0) charging, when changing the optimization frequency from c) and e) using the 2021 optimized time for the entire decade to the base case of optimizing annually, and d) and f) the base case of optimizing annually to optimizing daily. The size of the point represents the cumulative load (2021-2030) in each region. Underlying data available in Supporting Information S5.

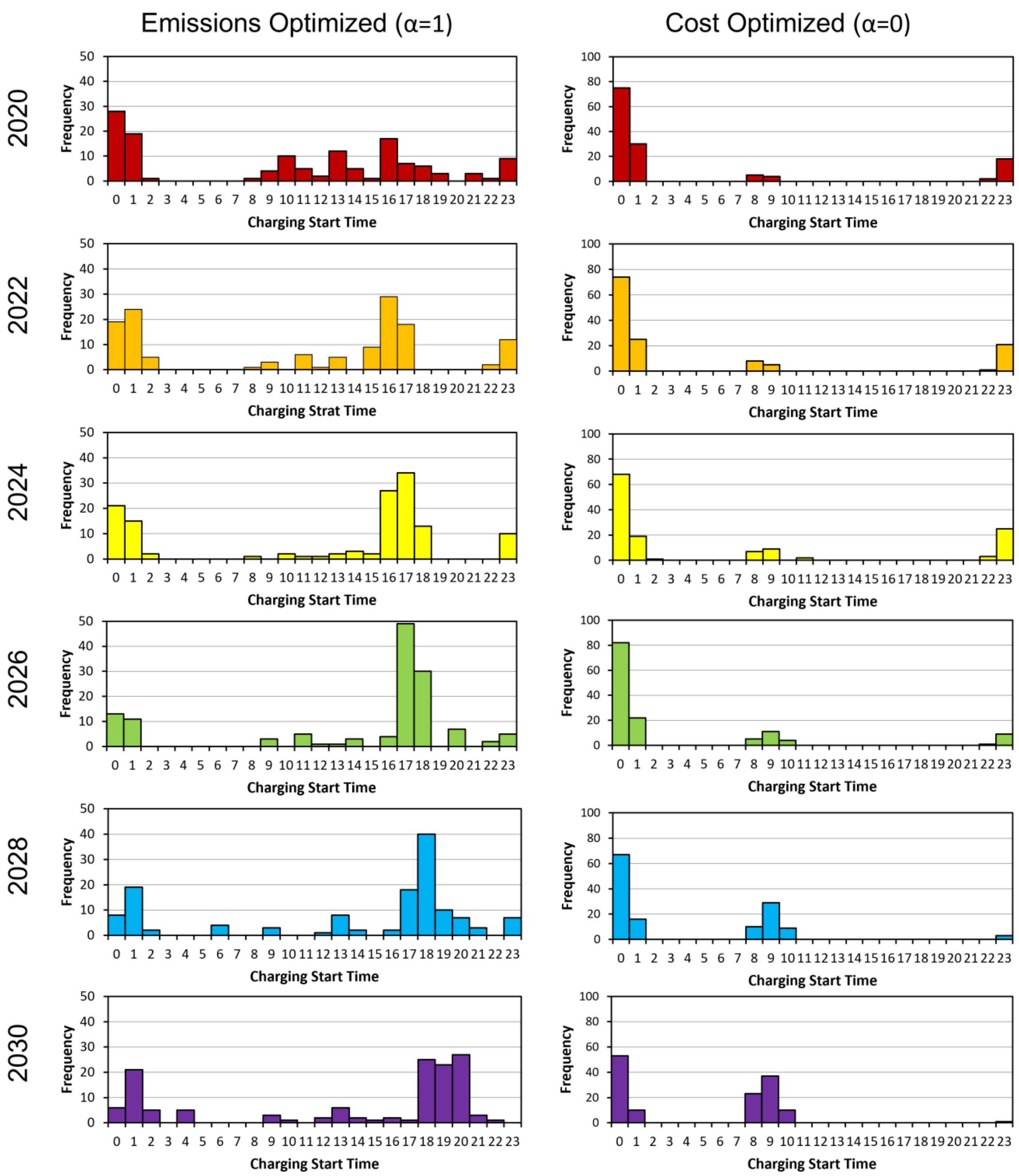

Figure 5. a) Emissions optimized emissions and b) cost optimized cost comparison when charging is allowed at any time (unconstrained charging) and only at nighttime (between 8pm and 8am) for three different optimization frequencies. Demand weighted average across 134 balancing areas. Underlying data available in Supporting Information S5.

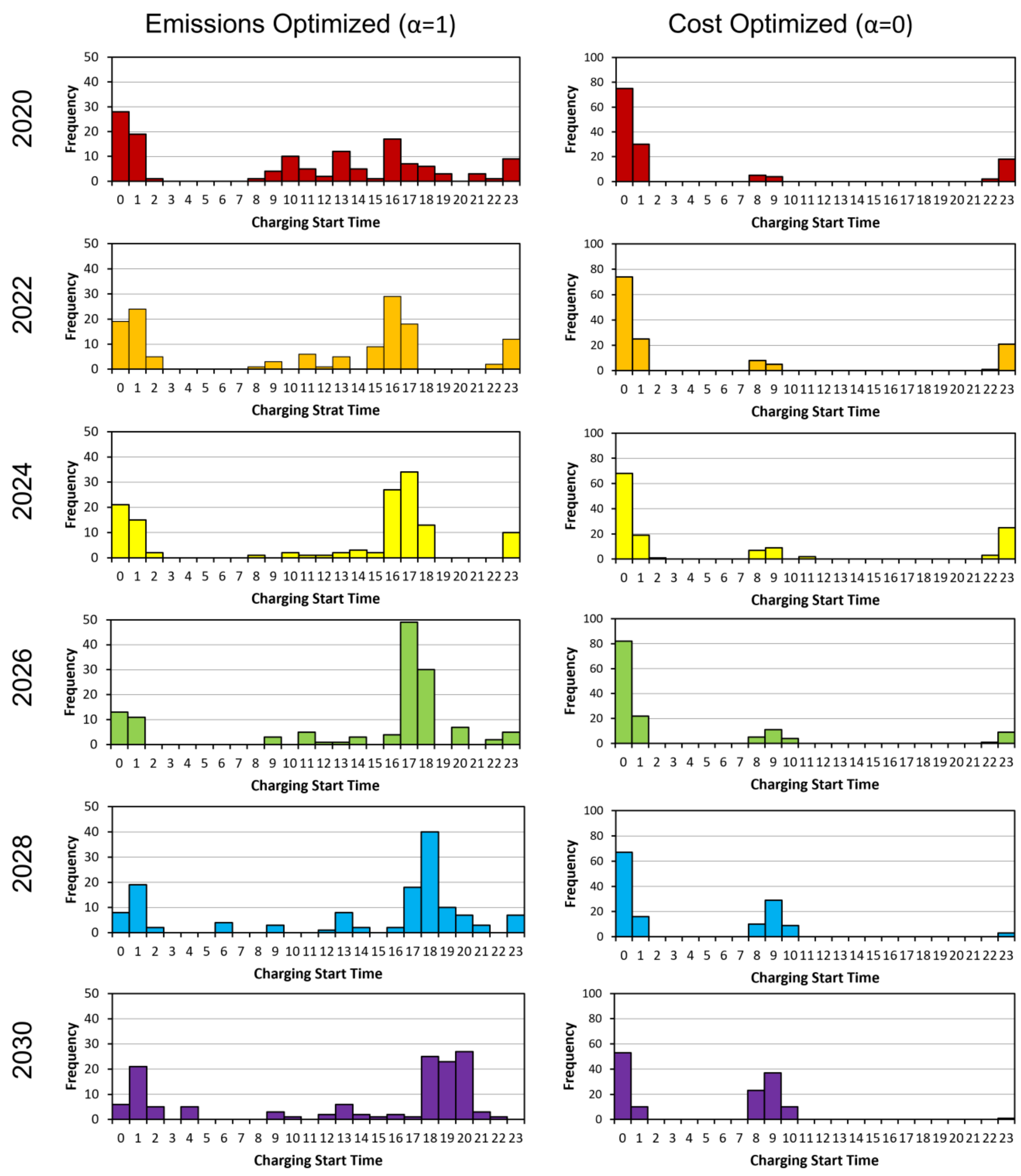

Figure 6. Pareto frontiers for four selected balancing areas from 2020-2030: a) balancing area 58, b) balancing area 101, c) balancing area 103, and d) balancing area 127. Underlying data available in Supporting Information S5.

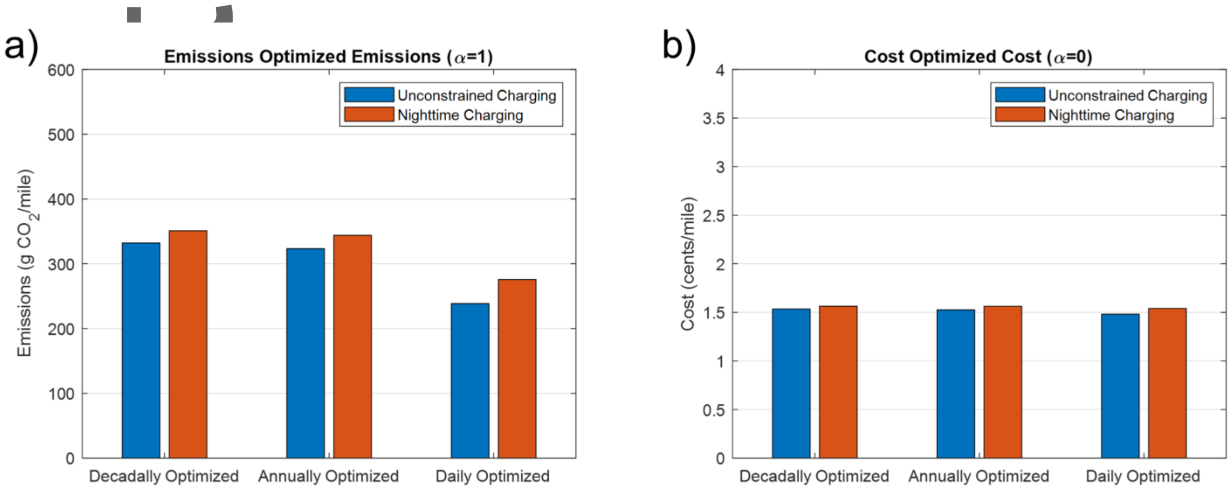

Figure 7. Price of carbon required to shift from cost optimized (α=0) charging times to emissions optimized (α=1) charging times in each balancing area, arranged by cost and proportion of cumulative electricity demand. Underlying data available in Supporting Information S5.

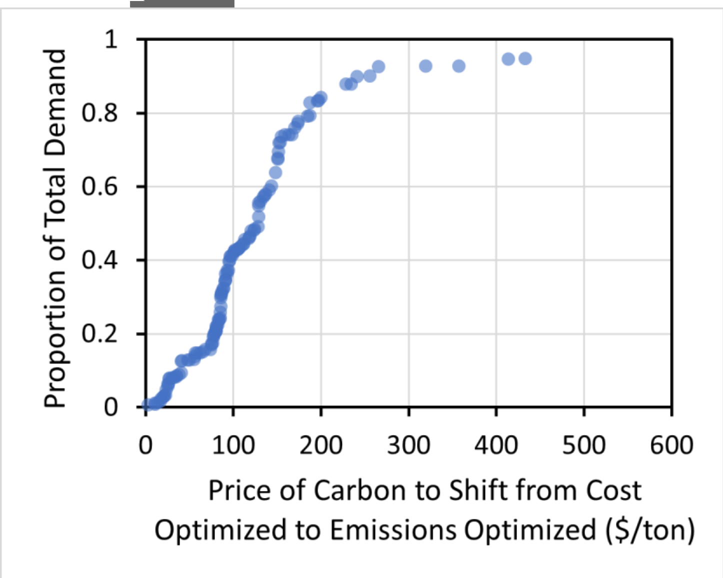

Figure 8. Annually optimized results in each balancing area for a) emissions-optimized emissions, b) emissions-optimized cost, c) cost-optimized emissions, and d) cost-optimized cost. Underlying data available in Supporting Information S5.