A MODELING APPROACH TO ESTIMATE HANDPRINT IMPACTS: APPLICATIONS IN GRID MANAGEMENT AND FLEET EV CHARGING

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Contents

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The **American Council for an Energy-Efficient Economy** (ACEEE), a nonprofit research organization, develops policies to reduce energy waste and combat climate change. Its independent analysis advances investments, programs, and behaviors that use energy more effectively and help build an equitable clean energy future.

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Data and Licensing Information

Acronyms

BAU	Business as usual
BTM	Behind the meter
C&I	Commercial and industrial
DC	Direct current
DCFC	Direct current fast charge
DERs	Distributed energy resources
ESG	Environmental, social, governance
EV	Electric vehicle
FIFO	First in, first out
FTM	Front of the meter
GEA	Generation, emissions, and assessment
GHG	Greenhouse gas
GMS	Grid management solution
GVWR	Gross vehicle weight rating
ICT	Information and communications technology
kW(h)	Kilowatt (hour)
MT	Metric ton
MW(h)	Megawatt (hour)
NREL	National Renewable Energy Laboratory
PNNL	Pacific Northwest National Laboratory
SOC	State of charge
T&D	Transmission and distribution

Glossary and Key Terms

Term	Definition
Behind the meter	On the customer side of the utility service meter
Carbon footprint	Total amount of GHG emissions generated by direct action
Carbon handprint	Difference in total emissions between the footprint of a baseline and an applied solution
Downstream	Operations relating to the movement or use of finished goods down the supply chain from a business
Embodied carbon	GHG emissions from the manufacturing, installation, transportation, maintenance, use, and disposal of building materials
Environmental, social, governance (ESG)	Standards for companies' behaviors relating to emissions, sustainability, and societal well-being, set by stakeholders
Front of meter	On the utility side of the service meter, substation level
Information and communications technology (ICT)	Infrastructure and components that enable systems optimization through technology-based data visualization and user access
Scope 1 emissions	Direct GHG emissions that occur from sources owned by a company
Scope 2 emissions	GHG emissions that a company causes by the production of energy it purchases and uses
Scope 3 emissions	GHG emissions that a company is indirectly responsible for up and down its value or supply chain, making them the most difficult to calculate and attribute
Transmission and distribution (T&D)	Refers to various stages in the infrastructure of transporting electricity from utilities to users
Voltage optimization	Systematic improvements and reductions in the voltage sent by energy producers to energy consumers, reducing energy use and electricity demand

Introduction

Companies throughout the U.S. economy are setting ambitious climate goals. However, the current greenhouse gas (GHG) monitoring protocols being used to frame and assess progress on these goals often do not adequately capture the entire extent of corporate emissions and emissions reduction profiles across scopes 1, 2, and 3. This is the case because the standardized method for measuring and reporting climate impact is assessed at the company level and does not take into account the impacts of goods and services across their entire life cycle, especially upstream and downstream of a company's activities (these emissions are referred to as scope 3). Additionally, traditionally measured *carbon footprints* do not consider reductions in downstream scope 3 emissions, or how the use of alternate approaches and technologies can make positive differences in carbon outputs. Definitions for scope 1 and 2 can be found in the glossary and key terms section above.

The development and implementation of critical emissions-reducing technologies, such as information and communication technologies (ICTs), offer a potent means of decreasing carbon emissions in a variety of applications across the economy. Given the value of ICTs in emissions reductions, it is essential that consistent methodologies are developed for assessing, quantifying, and calculating emissions reductions in the downstream supply chain. The concept of the *carbon handprint*, demonstrated in this work, is gaining recognition as a way to account for these net positive emissions reductions across a product's life cycle. Thus, the carbon handprint can play a key role in environmental, social, and governance (ESG) accounting and reporting by complementing the better-known *carbon footprint* approach, together providing a more comprehensive understanding of companies' emissions and emissions reductions (Elliott, Srinivasan, and Hoffmeister 2022).

This white paper focuses specifically on a proposed model and approach with example calculations for the net positive handprint effects of ICT solutions as applied in two use cases:

- A grid management solution (GMS) for the utilities sector, to optimize utility substations and better manage industrial electricity user loads (through voltage and capacity management) in a front-of-meter (FTM) application
- An electric vehicle fleet charging solution for the transportation sector, to optimize depot charging of electric vehicles (EVs) used in short-haul freight and drayage fleets in behind-the-meter (BTM) applications

The intention of this work is to demonstrate the value of handprint analysis in quantifying emissions reductions enabled by ICT technologies. In future work, those calculations may subsequently be used to attribute savings to multiple actors in the supply chain. This analysis offers a proof of concept for two different scenarios, demonstrates that net positive handprint impact can be estimated, and demonstrates that the proposed model and approach used for such calculations can be generalized and reused (with tailoring) in other technology use cases. This paper is largely focused on the two case studies, however.

Though the general pathway can be applied from this work, handprint methodologies for other applications will have to be modified to fit them specifically.

CARBON HANDPRINT

A carbon handprint can be defined as the difference between the emissions (footprint) of a baseline or business-as-usual (BAU) scenario and the emissions (footprint) associated with a solution in the downstream supply chain. A solution in this case is an ICT application, applied to that baseline scenario, which creates a net positive change (reduction) in emissions. For example, a company that has developed an ICT that lowers the emissions intensity of delivered electricity is increasing its handprint impact by reducing the carbon footprint of those purchasing electricity from any utility that has implemented the technology. In another example, a company that has developed an ICT to charge EVs optimally with the lowest emissions intensity is increasing its handprint impact by reducing the footprint of the vehicles being charged and of the customers using them. Figure 1 graphically illustrates the handprint concept in these two examples. It is important to note that the life cycle carbon footprint of the ICT solution itself should be subtracted from the total handprint. However, these impacts are typically de minimis.

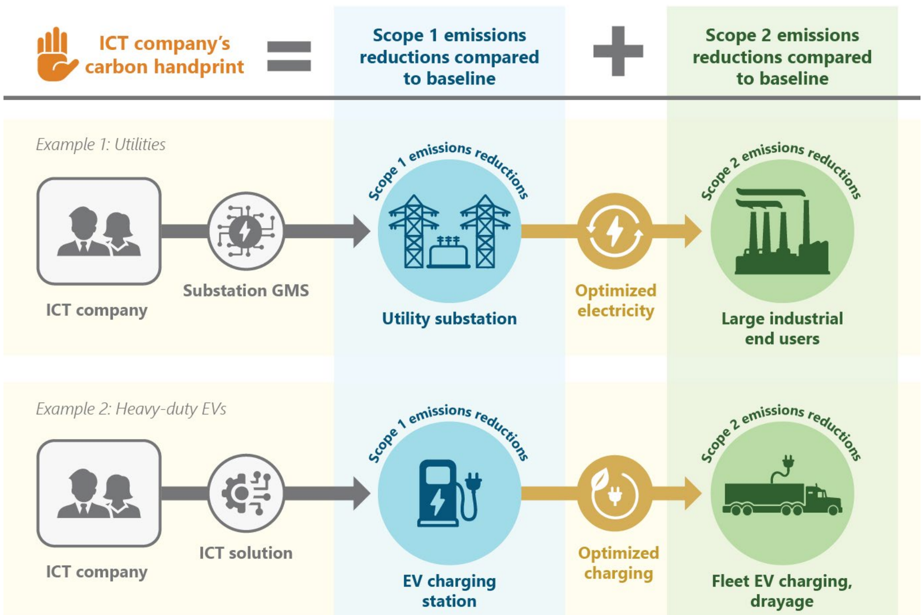

Figure 1. Examples of handprint as a company's impact on its customers' footprints compared to the customers' baseline

Maximizing a company's carbon handprint is therefore beneficial and often means reducing the footprint, or direct and indirect greenhouse gas (GHG) emissions, of other entities in the supply chain. Figure 2 depicts this relationship to show how a company can contribute to emissions reductions both by lowering its own footprint and simultaneously lowering the footprint of others through the ICT solution it deploys. The glossary at the start of the white paper provides additional details on terminology and definitions.

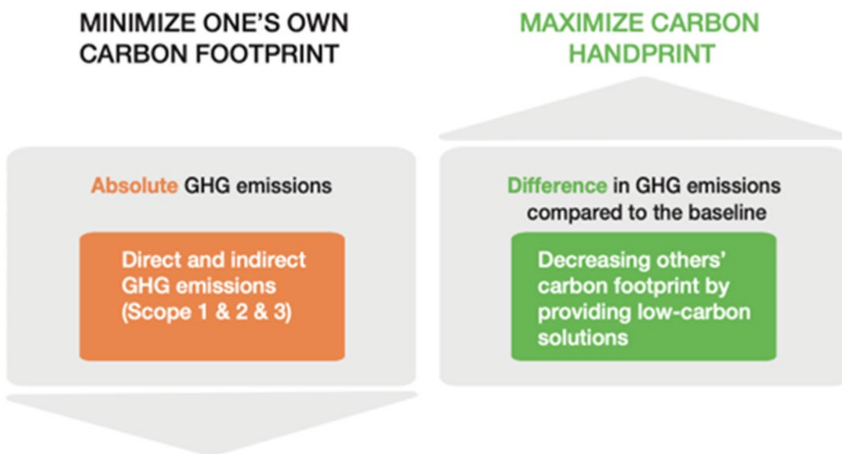

Figure 2. How handprint and footprint reductions work in concert. Source: Pajula et al. 2021.

The carbon handprint approach is especially useful in estimating emissions reductions from ICT applications when there are complex savings opportunities throughout the life cycle of such technologies, and inherent challenges in separating contributions from different actors in their value and supply chains. These challenges, however, are not within the scope of this paper and will be addressed in future research efforts.

In related efforts, ACEEE research (Elliott, Srinivasan, and Hoffmeister 2022) has found:

- Handprint accounting has the potential to more accurately identify emissions reductions from the use of ICT and assign credit to various actors in the value chain (as compared to accounting that just looks at carbon footprints), although a range of approaches to allocating credit are based on data availability and other considerations.
- Companies should strive to minimize their own footprint and decrease the footprint of others by providing ICT solutions that create handprint impact.
- Handprint calculation not only attributes reduction credit, but also encourages prioritization of technology development, investment, and adoption.

ROLE OF INTELLIGENT EFFICIENCY IN DECARBONIZATION

To fully contextualize the value of analyzing and attributing handprint impact, it is essential to recognize the role of ICT in enabling decarbonization of carbon- and energy-intensive sectors. ICTs allow a holistic, systems-based approach to energy savings collectively referred to as intelligent efficiency (Elliott, Molina, and Trombley 2012).[1] Intelligent efficiency savings in the downstream supply chain are carbon handprint savings. Because ICTs allow for better access to real-time information and can be responsive, predictive, and adaptive, they are an important tool for enabling critical emissions reductions through efficiency improvements across multiple economic sectors. ICTs also enable intelligent efficiency by optimizing complex systems through data visualization, precision controls, and other applications. According to prior ACEEE research, if homeowners and businesses were to take advantage of commercially available ICTs that promote system efficiency, the United States could reduce energy use by about 12–22% while the annual energy cost savings of ICTs in the commercial and manufacturing sectors could exceed $50 billion (Rogers et al. 2013). There is a wide spectrum of ICT applications, as the technologies have many uses across critical sectors of the economy, including for utilities and for transportation, the sectors from which we draw our use cases in this work.

The two real-world use cases we examine here enable significant energy savings and emissions reductions in their respective sectors. We found that the positive handprint impacts of both solutions can accelerate decarbonization and lay the groundwork for savings attribution to actors in the value and supply chains for these ICT solutions.

Utility Substation Use Case

Many utilities have made ambitious commitments to reduce their emissions as part of the decarbonization of the electric power system. These goals are often motivated by time-bound state and federal policies that require utilities to make significant advancements in reducing emissions. For example, California has mandated that all electricity produced in the state must be carbon free by 2045 (CARB 2022). As utilities aim to meet these goals, they need to determine the best technologies to adopt, including grid management solutions (GMS) and practices, that will reduce emissions while also maintaining reliability and resilience.

Currently, as much as 10% of electric energy produced by the grid is lost during transmission and distribution to customers (York et al. 2015). When implemented at the utility substation, a GMS reduces losses by better controlling and managing both the grid and customer loads through voltage optimization. The application allows utility substations to improve efficiency by matching grid supply to the specific load needs of their customers and saving energy by avoiding excess voltages. Lowering voltages can improve the end-use efficiency of equipment and reduce line losses on both sides of the meter (York et al. 2015). Also, the

[1] Intelligent efficiency uses ICT, the Internet of Things, big data, data analytics, and machine learning to reduce energy consumption and GHG emissions. See https://www.aceee.org/topic/intelligent-efficiency for more information.

GMS can help substations avoid costly, material- and carbon-intensive infrastructure upgrades to install additional transmission and distribution (T&D) capacity, thereby creating embodied carbon savings.

The substation GMS in the case we modeled maximizes the positive handprint of the company that produced the ICT solution by reducing the footprint (scope 1) of its utility customers, as well as the scope 2 emissions of those purchasing electricity from the utilities. The impact of this application and similar smart grid technologies, which will continue to expand as new ICT solutions are developed, can be significant and verifiable if supported with enough data. For example, in 2010 the Pacific Northwest National Laboratory (PNNL) estimated a total direct reduction of 12% in CO_2 emissions from nine smart grid technologies deployed across the economy in 2030 (Pratt et al. 2010).

Our representative analysis aims to quantify the handprint emissions reductions enabled by this substation GMS.

Electric Vehicle (EV) Use Case

The Biden administration has set a goal to leverage available government resources so all new heavy-duty vehicle sales will be net-zero emissions no later than 2040 (DOE 2022). For the foreseeable future, battery electric vehicles (BEVs) will be a significant, if not the primary, vector of achieving this goal. Charging these vehicles will lead to a significant new electric load on the electric grid. Due to their outsized and significant impact on U.S. emissions, addressing the charging of short-haul freight and drayage vehicle fleets is particularly important. The charging infrastructure to accommodate this emerging load will be located next to port distribution and other facilities. Stakeholders, including utilities, project developers, and grid operators, are investigating how best to plan charging assets to accommodate the increased electric load and required infrastructure.

Optimizing the timing and intensity of this charging is essential to control the costs both to vehicle and charging site operators and to the grid operators themselves, who must adapt to these transient loads. Mass charging from heavy-duty EV fleets is expected to overburden the electricity transmission and generation networks. Therefore, utility companies will need to control the supply and demand of electricity by implementing demand-response management approaches such as time-of-day price plans.

As in the substation use case, timing and intensity will also have a significant emissions impact, separate from the total scale of charging demand. Facilities that simply charge vehicles immediately upon arrival and on a first-come-first-served basis may increase emissions, marginal costs, and equipment and infrastructure costs.

The fleet EV charging solution to address the above challenges will be ICT-enabled control of customer-sited distributed energy resources (DERs), such as storage and renewable generation. This use case will examine the handprint impacts of an ICT application that includes both charging schedule control and grid integration for power delivery during peak periods. Future improvements to this solution may add more grid services such as frequency regulation, delivery schedule optimization, and renewable energy integration.

Data Needs for Future Model Revisions and Other Analyses

Significant amounts of data are required not only to enable companies to make estimates and take steps to reduce their GHG footprint, but also to foster the use of the handprint approach to accurately assign attribution to actors in complex supply chains. It is essential to gather all the data necessary to analyze companies' operations as well as data from energy providers. The calculations showcased in this report as proofs of concept were created based on all the relevant data that could be obtained at this point in time. Their accuracy and applicability will be improved as new and better data become available. Table 1 provides the data elements required for handprint calculations, uniquely for each use case and commonly to both, that would expand on the initial models developed for our use cases. It also includes possible sources for such data.

Table 1. Data elements required for handprint calculations

Substation GMS use case	Where data can be obtained	Fleet EV charging use case	Where data can be obtained
Marginal emissions	NREL's Cambium Datasets, independent research	Marginal emissions	NREL's Cambium Datasets, independent research
Substation level performance data in projected hourly load	Independent research, public service commission proceedings (OFTEN PROPRIETARY)	Electric pricing scheme (including schedules and demand charges)	Emissions and pricing are directionally and proportionally linked
Savings enabled by the application of the GMS solution	Independent research	Vehicle specification	Independent research
Capacity of analyzed substations for T&D deferral analysis	Independent research	Charger specification	DOE DC fast charging data
Best fit of future-based emissions scenario	Depends on trend being analyzed	Battery lifetimes and replacement costs	Independent research
Social cost of carbon	EPA regulatory documents	Arriving vehicle battery state of	Assumption, limited

Substation GMS use case	Where data can be obtained	Fleet EV charging use case	Where data can be obtained
		charge and power sources	
-		Contracts pricing information and limitations for supplying the grid with energy (including schedule)	Independent research

The Need for Handprint Calculators

While research on the handprint approach has continued for more than a decade, easy-to-use tools and methodologies for quantifying handprint savings from ICT solutions are limited. Emerging carbon footprint and GHG emissions calculators enable users to measure and track carbon emissions; some are based on advanced analytical capabilities and offer user-friendly interfaces (Greenhouse Gas Protocol 2023). However, a significant gap exists in calculating net-positive effects or handprint impacts. Few of the existing tools extend to the organizational level, neither do they help companies prioritize their product and service offerings based on their impact on customer emissions. Additionally a more holistic understanding of emissions profiles and reduction attribution is needed to guide technology development. Our literature review found no published, open-source handprint calculators. OpenCO_2, a Finnish emissions factor database, offers a similar service on a paid basis using life cycle assessments (OpenCO2.net 2022). Other organizations such as Gasmet, a Finnish technology company, have made efforts to calculate their carbon handprint at the organizational level, but their methodologies have not yet been published (Gasmet 2022). Moreover, we found no GHG emissions calculators that focus specifically on utility substations or EV fleet charging scenarios. Our proposed handprint calculators for two use cases that implement ICT solutions in different sectors not only fill a gap and offer easy-to-use tools to quantify handprint savings (or positive contributions to society), but also emphasize the importance of improving grid utilization and managing the additions of large electric loads.

Key Assumptions

We made assumptions on key inputs for our two use cases based on the available literature in order to obtain the most accurate, representative data. Shared assumptions between both use cases included the social cost of carbon and marginal emissions data. We used the social cost of carbon figure established by the Biden administration and published via the Interagency Working Group on the Social Cost of Greenhouse Gases' technical support document on the Social Cost of Carbon, Methane, and Nitrous Oxide (IWG on the Social

Cost of Greenhouse Gases 2022). We used marginal emissions data generated from NREL's Cambium tool (Gagnon, Hale, and Cole 2022).

To conduct the model calculations for the EV fleet charging use case, we had to set several inputs as fixed values, based on available information where it exists. Further details of these assumptions can be found in the EV use case methodology. We set EV charging speeds at 20 kW and 100 kW, representing the maximum 240 V charging capacity and a reasonable DCFC scenario (DOT 2022). We identified peak and trough days for each season and used those as representative data points for various calculations. We assumed electricity sale price to be 75% of the purchase price, while the pricing data we assumed to max out at 15 cents/kWh, varying proportionally with marginal emissions. Vehicle efficiency was based on available data on fuel economy from various manufacturer product specifications, with class 8 tractors used as a guide. All other inputs, including battery lifetime and costs, are placeholder values based on expert knowledge set within a reasonable range. None of the input placeholders should be considered to have predictive utility. Rather, they and the results they have generated are intended to demonstrate the model's proof of concept and value of the handprint analysis.

To conduct the calculations for the utility GMS use case, we obtained key inputs from the available literature. We set the voltage optimization savings potential based on several resources, including an ACEEE report on utility energy efficiency, an Electric Power Research Institute report on the design and assessment of voltage optimization systems, and a Utility Dive article on how voltage optimization is accelerating grid decarbonization (York et al. 2015; Utility Dive 2021; EPRI 2011). We obtained the social cost of carbon from the Biden administration's established social cost of carbon, published via the Interagency Working Group on the Social Cost of Greenhouse Gases' technical support document on the Social Cost of Carbon, Methane, and Nitrous Oxide (IWG on the Social Cost of Greenhouse Gases 2022). Marginal emissions data were generated from NREL's Cambium tool for 2024 (Gagnon, Hale, and Cole 2022). We obtained substation electrical load performance data from Con Edison, which publishes a single dataset of hourly load projections for each New York substation (National Grid 2022). Further details can be found in the utility case study methodology.

Handprint Calculator Methodology for Use Cases

The LUT University in Finland has developed the only published steps for calculating the carbon handprint (Pajula et al. 2021). The steps in figure 3 below are based on this approach. Though its application may differ slightly based on data availability and context of the measured solution, it offers a framework for handprint calculation methodology. Our model does not assign attribution to actors in the supply chain. Carbon accounting issues will need to be addressed by future work.

UTILITY USE CASE

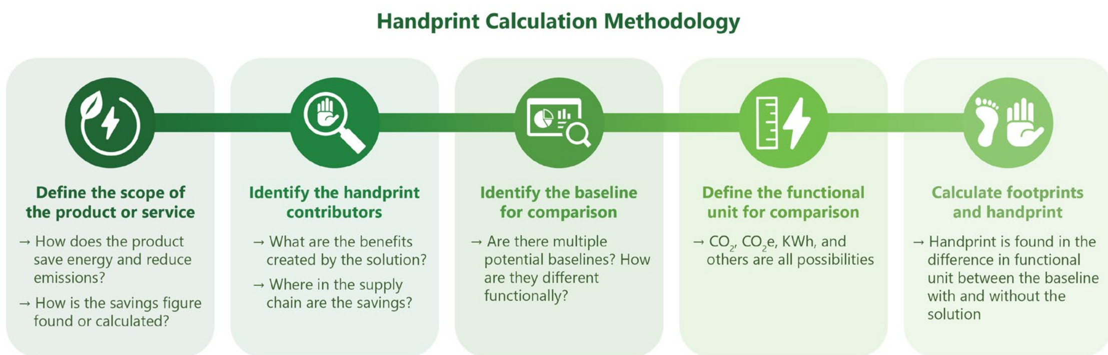

Figure 3. Handprint calculation methodology

Figure 4 below depicts the substation optimization analysis for each handprint figure determined. It includes the baseline footprints for the modeled scenario (which was repeated five times, once for each substation), as well as the footprint of the solution (same in each case), which was subtracted to find the handprint results.

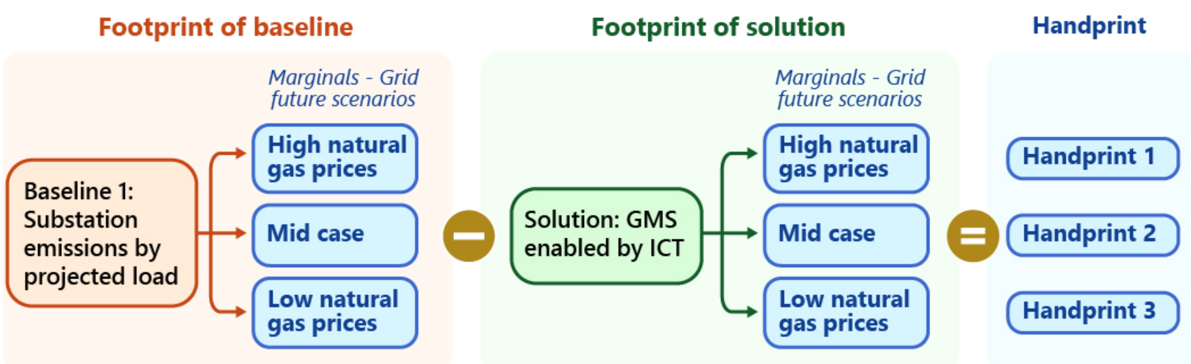

Figure 4. Substation optimization handprint scenarios

STEP 1: DEFINE THE SCOPE OF THE OFFERED PRODUCT OR SERVICE

The GMS solution optimizes grid services in front of the meter, giving utilities more control over delivered voltage to customers. It also reduces line losses and allows substations to reduce capacity and defer infrastructure investment, avoiding associated costs and embodied emissions in construction materials. To model our estimates of these savings, we applied a **4%** reduction rate in energy generation enabled by voltage optimization (Utility Dive 2021). We concluded this was a reasonable figure based on a review of the available literature.

STEP 2: IDENTIFY HANDPRINT CONTRIBUTORS

The handprint contributors, or the benefits conferred by the GMS solution resulting in reduced energy use and emissions compared to the baseline, include:

- Voltage optimization, as more precision controls in the substation create savings in generated electricity
- Improved capacity management at the substation level and reductions in the need for grid investments in transmission and distribution infrastructure
- Reductions in the carbon intensity of the grid through better integration and management of renewables in the grid; this impacts scope 2 emissions from delivered electricity by increasing the share of variable renewable power and minimizing the need to curtail renewables on the grid
- T&D deferral, enabling embodied carbon savings

STEP 3: IDENTIFY USERS AND BENEFICIARIES OF TECHNOLOGY

- Utility substations
- Grid regulators
- Electricity customers (especially large commercial and industrial (C&I) customers)

STEP 4: DEFINE THE BASELINE FOR POINT OF COMPARISON

Obtaining the baseline for comparison to the savings enabled by the GMS solution required obtaining substation-level performance data or projected hourly load for a substation or multiple substations. These data, along with emissions projections in specific grid regions, make it possible to project load-based emissions estimates. Unfortunately, such information is proprietary and often competitive, so it is not freely available for analysis. In our case, however, we were able to obtain substation-level data in New York State from a single dataset.

The data are made available by the Joint Utilities of New York, which is a collaboration of utilities aiming to advance state policy goals and respond to Public Service Commission proceedings (Joint Utilities of New York 2023). The group is composed of Central Hudson Gas and Electric Corporation, Consolidated Edison Company of New York, Inc. (Con Edison), New York State Electric & Gas Corporation, Niagara Mohawk Power Corporation d/b/a National Grid, Orange and Rockland Utilities, Inc., and Rochester Gas and Electric

Corporation. Con Edison publishes a single dataset of hourly load projections for each New York substation (National Grid 2022).

For grid-based emissions data, we used the National Renewable Laboratory's Cambium datasets, which include modeled hourly emissions, cost, and operational information projected through 2050 (Gagnon, Hale, and Cole 2022). These data include a region that is comprised of just New York State with a range of possible future scenarios for the electricity sector, which is important in accounting for the uncertainties associated with renewable energy integration.

To create a baseline through which we could calculate the handprint of the substation ICT solution, we used five Con Edison substation hourly load projection datasets for 2023, which were selected to represent the widest range of load demands possible. We applied these megawatt hour (MWh) projections to Cambium 2024 generation emissions projections for New York State in three future scenarios, in order to cover a range of grid possibilities. These scenarios include a mid-case, a low natural gas price case, and a high natural gas price case, all of which influence the carbon intensity of the grid due to differing amounts of projected renewably generated electricity. (These future scenarios are detailed further in the technical appendix.)

STEP 5: DEFINE FUNCTIONAL UNIT

For this analysis, we compared CO_2 emissions saved by carbon reductions associated with electrification and reduced carbon intensity of energy resources. The unit of CO_2 analyzed was in metric tons, delineated annually. Future analyses may look to include other GHGs or other factors for comparison in different time frames.

STEP 6: CALCULATE THE FOOTPRINTS OF EACH SOLUTION AND THE HANDPRINT

The footprint of the baseline for each of the five New York substations we included in this analysis was calculated by applying the Cambium hourly emissions factors to the projected hourly load for each of the substations. We calculated a footprint for each substation and for each emissions future analyzed by Cambium.

The footprint of the GMS solution applied to each of the five substations was calculated by decreasing the hourly load projections by the 4% we determined could be saved through voltage optimization. We then took the same hourly emissions factors used for the baseline and applied them to the new hourly load projections. This analysis was likely conservative: Due to data constraints, we were not able to account for the savings from reduced line losses, or from capacity reductions and associated savings by deferring new transmission and distribution (T&D) infrastructure.

The calculated handprint from the difference of these two footprints is modeled in the tables for each emissions future in tables 2, 3, and 4. The tables also include estimated economic damages avoided by using the solution at each substation. We calculated this by multiplying avoided emissions by the Biden administration's established social cost of carbon, $51 per metric ton of CO_2 (IWG on the Social Cost of Greenhouse Gases 2022).

It is important to note that while electricity is consumed by the use of newly implemented software, or by the associated hardware, we found these values to be de minimis in comparison to the handprint savings they enable. We determined that typical studies and data collection of energy consumption lead into power losses and technical power systems data rather than any auxiliary equipment. Additionally, any studies of auxiliary equipment include lighting, HVAC, motors and pumps, and other non-software or hardware related activities. DC battery chargers are the main power consumers for the software systems, since they charge the batteries/power supplies that provide power to the computer or other hardware that the software runs on; however, these figures are also influenced by battery charger efficiency. Software energy consumption will also depend on a myriad of other variables, including the size, type, and setting of the substation (EPRI 2012). Future studies and versions of the calculators may be able to find and include these values to assign the most accurate handprint savings. However, in our efforts to demonstrate proof of concept of handprint analysis, these figures were found to be largely out of scope.

Table 2. Mid-case: mid-range natural gas prices

Substation	Baseline annual emissions footprint (MT CO_2)	Solution annual emissions footprint (MT CO_2)	Annual handprint savings (MT CO_2)	Social cost of carbon—economic damages avoided ($)
1	196,803	188,931	7,872	$401,478
2	66,178	64,601	1,577	$80,447
3	67,582	64,879	2,703	$137,867
4	145,496	139,676	5,820	$296,812
5	208,237	199,908	8,329	$424,804

Table 3. Low natural gas prices

Substation	Baseline annual emissions footprint (MT CO_2)	Solution annual emissions footprint (MT CO_2)	Annual handprint savings (MT CO_2)	Social cost of carbon—economic damages avoided ($)
1	212,021	203,540	8,481	$432,523
2	72,461	69,764	2,696	$137,509
3	72,635	69,993	2,642	$134,719
4	156,284	150,430	5,854	$298,531
5	223,155	215,028	8,127	$414,464

Table 4. High natural gas prices

Substation	Baseline annual emissions footprint (MT CO_2)	Solution annual emissions footprint (MT CO_2)	Annual handprint savings (MT CO_2)	Social cost of carbon—economic damages avoided ($)
1	183,005	175,685	7,320	$373,331
2	62,521	60,020	2,501	$127,543
3	62,823	60,310	2,513	$128,160
4	135,351	129,937	5,414	$276,116
5	193,648	185,902	7,746	$395,042

RESULTS

The results from our handprint model indicate significant emissions savings potential for the GMS solution as compared to the substations' baseline energy use and CO_2 emissions. The handprint impact of the solution varies by substation and emissions future scenario, but in our analysis ranges from 1,500 metric tons (MT) of CO_2 to almost 8,500 (MT) of CO_2 within our parameters, reductions that are the equivalent of taking 320 to 1,800 gasoline-powered cars off the road (EPA 2023). These estimates are conservative because of the data limitations discussed above.

When applied to multiple substations, these savings increase significantly. Considering only the five substations analyzed, the combined savings range from 25,494 to 27,800 MT of CO_2. The handprint impact is highest for those substations with the highest projected energy demand and energy demand growth, especially in higher emissions future scenarios. The ability to maximize asset utilization, incorporate distributed energy resources (DERs), and minimize curtailment of renewables will deepen these savings even further on the pathway toward decarbonizing the grid.

These handprint impacts should be considered scope 3 reductions for the company manufacturing the ICT solution, scope 1 emissions reductions for the utility substation implementing the solution, and scope 2 emissions reductions for electricity customers. However, they should also be calculated externally to any carbon footprints in the supply chain and reported in conjunction with other actors as a collective handprint effort.

EV USE CASE

Figure 3 above depicts the steps taken to develop the EV use case model. Figure 5 below depicts the EV charging analysis for each handprint figure determined. It includes the baseline footprints for each scenario modeled, as well as the footprint of the solution (same in each case), which we subtracted to find the handprint results. This relationship was repeated for each of the four days analyzed.

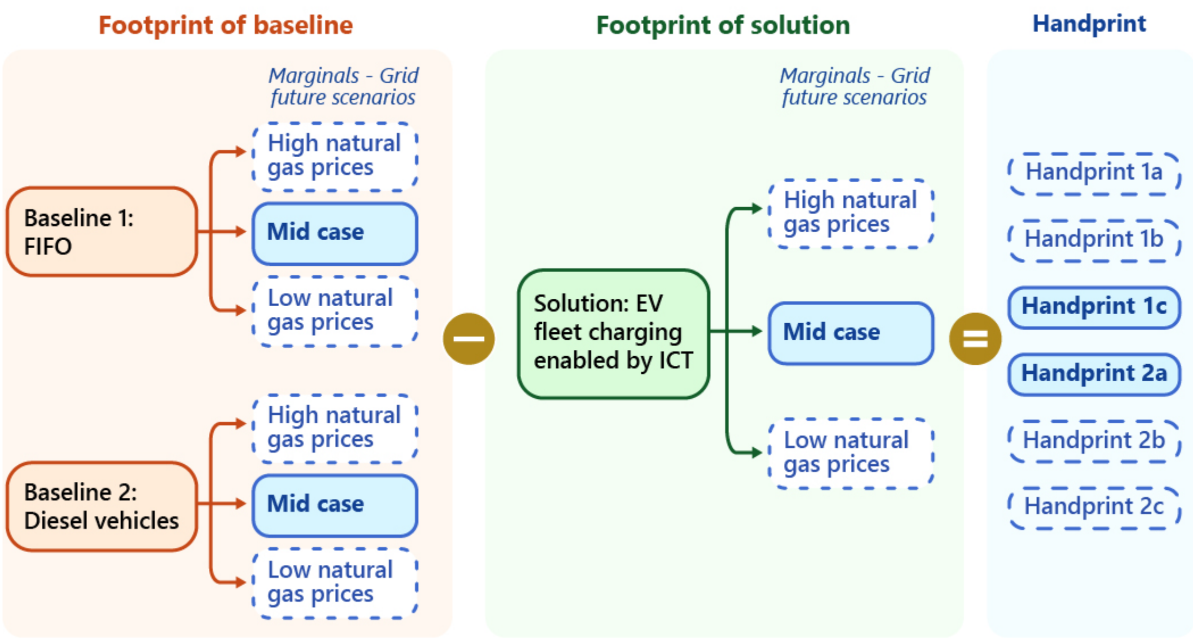

Figure 5. EV charging handprint scenarios

STEP 1: DEFINE THE SCOPE OF THE OFFERED PRODUCT OR SERVICE

The fleet EV charging solution optimizes charging services behind the meter, allowing charging stations to exert greater control over emissions, marginal costs, and equipment and infrastructure costs. The solution also enables control over the charging schedule and grid integration for power delivery during peak periods. There may also be value in other auxiliary grid services,[2] such as frequency regulation, though the current model only looks at power supply.

Our model toggled between different charger capacities, including level 2 chargers (240 V) and level 3 fast chargers (DCFC). The 240 V chargers are much cheaper than DC solutions and have much lower supporting infrastructure requirements. Their speed, however, is slower, requiring several hours to charge half of a class 8 vehicle (between 30,000–80,000 lb. gross vehicle weight rating (GVWR)) battery. This may limit the ability to optimize the charging schedule, or even to meet demand on tight schedules. DC chargers can charge several times faster than 240-V chargers, potentially providing 50% or more of a class 8 regional haul vehicle's capacity in an hour. The upper limit is highly dependent on the grid infrastructure's ability to support the high power draw, or on complex local storage solutions. This advantage, however, comes at a much greater equipment cost, as well as the need for supporting grid infrastructure. The site operator may be asked to help pay for infrastructure upgrades and still must wait long periods of time, sometimes months or years, for the utility to build this out before starting DCFC operations.

STEP 2: IDENTIFY HANDPRINT CONTRIBUTORS

The handprint contributors, or the benefits conferred by the fleet EV charging solution to reduce energy use and emissions compared to the baseline, include:

- Reductions in emissions
- Reductions in marginal costs
- Managing charging schedules
- Managing grid integration for power delivery during peak periods

STEP 3: IDENTIFY USERS AND BENEFICIARIES OF TECHNOLOGY

- Fleet EV charging depot operators

[2] Auxiliary grid services refer to services provided to grid operators, other than power supply, that are necessary to maintain the stability and efficiency of the power delivery and distribution system.

- Project planners (looking to build charging depots) or system integrators who are contracted by commercial and government fleet managers to design and install charging infrastructure for their fleets
- Grid operators
- EV charging customers (from the short-haul freight and drayage industries)
- Utilities
- Neighboring communities (which will experience reduced emissions impacts)
- Other grid customers (who will benefit from increased grid reliability)

STEP 4: DEFINE THE BASELINE FOR POINT OF COMPARISON

We considered more than one baseline case (BAU) for comparison to the savings enabled by the fleet EV charging solution.

The first base case is non-optimized charging for EVs alone. This is calculated assuming that vehicles are charged in the order that they arrive until they reach full capacity. This case is referred to as first-in-first-out (FIFO).

The second base case compares the savings against conventional diesel vehicles. In our model, we assumed a standard miles of demand that correspond with the kWh of demand of the EVs served.

STEP 5: DEFINE FUNCTIONAL UNIT, UNIT PROCESSES

The objective function of the model is to minimize the net weighted cost. Net weighted cost is the weighted sum of the external cost of the emissions from charging the vehicles and the direct monetary marginal costs associated with charging the vehicles. As the external costs are directly proportional to emissions, this measure provides an easy way for the site operator to balance costs, profits, and the benefits of emission reductions.

STEP 6: CALCULATE FOOTPRINTS AND COSTS OF EACH SOLUTION AND CALCULATE THE HANDPRINT

To calculate the handprint, we used marginal emissions data and defined the charging site characteristics as a 10-unit charger with variable maximum charging speeds of 20 or 100 kW per vehicle. We established a weighting factor to show the relative importance of private costs in the system and the cost of the emissions. Additional details on the choice for this value can be found in the technical appendix. The weighting factor is a variable that can be changed by the user. To run our analytical model, we used private cost preferences of 0.1, 1, and 1.5. We optimized a function to charge the vehicles, instead of on a FIFO basis, in a way that minimizes the net weighted cost of carbon, which is the social cost (or the total emissions of all the produced electricity multiplied by the social cost of carbon) added to the private cost preference weighting factor. In this manner, the model can serve as a demonstration of a solution that reduces the emissions associated with charging a small fleet of 10 EVs by optimizing charging times. The handprint calculated from the difference of the ICT-enabled scenario compared to business as usual or the baseline is shown in tables 5–8. These results are based on a fleet of 10 short-haul freight vehicles and consider scenarios in which we vary the weight of private cost, the charging speed and demand, demand charge, and the season.

Multiple limitations may affect the results of the model scenarios. For example, when aggregating vehicles into groups, there is a question of how to constrain group charging speeds. Also, insufficient data are available to determine embodied carbon reductions associated with the solution. Future models should seek to account for these details.

The handprints we calculated by running the model can be seen in the tables below. Together these tables represent the range of possible handprint values that the solution can enable within the constraints of the model. To extrapolate the results to yearly estimates, as seen in the substation GMS use case, it is necessary to use each representative season day and multiply it to represent a full quarter of the year. However, these results should be considered rough estimates, as marginal emissions and load demands differ substantially even within seasons. Example estimates are included in the results below.

It is important to note that, as in the substation use case, while electricity is consumed by using the newly implemented software and the associated hardware, we found these values to be de minimis in comparison to the handprint savings they enable. Future studies and versions of the calculators may be able to find and include these values to assign the most accurate handprint savings. However, in our efforts to demonstrate proof of concept for handprint analysis, we found these figures to be largely out of scope.

Table 5. Varied private cost preferences

Private cost preference	Season	Arrival time (hour)	Departure time (hour)	Aggregate demand (kWh)	Charger charge capacity (kWh)	Charger supply capacity (kWh)	Demand charge ($/kW)	Handprint to FIFO (kg CO_2)	Handprint to diesel (kg CO_2)
0.1	Winter	5	12	2,500	100	100	0.1	36.8	1,833.9
0.1	Spring	5	12	2,500	100	100	0.1	16.5	1,931.6
0.1	Summer	5	12	2,500	100	100	0.1	–21.8	1,663.5
0.1	Fall	5	12	2,500	100	100	0.1	–29.8	1,967.2
1	Winter	5	12	2,500	100	100	0.1	36.8	1,833.9
1	Spring	5	12	2,500	100	100	0.1	16.5	1,931.6
1	Summer	5	12	2,500	100	100	0.1	–21.8	1,663.5
1	Fall	5	12	2,500	100	100	0.1	–29.8	1,967.2
1.5	Winter	5	12	2,500	100	100	0.1	36.8	1,833.9
1.5	Spring	5	12	2,500	100	100	0.1	16.5	1,931.6
1.5	Summer	5	12	2,500	100	100	0.1	–21.8	1,663.5
1.5	Fall	5	12	2,500	100	100	0.1	–29.8	1,967.2

Table 5 varies private cost preference across the marginals from the different season days, maintaining arrival and departure times, as well as aggregate demand, charger capacity, supply capacity, and demand charge. These results demonstrate that private cost preference has little bearing on handprint impacts. This is the case because as long as they are both above zero and at reasonable values, the cost optimal schedule is likely to be similar. Rough estimated yearly savings in running this model range from 183 kg CO_2 over FIFO to approximately 676,000 kg CO_2 over diesel.

Table 6. Lower aggregate demand and reduced charger charge and supply capacity

Private cost preference	Season	Arrival time (hour)	Departure time (hour)	Aggregate demand (kWh)	Charger charge capacity (kWh)	Charger supply capacity (kWh)	Demand charge ($/kW)	Handprint to FIFO (kg CO_2)	Handprint to diesel (kg CO_2)
0.1	Winter	5	12	500	20	20	0.1	7.4	366.8
0.1	Spring	5	12	500	20	20	0.1	3.3	386.3
0.1	Summer	5	12	500	20	20	0.1	–4.4	332.7
0.1	Fall	5	12	500	20	20	0.1	–6.0	393.4
1	Winter	5	12	500	20	20	0.1	7.4	366.8
1	Spring	5	12	500	20	20	0.1	3.3	386.3
1	Summer	5	12	500	20	20	0.1	–4.4	332.7
1	Fall	5	12	500	20	20	0.1	–6.0	393.4
1.5	Winter	5	12	500	20	20	0.1	7.4	366.8
1.5	Spring	5	12	500	20	20	0.1	3.3	386.3
1.5	Summer	5	12	500	20	20	0.1	–4.4	332.7
1.5	Fall	5	12	500	20	20	0.1	–6.0	393.4

Table 6 examines the handprints from the model with the same variations in private cost preference as table 5, but with an aggregate demand of 500 kWh and reduced charger charge capacity and supply capacity (20 kWh). These results demonstrate a significantly lower handprint impact than in table 5, indicating the importance of charging capacity. Further analysis is included in the section below. Rough estimated yearly savings in running this model range from 27.4 kg CO_2 over FIFO to 34,583 kg CO_2 over diesel.

Table 7. Varied demand charge

Private cost preference	Season	Arrival time (hour)	Departure time (hour)	Aggregate demand (kWh)	Charger charge capacity (kWh)	Charger supply capacity (kWh)	Demand charge ($/kW)	Handprint to FIFO (kg CO_2)	Handprint to diesel (kg CO_2)
1	Winter	5	12	2,500	100	100	1	36.8	1,833.9
1	Spring	5	12	2,500	100	100	1	16.5	1,931.6
1	Summer	5	12	2,500	100	100	1	–21.8	1,663.5
1	Fall	5	12	2,500	100	100	1	–29.8	1,967.2
1	Winter	5	12	2,500	100	100	10	36.8	1,833.9
1	Spring	5	12	2,500	100	100	10	16.5	1,931.6
1	Summer	5	12	2,500	100	100	10	–21.8	1,663.5
1	Fall	5	12	2,500	100	100	10	–29.8	1,967.2

Table 7 maintains the same variables as table 5 but varies the demand charge to $1/kW and $10/kW. We found that demand charges also do not have much impact in our scenarios. This is again the case because, as with varying the private cost preference, the cost optimal schedule is likely to be similar. Rough estimated yearly savings in running this model range from 155 kg CO_2 compared to FIFO to approximately 675,000 kg CO_2 compared to diesel.

Table 8. Varied arrival and departure times

Private cost preference	Season	Arrival time (hour)	Departure time (hour)	Aggregate demand (kWh)	Charger charge capacity (kWh)	Charger supply capacity (kWh)	Demand charge ($/kW)	Handprint to FIFO (kg CO_2)	Handprint to diesel (kg CO_2)
1	Winter	13	20	2,500	100	100	0.1	–25.5	1,831.8
1	Spring	13	20	2,500	100	100	0.1	6.8	1,960.7
1	Summer	13	20	2,500	100	100	0.1	–116.9	1,436.2
1	Fall	13	20	2,500	100	100	0.1	12.5	1,958.6
1	Winter	13	20	2,500	100	100	1	–21.6	1,835.8
1	Spring	13	20	2,500	100	100	1	6.8	1,960.7
1	Summer	13	20	2,500	100	100	1	–116.9	1,436.2
1	Fall	13	20	2,500	100	100	1	12.5	1,958.6
1	Winter	13	20	2,500	100	100	10	–25.5	1,831.8
1	Spring	13	20	2,500	100	100	10	6.8	1,960.7
1	Summer	13	20	2,500	100	100	10	–116.9	1,436.2
1	Fall	13	20	2,500	100	100	10	12.5	1,958.6

Finally, table 8 alters the arrival and the departure times of the vehicles across a range of demand charges. Arrival and departure times are impactful compared to other model runs, creating negative handprint impacts in the FIFO case. Reasons for this are discussed below in the results summary section. However, altered demand charge within the context of varied arrival and departure times again does not affect outcomes. Rough estimated yearly savings in running this model range from –9,500 kg CO_2 over FIFO to approximately 655,841 kg CO_2 over diesel.

RESULTS SUMMARY

The solution enables emissions savings from optimized charging. However, these savings are variable, and application to real-world planning is limited by data availability. It should be noted that the maximum marginal emissions difference percentage is the maximum possible emissions savings. We found probable handprint savings of approximately 10% over a FIFO BAU if marginal hourly emissions differ by about 20% over the charge period, or about 50% of maximum possible; much higher values, or even emission increases, are possible. Just using electric vehicles will provide about 30–50% savings over diesel vehicles.

The most important observed factors were a combination of the marginal emissions factors (as reflected by season) and the arrival/departure schedule of the vehicles. The ability, or even desirability, to reduce emissions is highly dependent upon adjusting the vehicle's charging schedule to take advantage of time dependent differences in prices and emissions. For vehicles that happen to arrive at the lowest marginal emission time, FIFO will almost always be the lowest possible emission schedule, and any private pricing preference will increase emissions. A private cost weighting factor of zero would likely equal FIFO in this case and could reduce it in edge cases, such as when there is significant opportunity to provide power to the grid.

Private cost weighting factors and demand charges were not impactful inputs in our scenarios. Quite simply, so long as they are both above zero and at reasonable values, the cost optimal schedule is likely to be similar. While private costs will change significantly, actual emissions will not change much.

Capacity is another important variable. Non-DC charging solutions top out at about 20 kW, which could make schedules of 50% capacity in a few hours infeasible. Even when theoretically possible, there may not be availability to change the schedule meaningfully compared to FIFO. DC charging can exceed 200 kW and avoid this concern entirely, but it is very costly and must be coordinated with the utility to be deployed at scale. That said, when demand is proportional to charging capacity, handprints were also seen to be proportional to any changes in demand. Increases in capacity, therefore, are likely to enable more charging scenarios, rather than reliably change relative handprints.

Finally, the scale of savings depends on the difference in emissions factors, both over the day and compared to the arriving vehicle's' embodied emissions. We found changes of around 10% were possible if emissions vary about 20% over the day, but the specific schedule of that variance, and how it matches up to the vehicles' schedules, is an important factor.

One important limitation to note is that marginal emissions were assumed to be directly correlated with electric prices. While electric price and emissions are often related, a direct correlation is not always the case. A mismatch between changes in emissions and changes in price will likely reduce the scale of desirable emission reductions. However, this reduction in scale will relate to the cost weighting, which was seen to not be significant in our scenarios where emissions and private costs were directly linked.

Pilot Planning

For additional handprint applications and impact estimates, future phases of work should include pilot studies that verify and showcase the carbon emissions reduction potential from the two ICT solutions. On the utility substation side, pilots should demonstrate the savings from ICT-enabled substation distribution management, especially in regard to control of customer loads and customer-sited DERs. On the transportation fleet EV charging side, pilots should demonstrate the savings from ICT-enabled fleet EV charging solutions such as reductions in emissions, reductions in marginal costs, and better management of charging schedules.

Pilots are an essential piece of market transformation, advancing the commercialization of both emerging ICT and the handprint methodology for calculating downstream emissions reductions. Pilots not only demonstrate applicability but also contribute to end-user awareness and education, and inform manufacturers about the best pathways for entering particular markets. Identifying best partners and priorities, understanding barriers, and locating knowledge gaps are all essential pieces of the pilot planning process. The tremendous potential value in using the carbon handprint approach is only possible with the end-user buy-in that pilots can create.

Summary and Policy Considerations

SUMMARY

The ICT solutions described in both use cases enable significant emissions reductions in the supply chain. The analysis of these reductions using handprint methodology allows for a more complete understanding of those emissions and takes an important step toward more accurate attribution. The handprint models created to measure the savings included above are some of the first of their kind to be published because of the difficulty of finding and defining baselines for comparison. As more data become available, the accuracy of handprint analysis will only improve. ICT companies, utilities, grid regulators, policymakers, and others should look to handprints as an important new methodology for carbon accounting, and to the savings modeled in this white paper as a demonstration of the potential for real-world calculation.

POLICY CONSIDERATIONS

ICT solutions and calculators can help equip utilities to reach state and federal emissions reduction targets and pursue decarbonization options. A handprint calculator for product and service providers is a complement to a footprint calculator for utilities. Consistent baseline definitions and robust data collection that support handprint quantification will in turn help utilities compare technologies and prioritize their investments through the lens of carbon emissions reductions.

From a business standpoint, handprint analysis is essential in complementing a company's footprint to more accurately reward ICT implementation and intelligent efficiency. Crucially, this can help motivate technology companies to develop such technologies and install them at their customer sites, especially in the context of meeting scope 3 emissions reduction targets. A new landscape for technology companies exists in the wake of recent legislation including the Creating Helpful Incentives to Produce Semiconductors (CHIPS) and Science Act, Inflation Reduction Act (IRA), and the Bipartisan Infrastructure Law (BIL). Because these bills encourage and incentivize use of 100% carbon-free electricity in manufacturing facilities, companies have an increasing vested interest in helping to decarbonize the grid. Policy can play a role in market creation, whether through procurement policy, incentives, or tax breaks.

Perhaps most critically, if we want to approach accurate attribution for handprint impacts, which is essential for best practice accounting, for avoiding double counting, and for incentivizing reductions, we will need policy support for enhanced data collection and standardization of estimation protocols. Accurate attribution is necessary for reporting supply chain emissions reductions and understanding where mitigation is still required.

It is essential that policymakers consider a given supply chain and the handprints of its components when creating and updating protocols for evaluating and attributing emissions reductions (for example, the GHG protocol and the Securities and Exchange Commission (SEC)'s rule on "The Enhancement and Standardization of Climate-Related Disclosures for Investors"). Policymakers may also wish to consider how the idea of monetizing carbon handprint savings, which is starting to be discussed in some circles, may be used in market creation and the trading (buying, selling) of handprint credits. However, vigilance will be required to avoid some of the pitfalls of carbon trading systems and gaming of the system.

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Technical Appendix

UTILITY SUBSTATION USE CASE GUIDE

1. The utility substation model uses NREL's Cambium-based data for electricity generation emissions separated by NREL's generation, emissions, and assessment (GEA) regions. Figure A1 below is a map of the GEA regions. The model we ran includes a mid-case, a low natural gas price case, and a high natural gas price case (Gagnon, Hale, and Cole 2022).

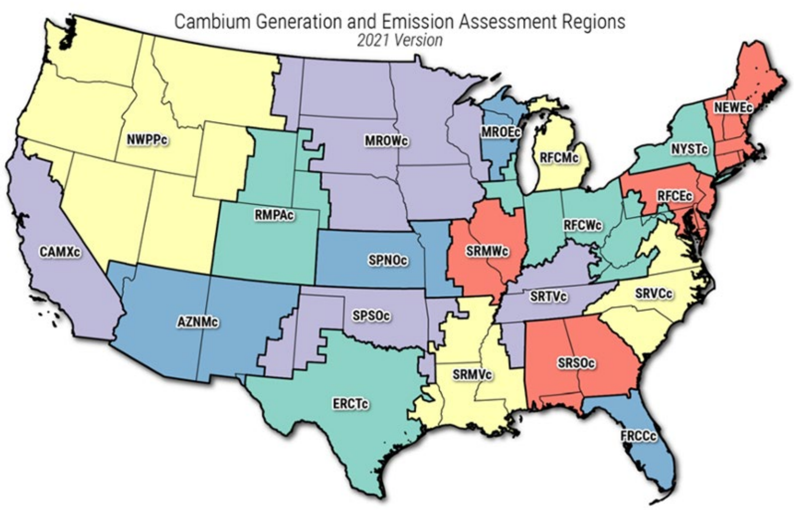

Figure A1. Map of GEA regions. Source: Based on Cambium's datasets: https://scenarioviewer.nrel.gov/.

2. We multiplied the handprint figures we found by a current estimate of the social cost of carbon, $51 per metric ton of CO_2 (IWG on the Social Cost of Greenhouse Gases 2022), to estimate the economic damages avoided by emissions reductions through the solution. This number is likely to increase, as the Environmental Protection Agency (EPA) has proposed increasing the cost to $190 per metric ton (Farah and Clark 2022).

EV CHARGING USE CASE GUIDE

1. To model a real-world handprint impact scenario, the model we ran uses hourly grid based marginal emissions data from NREL's Cambium for four representative days. It also includes cost data, sell back mechanisms, and demand charge figures. Our calculator used a baseline of 10 chargers.

For this analysis, we used marginal emissions, because average emissions should only be used when scheduling is done far in advance (multiple years), or usage patterns are predictable.

2. We used two BAU scenarios for the EV charging use case because emissions impacts will vary based on the schedule of charging needs, vehicle characteristics, and grid factors. The first base case assumes that vehicles are charged as fast as possible and on a first-come-

first-served basis. The second base case assumes use of diesel vehicles. This allows for a handprint comparison against both conventional vehicles and against non-optimized EV charging behavior.

3. For the purposes of our model, the only emissions tracked were GHG and these were represented by the social cost of carbon from the Biden administration's current figure. The second factor is a weighting factor to show the relative importance of the private costs in the system (electricity purchases and sales, battery degradation, and demand charges) and the cost of the emissions. This number was multiplied by the private costs.

4. Another essential piece of establishing the metrics of our model was defining characteristics of the vehicles arriving and needing to be charged. These data are summarized in table A1.

5. The next step was to set the calculations for all the costs, both private and social, associated with charging the vehicles. Private costs consist of the cost of each time unit's charging rate for all the vehicles, multiplied by the cost of electricity; the discharge rate of each time unit's charging rate for all the vehicles, multiplied by the difference between charge cycle cost and that time unit's electric sale price; and the demand charge multiplied by the greatest amount of power ever drawn, from all vehicles, during a single unit of time.

Social costs include the total emissions of all the produced electricity, multiplied by the social cost of those emissions; and the difference between the embodied emissions of each arriving vehicle's state of charge and each time unit's given discharge rate back to the grid, multiplied by the social cost of those avoided emissions. The latter value accounts for the fact that providing power back to the grid avoids emissions at that point of time, but that power still has associated emissions.

Table A1. Vehicle characteristics

Data point	Description
Demand	This is the amount of kWh that the vehicle's battery needs to reach full, or target, charge before leaving. This should also be reported in terms of total miles driven but can be alternatively derived from the vehicle's average efficiency, which would then also need to be provided.
Capacity	The total capacity of the vehicle's battery
Arriving state of charge	The state of charge of the vehicle's battery on arrival
Max vehicle charging speed	The maximum speed at which the vehicle can charge
Max vehicle withdraw rate	The maximum rate at which the vehicle can provide power to the grid; a value of 0 disallows this
Battery replacement cost	The cost of replacing the vehicle's battery

Data point	Description
Battery lifetime	The total number of kWh charge cycles for which the battery is rated
Charge cycle cost	The battery replacement cost divided by the battery lifetime
Arrive state of charge embodied emissions	The emissions associated with each kWh of arriving state of charge of the vehicle's battery. This is only necessary if the vehicle will be allowed to provide grid services. If the vehicle operator does not know this then the user can assume an average marginal emissions factor, consistent with grid emissions assumptions. The user should document all assumptions, data sources, and methods.