# EVALUATE: Electric Vehicle Assessment and Leveraging of Unified models toward AbatemenT of Emissions, Phase II

December 2024

A Research Report from the National Center for Sustainable Transportation

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**16. Abstract**

The EVALUATE (Electric Vehicle Assessment and Leveraging of Unified models toward AbatemenT of Emissions) project (Phases I and II) develops a rigorous methodology involving a high-fidelity system of systems model (i.e., vehicle powertrain, EV charging profiles and grid dispatch datasets) for the purpose of forecasting the emissions outputs of a class of vehicles and use cases. Phase I findings explored urban trips by households that operate light duty vehicles (LDVs) for daily personal use. Phase II, presented here, focuses on a series of targeted case studies that extend prior work from LDVs operated by individuals to service-oriented vehicles operated by small and medium businesses. Vehicles used in the present study are representative of public service fleets including the following: pickup trucks, vans, Medium Duty (MD) delivery vehicles, and refuse trucks. In one of the study's simulations for a MD use case where a specific marginal grid generating resource is identified on an hourly basis as the grid's means of supplying a particular EV charging event, estimated $CO_2$ emissions could be as much as 42% lower than a conventional gasoline vehicle, or as much as 24% higher than a conventional gasoline vehicle. This large variance is purely a function of when and how quickly the vehicle is recharged, and upstream grid factors. This study reveals key insights: (1) Higher temporal resolution is important to develop more accurate estimates of EV $CO_2$ emissions. Along with this, EV charge management is imperative for all use cases, and has profound implications on infrastructure and emissions; (2) Hybrid Electric Vehicles (HEVs) often performed as well as EVs in contemporary simulations on the basis of emissions benefits, suggesting that consideration of an array of vehicle technologies is important; (3) There is a growing need to focus on higher rate EV charging applications (e.g., DCFC), and related implications on grid demands and energy storage, as proxied by large vehicle batteries; and (4) The trend toward increasing electrification of the transportation sector will continue in conjunction with electrification across other sectors (e.g., buildings, data centers, industry). As such, associated cross-sector planning and study of concomitant emissions must be considered in context of other grid trends. Primary contributions of this effort are the development of new methodologies, integration of sub-system models and independent data sources, and decision support tools that estimate the environmental impacts of vehicle electrification. The study's methodologies and use cases can enhance understanding and scale-up in additional EV-grid applications, sectors and regions.

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## Disclaimer



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NCST

# EVALUATE: Electric Vehicle Assessment and Leveraging of Unified models toward AbatemenT of Emissions, Phase II

A National Center for Sustainable Transportation Research Report

December 2024


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# EVALUATE: Electric Vehicle Assessment and Leveraging of Unified models toward AbatemenT of Emissions, Phase II

## EXECUTIVE SUMMARY

Despite substantial progress and proactive policy support, the environmental impacts of electric vehicles (EVs) under the wide range of future deployment scenarios are incompletely understood. In particular, there remain major gaps in our knowledge under future scenarios where EVs demand a double-digit share of available electric power. Under such conditions, marginal $CO_2$ intensity during (off-peak) EV charging times will typically be higher than annual average $CO_2$ rates from the bulk power grid, upon which many current studies base their projections. The NCST EVALUATE (***Electric Vehicle Assessment and Leveraging of Unified models toward AbatemenT of Emissions***) project (Phase I) has explored this risk of diminishing returns and developed a series of tools to evaluate future marginal (i.e., next increment) $CO_2$ intensity in the Southeast U.S. as a function of both season and time-of-day. This modeling capability offers the potential for decision-makers and system operators to explore balanced conditions for intermediate-term EV deployment. That is, to take advantage of excess capacity at low $CO_2$ intensity while avoiding EV charging at times of high marginal emissions. Such a focus can be important in a pending transition period over the coming 5-10 years during which the grid will evolve and EV adoption may increase in ways that necessitate a high-resolution focus on temporal charging needs and concomitant emissions. One over-arching question that this research seeks to address is the extent to which scale-up trends in EV adoption under an array of use cases have been reconciled against this uncertainty around emissions outputs. It is a challenging question because uncertainty in emissions output is driven in part by charging behavior (e.g., when, where, kW rate level, etc.) and partly driven by the state of the grid and, by extension, the pedigree of delivered electricity in space and time (e.g., generation mix, dispatch, demand, rates, and signals).

Key contributions of our Phase I included the development of a rigorous methodology involving a high-fidelity system of systems model (i.e., vehicle powertrain, EV charging profiles, and grid dispatch datasets) for the purpose of forecasting the emissions outputs of a class of vehicles and use cases. The phase I findings were significant and explored light-duty vehicles (LDV), typical urban commuters, and households that operate LDVs for daily personal use. (See Phase I final report for more on the initial study and its key findings; [1]).

Phase II, whose results are presented and discussed here, focuses on a series of targeted case studies that extend prior work from LDVs operated by individuals to service-oriented vehicles operated by small and medium businesses. Vehicles used in the present study as representative public service fleets include the following:

- pickup trucks,
- vans,
- Medium Duty (MD) delivery vehicles, and
- refuse trucks.

To augment the analysis and build upon prior work, additional inquiries were made into the type and capacity of Electric Vehicle Supply Equipment (EVSE) (i.e., EV charging devices) that would be required for these larger vehicles and different use cases (i.e., Level 2 and 3 EVSEs). In conjunction, the research team assessed likely charging behavior that would be typical of small business in the subject categories. Again, the goal has been to better understand how vehicle use case, charging behavior, and assumptions around the grid, with a particular focus on marginal emissions, may affect the relative pros and cons of EVs as a substitute for the incumbent vehicle technology (i.e., gasoline or diesel consuming conventional Internal Combustion Engine Vehicles or Hybrid Electric Vehicles).

A secondary goal of this phase of the effort is to develop guidance and tools to assist stakeholders in understanding the implications of the use case scenarios and the simulation outputs. It is the team's intent that while the subject of this study has been granular and necessarily regional, the final report and findings can be disseminated to other regions with great effect. In addition, technology transfer activities are anticipated to share these NCST-developed tools with practitioners and decision-makers more broadly, so as to maximize the effectiveness of public and private investments in charging infrastructure. The guidance may also provide strategies to businesses seeking to deploy and/or invest in Electric Vehicles, as well as in electric power more broadly.

This convergence research has revealed important findings relative to the comparative emissions impact of vehicle charging during various times of the day. Whereas Phase I findings are valuable to an individual vehicle owner, the findings of Phase 2 are of much greater interest to businesses that operate fleets comprised of light-duty pickup trucks, vans, medium-duty delivery/moving trucks, as well as refuse trucks.

The pros and cons of replacing a conventional ICEV within the context of larger fleet vehicles that are operated by small and medium public or private businesses are similar in nature, but much greater in magnitude when compared to privately owned and operated cars. Interestingly, this has multiple dimensions including economic (i.e., return on investment, payback) as well as environmental (i.e., reduction in $CO_2$, improved air quality). To characterize the differences, the team compares results under five unique emission assumptions, each with its own relevance to the future state of the grid.

As an example, the study investigates rather extreme scenarios wherein a specific generation resource is assumed to be dispatched to meet a specific marginal EV charge. In this case, the "effective emissions rate" of that EV charging session is tied directly to a single generation type (i.e., "Marginal Resource X"). For multiple extreme cases, we observe that $CO_2$ emissions can more than double when charged in the early afternoon compared to an identical charging event during the overnight (i.e., off-peak). This finding suggests that it will be essential to adjust and/or coordinate charging schedules to reduce the environmental impacts of EVs. More specifically, to the extent emissions impacts are prioritized among other objectives, individuals and policymakers should be encouraged or incentivized to charge when marginal emissions are lowest whenever possible. This idea also has important implications for the location, type, and ownership models for tomorrow's charging infrastructure. This not only includes charging equipment, but it also has significant implications on the generation mix, as well as transmission and distribution networks. Translating and operationalizing this type of guidance will require a combination of education, access to rigorous and clear resources, signals between stakeholders (e.g., utilities and consumers), risk management analyses, and behavioral change. In this way, our two studies, taken together can shed light on the critical nature of assumptions involved with serving incremental new electric power demand to charge vehicles.

As in Phase I, this study is aimed at comparative analyses that provide insights into how a marginal assumption for $CO_2$ emissions compares. As before, marginal $CO_2$ assumptions generally yield higher $CO_2$ impacts, sometimes a lot higher, than identical simulations that assume weighted average emissions. This variance is broad, ranging from 46% lower to 24% greater, depending on a host of case-sensitive factors. A key contribution of this effort is to characterize the variance across a range of use cases.

This study manifests the reality that weighted average emissions in the U.S. remain on a declining trajectory due to coal retirements, and the scale-up of combined cycle natural gas plants and renewables. In the Southeast, 2023 is also experiencing the commissioning of new baseload nuclear generation, and Georgia is the only state in the country to add new nuclear since 2000. The overall environmental impact of these trends is favorable. However, EV growth as a demand sector for electric power has mixed outcomes because low carbon baseload (e.g., nuclear) will be consumed by current demand sectors, and renewables are generally considered non-dispatchable. As such, grid operators will generally deploy flexible generating resources to meet incremental loads like EVs.

The study has characterized the ***magnitude*** and the ***range*** of possible emissions impacts as compared to multiple baselines (i.e., for several targeted MD fleet segments and for the grid mix). A clear message that emerges is that decision-makers must avail themselves of better foresight and informed decision-making on near-term and longer-term timescales. More comprehensive awareness of vehicle use cases, and energy needs in time and space will help small businesses and utilities predict and plan for EV charging events. This research suggests that when marginal emissions can be at or below the weighted average values, environmental benefits stand to be greater.

A unique attribute of this study compared to prior efforts (including Phase I) is that its scope speaks more directly to small business owners and vehicle fleet operators. These stakeholder groups and their associated applications are known to realize a few advantages in comparison with individual vehicle owners driving LDVs. The reason is that the selected categories of service vehicles largely return to a central base and navigate similar, standardized routes on a recurring basis. They also travel sufficient but not overly excessive distances: a factor that may help approach the Goldilocks state. Finally, and perhaps not coincidentally, this audience seems to be targeted by automakers of late, given a limited growing number of new EV models entering the market.

Certain tax incentives are more flexible for small businesses than they are for personal vehicles [2]. Though both LDV and MD use cases have societal implications involving decisions around the generation mix and utility infrastructure, it is the potential to leverage an EV to save money that could pull the technology quickly ahead and spur scale up in other vehicle sectors.

The study has implications for policy and public investment, including an even more urgent need for managed and coordinated charging, and greater attention to resource planning. This is especially relevant for infrastructure funding, for which the Federal Government has deployed upwards of $7.5B to states and set a goal to realize 500,000 chargers by the year 2030 [3]. The report concludes with a few suggestions for future work, including the need to leverage this methodology to quantify the monetized value of $CO_2$ emissions in conjunction with other investment costs for capital and operations. Finally, the research team believes the model has relevance and can be scaled and adapted for conducting similar analyses in other regions.

Finally, this study has revealed four key insights relating to implications on policy and future work.

- EV charge management is imperative for all use cases, and has profound implications on infrastructure and emissions;
- Hybrid Electric Vehicles (HEVs) offer some compelling performance and emissions benefits, suggesting that decision-makers should explore a diverse range of vehicle types, use cases and multiple competing transportation solutions in overall assessments;
- Technologies that offer temporal flexibility to decouple the time at which electric power generation occurs and the time at which EV charging occurs may help maximize the environmental benefits of EVs. Though beyond the scope of this particular study, the authors suggest that battery storage (i.e., in many forms, including station storage for the grid and vehicle to grid concepts), may help reduce the carbon footprint of the grid in general, and EV charging by extension;
- The trend toward increasing electrification of the transportation sector will continue in conjunction with electrification across other sectors (e.g., buildings, data centers, and industry). As such associated cross-sector planning and study of concomitant emissions must be considered in context of other grid trends.

In short, it is imperative to not only manage EV charging events in time and space, but also consider our latitude to control or influence other large loads on the grid in conjunction with EV deployment growth. This study reveals that several Medium and Heavy-Duty EV use cases can offer significant benefits, but also makes it clear that decisions around charging operations, infrastructure and grid support must be conducted at a system level that considers vehicles, their use cases, as well as the temporal nature of grid generation. In this way, the electrification of transportation is more likely to result in measurable decarbonization gains, substantive environmental and health benefits, and reasonable returns on investment.

# 1.0 Introduction and Research Background

Vehicle electrification not only continues to garner momentum, but also public and private funding, and is considered a viable means of growing the national economy and decarbonizing major segments of the transportation sector. A growing body of evidence demonstrates that substitution of gasoline-consuming vehicles with electrified alternatives eliminates tailpipe emissions contributing to reductions in $CO_2$ emissions as well as in criteria pollutants. Whereas $CO_2$ reductions can favorably affect global climate change trends, pollutant emissions reductions can improve urban air quality on a more local scale, and by extension improve public health [4-7].

A key advantage of Electric Vehicles (EVs) compared to internal combustion engine vehicles (ICEVs) is that their carbon and emissions footprint is not fixed based on the vehicle technology from a given past model year, but instead can progressively improve in lock step with a grid that is evolving toward a cleaner and lower carbon generating mix.

Driven in part by policy, declining prices, and product availability, EV deployments are accelerating, having surpassed 2,000,000 vehicles sold in the U.S. fleet by Dec 2022 [8]. Though EVs still account for less than 1% of the domestic vehicle fleet, the growth is definitely accelerating. Projections for continued EV growth through the present "second decade" (i.e., 2020-2030) of mass deployment are varied, and uncertainty is a factor for both capital costs and energy costs. Still, many sources suggest sustained growth approaching double digit shares of the fleet by 2030.

EVs are increasingly seen as a win-win solution by many policymakers, in that they can provide benefits to consumers, automakers, and utilities, while also reducing environmental impacts. In spite of substantial progress and aggressive policy support, non-trivial barriers remain. These barriers may simultaneously threaten both broader adoption and certain beneficial outcomes of EV growth. Among one the most critical and poorly understood, is the need to ensure environmental benefits live up to their promise as deployments exceed 10% of the future fleet. This seems to be a kind of threshold of market penetration beyond which grid capacity, resource adequacy, broader electrification, levelized energy costs, and decarbonization may be challenged.

While much public attention is focused on light duty vehicle markets (including private party use, service-oriented use and fleets), significant opportunities are believed to exist in Medium Duty (e.g., courier, public transit, school busses) and certain Heavy Duty (e.g., intra-state or regional) applications [9]. For this reason, the EVALUATE research team has conducted a two-year, two-phase research investigation focused on methodologies and applications across major Light Duty and Medium Duty vehicle classifications.

Key contributions of our Phase I included the development of a rigorous methodology involving a high-fidelity system of systems model. This included a sub-system model for vehicle powertrains which provide accurate estimates of energy consumption for representative driving cycles. Additionally, it included a literature review, survey data, observed experimental data, and a protocol to inform EV charging profiles. And finally, it included a series of datasets and procedures developed to understand how electric power is dispatched and delivered at the bulk grid level. More specifically, it generated a high-resolution characterization of the emission rates associated with electric power generation on an hourly, daily, seasonal, and annual basis. While studies have explored each of these sub-systems independently, the research team has been among the first to develop them in an integrated manner to forecast the emissions outputs of a class of vehicles and a range of use cases. The phase I findings were significant and explored light-duty vehicles (LDV) through typical urban commuters and households that operate LDVs for daily personal use. [See Phase I final report for more on the initial study and its key findings, 1].

## 1.1 Motivation and scope

The over-arching goal of the EVALUATE project has been to ensure that reductions in $CO_2$ and pollutant emissions are more fully understood, and that decision-makers have guidance and tools to help realize them. The research team believes this will be imperative as EV market penetration scales up (e.g., for example from 2,000,000 vehicles to estimates of more than 30,000,000 through 2030).

To achieve this goal, Phase I of this project developed a system of integrated vehicle, transportation, and electric power system models designed to evaluate hourly marginal (i.e., next increment) $CO_2$ emissions rates for a regional study (i.e., Georgia) under various demand scenarios between now and 2030. As noted, the focus was on personal vehicles in the light-duty category.

Phase II of this project, presented here, demonstrates the usefulness of these tools in providing policy-relevant information to practitioners and decision-makers. As such, we focus on a series of targeted case studies that extend prior work from LDVs operated by individuals to service-oriented vehicles operated by small and medium businesses. Vehicles used in the present study as representative public service fleets include the following:

- pickup trucks,
- vans,
- Medium Duty (MD) delivery vehicles, and
- refuse trucks.

To augment the analysis and build upon prior work, additional inquiries were made into the type and capacity of EV charging devices (a.k.a. Electric Vehicle Supply Equipment or EVSE) that would be required for these larger vehicles and different use cases. For instance, Phase II has focused more extensively on medium rate and fast charging methods[1]. In conjunction, the research team assessed likely charging behavior that would be typical of small businesses in the

[1] i.e., Level 2 EVSE (which charge at a rate of about 3-19kW, and typically about 8kW) and Level 3 EVSE, which are also known as “DC Fasting Chargers” (which are greater than 20kW, can be as high as 400kW, and are often about 50kW)

subject categories. Again, the goal has been to better understand how vehicle use case, charging behavior, and assumptions around the grid, with a particular focus on marginal emissions, may affect the environmental impacts and other relative pros and cons of EVs as a substitute for the incumbent vehicle technology (i.e., gasoline or diesel consuming conventional Internal Combustion Engine Vehicles or Hybrid Electric Vehicles).

The selected scenarios and simulated outputs are based upon a series of case studies in the Atlanta, Georgia metropolitan area using local assumptions along with historical and projected grid data for Georgia Power and the Southern Company balancing authority. These case studies evaluate the influence of vehicle classification, usage, and charging strategies for EVs in both light-duty vehicles (e.g., pickup trucks and vans) and medium-duty trucks (e.g., class 3-6 delivery trucks, moving trucks, and refuse trucks). All case studies explore the relationship between the selected scenarios and the resulting carbon intensity of marginal electrical power generation. This investigation provides an important theoretical contribution to our overall understanding of vehicle electrification for intermediate market penetration rates. Equally important, the study demonstrates the ability of the EVALUATE modeling system to produce practical policy-relevant findings that are valuable to stakeholders that relate to our selected scenarios, the Southeast region, and more broadly.

This research is uniquely positioned to address critical gaps and inform strategic decisions that will be economically viable and favorably advance EVs, sustainable transportation solutions, and their concomitant policies. This research identified representative use cases that included Light and Medium Duty return-to-base fleets. Prior to the present study, the research team oversaw a Georgia Tech student-led effort that conducted a preliminary techno-economic investigation into residential service vehicles such as those used by HVAC, exterminator, plumbing, and landscaping personnel, with some high-level economic indicators depicted in Fig 1-1 [10]. To this, the current research team added new business-related scenarios including e-commerce, package delivery vehicles, moving trucks, and refuse trucks. In the present study, the team applies the marginal emissions methodology (that it developed in phase I) to these expanded use cases, to further demonstrate how the methodology can be applied, and yield some illustrative insights for several discrete vehicle categories and use case scenarios. Finally, the study provides guidance that can inform how decision-makers can optimize effectiveness and cost based on the team's approach (e.g., marginal emissions tools, expanded set of use cases, and insights).

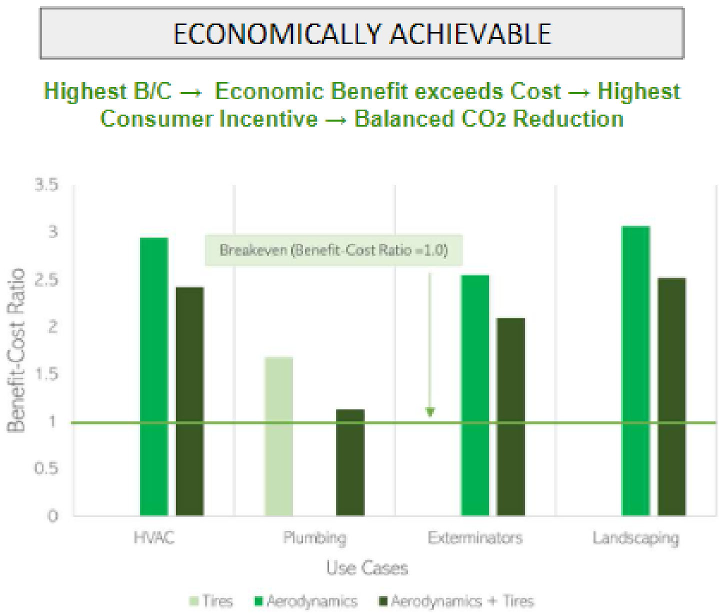


**Figure 1-1. B/C ratios for selected use cases in GA [10].**

## 2.0 Methodology

This research requires the synthesis of three independent sub-system models and data developed or identified by the research team in the areas of (a) vehicle propulsion and auxiliary power and energy need to satisfy prescribed trip/travel demands for a range of vehicle technologies and applications, (b) EV charging profiles that would be considered typical for the service, fleet and medium duty vehicle use cases, and (c) grid generation dispatch with commensurate consideration of emissions intensities for $CO_2$ and major criteria pollutants. The team has extensive experience developing high-fidelity sub-system models and applying them to both generalizable and regional scenarios. As an input to the two phases of the EVALUATE project, the team drew upon more than three years of prior efforts acquiring and conditioning open-source data, alternative vehicle architectures, customized datasets for regional electric power dispatch (e.g., 2018, 2023, and 2030), and numerous travel route pathways. Under the EVALUATE project, the team deepened its experience by integrating several of these sub-system resources into a holistic picture of emissions by vehicle type and use case. The scope of the second phase of this project has been to update and develop new, more accurate sub-system models and datasets that are granular and of specific relevance to service fleets and medium-duty vehicle operators. The end result of the two phases, therefore, is a set of integrated models built upon high-fidelity data from real-world use cases that generate a range of simulations. Throughout the EVALUATE project, the simulations are generated primarily to draw comparisons, understand the impact of fundamental assumptions around charging behavior and grid emissions, and develop initial guidance around the relative merits of EVs under representative use cases. The use of these tools to guide private sector fleets and medium-duty vehicle operators can be timely since few high-fidelity emissions calculators are available to accompany proprietary economic assessment tools.

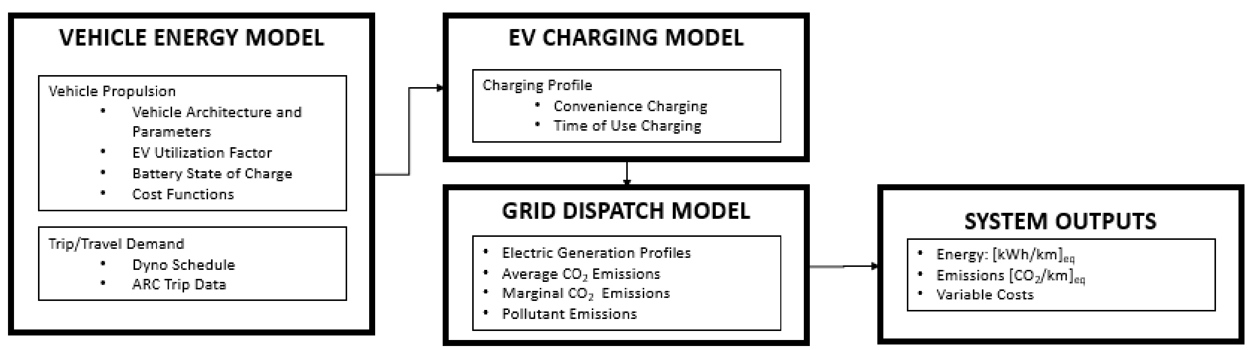


**Figure 2-1. General modeling methodology for integrating vehicle, charging, and grid parameters for comparative emissions analyses.**

The team's methodology was developed in Phase I and expanded in Phase II for the purpose of investigating a broader set of vehicles and charging profiles that typify urban service fleet and medium-duty delivery applications. A brief recap of the major steps in the analysis is presented here. First, physics-based vehicle energy consumption models are developed which facilitate comparisons among vehicle architectures that utilize energy from disparate primary sources (e.g., gasoline vs. grid electricity). As noted, the Phase II effort extended the modeling from light-duty cars used for personal use, to light-duty pickup trucks and vans used for service-oriented businesses. Additional models were derived and corroborated against background data to characterize medium-duty delivery trucks (e.g., Class 3-6 Package Delivery vehicles) and a heavy-duty urban application (i.e., refuse trucks). A related task involved the identification of driving cycles that approximate typical routes traveled by the associated vehicles. Together, the route data and powertrain models determine the energy consumption in each simulation. Our methodology affords access to established data and extends prior vehicle propulsion energy and emissions analyses [1, 11-14]. In Phase I of the EVALUATE project, the team utilized a 5-cycle EPA dyno schedule and fuel economy label weighting protocol and has continued to do so for the two light-duty vehicles investigated herein (i.e., pickup truck, and van) [1]. In addition, owing to the larger classes investigated in the present study, Phase II has also called for independently derived travel demands and data from the literature for representative use cases. For more details on the theory, model development, source data, and applications, please refer to [1, 14].

## 2.1 Vehicle technology categories

As discussed, we developed physics-based powertrain models developed in [1, 14] to accommodate target vehicle technologies of interest. In each vehicle category, we established characteristics for the baseline vehicles (e.g., gasoline-consuming ICEV and HEV). We then proceeded to develop an electrified powertrain model for each vehicle category. To facilitate a direct comparison among vehicles using dissimilar energy sources, we identify vehicle specifications for a given vehicle classification and hold constant key parameters such as vehicle power output, capacity to sustain the required torque and speed, vehicle footprint, passenger and cargo capacity, auxiliary power requirements, and so forth. Table 2-1 below depicts some of these operative specs. In developing our model and conducting simulations, we have made every effort to represent real-world vehicle characteristics across the categories of interest. For example, when an electrified variant has a greater gross vehicle weight than a comparable internal combustion vehicle within its class, we reflect that vehicle weight difference in the analysis. This is especially important at larger vehicle classes because EVs in these classes have proportionately heavier batteries, which then incur additional energy consumption. In this way, we provide simulated comparisons based on actual vehicles in the marketplace.

**Table 2-1. Overview of vehicle classes and use cases compared in the study.**

| Description | Vehicle Class | Application | Approximate Gross Vehicle Weight Range |
|---|---|---|---|
| **Pickup Truck** | Light Duty Truck | Urban Service Fleet | < 6,000 lbs |
| **Cargo Van** | Light Duty Truck | Service Vehicle or Courier | < 8,500 lbs |
| **Moving Truck** | Class 3-6 Medium Duty Truck | Delivery Truck<br>Moving Truck | 10,000 – 30,000 lbs |
| **Refuse Truck** | Class 8 Heavy Duty Truck | Refuse Collection/Disposal | 30,000 – 60,000 lbs |

## 2.2 Driving cycles

Five distinct driving cycles comprise EPA test and labeling protocols for light-duty passenger cars and pickup trucks [15]. The three 23°C (75°F) tests include a derivative of the Urban Dynamometer Driving Schedule (UDDS) known as the Federal Test Protocol (FTP), the high-acceleration aggressive driving schedule identified as the Supplemental FTP (US06), and the Highway Fuel Economy Driving Schedule (HWFET). The 35°C drive cycle is the Air Conditioning Supplemental FTP driving schedule referred to as SC03. The -7°C cold weather test schedule repeats the original FTP at the reduced temperature.

For the light-duty pickup and cargo van investigated in the study, we have adopted the EPA "5-cycle" protocol and created an approach whereby a weighted mix of driving schedules is obtained to approximate major modes (e.g., city, highway, combined). (Please see Phase I report Appendix A for more detail about the weighting of the constituent driving cycles, and the governing formulae.)

With the original development of the vehicle architecture models, and assumptions around the weighted driving cycle protocols, the team's next step was to develop a MATLAB/Simulink code that generated a series of energy consumption values based on inputs of vehicle type and driving cycle. These intermediate outputs were then combined to generate effective fuel economy values, analogous to the EPA 5-cycle approach, for the stipulated categories (city, highway, combined). This was done and a set of energy consumption outputs were generated. Using the example of the light-duty pickup truck and van, representative outputs are depicted in Table 2-2 and Table 2-3.

**Table 2-2. Effective fuel economy values for light-duty pickup truck in this study.**

| | ICEV (mpg) | HEV (mpg) | EV (kWh/mi) |
|---|---|---|---|
| **City** | 17.5 | 25.0 | 0.466 |
| **Highway** | 24.0 | 25.5 | 0.557 |
| **Combined (Wts: 0.43 city, 0.57 highway)** | 20.7 | 25.3 | 0.512 |

**Table 2-3. Effective fuel economy values for light-duty van in this study.**

| | ICEV-4Cyl (mpg) | ICEV-6cyl (mpg) | EV (kWh/mi) |
|---|---|---|---|
| **City** | 20.0 | 15.0 | 0.403 |
| **Highway** | 26.0 | 19.0 | 0.500 |
| **Combined (Wts: 0.43 city, 0.57 highway)** | 22.0 | 17.0 | 0.458 |

For the medium-duty and heavy-duty vehicles investigated in the study, we have used a combination of energy consumption data from literature with physics-based models whose characteristics are obtained from published vehicle specs and the literature. Attention has been paid to driving cycles that are most appropriate for the target vehicle and application. For instance, we have utilized a set of urban driving routes for medium-duty trucks (e.g., Courier Delivery), and we have utilized a series of real-world experimental data obtained from the literature for Heavy Duty Refuse Truck routes and schedules. The result is an additional set of comparative energy indices across the larger vehicle classes as shown in Table 2-4 and Table 2-5.

**Table 2-4. Effective fuel economy values for medium-duty moving trucks (Class 4-5) in this study.**

| | ICEV (mpg) | HEV (mpg) | EV (kWh/mi) |
|---|---|---|---|
| **Real-world MPG** | 8.7 | 10.0 | 1.00 |

**Table 2-5. Effective fuel economy values for heavy-duty refuse truck (Class 6-8) in this study.**

| | ICEV (mpg) | HEV (mpg) | EV (kWh/mi) |
|---|---|---|---|
| **Real-world MPG** | 3.0 | 3.3 | 3.0 |

## 2.3 Mapping to representative driving schedules

The next step was to define representative driving schedules for a range of small business and fleet needs serving a large urban area, such as metro Atlanta. For the light-duty pickup and van, we follow the approach used in Phase I, where we select two urban commutes of 80.5 km (50 miles) and 32.2 (20 miles) and a suburban vehicle use case of 48.2 km (30 mi). For urban commutes, presumably into and out of a city like Atlanta, it is reasonable to employ the EPA "combined" rating and protocol to determine energy consumption for these trips. For the suburban errand use case, it is reasonable to employ the EPA "city" rating and protocol. This is summarized in Table 2-6 below. Shown in Figure 2-2 is a notional depiction of a baseline vehicle's instantaneous power and cumulative energy for an example drive cycle. Figure 2-3 depicts a few of the standardized EPA dyno schedules that are fed into a 5-cycle weighting determination.

**Table 2-6. Representative daily driving routines were developed for the comparative scenario analysis.**

| Commute Description | Total Daily Distance Traveled km (Miles) | Relevant EPA fuel economy category/calculation used |
|---|---|---|
| **Inter-city transit** | 161 (100) | "Highway" |
| **Urban Service (moderate)** | 80.5 (50) | "Combined" |
| **Urban Service (short)** | 32.2 (20) | "Combined" |
| **Urban Service (nominal)** | 48.3 (30) | "City" |

While EPA protocols have been applied for LDV cars, pickups, and vans, we have relied upon a combination of physical models and the literature to define driving schedules for moving trucks and refuse trucks. [15-22]. Section 2.4 provides a more comprehensive discussion of the driving schedules assumed in this study for the moving trucks and refuse trucks. In short, we have relied upon experimental field data, as reported in peer-reviewed literature. We have also corroborated these observations against our physics-based models, in areas such as weight, aerodynamic drag coefficient, frontal area, and rolling resistance.

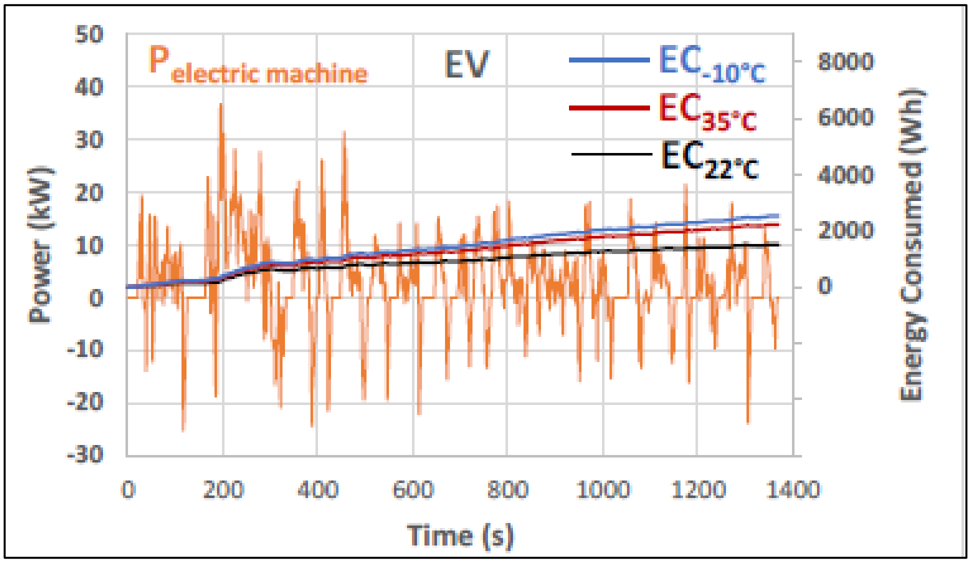


**Figure 2-2. Example power and energy consumption output of fundamental powertrain model for a LDV EV architecture [22].**

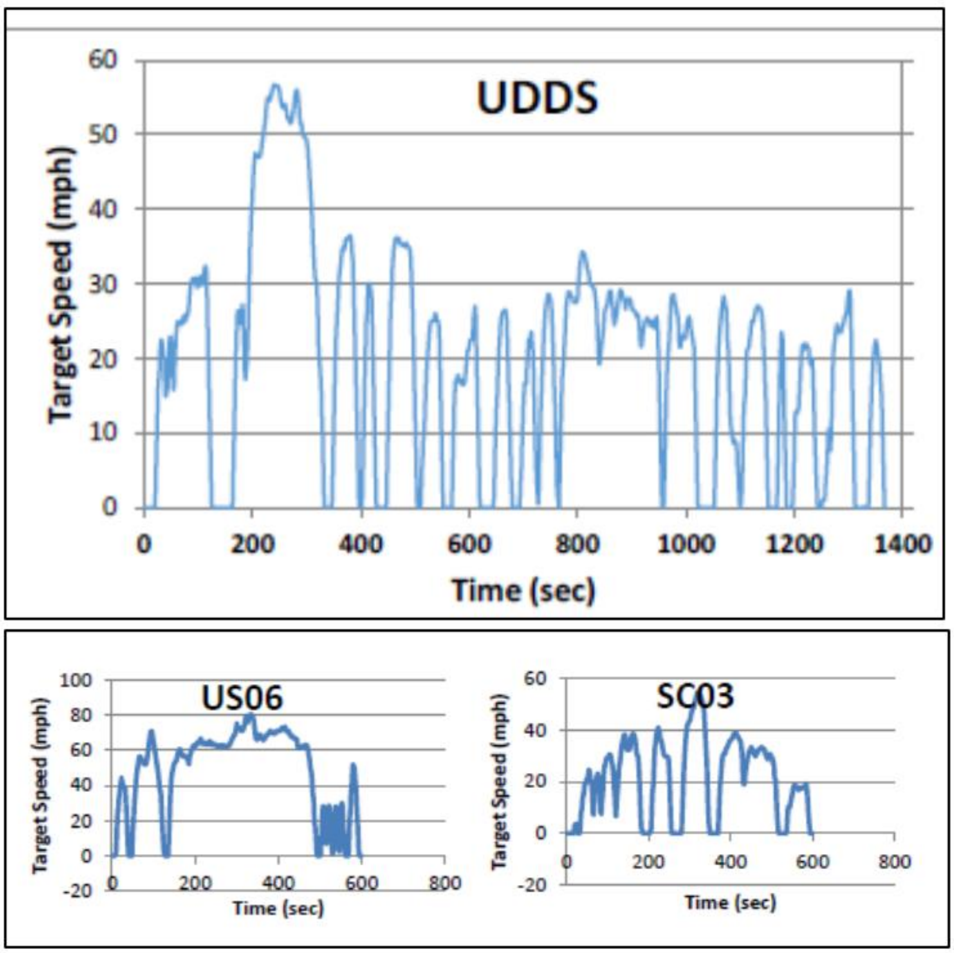


**Figure 2-3. Basic EPA dyno schedules as used in the light-duty model simulation.**

It is notable that for the medium-duty and heavy-duty cases studied in Phase II, both have the characteristic that the empty and full vehicle weight could be substantially different. This differentiates them from the LDV truck and van case, which are expected to remain within a narrow band for weight, whether empty or full. More on this can be found in [1]. This point is therefore reflected in the analysis, whereby a refuse truck gains significant payload throughout its route, and a Class 4 Moving Truck can carry cargo weight on par with the net vehicle weight.

## 2.4 Commercial EV charging profile development and simplified representative use cases

Constructing representative charging profiles for commercial fleet EVs is a distinct and, in many ways, a simpler exercise than doing the same for personal EVs. In our Phase I report, we consulted four primary data sources to explore observed charging behavior for personal EVs from which we manufactured representative charging profiles: a synthetic dataset generated by a separate Georgia Tech research team evaluating the benefits and challenges of smart charging algorithms [23-24]; the Georgia Power Electric Vehicle Rate scheme [25]; a ChargePoint dashboard portal and database that has been aggregated for workplace charging on the Georgia Tech campus since 2015; and a verbal consultation with Escalent, a third party research firm [26]. These independent data sources were corroborated and used to develop four representative charging profiles for personal EV charging events. The obvious difference between charging behavior for personal EVs and commercial EVs is the shift in emphasis from convenience charging (that is, plugging in the vehicle to charge when a public charger is open in a convenient location at reasonable prices or, most commonly, at the owner's home at the end of the day) to charging schedules constrained more severely in space and time by the demands of business. Fleet vehicles have operational obligations that must be fulfilled punctually and reliably. Commercial EV charging behavior is therefore primarily a function of business characteristics.

To develop charging profiles for commercial EVs, we envisioned conceivable business use cases for each vehicle type included in Phase II (light truck, van, moving truck, and refuse truck). In order to improve our understanding of daily vehicle usage for these vehicle-application combinations, we reviewed U.S. national vehicle miles traveled (VMT) data from the Vehicle Inventory and Use Survey [27]. This revealed that daily VMT for LDV are less than 50 miles about 82% of the time, and less than 100 miles about 93% of the time. Similarly, daily VMT for MD in the class 3-6 range are less than 50 miles 68% of the time, and less than 100 miles about 84% of the time. Such empirical data was useful in developing realistic daily driving demands that are explored in this study. Light trucks and vans may most typically be deployed by residential service businesses such as lawn care, and pest control or by electricians and plumbers. It is assumed that the on-road driving cycles (and thereby per-distance energy consumption) for these vocations are somewhat similar. As such, these business use cases were clustered into a representative category labeled "Residential Home Services." Representative driving cycles were then used to calculate the combined energy consumption rates of light trucks and vans belonging to residential service fleets, as described in the previous section. Similarly, we reasoned local moving trucks would have a fairly consistent mixture of on-road driving cycles and produced a combined energy consumption rate for a composite medium-duty truck, as described in the previous section. We then used a distribution of vehicle miles traveled (VMT) (20, 30, 50, and 100 miles per day) to calculate a series of cumulative energy consumption totals comparable to a diverse variety of business operations and scales. Modeled VMT figures were determined to be reasonable assumptions based on real-world operational data for service vans from NREL's FLEET DNA, which publishes 29 days of dynamometer driving data from four service vans in operation in the United States as shown in Figure 2-4 [28].

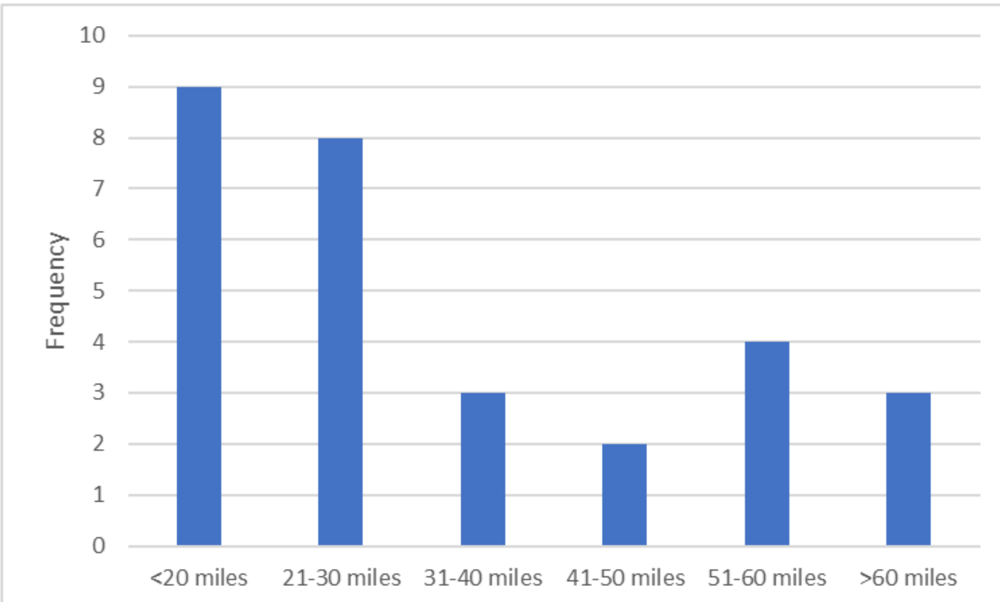


**Figure 2-4. Distribution of daily VMT for service vehicles [28].**

A similar approach was employed for refuse trucks. Driving cycles for refuse trucks are less variable than for other vehicles, but distances traveled might vary more depending on service area and distance to the landfill and are generally greater. We used higher vehicle miles traveled numbers (50, 75, and 100 miles per day) for the calculation of total cumulative energy consumption for refuse trucks.

It is in the nature of the businesses described by each use case that the vast majority of on-road activity occurs at predictable, well-defined times. From experience, "business hours" for residential home service businesses are very likely always during the day, between around 8 AM to 6 PM. This is similarly true for moving businesses, although with perhaps slightly less consistency to accommodate the occasional client requiring moving services outside of typical hours due to scheduling conflicts or other miscellaneous logistical reasons. Refuse truck service is even more regular, with well-defined service schedules and routes. Regardless, if business activity always or most often occurs during certain segments of the day, it leaves fewer segments of the day available for charging events. In terms of charging location, we reasoned further that most businesses with EV fleets would have two options for where to charge their vehicles: at the business home base or at a public EV charging station in the field.

It was under these assumptions that five commercial EV charging profiles were developed. Three charging profiles are representative of a business that charges their EVs at their business' "home base," some central garage, parking lot, or depot where vehicles return at the end of each day and domicile overnight, with each of the three profiles having a different "after-hours" start time for the charging event (5 PM, 8 PM, and 1 AM). Two charging profiles are representative of a business that charges vehicles during the workday using charging equipment in the field (starting at noon and 3 PM). To facilitate comparisons, we designed the charging profiles and only reported simulated outputs if the EV battery was recharged to 100%. The charging profiles were constructed using both Level 2 (8 kWh) and Level 3 (50 kWh) charging systems. We assumed businesses would tend to opt for the lowest charging level that fulfills charging demand within the time constraints of the business' activity. For the main batch of simulations, Level 2 charging systems were used for light trucks and vans, and Level 3 charging systems were used for moving and refuse trucks. Level 2 was sufficient to completely recharge the batteries of light trucks and vans using every charging profile at all VMT levels, except for field charging starting at 3 PM at 50 and 100 miles traveled per day. Level 3 was sufficient to completely recharge the batteries in every scenario. The Level 2 charging profiles are shown in Figure 2-5 as examples, with on-times of 5PM, 8PM, 1AM for the charging that occurs at the location of the "Business," and on-times of 12PM and 3PM for charging that occurs at locations in the "Field," respectively. Please note that the time axis has been shifted with a start at 8AM to accommodate charging cycles that extend past midnight on a given day.

The five charging profiles using Level 2 and Level 3 charging systems, four or three VMT levels depending on the use case, and four vehicle types enable the very broad applicability of our simulations and findings to many different business operations and scales.

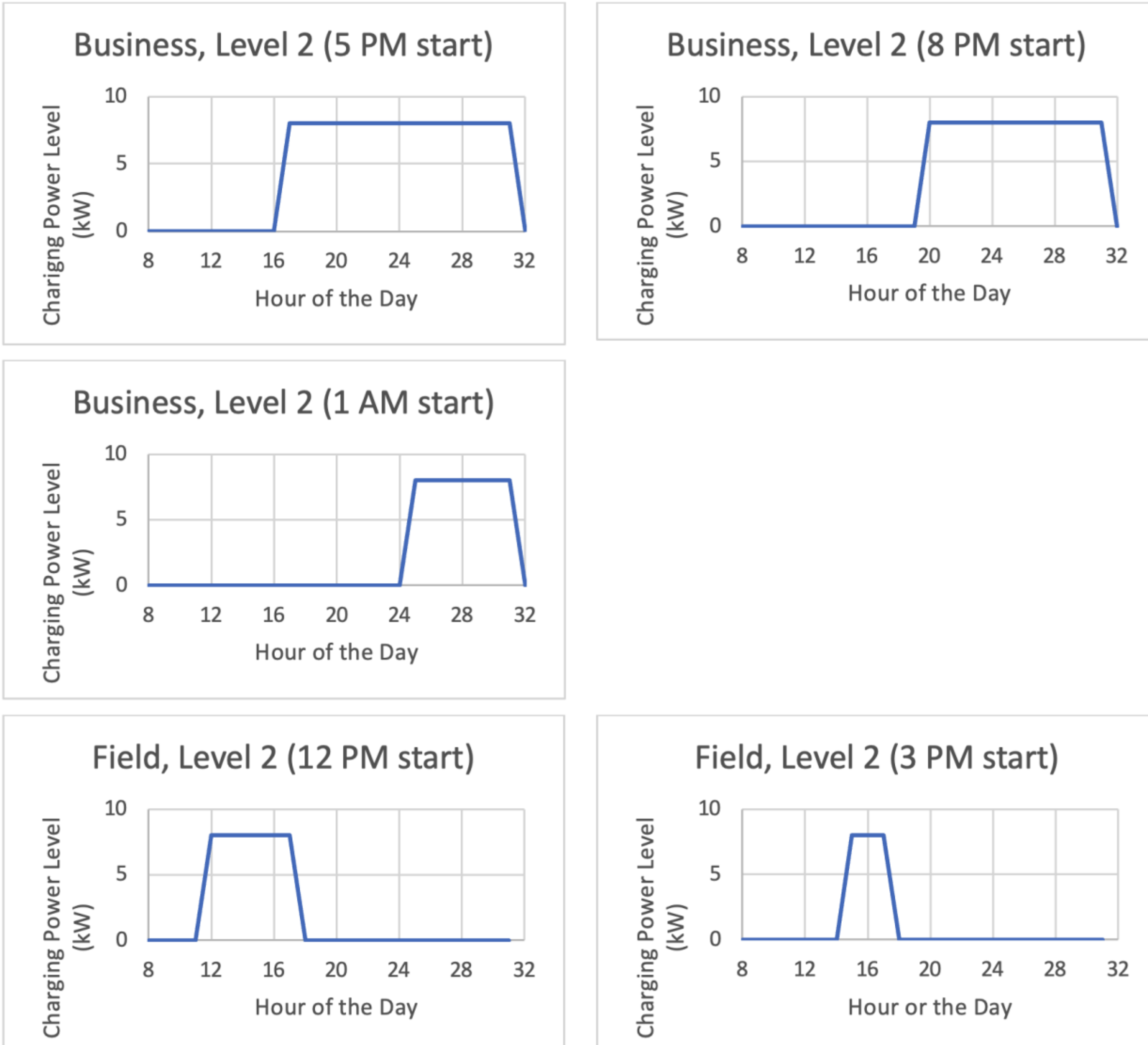


**Figure 2-5. Charging profiles: Level 2 for Home and Field Scenarios at Various Start Times.**

## 2.5 Overview of grid emissions vs. tailpipe emissions

This second phase of research leveraged the extended grid modeling and optimization work described in our Phase I report. We used the same merit-order dispatch estimation framework based on actual data reported by the Southern Company Balancing Authority (SERC-SOCO). These data are high-resolution (hourly) and provide high detail of individual plants and generating units for all technologies. The methods used to develop the dispatch model and generate the marginal grid emissions assumptions are described in detail in [29].

With similar motives to Phase I, demonstrating the nuanced implications of emissions assumptions for quantifying abatement and comparing EVs to other vehicle technologies requires the development of a series of grid emissions assumptions. For this Phase II effort, we used the same grid emissions assumptions as Phase I:

- Annual average
- Monthly average
- Hourly weighted mix
- Marginal hourly weighted mix
- Marginal resource X

Monthly average and hourly emissions were assembled for August, October, and December. Hourly and marginal hourly emissions were collected for representative days from each of those months. Grid characteristics, including total load, demand curves, and to some extent available generation resources, evolve seasonally. In warm climates (a category to which all of Southern Company's jurisdiction would probably belong), demand for electrical power and subsequently grid emissions intensity are highest during the summer months and particularly in the evenings as people return home, turn on their lights, stoves, and televisions, and crank up their air conditioning units. The SERC grid experiences similar (if slightly less extreme) fluctuations in the winter months, and less extreme (but far from invariant) fluctuations in the shoulder months of spring and autumn. Using example emissions from summer, winter, and shoulder months affords the exploration of emissions variations within a 24-hour day at different times of the year and their effects on total cumulative emissions from EV charging events. The abatement potential of EVs over ICEVs and HEVs, when modeled using high-resolution grid emissions rates, is highly nuanced and time dependent. Investigating this nuance and the barriers and opportunities it creates pertaining to commercial EVs is a main contribution of this research effort.

Grid emissions attributable to EV charging generated by our simulations are compared to tailpipe emissions from conventional and hybridized gasoline and diesel vehicles. Fuel consumption was calculated using the combined fuel economy of each vehicle type and vehicle miles traveled. $CO_2$ emissions were calculated using the $CO_2$ emitted from burning one gallon of gasoline (8.887 kg) and diesel (10.19 kg). This operation is described by the equation:

$$\frac{VMT}{Eff_{ICE,\,HEV}} \cdot Emissions_{G,\,D}$$

Where *VMT* is daily vehicle miles travelled, $Eff_{ICE,\,HEV}$ is the fuel efficiency of the ICE or hybrid vehicle in question, and $Emissions_{G,\,D}$ is the $CO_2$ emissions rate per gallon of gasoline or diesel fuel.

The simulations were performed using $CO_2$ as the pollutant of interest. Future work may incorporate similar exercises for other pollutants for which data is available (SOx, NOx, other particulates), but we expect those results to be proportional to $CO_2$.

## 2.6 System of Systems Model

For this Phase II effort, the team leveraged the proven power of the system-of-systems model developed and described in detail in the Phase I report to explore emissions resulting from a series of distinct scenarios for charging events of electrified commercial vehicles. The model was produced in MATLAB/Simulink and enables the integration of three sub-system models (vehicle energy, grid dispatch, and charging schedules) enabling in turn comprehensive, quantitative simulations of EV deployment for multiple driving cases under varying charging schedules and grid emissions assumptions. The architecture of the Simulink model is displayed in Figure 2-6. The initialization code, written in MATLAB, may be found in the Appendix.

The current version of the model does not automatically account for charging losses occurring during the transfer of energy from the charging infrastructure to the electric vehicle's battery system. These losses were corrected in a post-processing step wherein each total cumulative emissions output from the simulated charging events was multiplied by $1/\eta$. Following the findings by Channegowda et al (2015) and assumptions employed by our Phase I report, we selected $\eta=0.88$ for Level 2 and $\eta=0.90$ for Level 3 charging systems [30].

Simulation results are presented in the following sections. These, as with the team's Phase I results, represent what is believed to be an innovative method leveraging new data that yields a distribution of projections for $CO_2$ emissions across a variety of assumptions and plausible scenarios.

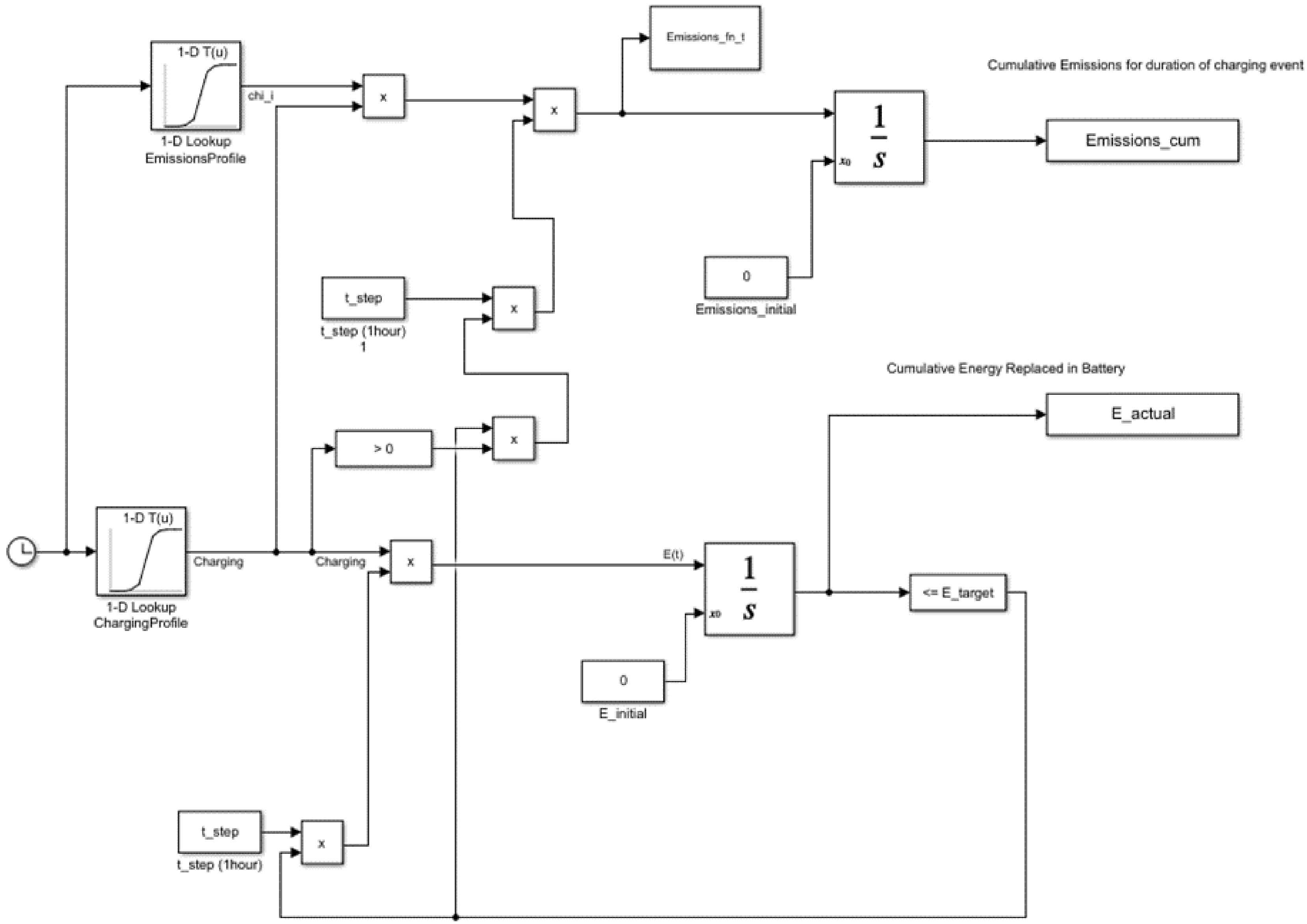


**Figure 2-6. Energy and emissions integrator, Simulink model.**

## 3.0 Results and Discussion

A series of modeling scenarios were defined and simulated using the system-of-systems modeling method. The variables utilized to craft distinct modeling scenarios are described in Table 3-1 and Table 3-2. Simulations were conducted iteratively to include every possible permutation of variable combinations across a representative 24-hour day from each of August, October, and December (with data available for the year 2018). For refuse truck simulations, higher VMT levels were used and field charging scenarios were omitted as they are not feasible charging events by the nature of typical on-road refuse truck activity.

**Table 3-1. Variables included in the system of systems modeling approach.**

| *Vehicle type* | *Vehicle technology* | *Daily VMT (miles)* | *Charging profile* | *Emissions profile* |
|---|---|---|---|---|
| **Light truck** | Battery-electric | 20 | Home base, 5 PM | Annual average |
| **Small van** | Internal combustion engine (gasoline) | 30 | Home base, 8 PM | Monthly average |
| **Moving truck** | Hybrid-electric | 50 | Home base, 1 AM | Hourly |
| | | 100 | Field, 12 PM | Hourly Marginal |
| | | | Field 3 PM | Hourly Marginal Resource X |

**Table 3-2. Variables included in system of systems modeling approach, refuse trucks.**

| *Vehicle type* | *Vehicle technology* | *Daily VMT (miles)* | *Charging profile* | *Emissions profile* |
|---|---|---|---|---|
| **Refuse truck** | Battery-electric | 50 | Home base, 5 PM | Annual average |
| | Internal combustion engine (diesel) | 75 | Home base, 8 PM | Monthly average |
| | Hybrid-electric | 100 | Home base, 1 AM | Hourly |
| | | | | Hourly Marginal |
| | | | | Hourly Marginal Resource X |

**Table 3-3. Energy consumption (kWh) of study vehicles by daily VMT level.**

| | ***20 miles (32 km)*** | ***30 miles (48 km)*** | ***50 miles (80 km)*** | ***75 miles (121 km)*** | ***100 miles (161 km)*** |
|---|---|---|---|---|---|
| ***Light trucks*** | 10.23 | 15.35 | 25.58 | -- | 51.15 |
| ***Small vans*** | 9.17 | 13.75 | 22.92 | -- | 45.84 |
| ***Moving trucks*** | 20.00 | 30.00 | 50.00 | -- | 100.00 |
| ***Refuse trucks*** | -- | -- | 160.00 | 240.00 | 320.00 |

Table 3-3 depicts the cumulative energy consumption in kWh for each vehicle type included in the study at different levels of daily VMT. These values are a primary input for the simulations, informing the model as to what quantity of energy must be replaced during a charging event to return the battery to its full state of charge. To ensure consistency of comparisons, simulation outputs were only collected for scenarios where the battery was fully recharged during the charging event.

Figure 3-1, Figure 3-2, and Figure 3-3 serve as comparative visualizations of simulation results for light-duty truck emissions rates in kilograms of $CO_2$ per kilometer. Each plot depicts relative emissions rates for a battery-electric truck under different emissions profiles and level 2 charging schedule assumptions for each VMT level at different times of the year. Emissions rates are plotted along with emissions from an ICEV baseline as well as an HEV to enable comparisons.

The plots represent additional corroborating evidence in favor of several pertinent takeaways from our Phase I study. The daily variance of electrical power grid emissions rates resulting from the switching on and off of dispatchable marginal generation resources by the grid operator in anticipation of or in response to evolving demand for power is high, especially during summer and winter months when temperature fluctuations are expected to be more extreme. Using monthly or annual average emissions rates fails to account for the nuanced fluctuations of real-world grid emissions rates (particularly relating to the generation resource on the margin), implying the true environmental benefits of EVs compared to ICEVs or HEVs are often misrepresented. Are environmental benefits then over- or understated? The directionality is not uniform. Vehicle use, charging patterns, and seasonal fluctuation of grid characteristics play important roles in determining actual environmental outcomes, positive or negative.

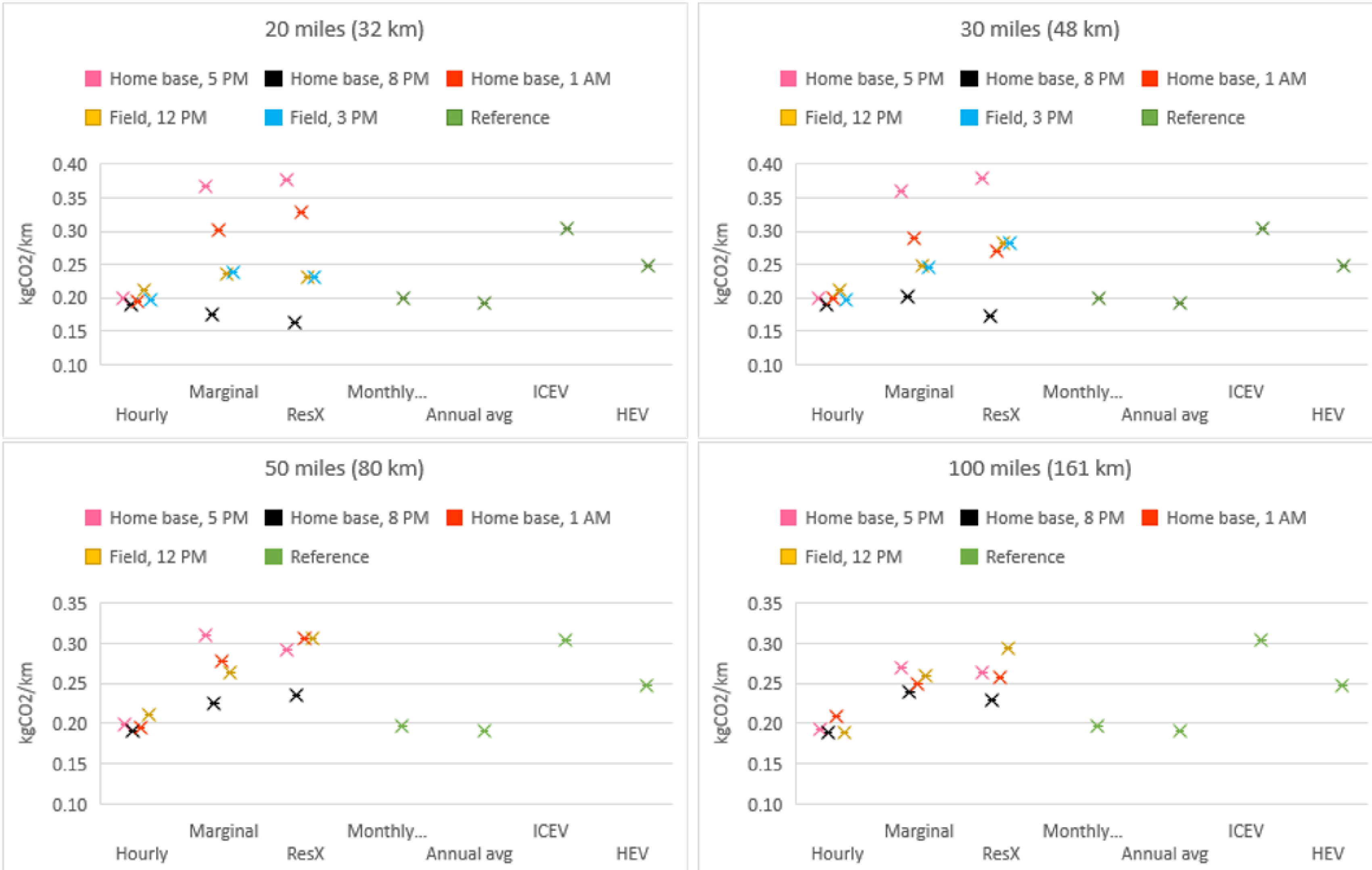


**Figure 3-1. Emissions rates for light truck, August.**

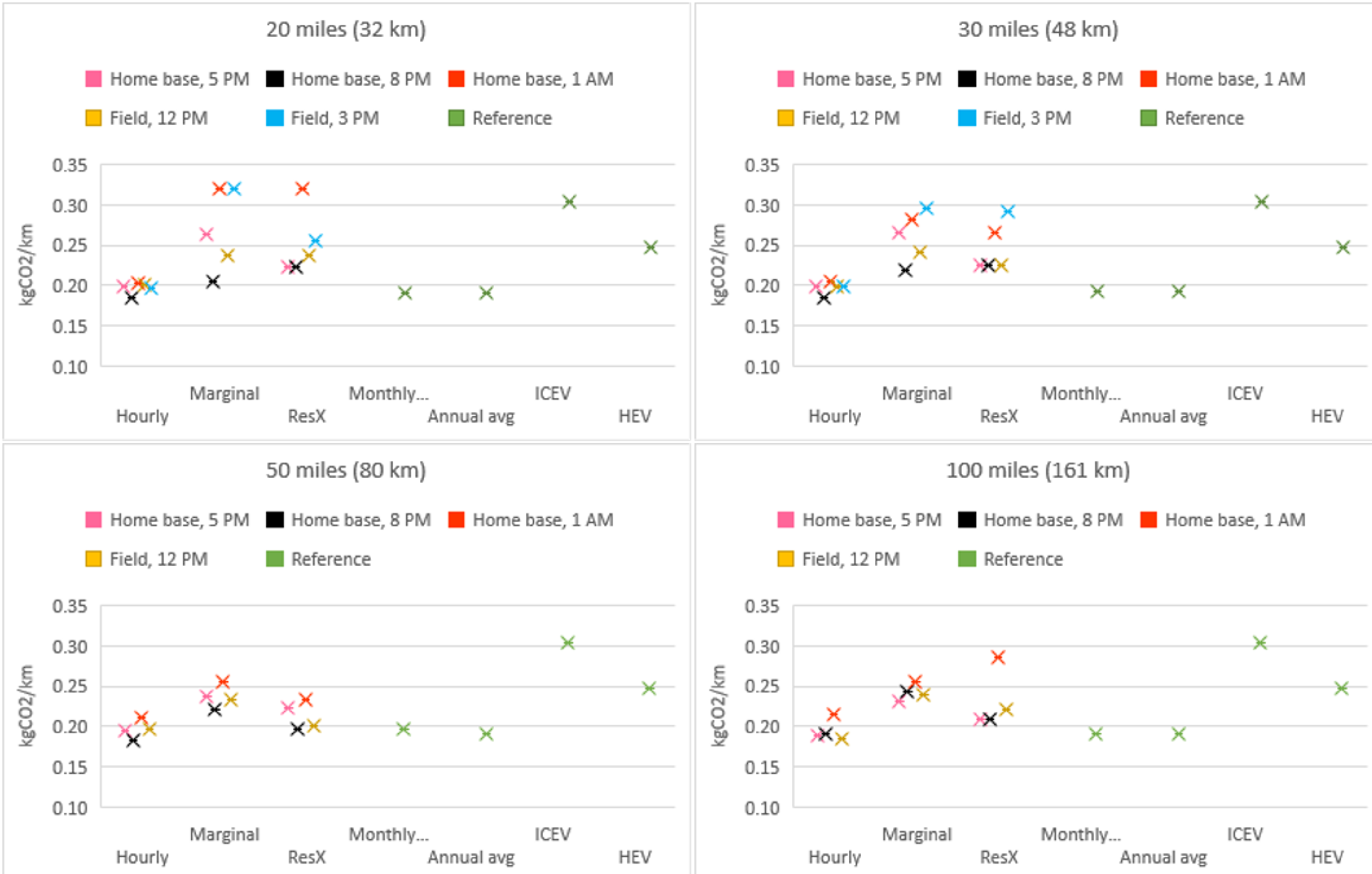


**Figure 3-2. Emissions rates for light truck, October.**

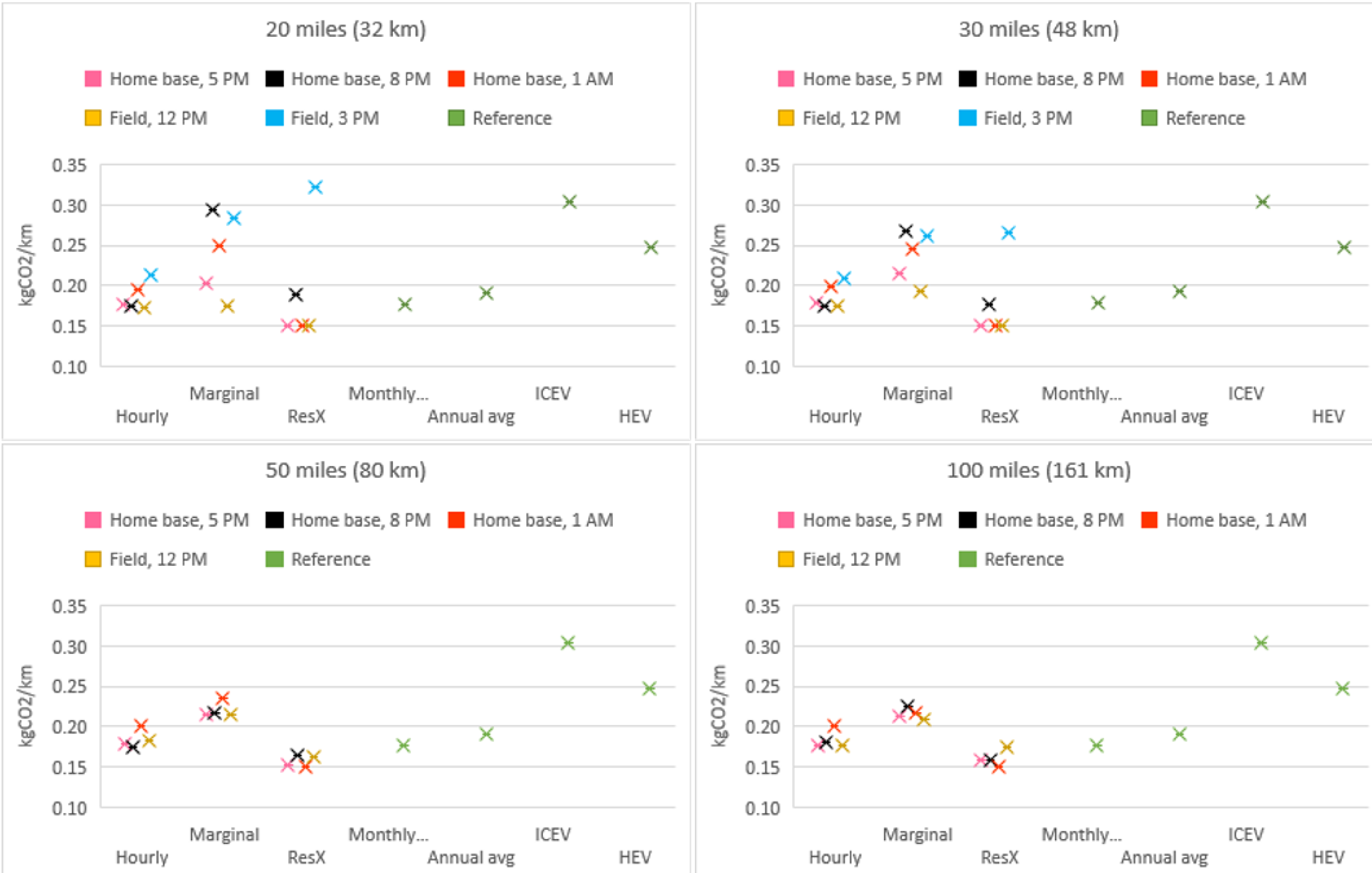


**Figure 3-3. Emissions rates for light truck, December.**

The above figures reveal that in these cases at least, employing hourly grid emissions rate data to guide inquiry into environmental benefits of EVs, while still at a higher resolution than annual or monthly average rates, minimizes the variation of marginal resources. As was concluded in the Phase I report, EVs are likely to require marginal resources *en masse* because they act together (with temporally similar charging trends) to force demand projections out of the expected regime, especially at growing rates of adoption. This Phase I conclusion is presented with the caveat, however, as Phase I dealt with personal EVs as opposed to the commercial EVs we are concerned with here. Still, this conclusion may well hold for commercial EVs, especially concerning the commercial applications explored in this phase of our research. The nature of many residential services, moving companies, and refuse operations is to operate during daytime hours (i.e., 9 AM to 5 PM or similar), leaving the largest window of logical charging times for the evening or overnight hours with the occasional exception. If most commercial vehicle activity occurs during the day, then most commercial EV charging will occur overnight. During a transition period of EV adoption growth, utilities will be able to accommodate the associated generation demand to support commercial EVs, but these needs will most likely be met by marginal resources. This has implications when considering the environmental benefits of commercial EVs because marginal resource emissions rates possess the highest temporal variations. When using marginal grid emissions rate (ResX) assumptions, the per-kilometer emissions of a battery-electric light truck traveling 20 miles per day were found to vary by as much as 131% depending on the charging schedule used (on the absolute, 5.24 kg $CO_2$when charging at the business starting at 8 PM up to 12.12 kg $CO_2$ when charging starting at 5 PM). Table 3-4 reports the percentage improvement (penalty) of CO2 emissions for an EV relative to an ICEV in the light truck category, assuming 20 miles per day of business use, under various charging profiles. Note that studies that assume an average CO2 emissions rate may predict a very different environmental impact than studies that take certain marginal dispatch factors into account.

Simple shifts in charging times that may have little impact on existing business operations may have sizeable impacts on emissions attributable to charging events, indicating substantial value for managed charging implementation.

**Table 3-4. Percent improvement in $kgCO_2/km$ over the ICEV baseline, light truck, 20 miles per day, August.**

| | Home base, 5 PM | Home base, 8 PM | Home base, 1 AM | Field, 12 PM |
|---|---|---|---|---|
| Hourly | -34% | -37% | -36% | -31% |
| Marginal | 21% | -42% | -1% | -22% |
| ResX | 24% | -46% | 8% | -24% |
| Monthly avg | -35% | -35% | -35% | -35% |
| Annual avg | -37% | -37% | -37% | -37% |
| ICEV | 0% | 0% | 0% | 0% |
| HEV | -18% | -18% | -18% | -18% |

While the Phase I study explored mostly passenger cars, as presented above, this study built upon it to explore light trucks in service fleet operations. Next, we turn to Medium Duty EV use cases, which appear to hold much near-term promise, and may be financially attractive without significant subsidies. Presented in Figures 3-4, 3-5 and 3-6 are simulations of CO2 emissions for a Moving Truck application of various vehicle miles traveled (20, 30, 50, 100 miles) during three principal seasons (August/Summer, October/Fall, December/Winter). While in some cases the variation in emissions rates for the different scenarios can be quite high, it is important to understand the cause and implications. For the scenarios with more VMT, there is a proportionally greater quantity of energy that needs to be replaced during the charging event. This can have the result of moderating the variance in emissions compared to shorter VMT scenarios. We infer this is because the emissions intensity of the electricity being used to charge the EV's battery pack is diluted the longer it is being actively recharged. At smaller levels of energy displacement, the vehicle's battery can be recharged entirely within one or several hours of charging. If this charging occurs within peak hours or whenever the carbon intensity of the grid and its marginal resources are highest, then the subsequent carbon intensity of the EV is similarly high. During longer charging events replenishing greater amounts of energy to the vehicle's battery, the charging event is likely to last beyond periods of peaking grid carbon intensity resulting in the deposit of less carbon-intensive electrical power to the battery for at least some of the charging event. This mechanism holds implications pertinent to commercial EVs, whose larger battery capacities, greater rates of energy consumption, and generally higher VMT necessitate longer charging events. Commercial EVs may have more opportunities than private light-duty EVs to reduce the carbon intensity of their operations by charging across periods of high and low grid emissions intensities alike. Still, the demands of business may predicate faster charging times to keep vehicles on the road and minimize range and scheduling anxieties. Growing penetrations of Level 3 (aka DC Fast Charging) systems would reduce charging times, raising carbon intensities absent charging management programs. The MD moving truck example for the various VMT cases, EV charging profiles and marginal emissions assumptions demonstrates that more research may be valuable to quantify with greater certainty how each of these factors can influence fleet emissions. Now is a particularly important time to evaluate these factors, as many MD EV cases are in a growth stage based on market and policy considerations.

The foregoing is also contingent on trends in emissions for grid generation. While it is beyond the scope of this study to forecast how grid generation will evolve to meet new demands, it is important to co-develop tools that can simulate the associated CO2 impacts of different EV and grid growth scenarios. As was the case with the personal vehicles in Phase I, there exists a future threshold of commercial EV penetration that will trigger a realignment of the existing trends observed in grid emissions. Commercial EVs demand more power on average than private vehicles and therefore will have greater effects on marginal emissions trends. Increased power demand at common charging times will give rise to additional marginal resources, which are likely to be fossil in nature, at least in the near-term.

The range of results depicted in the various scenarios across a range of vehicles suggests that all key stakeholders (e.g., businesses, grid operators, planners, etc.) may ultimately benefit from better foresight to charging events on both short term and longer-term time scales. Thus, the ability to manage charging events becomes an essential part of the suite of regulatory levers and cyber-physical infrastructure that can facilitate effective growth of commercial EV deployments. Efforts to optimize the benefits of managed charging seem to depend upon the effective acquisition, analysis, and conveyance of high-resolution information concerning EV charging and its various externalities between system users, grid operators, and policymakers. This research, by way of integrated systems modeling and use case simulation, argues that using averaged emissions rates, especially at lower temporal resolutions, may obscure information. By refining the temporal resolution of the input data for both charging events and grid generation profiles, stakeholders can be better equipped to optimize environmental benefits from EV growth, as well as inform business decisions, and guide policymaking.

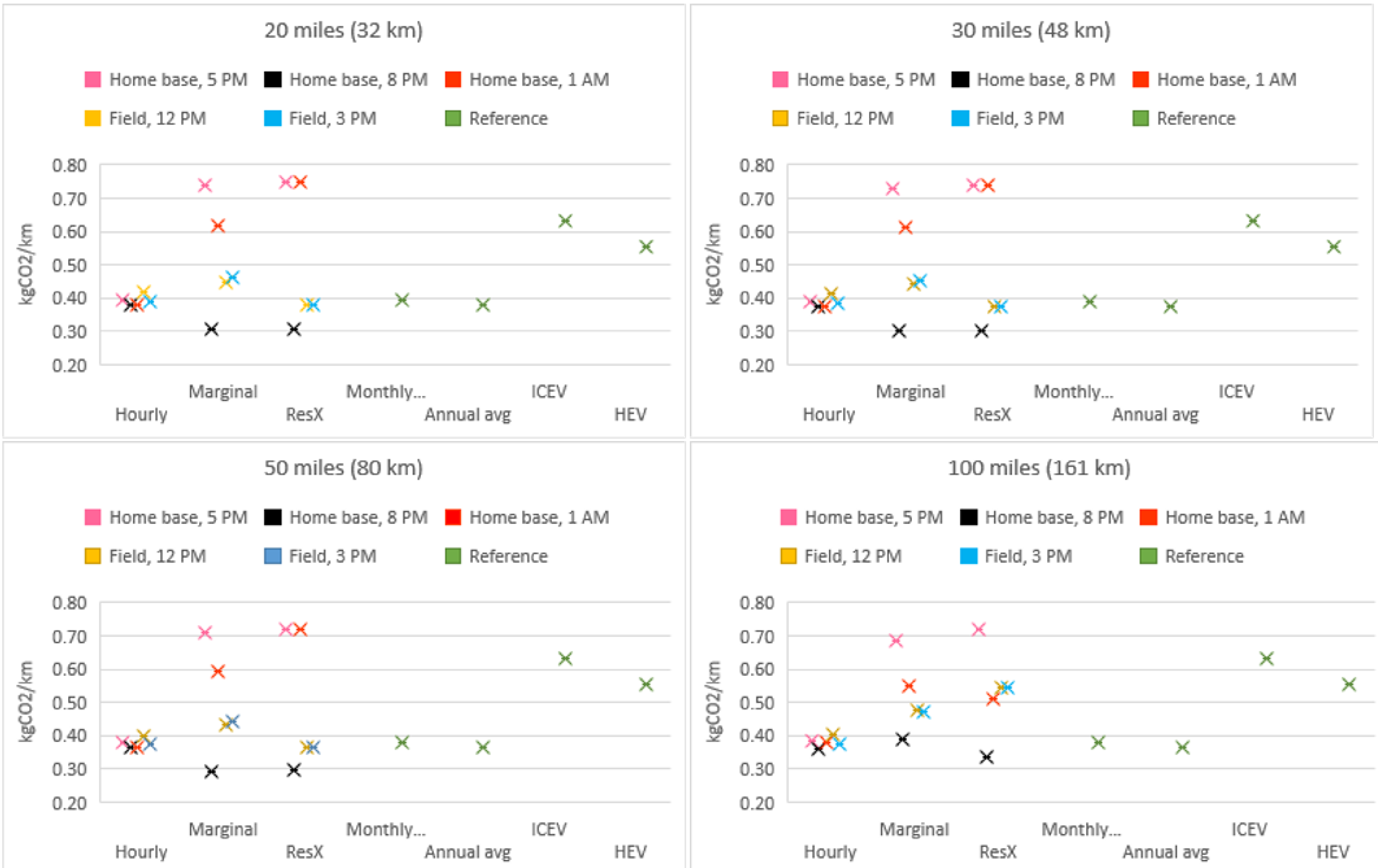


**Figure 3-4. Emissions rates for moving truck, August.**

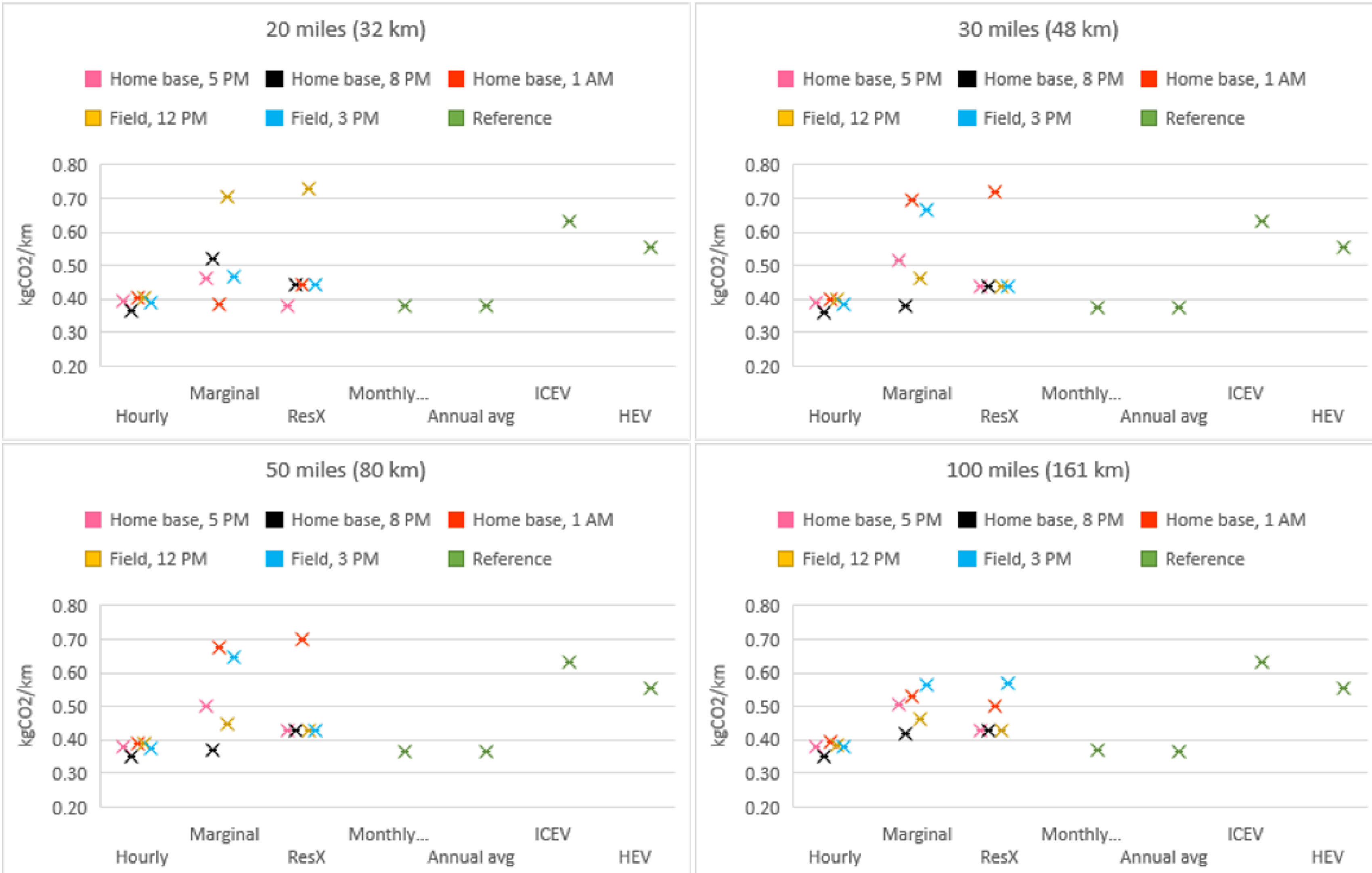


**Figure 3-5. Emissions rates for moving truck, October.**

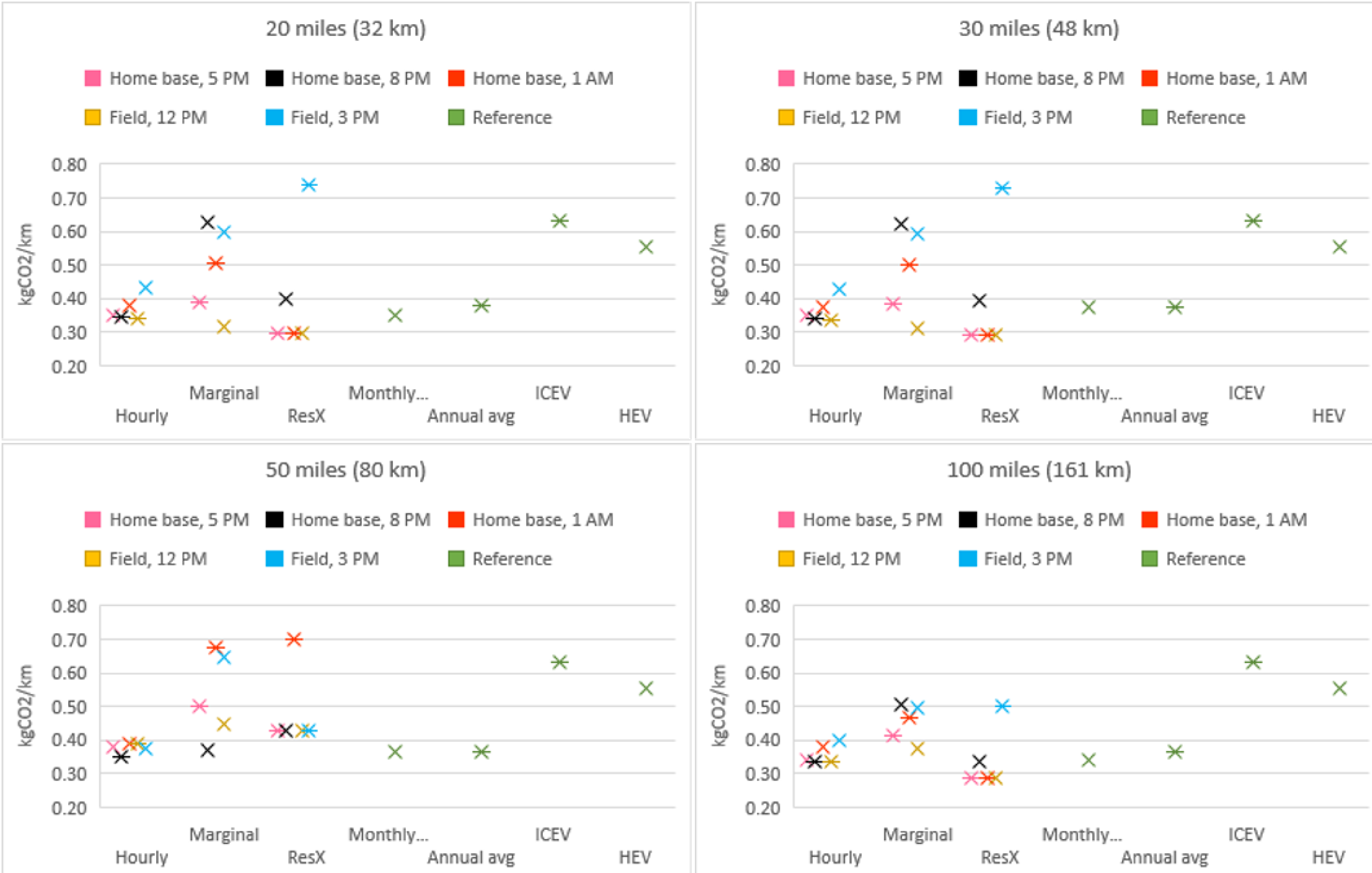


**Figure 3-6. Emissions rates for moving truck, December.**

## 4.0 Policy Implications

Electrification of commercial vehicles has the potential to help decarbonize the transportation sector and improve air quality. About four key policy implications relevant to a near-term transition in this domain seem to emerge from this research activity as follows:

- the importance of considering **charging profiles and grid generation data with higher temporal resolution**. This finding may suggest greater attention to interactive EV **charge management** and may also have follow on implications on **infrastructure**;
- the performance of **HEVs** on a CO2/km intensity basis, seem to be fairly competitive with several of the EV use cases modeled;
- the need to focus on **higher rate EV charging applications** (e.g., DCFC), and related implications on energy storage, as proxied by large vehicle batteries; and
- increasing electrification in the transportation sector and associated **emissions** must be considered in the context of other grid trends.

In the near- and intermediate-terms, coordinated EV charging is a critical component of an effective transition to battery-electric vehicles for a growing range of use cases. The prevailing generation dispatch mechanisms and physical constraints of the electrical power grid are inherently sensitive to shifting demand trends and require consideration of hourly factors. These sensitivities are expected to heighten as electrification increases from a multitude of sources, including not only EVs, but other intermittent, seasonal, and continuous loads (e.g., heat pumps, HVAC, and data centers). Anticipating the timing and magnitude of demand spikes, such as those resulting from EVs, is necessary from multiple time domains. First, as we have stated, an hourly or even sub-hourly view of charging and grid dispatch may be important to ensure emissions benefits are understood. And second, from a resource planning perspective, grid operators seek to optimize dispatch and infrastructure funding decision-making processes over a much longer time scale. Thankfully, a number of support policies and Federal funding resources are stimulating new R&D, pilots, and demonstrations at the intersection of grid modernization, charging communication protocol, smart charge management, EVs, and the increasingly distributed grid in order to mitigate unintended demand peaks resulting from both higher current charging and higher penetration of EVs.

In our simulations of CO2 output, hybrids performed on par with many EVs under marginal grid emissions scenarios. The recent EV policy environment included monetary incentives like tax credits to offset the relatively high purchase prices of EVs over their ICEV counterparts. This research may suggest that hybrids can provide some important benefits in parallel with EV growth, including reduced environmental impacts, and opportunities to reduce infrastructure investments by leveraging existing assets. It is also quite clear that a diverse fleet mix (whether for companies or society at large) may provide certain strategic advantages, and that “winner-take-all” policy architecture may be unwise. This research therefore emphasizes the need to conduct comparative studies as policy options are explored. Doing so can ensure that public dollars are more effective in reducing the impacts of transportation while maintaining the current expectations in performance. This can also help inform public and private investment decisions and accelerate paths to scale and impact.

The expansion of DCFC stands to improve the value of utility-scale battery storage systems. The shorter charging times enabled by Level 3 charging, while convenient and possibly economically motivated, introduce significantly more variance in emissions results. The authors of this work believe that much more attention to DCFC load growth and charge management in terms of research, financial justification, and policy planning is warranted. In Phase I, where we focused on Levels 1 and 2 charging rates, almost all the charging events lasted several hours which helped to smooth out the ebb and flow of marginal emissions resulting from the turning on and off of peak generation resources (chiefly coal and natural gas). Level 3 fast charging systems result in short, high-power charging events, which can yield counterintuitive emissions trends, as has now been initially revealed in this Phase II study. When a charging event facilitates the transfer of large amounts of energy over a short duration of time, the timing of the event becomes even more important in terms of emissions. This is because the entire battery (which for a Medium or Heavy Duty vehicle may be a few hundred kWh, or several times the size of a passenger car) may be charged with relatively high-$CO_2$ electrical power if the charging occurs during a period when the marginal resource mix is dominated by coal as opposed to a period of a less carbon-intensive mix dominated by natural gas. A high-powered charging event such as those resulting from commercial vehicles with larger battery capacities is subject to highly erratic, bidirectional swings in emissions intensity.

In the near term, in terms of electric power generation capacity and quality, the argument that more renewables will help accelerate EV adoption while mitigating environmental impacts has not been fully reconciled against space and time considerations. The large and variable (current draw) rates at which electric power is called for by DCFC events present a challenge to electricity infrastructure planners and developers in identifying optimal strategies; this includes the sizing of distribution equipment, its location, and decisions around the upstream generation mix. Case in point for renewable energy projects, there is often a mismatch in terms of nameplate capacity, capacity factor, and its effective power delivery rate relative to the demands of a fleet of EVs charged at Level 3 conditions. Technological research and policies to address this mismatch require more in-depth study.

As the grid decarbonizes over the longer term (e.g., decades into the future), the potential adverse impacts of marginal emissions from predominantly fossil fuel resources will subside. However, there will remain a need for decision-support tools to assist at many stages of this transition to a future state.

More attention to firmed renewables via long-duration storage or vehicle-to-grid approaches will also be valuable. Because Level 3 Fast Charging is more likely to experience a higher magnitude and variance of emissions, incorporating battery storage infrastructure, either at the utility-scale or as smaller, distributed units, may become an attractive solution for reducing the emissions impact of vacillations between different marginal emissions regimes. At the utility scale, the grid operator can use battery storage as a reservoir of low-carbon electrical energy for use as a marginal peaking resource. It can charge batteries during periods of low $CO_2$, like during off-peak hours or when renewable generation shares are highest, banking low-carbon electricity and relieving part of the burden currently borne by traditional fossil resources called on to meet marginal demands. This would reduce the fossil fuel dominance of currently observed marginal mixes and therefore reduce the magnitude of vacillations between regimes.

Additionally, it may be that greater investments in distributed (i.e., consumer side) battery storage infrastructure coupled with EV charging infrastructure could be valuable. Distributed battery storage systems could, in principle, perform a similar function as utility-scale batteries. A key difference is that they would likely be privately owned or jointly owned, suggesting a need for coordination around command and control in order to yield social benefits. Another difference is that it would require many small projects on the distributed side, compared to a few larger utility-scale projects. This can have advantages, such as a reduced need for new transmission investments, but also challenges, such as the need to build out intelligent distribution infrastructure to support it. Incentivizing private battery storage may be a cost-effective method for shifting demand on the electrical power grid off of peak hours, improving the utility's ability to effectively manage increasing load due to growing EV shares and activity. Further investigation is required to explore the operational nuances and cost components of battery storage systems as described here, but as far as this research can conclude it may be an effective strategy for tackling the fast-charging problem.

A fourth, potentially critical, policy implication is the notion that vehicle electrification will not happen in a vacuum as far as the grid is concerned. Thus far in our study, we've exclusively looked at new heavy electric loads (e.g., from vehicle charging) as additive to existing and future demands. Furthermore, it is also reasonable to assume that most of the electricity generation from renewables will essentially be fully consumed by so-called "baseline" demands for the foreseeable future. In other words, renewables still account for a modest enough share of the total mix that they will be consumed, with or without any EV growth at all. In fact, with the increasing pressure to retire coal plants, much new low-carbon generation is needed to simply offset those resources. However, if EVs could be deployed within a broader frame, that could go a long way toward reducing uncertainties raised by marginal emissions scenarios. Such a broader frame would manage demand, intelligently control EV charging, prioritize overall efficiency gains, and focus on conservation, avoidance, or substitution. In this way, the assumption of average hourly mix or even average daily mix might be more relevant than the uncertainty around a specific marginal resource assumed to meet the incremental kWh required by a particular EV charging session. While the study offers some suggestions for tools and next steps during the near-term and transition period, this broader framing seems to be a difficult hypothesis to test with certainty over the longer term.

In addition, it seems there is talk of greater electrification, not less, when it comes to other sectors like residential heat pumps, data centers, industrial heat, or other energy-intensive processes that currently use thermal methods such as fossil fuels. While broader interactions across electric power use segments are beyond the scope of this study, the potential policy implications of those interactions and factors could be profound. **For now, it may be**

**reasonable to assert that as EVs are deployed, it is imperative to not only manage the EV charging events in time and space but also consider our latitude to control or influence other large loads on the grid in conjunction with EV deployment growth. Doing so can help ensure that the electrification of transportation results in meaningful decarbonization gains.**

# 5.0 Future Work

## 5.1 Future work

This Phase II study has built upon a Phase I study that developed a systems methodology to explore important questions about EV growth relative to new vehicle categories and use cases. This report pursued "future work" that was identified during the first research investigation which focused exclusively on light-duty passenger vehicles. The now "present work" has specifically explored fleet and commercial use cases involving medium and heavy-duty vehicles and augmented the findings in depth and breadth. Our study has demonstrated the usefulness of the methodology developed in Phase I, which integrated vehicle powertrain, charging profile and grid generation mix sub-systems. The present study investigates an enhanced understanding of MD/HD EV emissions and several promising scenarios and use cases that can help optimize charging schedules and minimize $CO_2$ emissions.

At the same time, this study has also touched on additional dimensions which are suggestive of future work. These include the need to consider grid characteristics relative to energy, emissions, decision-making, and planning out to 2030, first of all, and then eventually to 2040 and beyond. It also suggests that tools need to be capable and scalable to conduct similar analyses in other regions. Following are some specific suggestions for deepening, extending, and scaling the present work:

- Extend the model to explore future projections of electric grid characteristics and response to EV growth with data from travel demand models and other regions
    - Convert historical electric grid basis to predictive tools for approximating grid dispatch characteristics and protocols into the near and intermediate future (e.g., 2030, 2040);
    - Pay particular attention to the interplay of deep deployment and popular charging times (such as overnight), as such insights will enable decision-makers to strategize to manage EV growth;
    - Deepen the understanding of Level 3 Fast Charging adoption scenarios and their associated impacts on emissions, demand, and overall costs;
    - Develop guidance and toolkits to assist others in adapting EVALUATE for other regions.
- Forecast future grid compositions and marginal resources to predict and inform policy
    - Seek more integrated and holistic approaches to electrification and load growth, including the positive and negative interactions of EV charging demands relative to other load growth sectors (e.g., data centers, heat pumps, industrial heat);

- Understand how marginal resources will be deployed as growth in EV market share increases demand for electrical power given other demand trends;
- Consider the geospatial distribution of pollutants, health impacts, and equity impacts
    - Conduct comparative analyses between concentrated (point-source) emissions and dispersed (mobile-source) emissions; characterize and compare the two from an air quality and public health perspective.
    - Consider environmental justice concerns, the social impact of electric vehicles, public and private costs, affordability, access to vehicles and chargers, etc.
- Innovation
    - Develop technology transfer guidance for practitioners and decision-makers to maximize the effectiveness of upcoming public and private investments;
    - Consider battery charging (i.e., multiple technologies, durations, spatial/temporal characteristics) as a grid resource and the potential for vehicle-to-grid (bidirectional) flows of energy.

## 5.2 Limitations

In both phases of our study, we have proposed and investigated rigorous approaches that estimate the variability associated with $CO_2$ and other emissions involving electric vehicles. This required a simulation framework that explored multiple parameters concurrently to yield broad comparisons. In this way, we explore a growing set of electric vehicles as compared to a baseline case (e.g., gasoline vehicles). We explore a representative and diverse suite of use cases, driving cycles, and charging profiles for a range of users, including individual commuters, fleets, small businesses, as well as municipal transit and services. The simulations estimate $CO_2$ emissions under a range of scenarios useful to inform decisions, investment, and policy.

As noted, prior studies often utilize annualized averages for grid-level C02 emissions to simplify the analysis. In our research review of other tools and dashboards (e.g., ChargePoint charge event portals, EPA locality $CO_2$ estimator via zip code, EIA projections of EV electricity demand), we observed that a very basic algorithm is typically utilized (such as a fixed or weighted average value for grid emissions) that does not consider time of day or seasons of the year. We acknowledge such traditional approaches provide a kind of first-order, initial estimation that can be useful to some audiences in some contexts. However, it is imperative to recognize and explain the limitations of this approach, and the risk of relying too heavily on average emissions estimates. The reason is that such estimates are subject to change in the future, and also subject to variability during the present on multiple timescales (e.g., hourly, daily, seasonally). This Phase II effort emphasizes the need to focus on Level 3 Fast Charging because this sub-category of charging stands to incur higher rates and potential uncertainty. Not only will better assumptions be needed to estimate emissions resulting from Level 3 charging, but they will also be imperative to inform infrastructure siting to build out charging networks and inform resource planning for the grid at large.

Next steps should consider the benefits, tradeoffs, assumptions, and limitations associated with the methodology, practicality, and intent of related research. The authors believe continued attention, in particular during the near-term transition period, can facilitate more direct comparisons of EVs and use cases to other technologies as penetration rates grow.

Several summary statements emerge from this body of work. It is clear that at certain modest levels of EV deployment, a weighted average mix of resources may not be illogical or inaccurate in estimating $CO_2$ impacts. It is beyond the scope of this study to determine exactly at what penetration rates things change. However, it can be stated that with significant increases in EV charging, in particular at certain hours of the day and seasons of the year, the assumption of weighted mixes breaks down. The study demonstrates that the breakdown can be quite pronounced for use cases involving greater vehicle miles traveled, for charging sessions occurring in the field, and for charging occurring during periods of peak grid demand. The breakdown also seems pronounced for scenarios involving Level 3 charging.

These findings reveal that managing charging events throughout the 24 hours of the day and across LD, MD, and HD use cases in distinct ways should merit greater attention. Furthermore, charge management alone will likely be inadequate as EV shares grow to much greater levels. Future study is anticipated to further inform decision-making around near and intermediate term scenarios including new interactive methods of forecasting both EV demand and grid resources. Historical approaches to dispatch are already underway toward predictive forecasting approaches. Ideally, scenarios will be developed that can better simulate future resources both fossil and non-fossil in order to meet load growth to support electric transportation, as well as additional demand growth from the electrification of other sectors like data centers, heating and cooling, and industrial processes.

## 6.0 Conclusion

Together with its Phase I counterpart, this Phase II study explores a systems-of-systems methodology to simulate viable grid-charging-vehicle scenarios of increasing interest for planning and policy-making. Collectively, our team has considered a range of vehicle categories (e.g., LD, MD, HD) and use cases (i.e., personal vehicle commutes, transportation services for small businesses, fleets, transit, and municipal services). The Phase II effort in particular has refined the methods introduced in Phase I and deepened our understanding of several potentially compelling EV applications including electric pickup trucks used by small businesses in service-oriented urban applications, medium-duty fleets, and other specialized uses where vehicles have predictable routes and return to base on a regular basis.

The study's simulation reveals that the CO2 emissions intensity of a battery-electric light truck traveling 20 miles per day could vary dramatically depending on the charging schedule used. Under the study's marginal resource X (ResX) grid condition where a specific marginal resource is needed on an hourly basis to meet a particular EV charging event, estimated CO2 emissions could be as much as 42% lower than a baseline ICEV, or as much as 24% higher than the same baseline. This large variance is purely a function of when and how quickly the vehicle is recharged. Thus, this example suggests such tools will be important to ensure environmental benefits are realized.

While the simulated use cases yield valuable guidance in their own right, the collective work reveals that such modeling and simulation-based comparisons are generalizable and extendable. In both studies, great lengths have been taken to develop rigorous physics-based vehicle models, including consideration of architectures, powertrain, overall accessory loads, and sensitivity to drive cycle and external ambient temperatures. Similar attention to detail has been paid to developing practical and representative EV charging profiles, reasonable mapping of standard drive cycles to real-world trips and travel behavior, and high-fidelity analyses of existing grid dispatch methods based on real-world data. By making the datasets and source codes publicly available, it is the authors' hope that such methodologies can be expanded, and new regional applications and business use cases can be explored.

To recap again here for context, the Phase I study introduced a methodology that accounts for energy and emissions during the use phase of vehicle emissions across a range of light-duty car types, including ICEV, HEV, and EV. This comparative approach enabled a head-to-head assessment of the vehicle technologies relative to a variety of private vehicle use cases. The Phase I effort revealed that EVs can contribute to reduced emissions, but their quantitative benefits are highly sensitive to when and how the vehicles are charged. This factor was shown to deliver results (in terms of $CO_2$ emissions per km driven) that could have a variance in the same order as the mean emissions. These initial results highlighted the importance of probing deeper into the interplay between charging profiles and vehicle classes. The study further revealed that driving cycles and use cases are of secondary importance, which can also contribute substantially to the variance in emissions for a given vehicle type and charging profile. A third factor is the overall limit of an EV battery capacity, which is more of a determinant of whether a given EV can actually substitute for a comparable ICEV. It should be noted that EV battery range did limit any drive cycles undertaken in the passenger car comparisons, and the model can readily accommodate EVs of any specified range. Phase I revealed a few "higher order" factors that influence the relative environmental benefits, but a major takeaway is that the timing and duration of a vehicle charging event under the marginal emissions assumptions can affect the environmental impacts by up to 100%.

In this Phase II effort, we deepen our investigation to include additional use cases of priority interest, while applying the original methodology developed in Phase I. The timing of this study happens to overlap with the commercial release of several high-profile light duty full-size electric pickup trucks, courier vans, transit buses, and school buses which have been publicized broadly in the media and studied extensively in research and development circles. Thus, Phase II stands to illuminate new insights via investigation of potentially important public and private use cases that leverage these new electric vehicle offerings, as a means of reducing emissions and energy. These use cases show particular promise because many small businesses operate on fairly predictable cycles and return to a central base at the end of the workday.

This Phase II study reveals that the trends observed in Phase I not only continue to be relevant but are in fact more pronounced and important. For example, the sensitivity to the time of charging is greater, accounting now for a variance in excess of 100%, as explained above. Our study suggests this is attributable to a few primary reasons.

First of all, while the daily mileage experienced by a fleet vehicle may not be significantly greater than commuter-type sedan applications, due to the increased energy intensity of these larger vehicles, the energy consumption on a daily basis is considerably higher.

Secondly, we forecast that fleet vehicles used for commercial purposes are likely to use Level 3 Fast Charging methods, for economic reasons, which can further intensify the variance associated with regional marginal assumptions.

Finally, while previous studies have discussed this phenomenon in subjective terms, benefits for the larger vehicle classes and associated business cases have not, to our knowledge, been quantified in this way. Meaning they have not taken the approach of considering vehicle, powertrain and use-case characteristics in view of the larger system of charging profiles and upstream grid factors. Few studies that we are aware of have taken the full spectrum approach, leveraging specification data on new vehicles, considering rigorous energy consumption, physics-based models, real-world characteristics of a grid, dispatch, and probable electric vehicle charging profiles in a contemporary manner.

These methodologies and some of the simulated results should have considerable value to fleet operators, small business owners, service-oriented, vehicle operations, as well as officials that do utility planning resource planning, and charging infrastructure. In addition, these methodologies can be extended quite broadly to consider the local grid context in other regions, as well as refined use cases that match vehicle types to a growing set of electrified transportation applications.

These studies reveal a few takeaways and signal a few notes of caution. These fleet and MD/HD vehicles are more energy-intensive and will consume more energy per day compared to LDVs, even though they may travel the same number of miles. For this reason, charge management is much more critical. A related need is more timely communication between vehicle fleets, charging service providers, and utilities to ensure charge management is transparent and mutually beneficial. Furthermore, because these larger vehicles are likely to utilize Level 3 Fast Charging in the interest of overall economic and value proposition, there is renewed attention to “get it right” from the $CO_2$ perspective as well.

The study implies that one approach that may mitigate adverse consequences is to schedule overnight charging of Medium and heavy-duty vehicles at predictable locations. Doing so could enable grid dispatch operators to increase intermediate loads with the use of highly efficient combined cycle plants or via the release of stored energy from renewables. This would obviously require more advanced planning and data acquisition but could readily be achieved through well-orchestrated pilot programs involving fleet operators, charge managers, and utility operators.

Another potential benefit that seems impactful from the use of light-duty, electrified service trucks and vans is that as EVs become more prevalent, the randomization of charging events could potentially become advantageous by spreading out uncertainty and lowering the potential for adverse peaks. Again, if this information were made available to grid operators, more optimal planning decisions could be made. This would not only yield more cost-effective dispatch on a daily basis, it would also reduce emissions and ensure that longer-term investments into local electric vehicle supply equipment (EVSE), grid distribution, transmission, and generation assets become optimized from the standpoint of society as well as individual consumers and businesses.

Primary contributions of this effort are therefore the development of new methodologies, integration of sub-system models and independent data sources, and enhanced tools for quantifying CO2 impacts associated with vehicle electrification. The Phase II study refines the methodology and assesses EV use cases that show particular near-term promise.

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# 8.0 Data Summary

## Products of Research

The following data were collected and used in the study. Relevant source data and methodologies are cited.

- Electric Vehicle energy consumption [11-14,32]
    - MATLAB/SIMULINK Codes
        - Vehicle parameters
        - Powertrain characteristics
        - Battery specs and control variables
    - EPA dynamometer schedules [15]
- EV charging [25-26, 28, 31]
- Electric Grid marginal emissions [29, 31]
- $CO_2$ and other criteria pollutants [30, 33]

Sub-system models involve datasets that are on file and disclosed in prior published work. The relevant data have been disclosed in part, represented graphically, and/or disclosed as tables within the body of this report, or its appendices. Interim datasets and the outputs of specific simulations are also available in the appendices on file and accessible electronically. The methodologies have been described and presented such that future sets of (source or interim) data can be utilized by existing or new models to generate new simulation outputs.

## Data Format and Content

The data used and generated in this study has taken the form of Excel spreadsheet data, excel models, Excel-based lookup tables, MATLAB initialization codes, MATLAB Source codes, SIMULINK system, and sub-system models. Other public datasets have been acquired and conditioned for use in this study.

## Data Access and Sharing

Some of the data and outputs from this study have been presented in the body of the report and in the appendices. Additional data and files are included in a dataset file and published at https://doi.org/10.5281/zenodo.14347458.

## Reuse and Redistribution

Reuse and/or redistribution of the data and methods is encouraged by the general public. The authors request appropriate citation and attribution of the present study (or the source data, publications, and prior work upon which it rests). When citing, please refer to the DOI identifiers for the written report and datasets of the present work as may be appropriate.

## 9.0 Appendices

### 9.1 Appendix A – Additional simulation outputs from selected scenarios

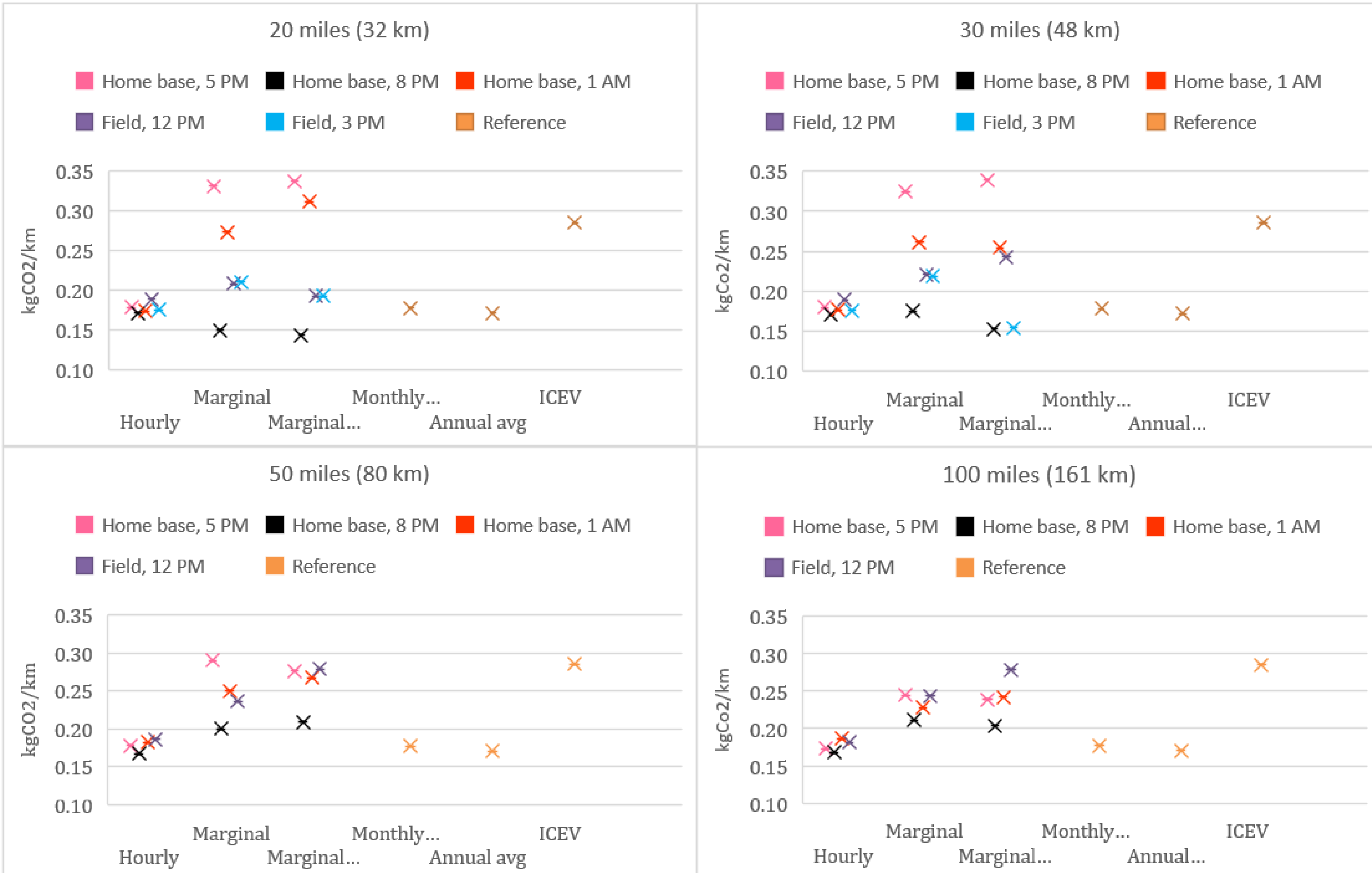


**Figure A-1. Emissions rates for small van, August.**

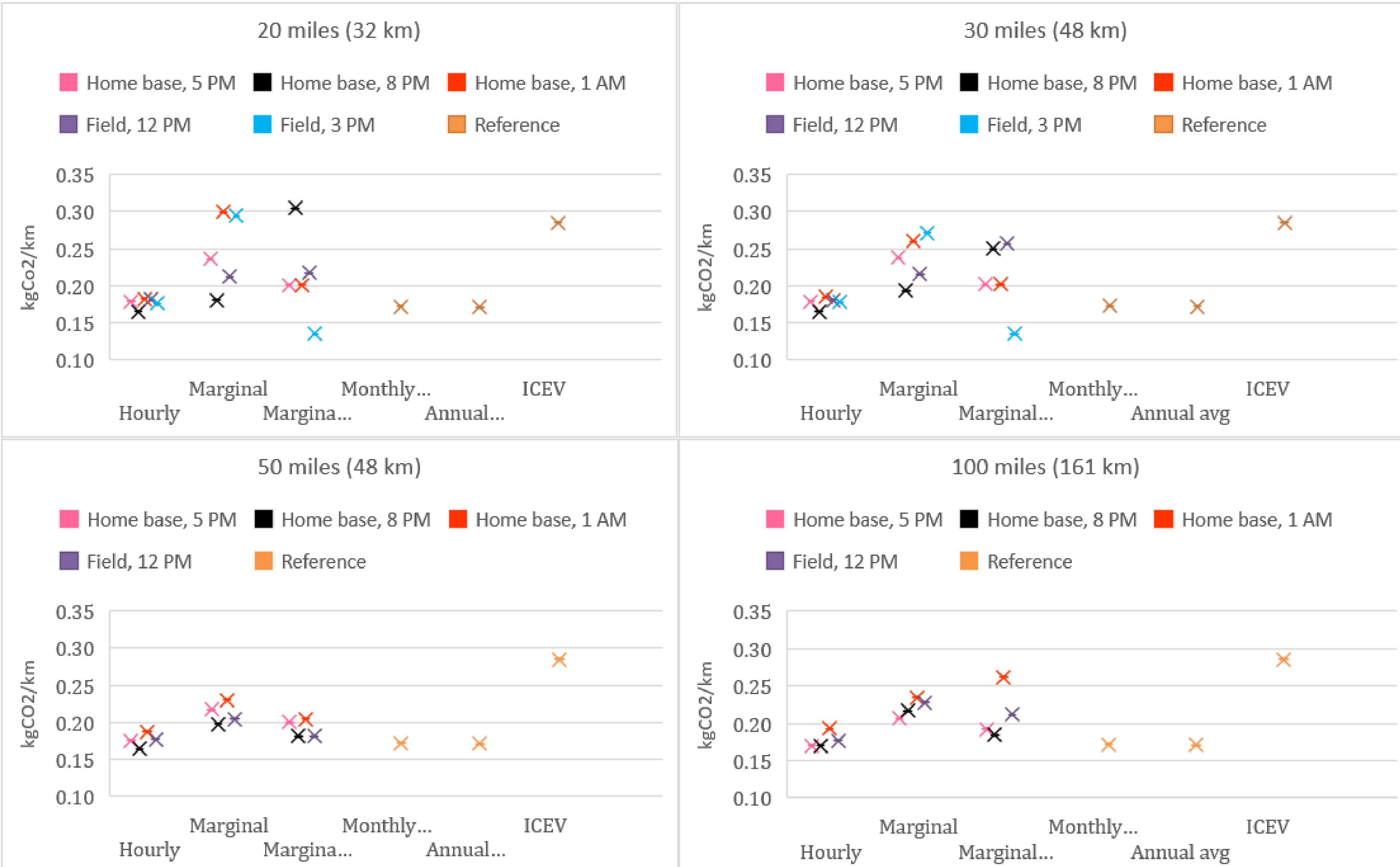


**Figure A-2. Emissions rates for small van, October.**


**Figure A-3. Emissions rates for small van, December.**

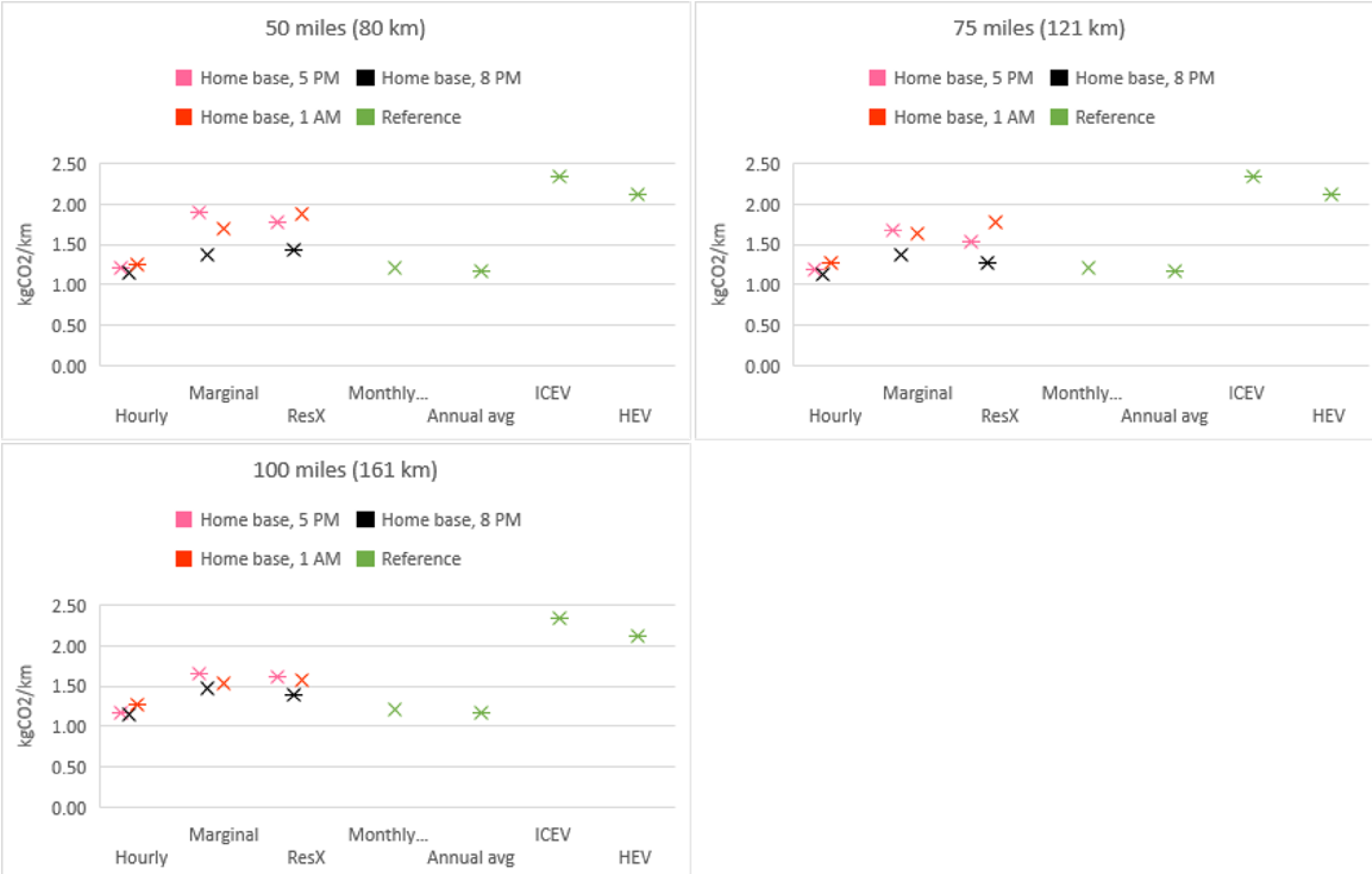


**Figure A-4. Emissions rates for refuse truck, August.**


**Figure A-5. Emissions rates for refuse truck, October.**

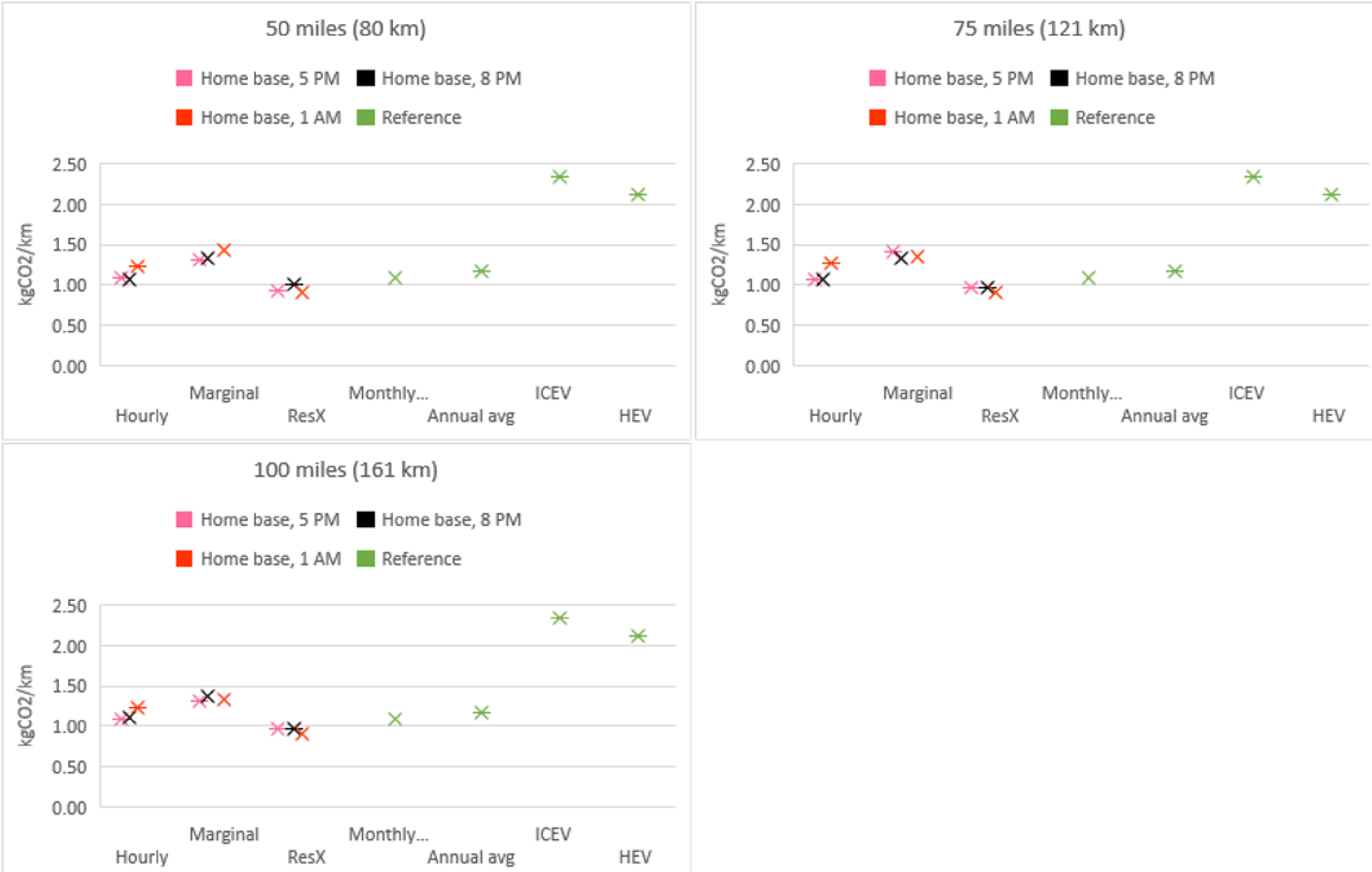


**Figure A-6. Emissions rates for refuse truck, December.**

## 9.2 Appendix B – EPA five-cycle computations

**Computation of EPA five-cycle city and highway fuel economy**

Formulae for computing official city, highway and combined fuel economy estimates per the U.S. Environmental Protection Agency official rule [13].

$$CityFE = 0.905 * \left(1/\left(StartFC + RunningFC_{City}\right)\right) \tag{A.1}$$

$$RunningFC_{City} = 0.82 * \left[\frac{0.89}{FE_{FTP\_75}} + \frac{0.11}{FE_{US06City\_75}}\right] + 0.18 * \left[\frac{1}{FE_{FTP\_20}}\right] + 0.14 * [FC_{AC}] \tag{A.2}$$

$$HighwayFE = 0.905 * \left(1/\left(StartFC + RunningFC_{Hwy}\right)\right) \tag{A.3}$$

$$RunningFC_{Hwy} = 1.07 * \left[\frac{0.79}{FE_{US06\_Hwy\_75}} + \frac{0.21}{FE_{HWFET\_75}}\right] + 0.05 * [FC_{AC}] \tag{A.4}$$

Above, FE=Fuel Economy, FC=Fuel Consumption and EC=Energy Consumption. Subscripts represent either test cycles or HVAC modes where the number following an underscore indicates the test temperature in °F.

## 9.3 Appendix C – Charging profiles

**Table C-1. Charging efficiency for Chargers of Different Levels and Capacities**

| Charging Level (kW) | η | Power (kW) | Sources |
|---|---|---|---|
| 2 | 0.88 | 8 | [30] |
| 3 | 0.9 | 50 | [30] |

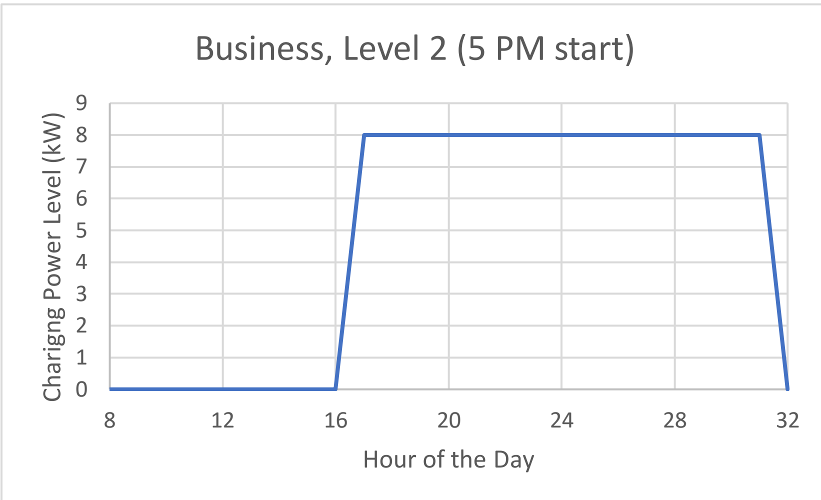


**Figure C-1. EV Charging Profile (L2): Business Home Base 5PM to 8AM**

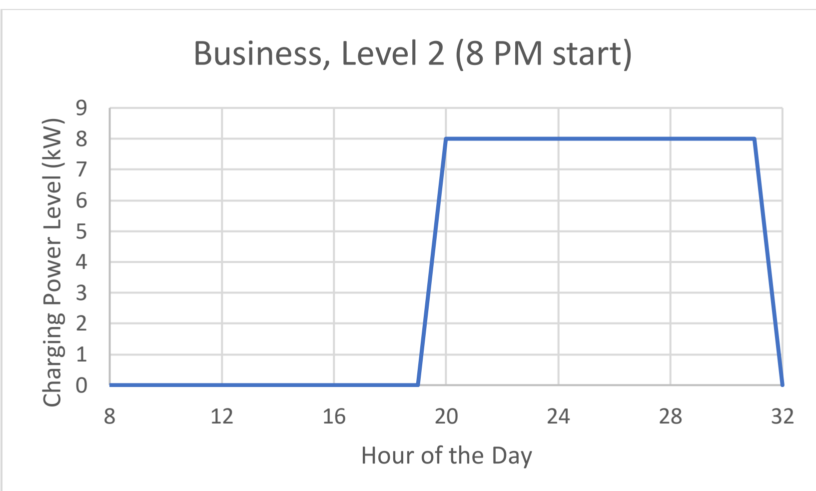


**Figure C-2. EV Charging Profile (L2): Business Home Base 8PM to 8AM**

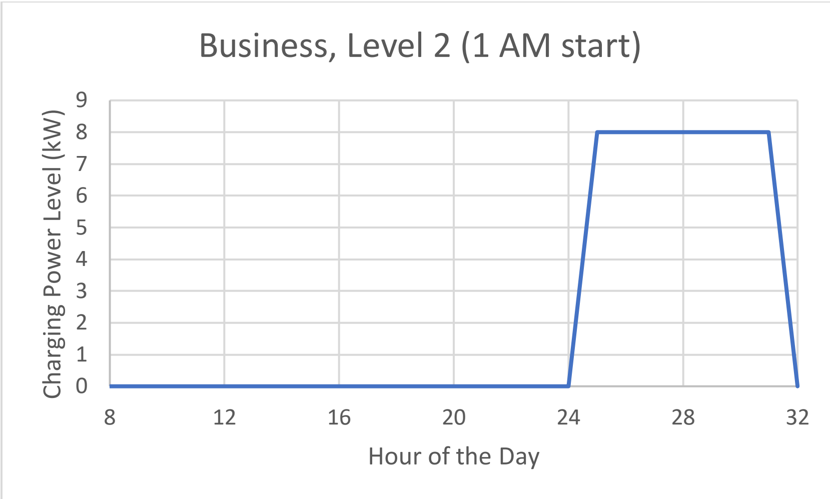


**Figure C-3. EV Charging Profile (L2): Business Home Base 1AM to 8AM**

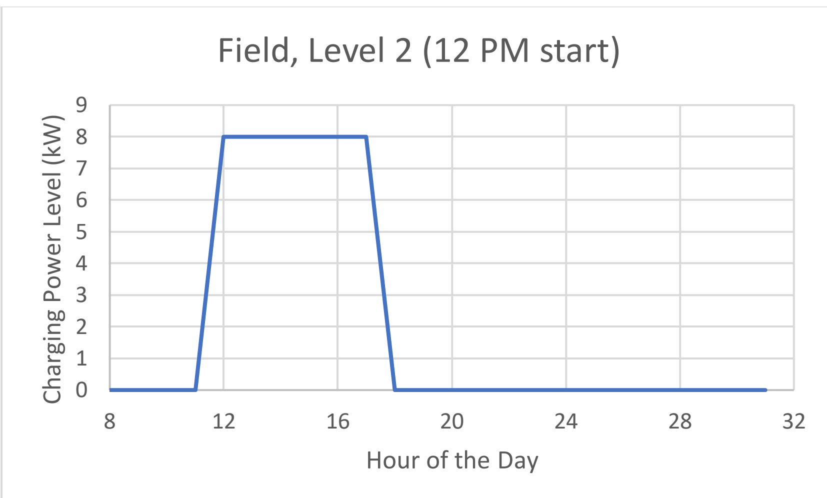


**Figure C-4. EV Charging Profile (L2): Field 12PM until fully charged (SOC=1.0)**

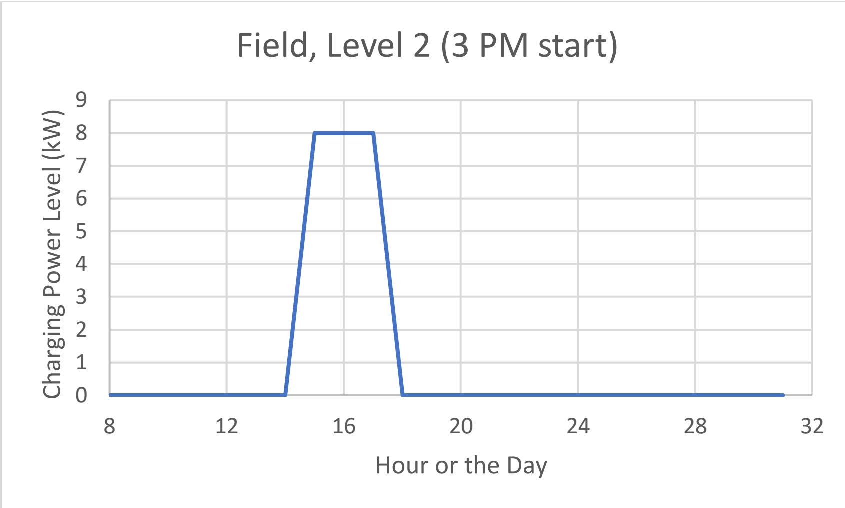


**Figure C-5. EV Charging Profile (L2): Field 3PM until fully charged (SOC=1.0)**

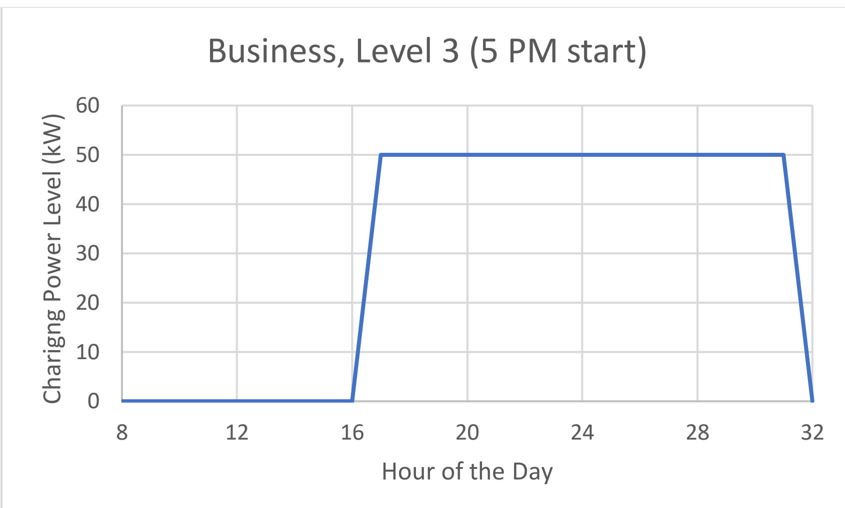


**Figure C-6. EV Charging Profile (L3): Business Home Base 5PM to 8AM**

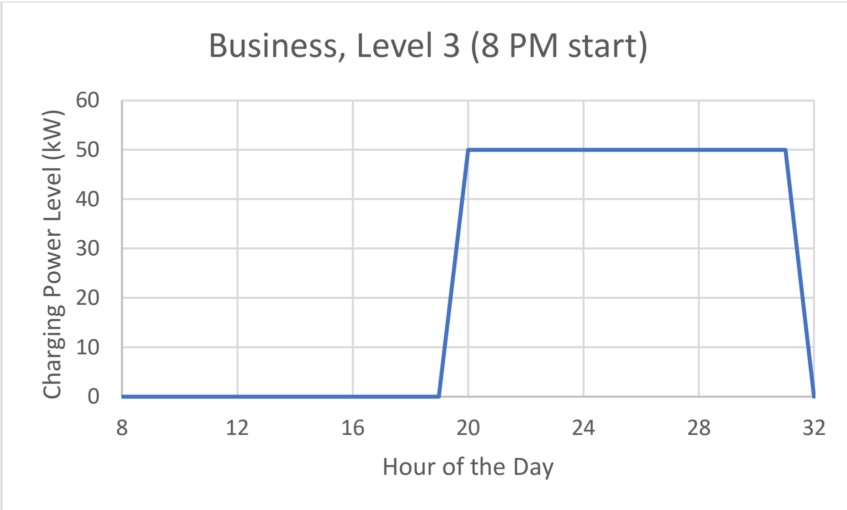


**Figure C-7. EV Charging Profile (L3): Business Home Base 8PM to 8AM**

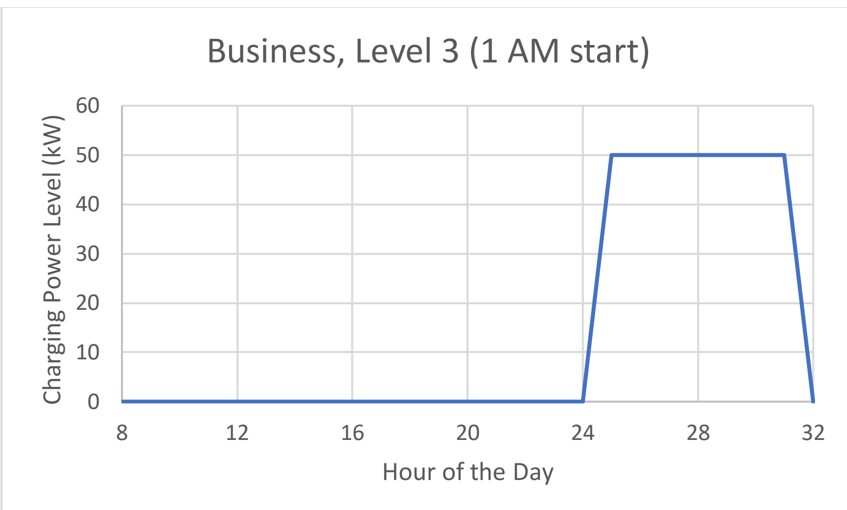


**Figure C-8. EV Charging Profile (L3): Business Home Base 1AM to 8AM**

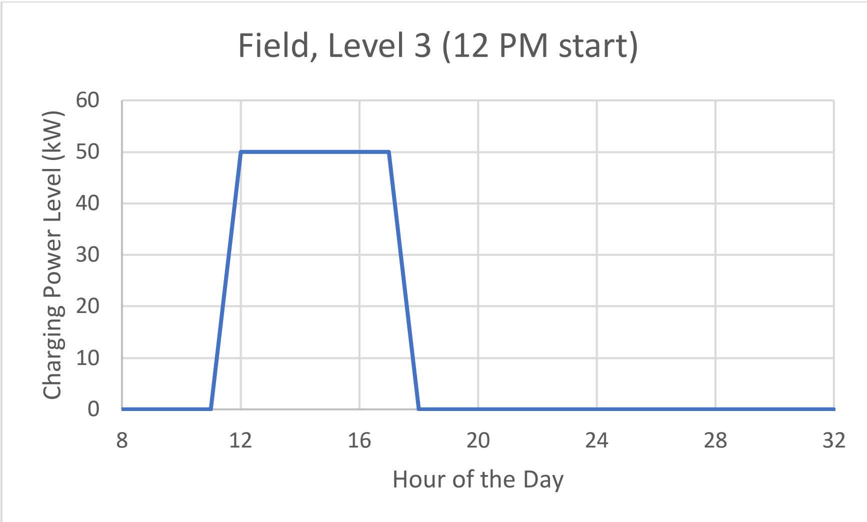


**Figure C-9. EV Charging Profile (L3): Field 12PM until Fully Charged (SOC=1.0)**

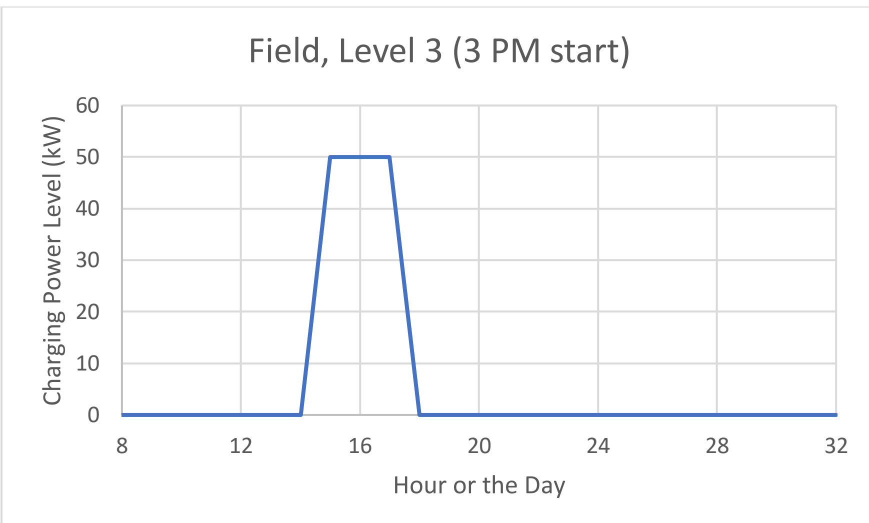


**Figure C-10. EV Charging Profile (L3): Field 3PM until Fully Charged (SOC=1.0)**

## 9.4 Appendix D – MATLAB initialization code

```
%Initialization
clear;
close all;

load [insert charging profile file name here];
load [insert emissions profile file name here];


hours = 24; %no hours in day
E_init = 0.0; %Initial Energy Transferred
E_target = [insert target energy value]; %Target Value of Energy Consumption in kWh
X_init = 0; %Initial Ontime State Variable
t_step = 1/60; %time step, set to 1/60 hour
eta_charging=0.88; %efficiency of Level 2 charger
eta_ref=0.83; %efficiency of Level 1 charger
```

## 9.5 Appendix E – Output data

**Table E-1. Output table of CO2 intensity for vehicle types, use cases, charging profiles, and months of the year.**

| **LIGHT TRUCKS** | **AUGUST** | | | | | **OCTOBER** | | | | | **DECEMBER** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **LEVEL 2** | **Charging profile** | | | | | **Charging profile** | | | | | **Charging profile** | | | | |
| **20 MILES PER DAY** | **HB17** | **HB20** | **HB1** | **F12** | **F15** | **HB17** | **HB20** | **HB1** | **F12** | **F15** | **HB17** | **HB20** | **HB1** | **F12** | **F15** |
| | kg$CO_2$/km | | | | | kg$CO_2$/km | | | | | kg$CO_2$/km | | | | |
| Hourly emissions (EV) | 0.20 | 0.19 | 0.19 | 0.21 | 0.20 | 0.20 | 0.18 | 0.20 | 0.20 | 0.20 | 0.18 | 0.17 | 0.19 | 0.17 | 0.21 |
| Monthly avg emissions (EV) | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.18 | 0.18 | 0.18 | 0.18 | 0.18 |
| Annual avg emissions (EV) | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 |
| ICEV | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 |
| HEV | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 |
| Marginal (EV) | 0.37 | 0.18 | 0.30 | 0.24 | 0.24 | 0.26 | 0.21 | 0.32 | 0.24 | 0.32 | 0.20 | 0.29 | 0.25 | 0.17 | 0.28 |
| Marginal ResX (EV) | 0.38 | 0.16 | 0.33 | 0.23 | 0.23 | 0.22 | 0.22 | 0.32 | 0.24 | 0.26 | 0.15 | 0.19 | 0.15 | 0.15 | 0.32 |
| **30 MILES PER DAY** | | | | | | | | | | | | | | | |
| Hourly emissions (EV) | 0.20 | 0.19 | 0.20 | 0.21 | 0.20 | 0.20 | 0.18 | 0.21 | 0.20 | 0.20 | 0.18 | 0.17 | 0.20 | 0.17 | 0.21 |
| Monthly avg emissions (EV) | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.18 | 0.18 | 0.18 | 0.18 | 0.18 |
| Annual avg emissions (EV) | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 |
| ICEV | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 |
| HEV | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 |
| Marginal (EV) | 0.36 | 0.20 | 0.29 | 0.25 | 0.25 | 0.27 | 0.22 | 0.28 | 0.24 | 0.30 | 0.21 | 0.27 | 0.24 | 0.19 | 0.26 |
| Marginal ResX (EV) | 0.38 | 0.17 | 0.27 | 0.28 | 0.28 | 0.22 | 0.22 | 0.27 | 0.22 | 0.29 | 0.15 | 0.18 | 0.15 | 0.15 | 0.27 |
| **50 MILES PER DAY** | | | | | | | | | | | | | | | |
| Hourly emissions (EV) | 0.20 | 0.19 | 0.20 | 0.21 | | 0.19 | 0.18 | 0.21 | 0.20 | | 0.18 | 0.17 | 0.20 | 0.18 | |
| Monthly avg emissions (EV) | 0.20 | 0.20 | 0.20 | 0.20 | | 0.19 | 0.19 | 0.19 | 0.19 | | 0.18 | 0.18 | 0.18 | 0.18 | |
| Annual avg emissions (EV) | 0.19 | 0.19 | 0.19 | 0.19 | | 0.19 | 0.19 | 0.19 | 0.19 | | 0.19 | 0.19 | 0.19 | 0.19 | |
| ICEV | 0.30 | 0.30 | 0.30 | 0.30 | | 0.30 | 0.30 | 0.30 | 0.30 | | 0.30 | 0.30 | 0.30 | 0.30 | |
| HEV | 0.25 | 0.25 | 0.25 | 0.25 | | 0.25 | 0.25 | 0.25 | 0.25 | | 0.25 | 0.25 | 0.25 | 0.25 | |
| Marginal (EV) | 0.31 | 0.23 | 0.28 | 0.26 | | 0.24 | 0.22 | 0.26 | 0.23 | | 0.22 | 0.22 | 0.24 | 0.22 | |
| Marginal ResX (EV) | 0.29 | 0.23 | 0.31 | 0.31 | | 0.22 | 0.20 | 0.23 | 0.20 | | 0.15 | 0.17 | 0.15 | 0.16 | |
| **100 MILES PER DAY** | | | | | | | | | | | | | | | |
| Hourly emissions (EV) | 0.19 | 0.19 | 0.21 | 0.19 | | 0.19 | 0.19 | 0.21 | 0.19 | | 0.18 | 0.18 | 0.20 | 0.18 | |
| Monthly avg emissions (EV) | 0.20 | 0.20 | 0.20 | 0.20 | | 0.19 | 0.19 | 0.19 | 0.19 | | 0.18 | 0.18 | 0.18 | 0.18 | |
| Annual avg emissions (EV) | 0.19 | 0.19 | 0.19 | 0.19 | | 0.19 | 0.19 | 0.19 | 0.19 | | 0.19 | 0.19 | 0.19 | 0.19 | |
| ICEV | 0.30 | 0.30 | 0.30 | 0.30 | | 0.30 | 0.30 | 0.30 | 0.30 | | 0.30 | 0.30 | 0.30 | 0.30 | |
| HEV | 0.25 | 0.25 | 0.25 | 0.25 | | 0.25 | 0.25 | 0.25 | 0.25 | | 0.25 | 0.25 | 0.25 | 0.25 | |
| Marginal (EV) | 0.27 | 0.24 | 0.25 | 0.26 | | 0.23 | 0.24 | 0.26 | 0.24 | | 0.21 | 0.22 | 0.22 | 0.21 | |
| Marginal ResX (EV) | 0.26 | 0.23 | 0.26 | 0.29 | | 0.21 | 0.21 | 0.29 | 0.22 | | 0.16 | 0.16 | 0.15 | 0.17 | |

| **SMALL VANS** | | | **AUGUST** | | | | | **OCTOBER** | | | | | **DECEMBER** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **LEVEL 2** | | | **Charging profile** | | | | | **Charging profile** | | | | | **Charging profile** | | |
| **20 MILES PER DAY** | **HB17** | **HB20** | **HB1** | **F12** | **F15** | **HB17** | **HB20** | **HB1** | **F12** | **F15** | **HB17** | **HB20** | **HB1** | **F12** | **F15** |
| | | | $kgCO_2/km$ | | | | | $kgCO_2/km$ | | | | | $kgCO_2/km$ | | |
| Hourly emissions (EV) | 0.18 | 0.17 | 0.17 | 0.19 | 0.18 | 0.18 | 0.17 | 0.18 | 0.18 | 0.18 | 0.16 | 0.16 | 0.17 | 0.15 | 0.19 |
| Monthly avg emissions (EV) | 0.18 | 0.18 | 0.18 | 0.18 | 0.18 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.16 | 0.16 | 0.16 | 0.16 | 0.16 |
| Annual avg emissions (EV) | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 |
| ICEV | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 |
| Marginal (EV) | 0.33 | 0.15 | 0.27 | 0.21 | 0.21 | 0.24 | 0.18 | 0.30 | 0.21 | 0.29 | 0.18 | 0.27 | 0.23 | 0.15 | 0.26 |
| Marginal ResX (EV) | 0.34 | 0.14 | 0.31 | 0.19 | 0.19 | 0.20 | 0.20 | 0.30 | 0.20 | 0.22 | 0.13 | 0.17 | 0.13 | 0.13 | 0.31 |
| **30 MILES PER DAY** | | | | | | | | | | | | | | | |
| Hourly emissions (EV) | 0.18 | 0.17 | 0.18 | 0.19 | 0.18 | 0.18 | 0.17 | 0.18 | 0.18 | 0.18 | 0.16 | 0.16 | 0.18 | 0.16 | 0.19 |
| Monthly avg emissions (EV) | 0.18 | 0.18 | 0.18 | 0.18 | 0.18 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.16 | 0.16 | 0.16 | 0.16 | 0.16 |
| Annual avg emissions (EV) | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 |
| ICEV | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 | 0.29 |
| Marginal (EV) | 0.32 | 0.18 | 0.26 | 0.22 | 0.22 | 0.24 | 0.19 | 0.26 | 0.22 | 0.27 | 0.19 | 0.25 | 0.22 | 0.17 | 0.24 |
| Marginal ResX (EV) | 0.34 | 0.15 | 0.25 | 0.24 | 0.15 | 0.20 | 0.20 | 0.25 | 0.20 | 0.26 | 0.14 | 0.16 | 0.14 | 0.14 | 0.25 |
| **50 MILES PER DAY** | | | | | | | | | | | | | | | |
| Hourly emissions (EV) | 0.18 | 0.17 | 0.18 | 0.19 | | 0.18 | 0.16 | 0.19 | 0.18 | | 0.16 | 0.16 | 0.18 | 0.16 | |
| Monthly avg emissions (EV) | 0.18 | 0.18 | 0.18 | 0.18 | | 0.17 | 0.17 | 0.17 | 0.17 | | 0.16 | 0.16 | 0.16 | 0.16 | |
| Annual avg emissions (EV) | 0.17 | 0.17 | 0.17 | 0.17 | | 0.17 | 0.17 | 0.17 | 0.17 | | 0.17 | 0.17 | 0.17 | 0.17 | |
| ICEV | 0.29 | 0.29 | 0.29 | 0.29 | | 0.29 | 0.29 | 0.29 | 0.29 | | 0.29 | 0.29 | 0.29 | 0.29 | |
| Marginal (EV) | 0.29 | 0.20 | 0.25 | 0.24 | | 0.22 | 0.20 | 0.23 | 0.20 | | 0.19 | 0.20 | 0.21 | 0.19 | |
| Marginal ResX (EV) | 0.28 | 0.21 | 0.27 | 0.28 | | 0.20 | 0.18 | 0.20 | 0.18 | | 0.13 | 0.15 | 0.13 | 0.13 | |
| **100 MILES PER DAY** | | | | | | | | | | | | | | | |
| Hourly emissions (EV) | 0.17 | 0.17 | 0.19 | 0.18 | | 0.17 | 0.17 | 0.19 | 0.18 | | 0.16 | 0.16 | 0.18 | 0.17 | |
| Monthly avg emissions (EV) | 0.18 | 0.18 | 0.18 | 0.18 | | 0.17 | 0.17 | 0.17 | 0.17 | | 0.16 | 0.16 | 0.16 | 0.16 | |
| Annual avg emissions (EV) | 0.17 | 0.17 | 0.17 | 0.17 | | 0.17 | 0.17 | 0.17 | 0.17 | | 0.17 | 0.17 | 0.17 | 0.17 | |
| ICEV | 0.29 | 0.29 | 0.29 | 0.29 | | 0.29 | 0.29 | 0.29 | 0.29 | | 0.29 | 0.29 | 0.29 | 0.29 | |
| Marginal (EV) | 0.24 | 0.21 | 0.23 | 0.24 | | 0.21 | 0.22 | 0.23 | 0.23 | | 0.19 | 0.20 | 0.20 | 0.20 | |
| Marginal ResX (EV) | 0.24 | 0.20 | 0.24 | 0.28 | | 0.19 | 0.18 | 0.26 | 0.21 | | 0.14 | 0.14 | 0.13 | 0.17 | |

| **Composite MD Class 4/5** | | | **AUGUST** | | | | | **OCTOBER** | | | | | **DECEMBER** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **LEVEL 3** | | | **Charging profile** | | | | | **Charging profile** | | | | | **Charging profile** | | |
| **20 MILES PER DAY** | **HB17** | **HB20** | **HB1** | **F12** | **F15** | **HB17** | **HB20** | **HB1** | **F12** | **F15** | **HB17** | **HB20** | **HB1** | **F12** | **F15** |
| | | | $kgCO_2/km$ | | | | | $kgCO_2/km$ | | | | | $kgCO_2/km$ | | |
| Hourly emissions (EV) | 0.40 | 0.38 | 0.38 | 0.42 | 0.39 | 0.40 | 0.37 | 0.40 | 0.40 | 0.39 | 0.35 | 0.35 | 0.38 | 0.34 | 0.43 |
| Monthly avg emissions (EV) | 0.39 | 0.39 | 0.39 | 0.39 | 0.39 | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 | 0.35 | 0.35 | 0.35 | 0.35 | 0.35 |
| Annual avg emissions (EV) | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 |
| ICEV | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 |
| HEV | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 |
| Marginal (EV) | 0.74 | 0.31 | 0.62 | 0.45 | 0.46 | 0.52 | 0.39 | 0.70 | 0.47 | 0.68 | 0.39 | 0.63 | 0.51 | 0.32 | 0.60 |
| Marginal ResX (EV) | 0.75 | 0.31 | 0.75 | 0.38 | 0.38 | 0.44 | 0.44 | 0.73 | 0.44 | 0.44 | 0.30 | 0.40 | 0.30 | 0.30 | 0.74 |
| **30 MILES PER DAY** | | | | | | | | | | | | | | | |
| Hourly emissions (EV) | 0.39 | 0.38 | 0.38 | 0.41 | 0.38 | 0.39 | 0.36 | 0.40 | 0.40 | 0.38 | 0.35 | 0.34 | 0.38 | 0.33 | 0.43 |
| Monthly avg emissions (EV) | 0.39 | 0.39 | 0.39 | 0.39 | 0.39 | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 | 0.35 | 0.35 | 0.35 | 0.35 | 0.35 |
| Annual avg emissions (EV) | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 |
| ICEV | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 |
| HEV | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 |
| Marginal (EV) | 0.73 | 0.30 | 0.61 | 0.44 | 0.45 | 0.51 | 0.38 | 0.69 | 0.46 | 0.67 | 0.38 | 0.62 | 0.50 | 0.31 | 0.59 |
| Marginal ResX (EV) | 0.74 | 0.30 | 0.74 | 0.37 | 0.37 | 0.44 | 0.44 | 0.72 | 0.44 | 0.44 | 0.29 | 0.39 | 0.29 | 0.29 | 0.73 |
| **50 MILES PER DAY** | | | | | | | | | | | | | | | |
| Hourly emissions (EV) | 0.38 | 0.37 | 0.37 | 0.40 | 0.37 | 0.38 | 0.35 | 0.39 | 0.39 | 0.37 | 0.34 | 0.33 | 0.37 | 0.32 | 0.41 |
| Monthly avg emissions (EV) | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.34 | 0.34 | 0.34 | 0.34 | 0.34 |
| Annual avg emissions (EV) | 0.36 | 0.36 | 0.36 | 0.36 | 0.36 | 0.36 | 0.36 | 0.36 | 0.36 | 0.36 | 0.36 | 0.36 | 0.36 | 0.36 | 0.36 |
| ICEV | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 |
| HEV | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 |
| Marginal (EV) | 0.71 | 0.29 | 0.59 | 0.43 | 0.44 | 0.50 | 0.37 | 0.68 | 0.45 | 0.65 | 0.37 | 0.60 | 0.48 | 0.30 | 0.57 |
| Marginal ResX (EV) | 0.72 | 0.29 | 0.72 | 0.36 | 0.36 | 0.43 | 0.43 | 0.70 | 0.43 | 0.43 | 0.29 | 0.38 | 0.29 | 0.29 | 0.71 |
| **100 MILES PER DAY** | | | | | | | | | | | | | | | |
| Hourly emissions (EV) | 0.38 | 0.36 | 0.38 | 0.40 | 0.38 | 0.38 | 0.35 | 0.39 | 0.38 | 0.38 | 0.34 | 0.33 | 0.38 | 0.33 | 0.40 |
| Monthly avg emissions (EV) | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.34 | 0.34 | 0.34 | 0.34 | 0.34 |
| Annual avg emissions (EV) | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 |
| ICEV | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 | 0.63 |
| HEV | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 |
| Marginal (EV) | 0.69 | 0.39 | 0.55 | 0.48 | 0.47 | 0.51 | 0.42 | 0.53 | 0.46 | 0.56 | 0.41 | 0.51 | 0.47 | 0.37 | 0.50 |
| Marginal ResX (EV) | 0.72 | 0.33 | 0.51 | 0.55 | 0.55 | 0.43 | 0.43 | 0.50 | 0.43 | 0.57 | 0.29 | 0.34 | 0.29 | 0.29 | 0.50 |

| Refuse | AUGUST | | | | | OCTOBER | | | | | DECEMBER | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **LEVEL 3** | **Charging profile** | | | | | **Charging profile** | | | | | **Charging profile** | | | | |
| **50 MILES PER DAY** | **HB17** | **HB20** | **HB1** | **F12** | **F15** | **HB17** | **HB20** | **HB1** | **F12** | **F15** | **HB17** | **HB20** | **HB1** | **F12** | **F15** |
| | $kgCO_2/km$ | | | | | $kgCO_2/km$ | | | | | $kgCO_2/km$ | | | | |
| Hourly emissions (EV) | 1.21 | 1.14 | 1.25 | | | 1.19 | 1.12 | 1.29 | | | 1.09 | 1.07 | 1.23 | | |
| Monthly avg emissions (EV) | 1.21 | 1.21 | 1.21 | | | 1.17 | 1.17 | 1.17 | | | 1.08 | 1.08 | 1.08 | | |
| Annual avg emissions (EV) | 1.16 | 1.16 | 1.16 | | | 1.16 | 1.16 | 1.16 | | | 1.16 | 1.16 | 1.16 | | |
| ICEV | 2.35 | 2.35 | 2.35 | | | 2.35 | 2.35 | 2.35 | | | 2.35 | 2.35 | 2.35 | | |
| HEV | 2.13 | 2.13 | 2.13 | | | 2.13 | 2.13 | 2.13 | | | 2.13 | 2.13 | 2.13 | | |
| Marginal (EV) | 1.90 | 1.38 | 1.70 | | | 1.45 | 1.35 | 1.56 | | | 1.31 | 1.33 | 1.44 | | |
| Marginal ResX (EV) | 1.79 | 1.43 | 1.87 | | | 1.36 | 1.21 | 1.43 | | | 0.93 | 1.01 | 0.91 | | |
| **75 MILES PER DAY** | | | | | | | | | | | | | | | |
| Hourly emissions (EV) | 1.19 | 1.14 | 1.27 | | | 1.16 | 1.15 | 1.32 | | | 1.08 | 1.08 | 1.26 | | |
| Monthly avg emissions (EV) | 1.21 | 1.21 | 1.21 | | | 1.17 | 1.17 | 1.17 | | | 1.08 | 1.08 | 1.08 | | |
| Annual avg emissions (EV) | 1.16 | 1.16 | 1.16 | | | 1.16 | 1.16 | 1.16 | | | 1.16 | 1.16 | 1.16 | | |
| ICEV | 2.35 | 2.35 | 2.35 | | | 2.35 | 2.35 | 2.35 | | | 2.35 | 2.35 | 2.35 | | |
| HEV | 2.13 | 2.13 | 2.13 | | | 2.13 | 2.13 | 2.13 | | | 2.13 | 2.13 | 2.13 | | |
| Marginal (EV) | 1.68 | 1.37 | 1.63 | | | 1.41 | 1.38 | 1.59 | | | 1.41 | 1.33 | 1.36 | | |
| Marginal ResX (EV) | 1.54 | 1.27 | 1.79 | | | 1.36 | 1.12 | 1.70 | | | 0.98 | 0.98 | 0.91 | | |
| **100 MILES PER DAY** | | | | | | | | | | | | | | | |
| Hourly emissions (EV) | 1.18 | 1.15 | 1.28 | | | 1.16 | 1.17 | 1.32 | | | 1.08 | 1.11 | 1.24 | | |
| Monthly avg emissions (EV) | 1.21 | 1.21 | 1.21 | | | 1.17 | 1.17 | 1.17 | | | 1.08 | 1.08 | 1.08 | | |
| Annual avg emissions (EV) | 1.17 | 1.17 | 1.17 | | | 1.17 | 1.17 | 1.17 | | | 1.17 | 1.17 | 1.17 | | |
| ICEV | 2.35 | 2.35 | 2.35 | | | 2.35 | 2.35 | 2.35 | | | 2.35 | 2.35 | 2.35 | | |
| HEV | 2.13 | 2.13 | 2.13 | | | 2.13 | 2.13 | 2.13 | | | 2.13 | 2.13 | 2.13 | | |
| Marginal (EV) | 1.66 | 1.47 | 1.53 | | | 1.41 | 1.49 | 1.56 | | | 1.30 | 1.37 | 1.33 | | |
| Marginal ResX (EV) | 1.61 | 1.40 | 1.58 | | | 1.27 | 1.28 | 1.76 | | | 0.97 | 0.97 | 0.92 | | |

## 9.6 Appendix F – Emissions from charging event variation example – moving truck, 50 miles, August

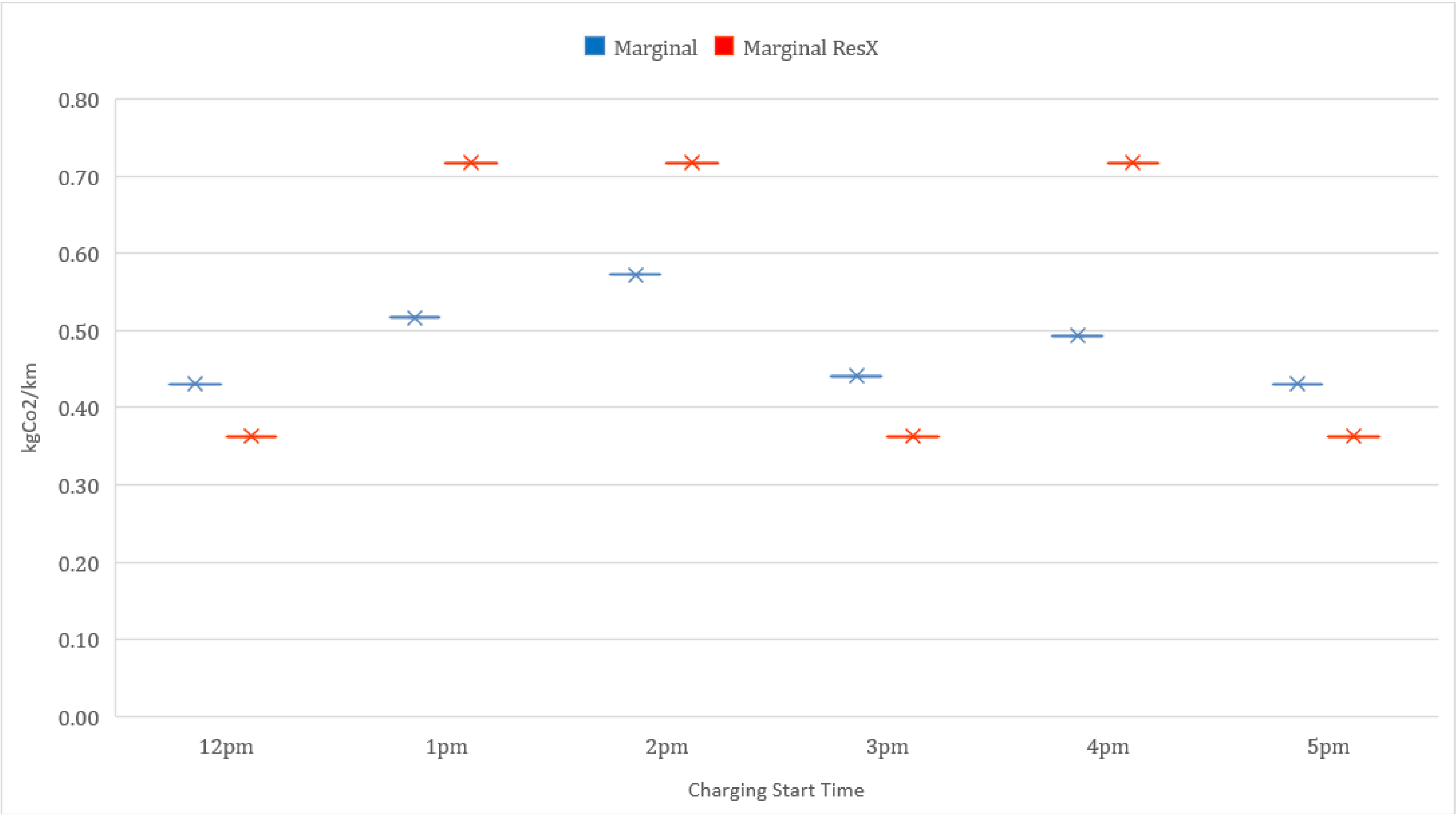


**Figure F-1. Example comparing the CO2 intensity under two different grid assumptions for an MD moving truck, 50 mile, August simulation**