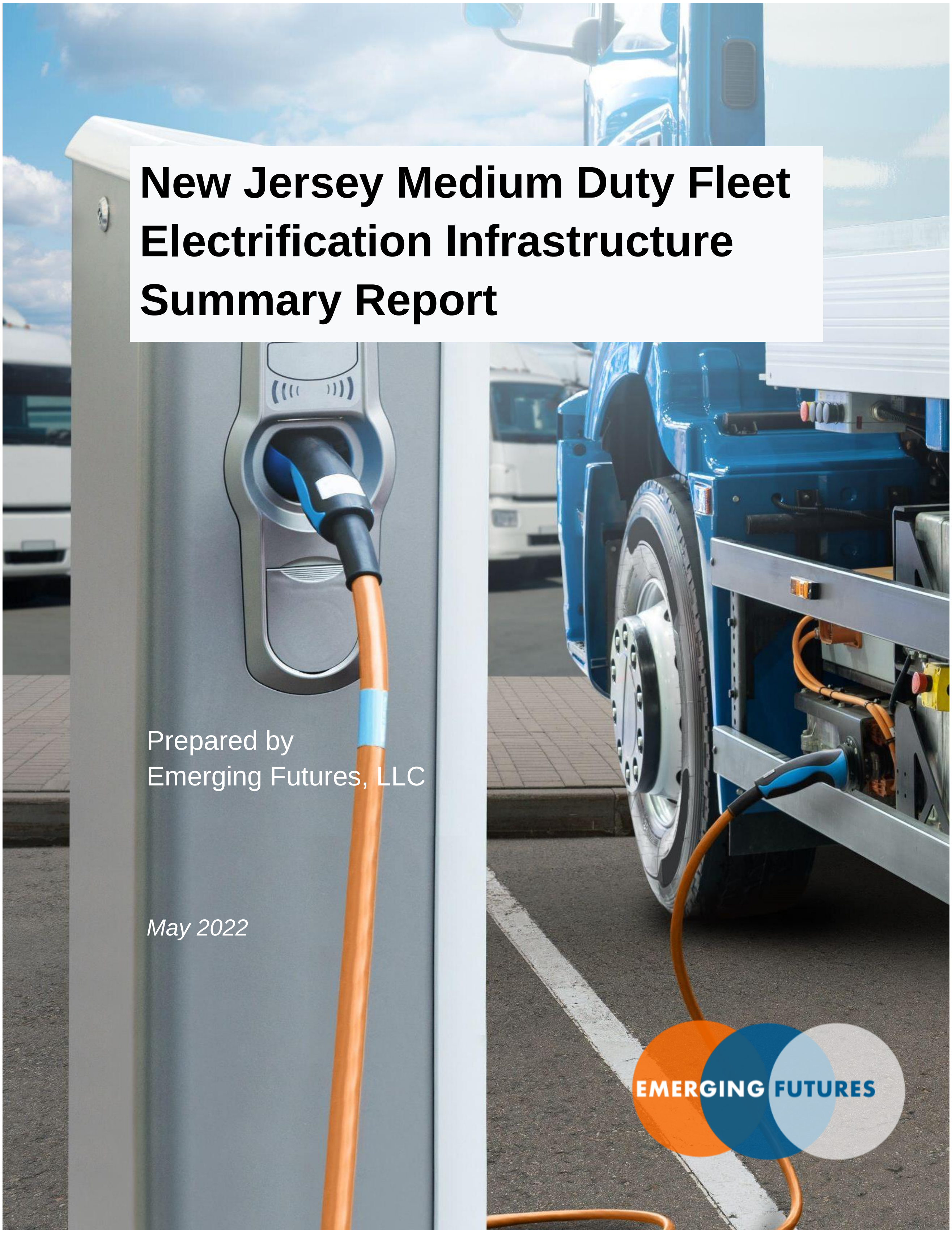

New Jersey Medium Duty Fleet Electrification Infrastructure Summary Report

Prepared by
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Executive Summary

According to the New Jersey Department of Environmental Protection, medium- and heavy-duty (MHDV) trucks and buses account for 4% of vehicles on the road but cause nearly 25% of transportation greenhouse gas emissions. In addition, fleet emissions are a particular problem for overburdened communities. Many of these communities are located near freight corridors, ports and distribution centers and are disproportionately exposed to harmful pollutant levels. The good news is that New Jersey policymakers are making clear steps to transition the MHDV sector to zero emissions. New Jersey's 2019 Energy Master Plan calls for electrification of the state's transit fleet; industry partnerships to develop electrification incentives; and expansion of clean transportation options in low- and moderate-income communities that are disproportionately impacted by diesel pollution. Furthermore, New Jersey also signed on to a multi-state agreement committing to transition trucks and buses in the state entirely to zero-emission vehicles, starting with 30% of vehicle sales by 2030, and became the first state on the East Coast to adopt the Advanced Clean Trucks (ACT) rule—which requires an increasing number of zero-emission truck sales each year in the state. Commercial fleets of battery-electric MHDVs have increased, and medium- to large-scale vehicle purchases are beginning to occur in leading fleets. It's clear the deployment of electric MHDVs is accelerating in New Jersey, in particular classes 3 through 7.

One of the biggest challenges for trucks and buses to electrify is ensuring there is enough charge to meet their driving needs. These fleets can have tight operating schedules, cold weather, long driving ranges and heavy loads. Given these challenges, it has been unclear from a public and industry perspective whether and how fleets that depend on these vehicles will be able to meet charging and operational demands with existing electric vehicle technology. While many reports and studies have evaluated the market readiness of these trucks, many have relied on simulated and not actual fleet operational data which is needed to realistically quantify the needs, costs and operational conditions involving vehicle charging.

Previous analysis was done by Gladstein, Neandross and Associates,[1] which used real operational data from two class 8 fleets in California to assess the charging needs and associated costs. The current study stems from this work, using operational data from five real fleets of class 3 through 7 trucks, to evaluate the costs and capabilities of charging systems, and the impact of electric rate design on the ability of fleets to deploy electric vehicles in the medium- and heavy-duty market segment in New Jersey. In doing so, the analysis seeks to enhance the body of public knowledge on the needs and implications associated with charging systems and utility rates. Further, this study will evaluate the grid impacts of electrifying New Jersey's entire class 3 through 7 trucks and the impact of employing technologies such as managed charging and onsite solar and battery storage to reduce grid buildout needs and costs.

At the outset of the analysis, five key issue areas were assessed:

[1] http://blogs.edf.org/energyexchange/files/2021/03/EDF-GNA-Final-March-2021.pdf

1. Fleet needs: How effective will electrification be at meeting fleet operational needs without modification of routes and timetables?
2. Cost effectiveness: What is the upfront capital cost of charging infrastructure seen by typical fleets electrifying in New Jersey? In the current market climate, will fleets see fuel cost savings for fleets that electrify? Is there a correlation between finding cost parity and the truck size of a fleet depot?
3. Charging rates and managed charging: Under what charging scenarios can a target facility maximize the fraction of trips successfully charged while minimizing power demands and expected infrastructure costs? Also, how are the costs of charging and peak load impacted by managed charging under different electric rate variants?
4. Onsite solar and battery: What role do depot solar photovoltaics (PV) and battery have on the charging infrastructure costs of each deployment? Also, how do solar PV and battery scenarios affect the aggregate facility load profile under various utility rates?
5. New Jersey-wide grid impact: What is the aggregated peak load in New Jersey if all class 3 through 7 fleets electrify? How much does managed charging and onsite solar and battery reduce expected peak load and grid buildout costs?

Five fleets types in New Jersey were selected, shown below in Table ES-1, with depot sizes based on average sizes for each market segment seen in New Jersey. Data on average daily energy use and average vehicle efficiency were based on actual vehicle fuel consumption (gasoline and/or diesel) and miles driven.

Table ES-1: Summary of Fleet Scenarios for Study

Vehicle use case	Vehicle class	Depot size	Average energy use (kWh/day)	Average efficiency (kWh/mi)	Battery capacities (kWh)	Max charging capacities (kW)
Landscaping	3	2	82	1.04	140	20,50,100
Food service	4	4	89	1.11	156	20,50,100
Wired telecom	5	11	122	1.93	226	30,50,100
Armored car	6	7	259	3.36	343	60,100,150
Yard tractors	7	2	50	3.50	80, 160	20,50,100

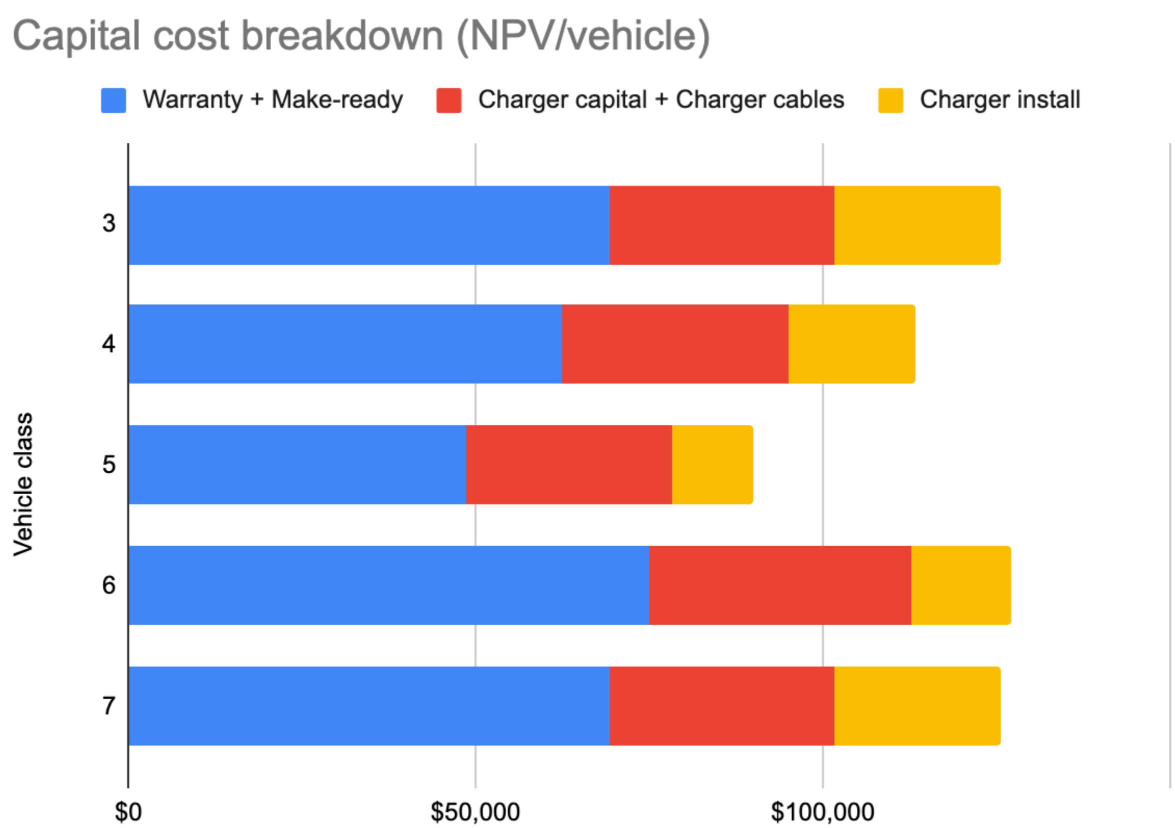
Various scenarios for each use case, which varied the charging station power, truck battery capacity, and number of charging sessions as all fleets, with exception of class 7 yard trucks, had long overnight charging windows with multiple breaks during daily driving schedules. With one daily charging session on average nearly 80% of trips were able to successfully be electrified; see Table ES-2. Noting that as the class 7 trucks data was based on an already electrified fleet the ability to meet fleets needs was not assessed or included in this result. Further, when increased to two and three charging sessions, all of which could be done with the amount of non-driving time of each fleet, an average of 98% of the fleets' trips could be successfully covered with an electric truck. This means that with either enroute charging or by slightly modifying fleet operations to allow mid-shift charging, almost all trips could be met with existing battery electric technology.

Table ES-2: Summary of Results of Successful Electric Trips per Vehicle Use Case

Vehicle use case (class)	Number of daily charging sessions		
	1	**2**	**3**
Landscaping (3)	84.53%	99.4%	99.9%
Food service (4)	81.52%	97.1%	99.5%
Wired telecom (5)	86.21%	99.0%	99.9%
Armored car (6)	66.38%	88.8%	96.6%

For each of the use cases defined charger and battery pack scenarios, the 20-year net present value of infrastructure and electricity costs under a transition to electric trucks were evaluated. When unmanaged, the upfront capital cost of charging infrastructure per vehicle ranged from between \$90k and \$125k. In Figure ES-1 below, it can be seen that the bulk of the upfront capital cost is a result of the make-ready costs and warranty costs. The study showed that approximately 30% of the upfront charging infrastructure costs were as a result of make-ready. This would suggest that policy and incentive support to reduce make-ready costs for fleets would have a significant impact on the total cost of infrastructure for fleets.

Figure ES-1: Breakdown of capital costs for each use case using unmanaged charging.



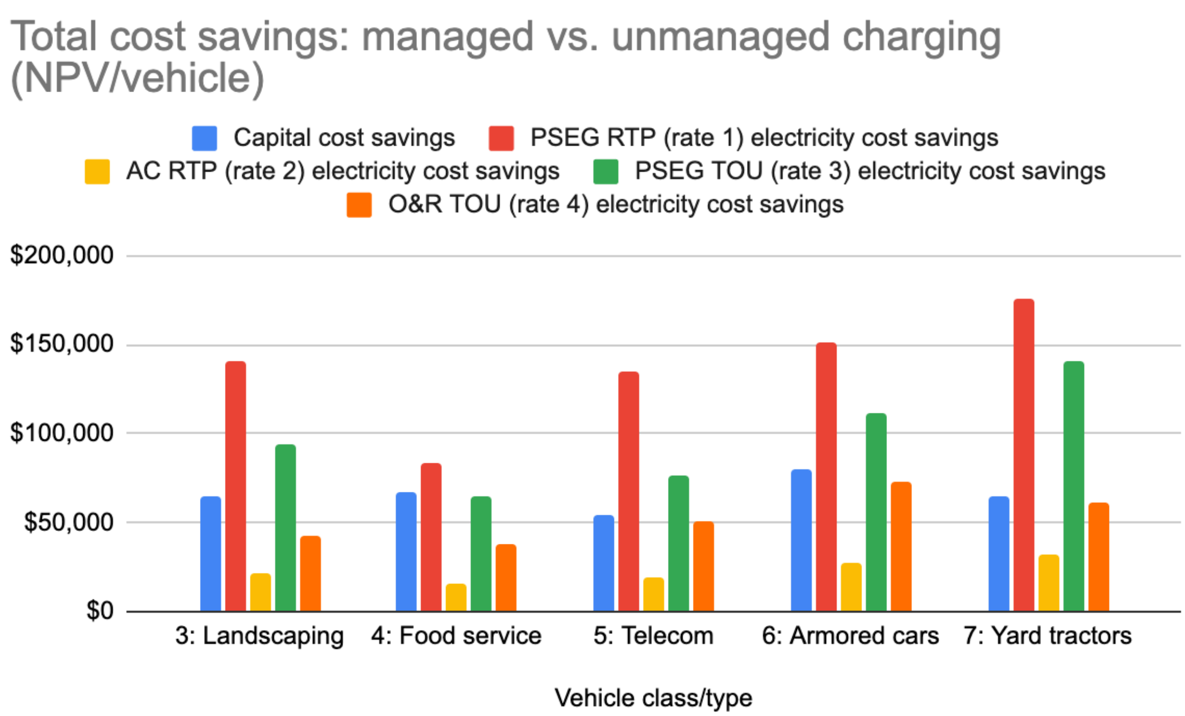
To mitigate these costs the impact of managing the charging of a depot, and thus reducing the number of charging stations and peak charging power was explored. It was found that by implementing managed charging, upfront capital costs were able to be reduced by $50k to $80k per vehicle. This alone would result in significant savings for a fleet and should be actively explored when developing electrification plans.

Four existing electricity rates in New Jersey were used to evaluate the cost of charging for use of the fleet scenarios. Two were time-of-use (TOU) rates and the other two were hourly real time pricing (RTP) for the energy portion of the electricity bill. It was shown that average annual charge per vehicle ranging from $191k (PSEG RTP) to $29k (Atlantic City TOU), and the overall range in cost varying from 22% to 240% of capital costs. Further across the board the largest portion of the electricity bill was the demand charge (defined as the sum of capacity, generation, transmission, distribution, and delivery charges, where applicable, that scaled with power, e.g., $/kW) ranging from 50% to 95% of the bill. Rates design solutions should be explored to reduce electricity costs for commercial fleets.

For all rates evaluated, managed charging by the fleets results in significant energy cost savings over unmanaged charging seeing annual savings per vehicle anywhere from $20k to over

$150k, shown in Figure ES-2. This was due largely to spreading the charging over the entire overnight charging window to reduce the peak power in an effort to demand charges. However it should be noted that many fleets may not have capability to manage charging due to operational constraints and therefore rate design that explores demand charge mitigation as well as programs that educate and increase managed charging tactics will be important to meet New Jersey's electrification targets.

Figure ES-2: Total cost savings per vehicle of managed and unmanaged charging.



The impact of onsite solar and battery on charging total cost of infrastructure was evaluated. The solar and battery capacities were sized to be able to accommodate 80% of the peak load for each depot scenario. It was found that when applying onsite solar + battery to the charging infrastructure, there is a significant savings in electricity cost seen, ranging from $20k to $208k (NPV/vehicle) when compared to unmanaged charging, or 75% to 93% savings. However, when compared to managed charging, the savings are still there but significantly reduced to $2k to $33k, or 19% to 63%. While there is electricity savings across the board, they do not take into account upfront costs required to install onsite solar and battery. As the fleets for these use cases often have significant dwell times overnight, they can already reduce a majority of their electricity costs with managed charging. To ensure rollout of onsite solar and battery at depots to maximize resiliency and further reduce grid buildout, other revenue opportunities and programs for these resources to offer grid services should be explored to bring down the cost of ownership.

A key finding was that when comparing the cost of charging with electricity with gasoline and/or diesel fueling, there is annual fuel cost savings of 38-78% for all vehicles use cases. It is important to emphasize that this was only the case when charging was managed to lower the peak load. For fleets to see fuel cost savings it is important for them to explore managed charging techniques or rates which mitigate demand charges.

However, despite these fuel cost savings, when evaluating the total cost of infrastructure and electricity compared to traditional fueling there was only cost savings for the wired telecom (class 5) use case, which had the largest number of vehicles in the depot.

Table ES-3: Fuel cost savings: Total cost of ownership (electricity and infrastructure) versus gasoline/diesel fuel cost, annual cost for depot.

		Best (Managed, AC RTP)	
Vehicle use case	Fuel cost ($/yr)	Total cost of ownership ($/yr)	Savings relative to fuel costs ($/yr)
Landscaping (Class 3)	$5,385	$13,653	-$8,268
Food service (Class 4)	$15,959	$22,616	-$6,657
Wired telecom (Class 5)	$63,841	$54,408	$9,433
Armored car (Class 6)	$41,084	$45,009	-$3,924
Yard tractors (Class 7)	$3,440	$14,473	-$11,033

A key influence on finding cost savings when including the cost of infrastructure was the size of the fleet using the depot. While the number of trucks for each use case was set to be the average for that market segment the study explored evaluating the impact of scaling trucks on the total cost of ownership. It was found that cost parity was found for each use case when scaled to between 8 and 15 trucks. However, that breakeven point would change depending on operating conditions of the fleet (shorter time windows, driver shift constraints, etc.). What is clear is that because smaller fleets are less likely to be economical to electrify, in early stages, additional or focused support for smaller fleets should be prioritized in programs and funding schemes.

In the second half of the study the results were scaled to estimate the peak load impact of electrifying all class 3 through 7 trucks in New Jersey as well as the impact of implementing managed charging and onsite solar and battery at these depots. It was found that significant on-peak load reductions can be seen with ~8,400 MW for managed charging, to ~10,000 MW for managed charging with solar + battery. This translates to avoided grid infrastructure cost savings of up to $1.803 billion for managed charging, and up to $2.150 billion when paired with onsite solar + battery. It should be noted that these savings were based on current grid expansion costs, as grid costs in the future may be more expensive, thus even larger savings by exploring these solutions.

Introduction

Background

Deployment of electric medium- and heavy-duty vehicles (MHDVs) is accelerating worldwide. Not only are more battery electric vehicles becoming commercially available, but policies at the local, state and federal levels encouraging zero emissions vehicle adoption are expanding, as recently exemplified with the signing into law of the Advanced Clean Trucks requirements in New Jersey in December 2021, and the draft Medium-and Heavy-Duty Zero-Emission Vehicle Action Plan by the Northeast State for Coordinated Air Use Management (NESCAUM).

In order to meet these ambitious targets it is even more important for states such as New Jersey to understand the cost barriers associated with charging infrastructure so it can also begin accelerating the adoption of electric MHDVs. While we understand that every depot is unique, our approach of simulating several representative depots located in New Jersey of varying sizes, vehicle classes, schedules, and seasonal variation in electricity demand, can provide valuable insight into what does and does not work for certain MHDV market segments.

Study objectives

The purpose of this project was to realistically model electrification of MHDV fleets, class 3 through 7, in New Jersey, using a set of case studies representing different vehicle classes and use cases.

Two types of vehicle charging approaches were compared. The first, unmanaged charging, is when vehicles charge at full power as soon as trucks return to the depot. The second, managed charging, is when fleets optimize their charging times and charging power to reduce the cost of charging, resulting in charging during periods of lowest cost, which includes both energy- (per kWh) and peak power- (per kW) based costs. This latter cost is commonly referred to as a demand charge, which is defined as the sum of capacity, generation, transmission, distribution, and delivery charges, where applicable, that scaled with power, e.g., $/kW.

The study also included the scenarios with an onsite solar photovoltaic (PV) system connected to a battery at the depot, providing supplemental electricity to the vehicle charging system. Previous work by GNA has demonstrated the importance of such systems to lower the total cost of ownership for electric vehicle depots. Managed charging simulations were performed both with and without a solar PV + battery system.

The study objectives were:

1. Determine depot electrification readiness by vehicle class.
2. Calculate the total cost to depot owners under different assumptions of vehicle type, rate structure, season, and evaluating potential fuel cost savings for each use case.

3. Determining the impact of managed charging and depot solar and battery on the total cost of ownership of charging infrastructure.
4. Calculate avoided cost and other impacts to grid operators, emphasizing grid expansion savings from managed charging and onsite PV.

Methodology

Overview

The approach used in this study began with a mixture of real vehicle fleet use data from New Jersey, New York, and California spanning vehicle classes 3 to 7. Each vehicle class was represented by one common use case for which ample data was available (detailed below); usage patterns were vetted by industry stakeholders as representative of on-the-ground experience. Input data consisted of a mixture of gasoline/diesel and electric vehicle driving and idle periods spanning between 5 and 19 months, with most vehicle classes encompassing 12 months. For electric vehicle data, the fleet operated on a 24 hours/day schedule with several recharging events per day. For gasoline/diesel vehicles, vehicle odometer readings reported during refueling events every few days were converted into average daily driving distances and average fuel consumption, which were then converted to equivalent daily electricity consumption using typical engine efficiencies. For both types of data, simulations drew usage data randomly for each day within a season to provide representative usage patterns that varied day-to-day and season-to-season. Vehicle battery capacities were based on the largest commercially available for each vehicle class.

Part 1: Depot electrification

Seven-day vehicle use simulations were performed for each vehicle class in four seasons for a wide range of simulation parameters (optimization type, electric rate structure, number of charging ports, charger power, and when present, solar PV and battery capacities). For each scenario, results from these representative weeks were scaled to estimate the annual behavior of a fleet.

Three optimization types (unmanaged charging, managed charging, and managed charging with a solar photovoltaic (PV) and battery storage system) were modeled. Unmanaged charging was not an optimization at all, as it always charged at full power as soon as vehicles were plugged in. Managed charging, by contrast, attempted to minimize charging cost for the depot, where cost was driven by one the four New Jersey electricity rate structures modeled based on real rate data (see Appendix A: Data, Electricity rate data section). For these optimizations, a 24-hour look-ahead schedule was assumed that began at 3 pm each afternoon (consistent with PSE&G's day-ahead pricing schedule) and continued over the next 24 hours, where charging was optionally scheduled in advance.

Rate costs consisted of an hourly cost proportional to the energy consumed (expressed in $/kWh) plus a cost proportional to the maximum monthly power flow in any hour (expressed in $/kW, usually called the "demand charge"). Both of these rate components varied seasonally, and sometimes by time of day. For two of the four rate structures, a real-time pricing approach was modeled, whereby the energy cost consisted of both a fixed cost per kWh plus a cost which varied each hour of the year based on market forces; for this data, we used New Jersey average real-time locational marginal prices from PJM market data.

The simulation tool used in this study is called V2G-Sim, which was developed at Lawrence Berkeley National Laboratory and built to study the effects of vehicle electrification on electric grids. The version developed for this study was heavily modified from the original and grew out of work that Emerging Futures performed for the Midcontinent Independent System Operator in 2019-2020. The model has been used successfully in a number of previous peer-reviewed studies. For more information, see Appendix B: V2G-Sim modifications.

Based on the charging needs of each fleet and scenario, charging infrastructure equipment including onsite solar and battery was selected (See assumptions in section on Scenarios Performed). The cost of charging infrastructure, including chargers, cables, installation, warranties, contracts, utility and customer make-ready, and when present solar PV and battery systems, were not part of the optimization but were imposed as fixed annual costs depending on the configuration simulated. Cost data were gathered from several electric vehicle charging reports, as well as some installation contracts that were made available to us. All assumptions are documented in Appendix A: Data, Total cost of ownership section.

Part 2: Grid impacts

Results from Part 1 were used to calculate New Jersey-wide grid impacts, by extrapolating results at the depot level as if all vehicles in each vehicle class in the state were electrified, using total New Jersey vehicle registrations by class. The main impacts explored were:

1. Increase in peak power demand for each optimization type (unmanaged charging, managed charging, and managed charging with solar PV plus battery).
2. Avoided grid upgrade costs based on how much lower peak load from vehicle charging is when managed charging is implemented, compared to unmanaged charging. We explored grid savings when switching to both managed charging, and managed charging with solar PV plus battery. A range in cost per MW of peak power was adopted, based on two complementary methods of estimating utility costs of providing new grid infrastructure (for more information, see Appendix A: Data, Grid expansion savings):
    a. The first method used the highest-cost demand charge of the rate structures modeled in this study, which provided a minimum estimate for the utility's actual cost of providing peak power.
    b. The second method used estimated total grid expansion costs from 2021 through 2050 for New Jersey Jersey to determine a maximum estimated cost per MW. These costs were based on a 2020 report released by ChargeEVC.
3. New Jersey-wide total cost of ownership for vehicle charging across all vehicle classes modeled, by aggregating total cost for each vehicle class and scaling it to all of New Jersey.

It is worth reiterating that only class 3-7 trucks were modeled in this study, and therefore New Jersey-wide grid results do not include other vehicle classes like passenger or class 8 trucks.

Vehicle class assumptions

Table 1 summarizes the vehicle use cases used to represent on the ground fleets. Each use case is based on real-world measured vehicle use for New Jersey and New York (for classes 3-6) and California (for class 7), with input from industry stakeholders to ensure vehicle use patterns were representative of on-the-ground experience in New Jersey. Depot sizes assigned for each use case were based on the average number of vehicles in each vehicle class in the empirical data, which varied from 2 (landscaping and yard tractors) to 11 (wired telecom). While in reality fleets are often comprised of more than one vehicle type, for this study and the five use cases ultimately selected, each was assigned to one dominant vehicle class from that market segment.

Table 1

Vehicle use cases modeled

Vehicle use case	Vehicle class	Depot size	Average energy use (kWh/day)	Average efficiency (kWh/mi)	Battery capacities (kWh)	Max charging power (kW)
Landscaping	3	2	82	1.04	140	19
Food service	4	4	89	1.11	156	21
Wired telecom	5	11	122	1.93	226	31
Armored car	6	7	259	3.36	343	56
Yard tractors	7	2	50	3.50	80, 160	22

Note: Fuel efficiency for yard tractors was inferred based on an average fuel efficiency for class 7 and 8 trucks in New Jersey from Geotab.

Data on average daily energy use and average vehicle efficiency were based on actual vehicle fuel consumption (gasoline and/or diesel) and miles driven; the fuel consumption was converted into an equivalent electrical energy consumption estimates based on the average engine efficiencies of fuel (gasoline or diesel)-based and electric engines (see Appendix A: Data, Energy use estimates). The impact of seasonal temperature differences on vehicle battery efficiency was included in the model and estimated based on average outdoor temperature in 2020 and 2021; see Appendix A: Data, Seasonal energy demand multipliers section for more details on how seasonal demand multipliers were calculated.

Capacities of vehicle batteries were based on the largest existing commercially available batteries in each vehicle class at the time of our analysis (mid-2021), based on information provided by the Snohomish County Public Utility District (SNOPUD). For details, see the section on Battery capacity estimates in Appendix A: Data. For yard trucks, the usage data originated from existing battery electric vehicles, so the same configurations and capacities were used without modification. These vehicles were procured in 2020 and were similarly the largest battery capacity available on the market for class 7 yard trucks at that time.

To determine the charging power needed for each fleet use case, the average daily energy consumption to meet the fleet's need was calculated; this was divided by the available charging window for each use case during weekday operations. This latter information was unique to each vehicle class and was based on an understanding of depot operator schedules as communicated to Emerging Futures from our data suppliers. The base charging power was rounded slightly to conform to standard charging station capacities offered in the industry (e.g., 20, 30, or 60 kW). These maximum charging power values were chosen to capture nearly the full range of daily vehicle energy consumption, but in some cases not all vehicle driving itineraries were able to be fully charged overnight. Therefore, multiple charging infrastructure configurations were explored using higher maximum charging power values, ranging from 50 to 150 kW depending on fleet use case. These were based on standard increments from these base levels, and were used in some of the simulation runs to determine the ability of fleets to electrify using existing technology.

Electricity rates

To assess the cost of charging, we selected four rate structures from three utilities operating in New Jersey: Public Service Enterprise Group (PSEG), Atlantic City Electric, and Orange and Rockland Utilities, Inc. The rates were selected to cover a diverse set of rate structures currently offered to commercial customers at their rated peak power. They were also based on real 2021 rates in New Jersey in order to explore variations in how electricity costs vary with time of day, time of year, and amount of power consumed. Table 2 summarizes the main differences among these four rate structures. All four rate structures included some degree of seasonal variation in cost. Detailed information is provided in the Rate structures section of Appendix A: Data.

Table 2

Rate structures modeled in this study

No.	Description	Label	RTP[1] included?	Demand holiday?	Maximum demand charge ($/kW)	Notes
1	PSEG rates with RTP	PSEG RTP	Yes	Partial	31.07	Demand charge reflects discount of 50% over full rate; rate sheet depends on peak monthly power[2]
2	Atlantic City Monthly Generating Service - Secondary with RTP	AC RTP	Yes	Partial	4.21	
3	PSEG Basic Generating Service - Residential Small Commercial Pricing	PSEG TOU	No	No	18.32	

	with TOU[3] rate					
4	Orange and Rockland Basic Generating Service - Residential Small Commercial Pricing with TOU rate	O&R TOU	No	No	5.82	Summer time-of-use rate has 3 tiers

[1] Real-time pricing
[2] Rate sheet used: General Light and Power (GLP: <150 kW) or Large Power and Lighting - Secondary (LPL-S: >150 kW)
[3] Time-of-use

For two of the rates (PSEG RTP and AC RTP), a real-time price (RTP) that varied hourly throughout the year was added to the actual rate structure. This RTP was based on data from PJM's locational marginal prices from August 5, 2020 through August 4, 2021. More details are provided in Appendix A: Data, Real-time pricing data. These rates also offered a partial demand charge holiday depending on the peak power of each fleet use case. The remaining two rates were time-of-use (TOU) rates which offered peak and off-peak prices and for one of the rates an additional summer off peak price for the energy portion of the fleet's electricity bill. There was no time variance in price for the demand portion of the bill for any rate except for the PSEG RTP rate, which had different peak and off-peak demand charge rates during the summer (June through September).

Charging infrastructure costs

Other depot charging infrastructure ownership cost elements included the following:

- Solar PV capital
- Solar battery capital
- Charger capital
- Charger cables
- Managed charging contract
- Charger installation
- Charger warranty
- Utility make-ready
- Customer make-ready

These cost assumptions were obtained from a variety of sources as detailed in the Total cost of ownership section of Appendix A: Data. In several cases, empirical linear or nonlinear fits to the data were required in order to interpolate to the capacities simulated in our model. These fits are also documented in the Total cost of ownership section.

Fleet scenarios

For each vehicle use case, several hundred simulations were performed representing combinations of parameter assumptions, which are summarized in Table 3. In total, more than 4,400 simulations were performed.

Table 3

Summary of simulations performed

Vehicle use case	**Vehicle class**	**Vehicle Battery Capacity (kWh)**	**Months**	**Capacity per charging station (kW)**	**Rate structure***	**Solar PV (kW)**	**Solar battery (kWh)**	**# ports***	**Total no. of runs**
Landscaping	3	140	1,4,7,10	20,50,100	1-4	23	50,100,200	2	352
Food service	4	156	1,4,7,10	20,50,100	1-4	64	140,280,560	2,4	688
Wired telecom	5	226	1,4,7,10	30,50,100	1-4	294	645,1290,2580	2-10	1696
Armored car	6	343	1,4,7,10	60,100,150	1-4	220	480,960,1920	2-6	1024
Yard tractors	7	80, 160	1,4,7,10	20,50,100	1-4	23	50,100,200	2	688
Total									4448
*Optimization type									
1	Unmanaged charging								
2	Managed charging								
3	Managed charging with solar PV + battery storage								
*Rate structure									
1	PSE&G RTP								
2	Atlantic City RTP								
3	PSEG TOU								
4	Orange/Rockland TOU								
*# ports									
even-number restriction	limited to two ports per charger; >2 ports indicates multiple chargers								

Four different weeks throughout the year were simulated to represent the four seasons. For each week, vehicle use data were drawn from a single month of a corresponding season when available (December or January for winter, April for spring, July for summer, and October for autumn). For one vehicle use case (armored cars), data were not available for the summer and autumn, so for these two seasons, all available data (from December through May) were sampled, and seasonal energy use multiplier were applied to estimate the energy demand experienced for those time periods. This multiplier was determined using the seasonal effect seen in similar vehicle classes. Simulations were performed for three maximum charging station power levels that depended on vehicle use case, as discussed earlier.

Three optimization types (unmanaged, managed, and managed with solar PV + battery) were simulated. For the unmanaged charging optimization, none of the remaining parameters described below were varied, but we did calculate the electricity cost for each of the four rate structures simulated. For the other two optimization types, electricity cost was explicitly minimized, so separate simulations were performed for each rate structure. As stated above, four rate structures were applied to determine the cost of charging: two real-time pricing structures (PSE&G RTP, and AC RTP), and two time-of-use pricing structures (PSE&G TOU, and O&R TOU).

For the solar PV scenarios, three different solar battery sizes were simulated. The middle value was chosen based on the daily energy consumed by the depot when averaged over the week, multiplied by the seasonal energy consumption multiplier averaged over the year. The low and high values were then set equal to 50% and 200% of this value. The PV array power was sized to provide 80% of the average annual vehicle demand, based on the recommendation in the GNA report. Details are provided in Appendix A: Data.

Based on industry practices, each charger was assumed to have two ports, meaning it could charge up to two vehicles simultaneously. To investigate the impact on total cost of infrastructure, a few additional scenarios were run for fleet classes 3, 4, and 5 to explore increasing the number of ports (e.g., additional chargers) per depot. This was due to the longer dwell times for these use cases and therefore were good candidates to explore higher numbers of charging ports per depot.

The depot power levels were chosen based on standard transformer ratings (150 or 500 kVA, equivalent to kW). 150 kW was used for the two smallest depot size use cases (landscaping and yard tractors), where maximum demand was always less than 150 kW, while 500 kW were used for the other vehicle use cases.

Model descriptions

For each fleet, a charging load profile, based on real world driving data, and a charging optimization model was developed. These were simulated using a simulation tool developed by Lawrence Berkeley National Laboratory called V2G-Sim. Detailed information about the optimizations using this tool are detailed in Appendix B: V2G-Sim modifications.

Input data for the simulations was derived from real-world driving data supplied by industry stakeholders. As described in the Methodology overview, vehicle odometer readings from gasoline or diesel vehicles reported every few days during refueling events were captured and processed to provide estimated daily driving over a period of approximately 12 months for most vehicle use cases; in one case (armored cars, class 6), only five months of driving data were available. Together with fuel consumption estimates and average efficiencies of gasoline and diesel engines, daily distances were converted into equivalent daily electricity charging load profile distributions. Fleet load values were scaled by seasonal multipliers reflecting average outdoor temperatures in New Jersey, which drove ancillary cabin loads (heating or air conditioning) that increased electricity consumption in most seasons. Details of these conversion steps along with the extensive data cleaning and preparation required are documented in detail in Appendix A: Data. For one vehicle use case (yard tractors, class 7), actual electric vehicle consumption data were available every few minutes over a 19-month period, so were used without modification.

Once operational and driving data were converted into electricity charging load profiles, seven-day simulations were generated by sampling randomly from daily data within a given season to generate typical driving patterns that varied day-to-day. These load patterns drove the optimization model for recharging vehicles at the depot during periods of non-use. For vehicle classes 3-6, this occurred at night, whereas for vehicle class 7 that operated 24 hours/day, recharging occurred in short periods throughout the day. For all vehicle classes, there was a period of 1-3 days each week ending on Sunday where vehicles were not operated and could fully recharge. Simulations always began on Sunday at 3 pm and extended to the following Sunday at 3 pm; the resulting time series data from 12 am to 3 pm on the second Sunday were shifted to the first Sunday for presentation purposes, in order to provide seven full days of data from 12 am to 12 am.

Types of charging optimizations performed

For each scenario and for all four of the rate structures, three types of charging optimizations were performed:

1. Unmanaged charging: Vehicles were connected to a power source as soon as they returned to the depot, and could charge at full power until their batteries were full. No optimization was performed; the cost of providing such power was simply calculated as an output.
2. Managed charging: Vehicles were also connected to a power source as soon as they returned to the depot, but charging was based on an optimization algorithm that aimed to minimize the total cost of electricity paid by the depot owner. As a result, charging was concentrated during periods of lowest cost, while also minimizing the demand charge based on the highest hourly power demand in a given month. This model was adapted for each rate structure.
3. Managed charging with solar PV + battery: Managed charging was performed as above, but with the addition of a large solar PV system connected to a large battery.

Results

Part 1: Depot electrification

Result 1: Can depots electrify?

Using real fleet trip data, we evaluated the fraction of vehicle trips that could be served as a function of daily charging sessions using existing commercially available technology, shown in Table 4. Our default assumption is a single charging session, which occurs in the evening after completing the day's travel. We found that vehicle classes 3-5 had served trip fractions between 81.5% and 86.2%, while class 6 (armored cars) stood out with the lowest fraction of served trips (66.4%).

Table 4

Served trips by vehicle class, as a function of the number of daily charging sessions

Vehicle use case (class)	Number of daily charging sessions		
	1	2	3
Landscaping (3)	84.53%	99.4%	99.9%
Food service (4)	81.52%	97.1%	99.5%
Wired telecom (5)	86.21%	99.0%	99.9%
Armored car (6)	66.38%	88.8%	96.6%

Note that yard tractors operated 24 hours a day, 5 days a week, allowing for many daily opportunities for recharging; 100% of vehicle trips in the database could be served by our assumed charging infrastructure.

To reduce the number of unserved trips, the number of recharge events could be increased, e.g., by adjusting operating schedules and/or charging while away from the depot, and either returning to the depot throughout the day, or using additional charging infrastructure (such as public charging). These additional charging sessions represent hypothetical cases that would involve changing vehicle schedules, however. Table 4 provides revised estimates of the fraction of served trips, which increase considerably with two daily charging sessions, and climbs to almost 100% for classes 3-5 (and 96.6% for class 6) for three daily charging sessions.

Table 5 provides additional charging characteristics, including the average and maximum travel distances, available daily charging times (excluding weekend), and required charging times for different assumed travel distances and charging power levels. Note that for all vehicle classes, we assumed there were two ports per charger, so the available daily charging time was typically half the duration shown, if the two vehicles sharing a charger had about the same energy consumption (though this was not always the case). Additional ways to serve 100% of trips could come from increased battery sizes coming onto the market, en-route charging, higher charging power, or single port charging.

Table 5

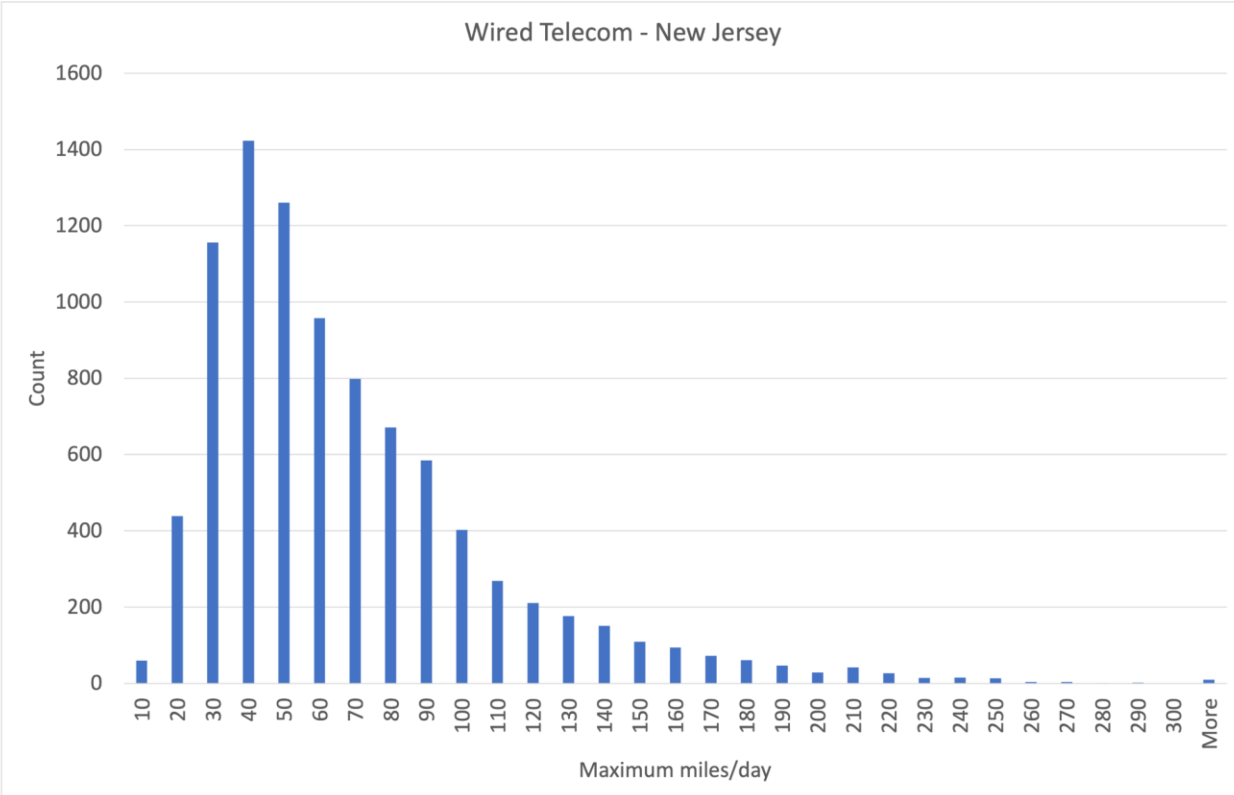
Charging characteristics by vehicle class

	Daily travel distance (mi)		Charging time (h)			
Vehicle use case (class)	Average	Maximum	Daily available (excluding weekends)	Average energy need, default rated power	Maximum energy need, highest rated power	Maximum charging power (kW)
Landscaping (3)	78.3	423	13.0	4.27	4.40	100
Food service (4)	80.0	596	12.5	5.52	7.12	100
Wired telecom (5)	63.2	400	12.0	4.55	9.49	100
Armored car (6)	77.2	288	14.0	5.42	8.34	150
Yard tractors (7)	N/A	N/A	2.49	2.51	0.59	100

Figure 1 shows the distribution of daily mileages for wired telecom vehicles (class 5). Only 10% of trips were >118 miles/day, 1% of trips were >210 miles/day, and 0.1% of trips were >300 miles/day. Other vehicle classes showed similar skewed distributions; another vehicle class example is shown in Figure A3 in Appendix A.

Figure 1

Histogram of daily mileage traveled by wired telecom vehicles



We find that for all vehicle classes, the default charging power is adequate to recharge vehicles for the average energy need at the default rated power level, but for vehicle classes 3-6, the default charging power is not adequate to recharge for the maximum energy need (represented by a single data point per vehicle class, which constituted <0.1% of all trips for vehicle classes 3-5, and <0.5% of all trips for vehicle class 6). However, the highest rated power level makes it possible to recharge even the maximum energy need in the available time for recharging.

Our underlying assumptions for these estimates are summarized in Table 6. While the average daily energy use was lower than the battery capacity in all cases, for the maximum (daily) session energy use cases, the limiting factor is battery capacity—more than three times the rated capacity for classes 3 and 6, and more than four times for vehicle classes 4 and 5. However, as for all cases these are significant charging windows, and stops to allow for a second charging session as well as to allow for en-route fast charging could meet energy needs.

Table 6

Vehicle trip data and assumptions by vehicle class

Vehicle use case	Vehicle class	Number of data points	Default charging power (kW)	Battery capacity (kWh)	Average daily energy use (kWh)	Maximum session energy use (kWh)
Landscaping	3	1086	20	140	85	440

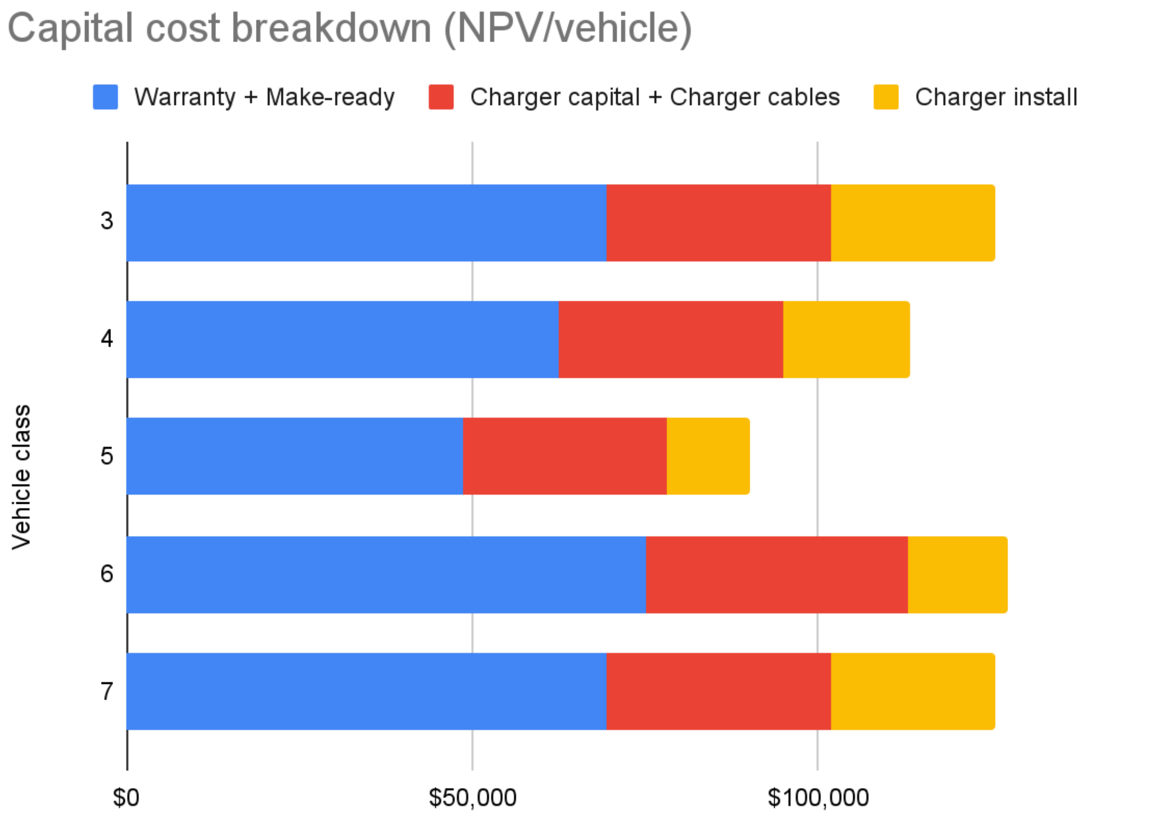
Food service	4	3468	20	156	110	712
Wired telecom	5	9106	30	226	136	949
Armored car	6	232	60	343	325	1,251
Yard tractors*,**	7	7292	20	80	50	59
*Yard tractors had 80 or 160 kWh battery, but the average and maximum per-shift consumption were 8.4 and 59.3 kWh.						

Result 2: Cost of charging infrastructure

For each depot use case the total cost of charging infrastructure (including hardware, contracts, installation, warranties, and make-ready) was calculated. Figure 2 shows the cost of all charging infrastructure expressed as net present value (NPV) per vehicle. Results are shown for unmanaged charging, broken down by cost category for vehicle classes 3-7. The main cost categories were warranty and make-ready costs, charger capital plus charger cable (which were a minor contribution) costs, and charger installation costs. Although individual cost contributions vary with vehicle class, the total cost is similar, ranging from ~$90,000 to ~$127,000 per vehicle. In all cases at least half of the capital cost for charging infrastructure was attributed to make-ready + warranties, and up to 32% for make-ready alone.

Figure 2

Capital cost breakdown for unmanaged charging by vehicle class



Costs changed considerably for managed charging optimizations. For instance, Figure 3 shows a comparison among the three optimization types for Food service (class 4). Most cost categories are much lower for the two managed charging optimizations due to lower maximum charger requirements and hence cheaper equipment. As an example, for the four-vehicle Food service fleet, unmanaged charging requires two 100 kW chargers, whereas managed charging requires only a single 50 kW charger resulting in capital cost savings of over $50,000. In addition, for managed charging with solar PV + battery, as expected there are significant additional capital costs for this equipment. This pattern of capital cost variation with optimization type is similar across all vehicle classes. Note, this added cost for onsite solar and battery does not reflect the electricity cost savings the fleet would see and will be explored further in section Results 5: Managed charging with solar PV + battery impacts.

Figure 3

Breakdown of capital costs for Food service among the three optimization types

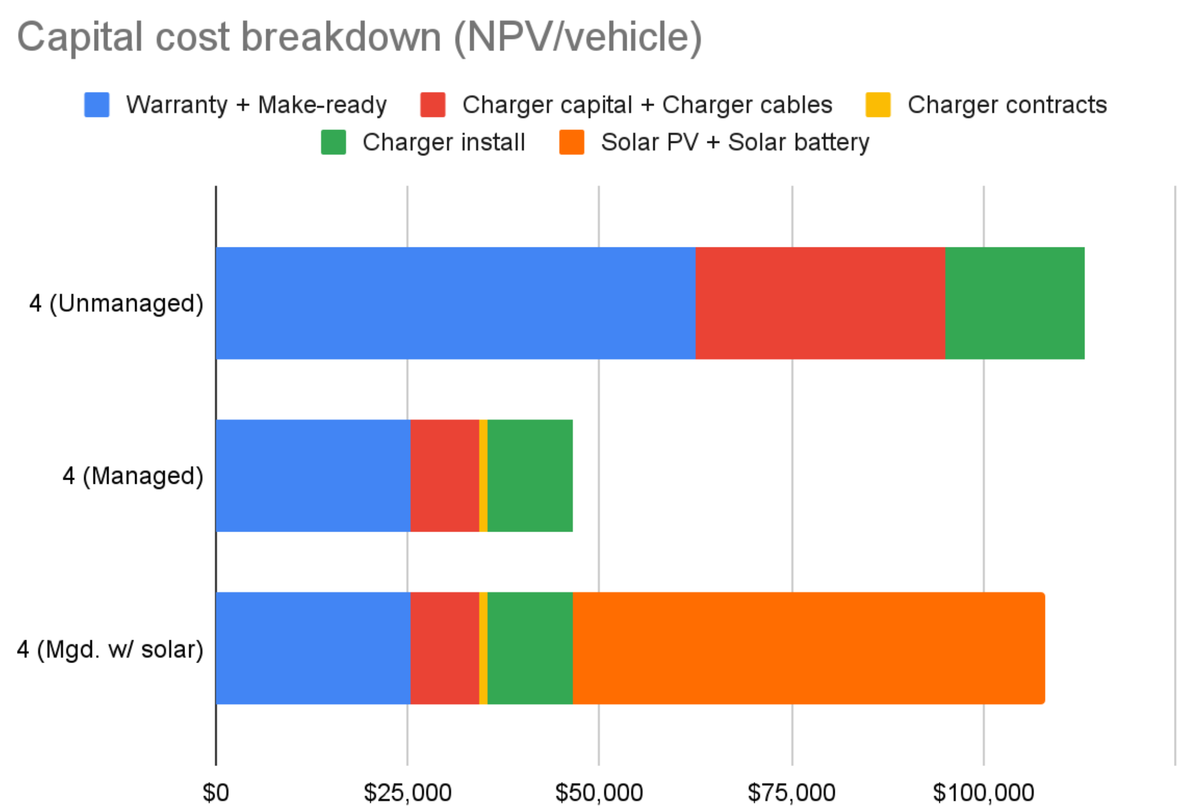


Table 7 provides this breakdown for all vehicle classes and optimization types.

Table 7

Capital costs (NPV/vehicle) by vehicle class and optimization type

Vehicle class/type and optimization type	Warranty + Make-ready	Charger capital + Charger cables	Charger contracts	Charger install	Solar PV + Solar battery
3 (Unmanaged)	$69,389	$32,409	$0	$23,710	$0
4 (Unmanaged)	$62,521	$32,409	$0	$18,312	$0
5 (Unmanaged)	$48,759	$29,463	$0	$11,832	$0
6 (Unmanaged)	$75,016	$37,850	$0	$14,396	$0
7 (Unmanaged)	$69,389	$32,409	$0	$23,710	$0
3 (Managed)	$31,267	$5,991	$1,900	$21,382	$0
4 (Managed)	$25,492	$8,947	$950	$11,113	$0
5 (Managed)	$18,054	$9,761	$345	$8,050	$0
6 (Managed)	$24,224	$12,085	$543	$9,937	$0

7 (Managed)	$31,267	$5,991	$1,900	$21,382	$0
3 (Mgd. w/ solar)	$31,267	$5,991	$1,900	$21,382	$44,061
4 (Mgd. w/ solar)	$25,492	$8,947	$950	$11,113	$61,610
5 (Mgd. w/ solar)	$18,054	$9,761	$345	$8,050	$103,319
6 (Mgd. w/ solar)	$24,224	$12,085	$543	$9,937	$121,196
7 (Mgd. w/ solar)	$31,267	$5,991	$1,900	$21,382	$44,061

Note that these capital costs do not include any infrastructure incentives aside from 26% federal sales tax credits for solar PV and storage.

Result 3: Unmanaged charging impacts

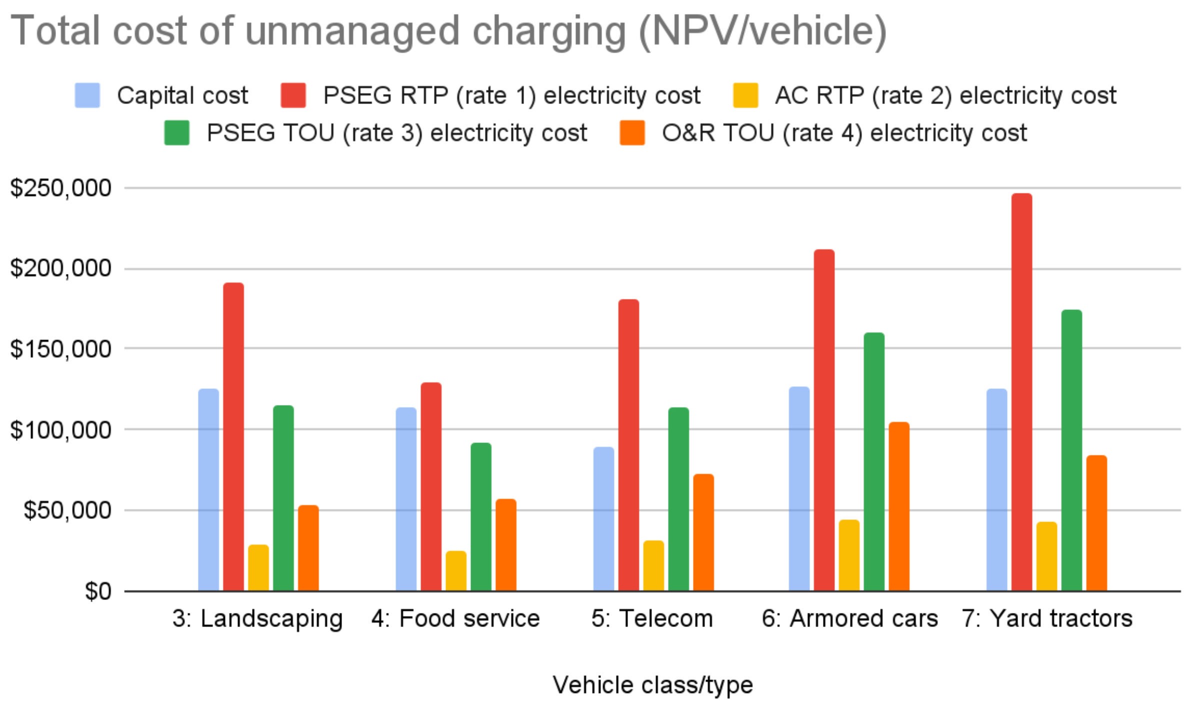
Electricity costs

As introduced earlier, four existing rate structures in New Jersey were used to evaluate the potential cost of charging for these selected fleet use cases. The four rate structures, outlined in Table 2, are: PSEG RTP (rate 1), AC RTP (rate 2), PSEG TOU (rate 3), and O&R TOU (rate 4). The two PSEG-based rate structures (1 and 3) have generally higher demand charges than the other two rate structures. All four rate structures included some degree of seasonal variation in cost. For our simulations, we find that PSEG RTP typically results in the highest monthly electricity costs, whereas AC RTP results in the lowest costs. The other two rate structures result in intermediate costs.

For unmanaged charging, electricity costs varied considerably with rate structure, with the average annual charge per vehicle ranging from $191k (rate 1) to $29k (rate 2), and the overall range in cost varying from 22% to 240% of capital costs. See Figure 4. For all vehicle classes the Atlantic City RTP (rate 2) resulted in the lowest cost for charging.

Figure 4

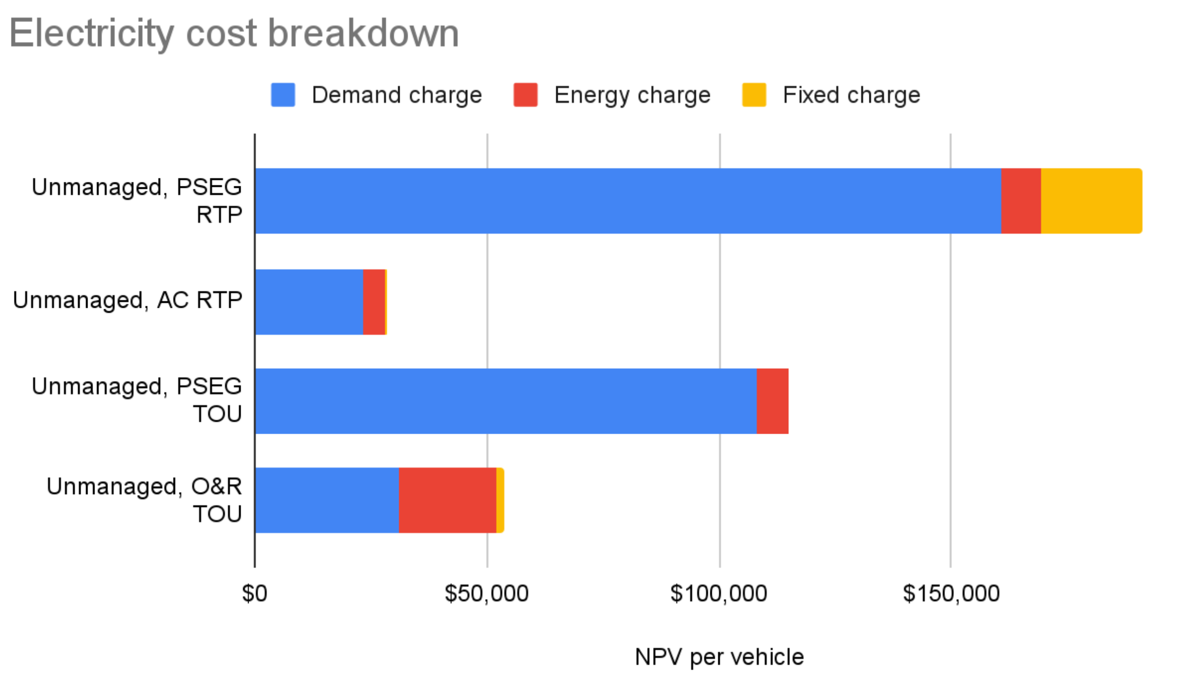
Total cost of unmanaged charging, broken down into capital and electricity costs



In Figure 5, we break down the electricity cost for the four rate structures for vehicle class 3 (landscaping). We see that 58-94% of the fleet's electricity bill (depending on rate structure) is due to demand charges. The pattern observed for other vehicle classes was similar. As the vehicles' charging is unmanaged, the maximum rated charging power at the depot is used as trucks are typically arriving to the depot to charge at the same time. Therefore, the peak power is very high for a short duration of time causing a significant portion of the electricity bill to be attributed to peak demand.

Figure 5

Breakdown of unmanaged charging electricity cost for landscaping



Result 4: Managed charging impacts

For all use cases a managed charging optimization was simulated and the same rates applied to evaluate the impact on a fleet's electricity bill as well as up-front hardware costs. We find that both capital and electricity costs are lower for managed charging than unmanaged charging for every vehicle class and rate structure, indicating a clear advantage. The cost savings, unsurprisingly, were highest for the highest-cost electricity rate (PSEG RTP), and lowest for the lowest-cost rate (AC RTP). See Figure 6.

Figure 6
Savings in total cost of managed vs. unmanaged charging

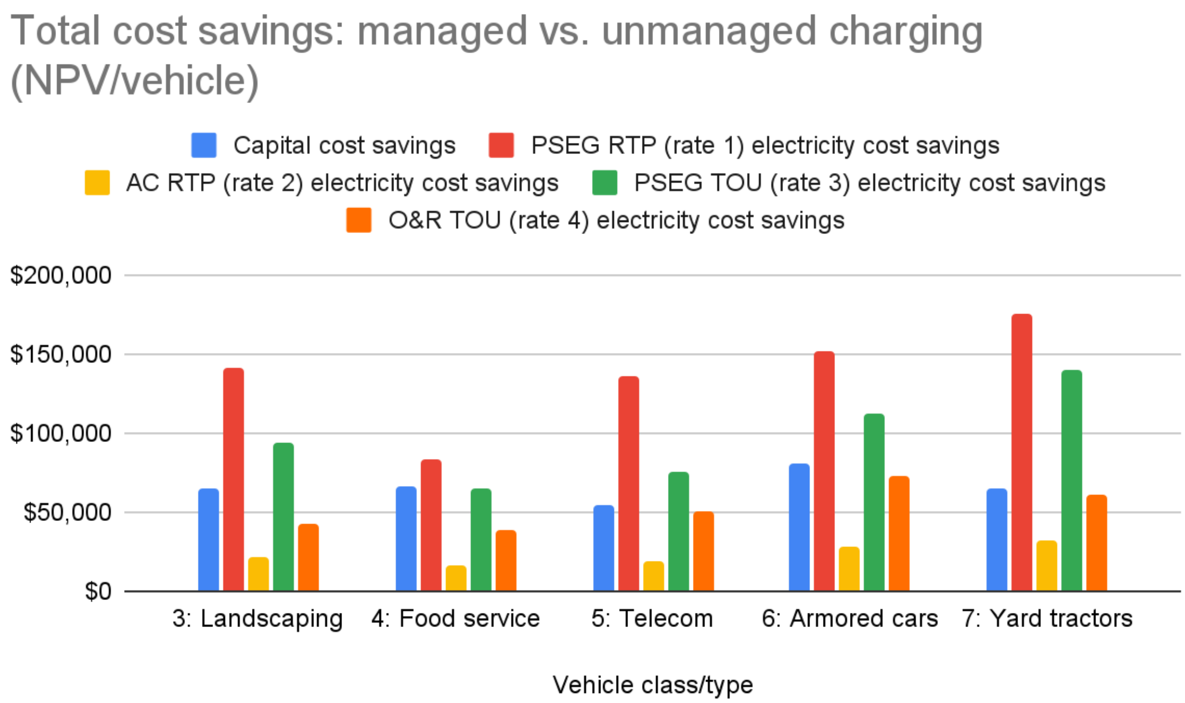


Table 8 shows the absolute cost breakdown by vehicle class and rate structure. Here one can see annual electricity cost savings can range from ~$15k to ~$175k depending on the rate structure.

Table 8

Total cost of managed vs. unmanaged charging for best and worst rate structures (NPV/vehicle)

Vehicle class/type	PSEG RTP (unmanaged)	PSEG RTP (managed)	AC RTP (unmanaged)	AC RTP (managed)
3: Landscaping	$191,050	$49,996	$28,569	$6,484
4: Food service	$129,409	$45,909	$24,845	$9,009
5: Telecom	$181,360	$45,917	$31,351	$12,352
6: Armored cars	$212,287	$60,800	$44,199	$16,340
7: Yard tractors	$246,160	$70,267	$42,686	$10,508

Figure 7 shows the difference in charging pattern over a 48-hour period for food service, which is a fleet of four class 4 vehicles, illustrating how much lower the peak rate is when charging is spread across the entire available charging window, in this case overnight, rather than being concentrated in the first few hours for unmanaged charging. This reduction results in $66,739 lower capital costs (NPV per vehicle) for charging equipment, and between $15,836 (AC RTP rate) and $83,500 (PSEG RTP rate) lower electricity costs (NPV per vehicle), mainly due to reduced peak demand and as a result demand charges.

Figure 7

Time series of food service vehicle charging for unmanaged and managed charging

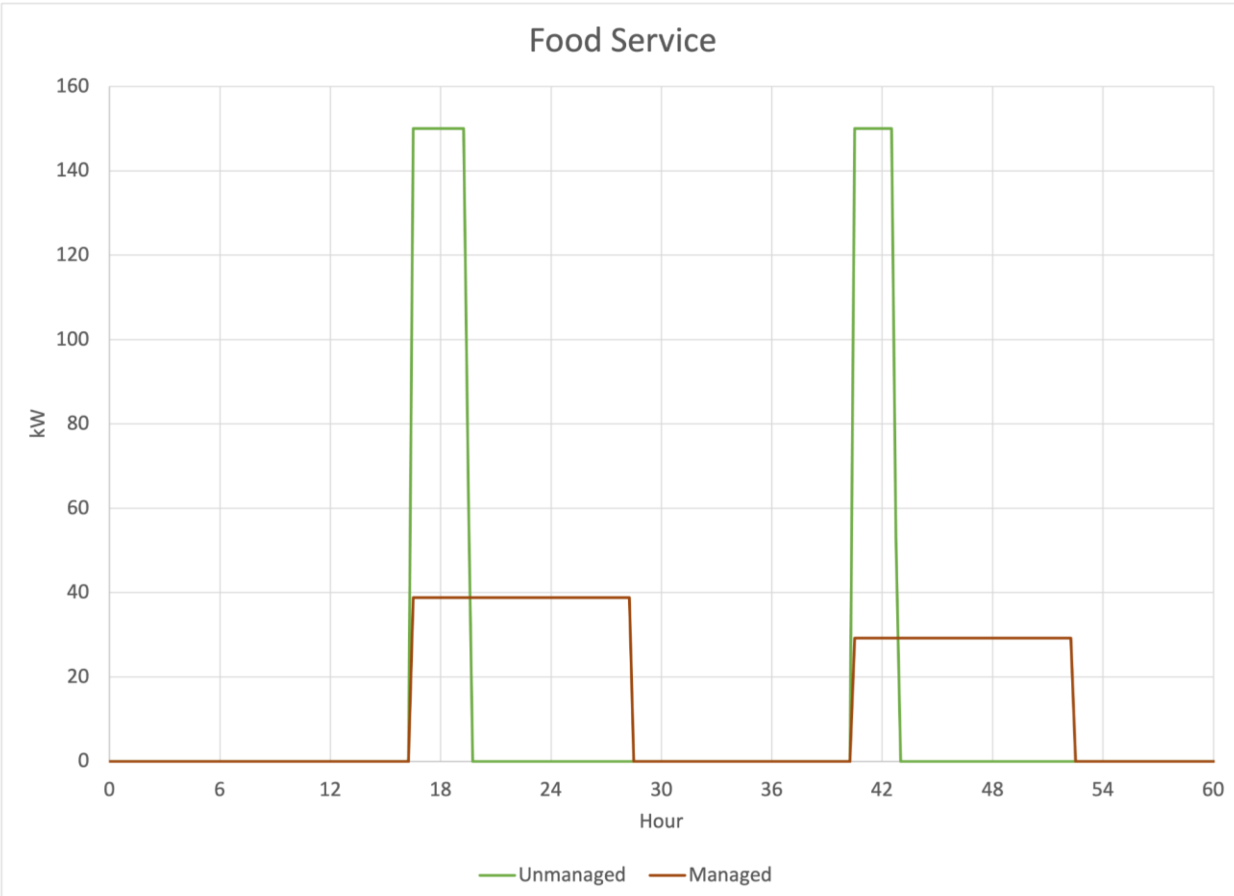
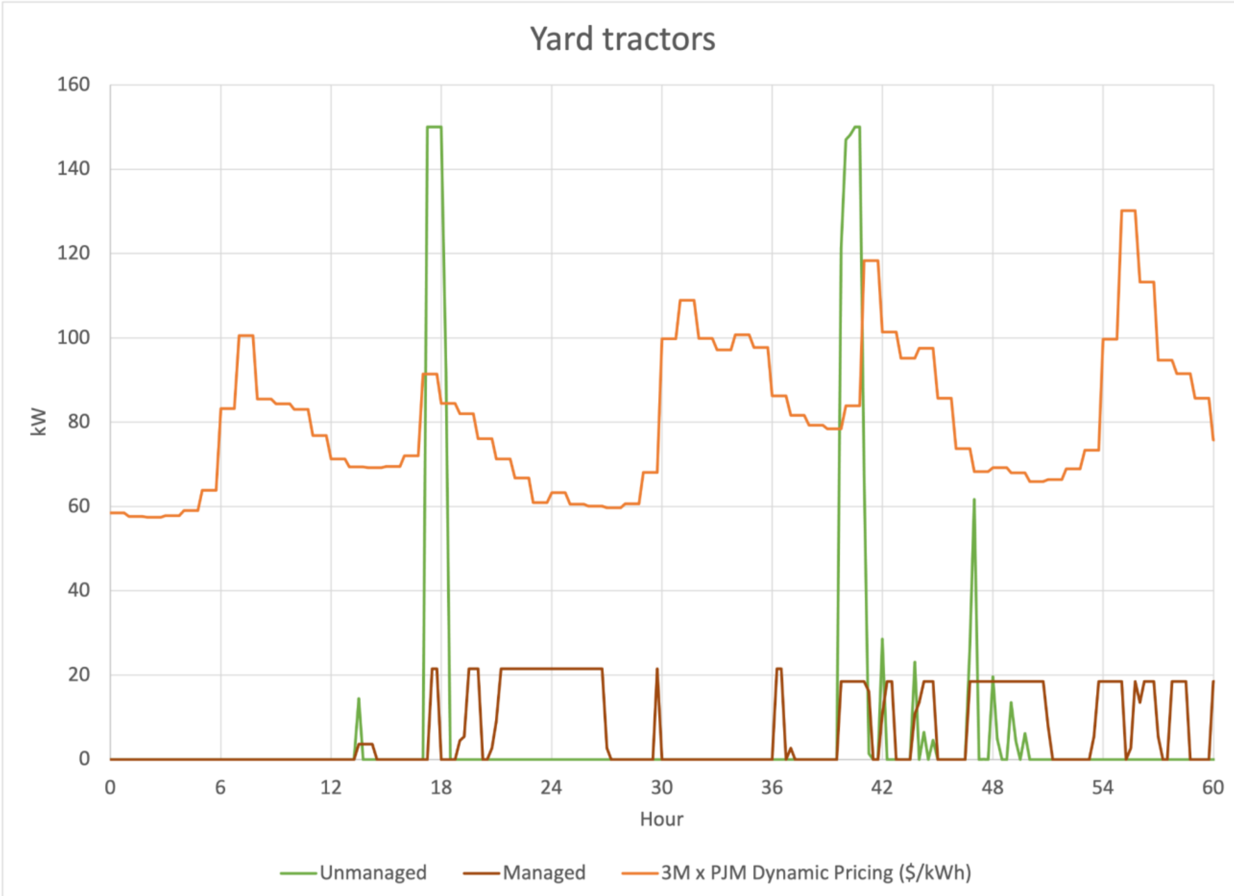


Figure 8 shows the differences for yard tractors, which illustrate a similar reduction in peak rates for managed charging as for food service. However, unlike food service (and other simulated vehicle classes), yard tractors are able to charge for short periods throughout their around-the-clock operational schedule. As a result, the managed charging savings are even higher because the fleet's charging can be spread across more hours and as a result is able to significantly reduce its peak power. Moreover, charging tends to take place during periods of lower hourly energy price.

Figure 8

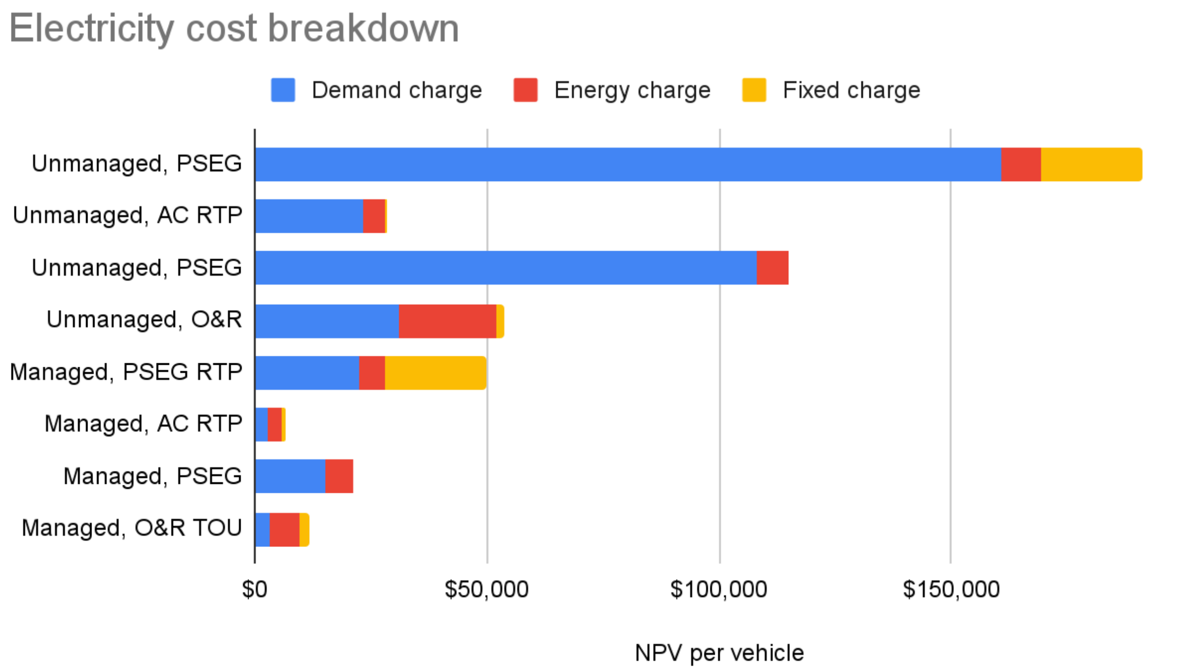
Time series of yard tractor vehicle charging for unmanaged and managed charging



Electricity costs are broken down into demand charges and other costs for landscaping in Figure 9, illustrating the large reductions in demand charges between unmanaged and managed charging. Despite these large reductions, the overall order of costs among the four rates remains the same with rate 2, Atlantic City RTP, resulting in the lowest electricity costs for all scenarios. This pattern holds true for all vehicle classes modeled.

Figure 9

Comparison of electricity cost breakdown for unmanaged vs. managed charging for landscaping



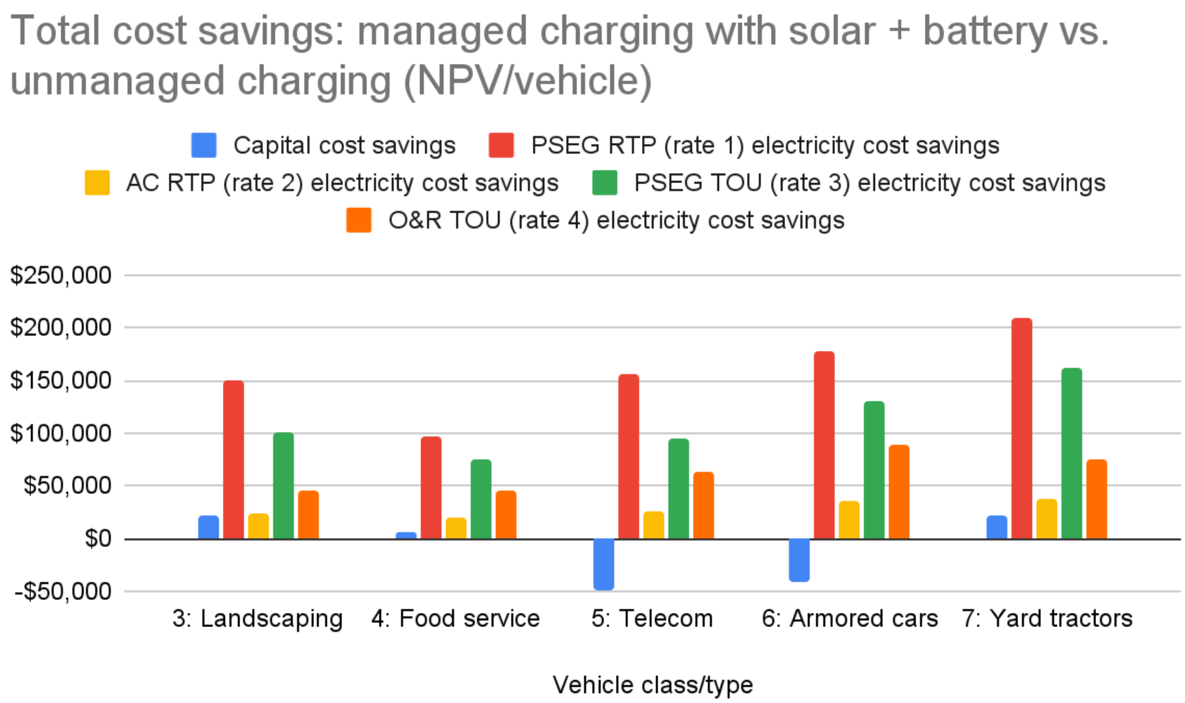
Result 5: Managed charging with solar PV + battery impacts

Electricity costs

When applying onsite solar + battery to the charging infrastructure, there is a significant annual savings in electricity cost seen, ranging from $20k to $208k when compared to unmanaged charging, or 75% to 93% savings. Figure 10 illustrates this by showing differences from unmanaged charging, for every vehicle class as well as the capital cost investments required. When comparing to unmanaged charging it is clear that the savings with managing charging with solar and storage outweighs added capital cost for hardware for all vehicle classes. However, to get a full picture of the cause of these significant savings, including capital cost savings for vehicle classes 5 and 6, it is more pragmatic to compare the savings of onsite solar and storage to the managed charging scenarios.

Figure 10

Savings in total cost of managed charging with solar + battery vs. unmanaged charging



In Table 9 the savings, ranging from $2k to $33k, of onsite solar and battery storage compared to managed charging, or 19% to 63%, can be seen. However, due to the hardware costs of the onsite solar and battery as well as the significant hardware savings seen from managing charging, the electricity cost savings are no longer able to offset the higher capital costs. Although, for yard tractors the trade-off is closer to break-even for PSEG RTP (the most expensive rate) than for any other vehicle class/rate combination. Therefore, fleets which have constrained charging windows and minimal capabilities to manage their charging are most likely to see a return of investment in solar and storage. Savings could also be seen if the onsite solar and storage was utilized for other grid services.

Table 9

Total cost savings of managed charging with solar + battery vs. managed charging by vehicle class, broken down into capital and electricity costs by rate structure (NPV/vehicle). A negative cost savings indicates a cost increase.

Vehicle class/type	*Capital cost savings*	*PSEG RTP (rate 1) electricity cost savings*	*AC RTP (rate 2) electricity cost savings*	*PSEG TOU (rate 3) electricity cost savings*	*O&R TOU (rate 4) electricity cost savings*
3: Landscaping	-$44,061	$9,298	$2,166	$6,654	$3,741
4: Food service	-$61,610	$13,991	$3,787	$10,655	$8,109
5: Telecom	-$103,319	$21,232	$6,627	$17,862	$12,378

6: Armored cars	-$121,196	$25,580	$7,686	$19,482	$15,255
7: Yard tractors	-$44,061	$32,503	$6,225	$20,846	$13,982

There were significant peak power reductions seen for each use case. Figure 11 shows a comparison of charging profiles for food service for managed charging with vs. without solar + battery. The total daily load is the same in each case. Although power levels vary throughout the charging period, there is a reduction in maximum grid power from 38.8 kW to 27.0 kW for the four-vehicle fleet, which is supplemented by power from stored solar energy.

Figure 11

Comparison of managed charging profiles with vs. without solar + battery for food service vehicles

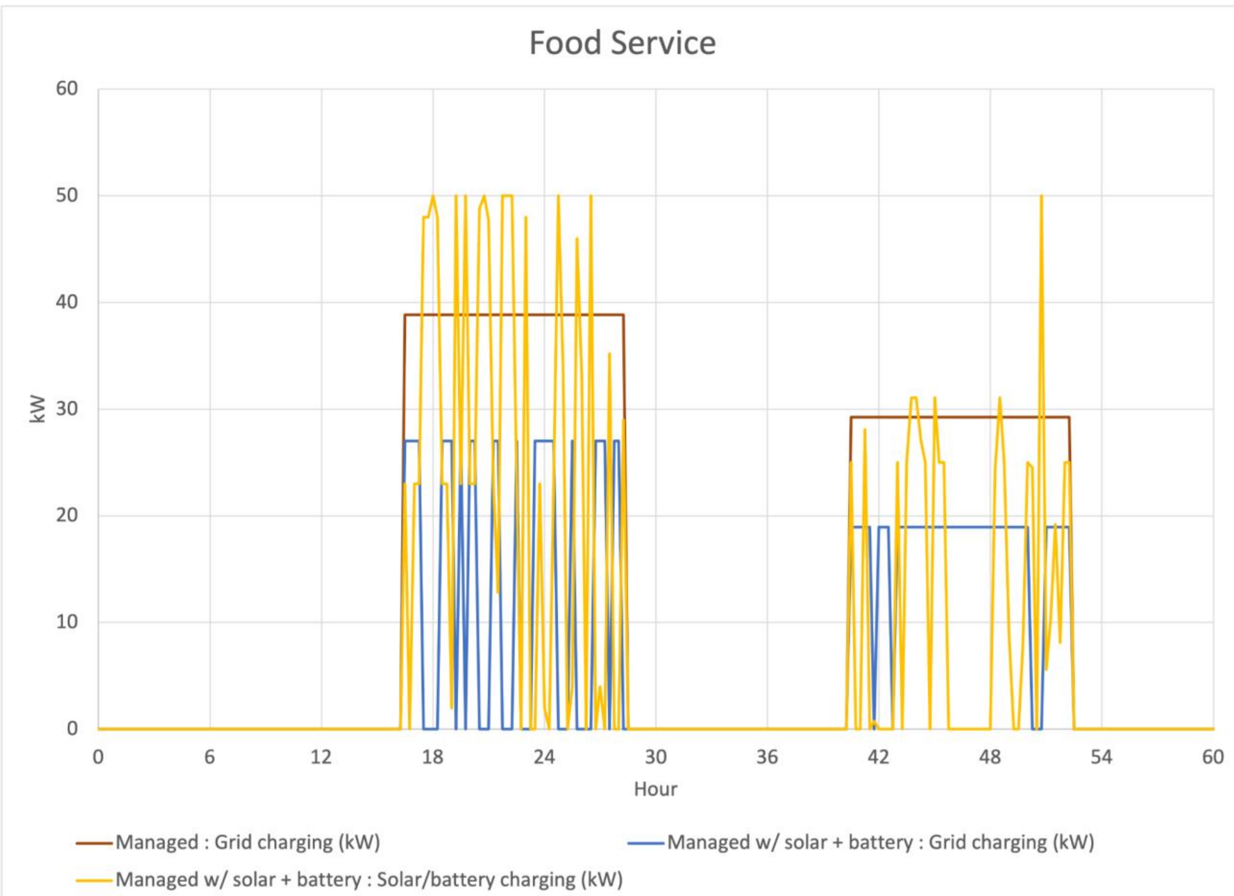
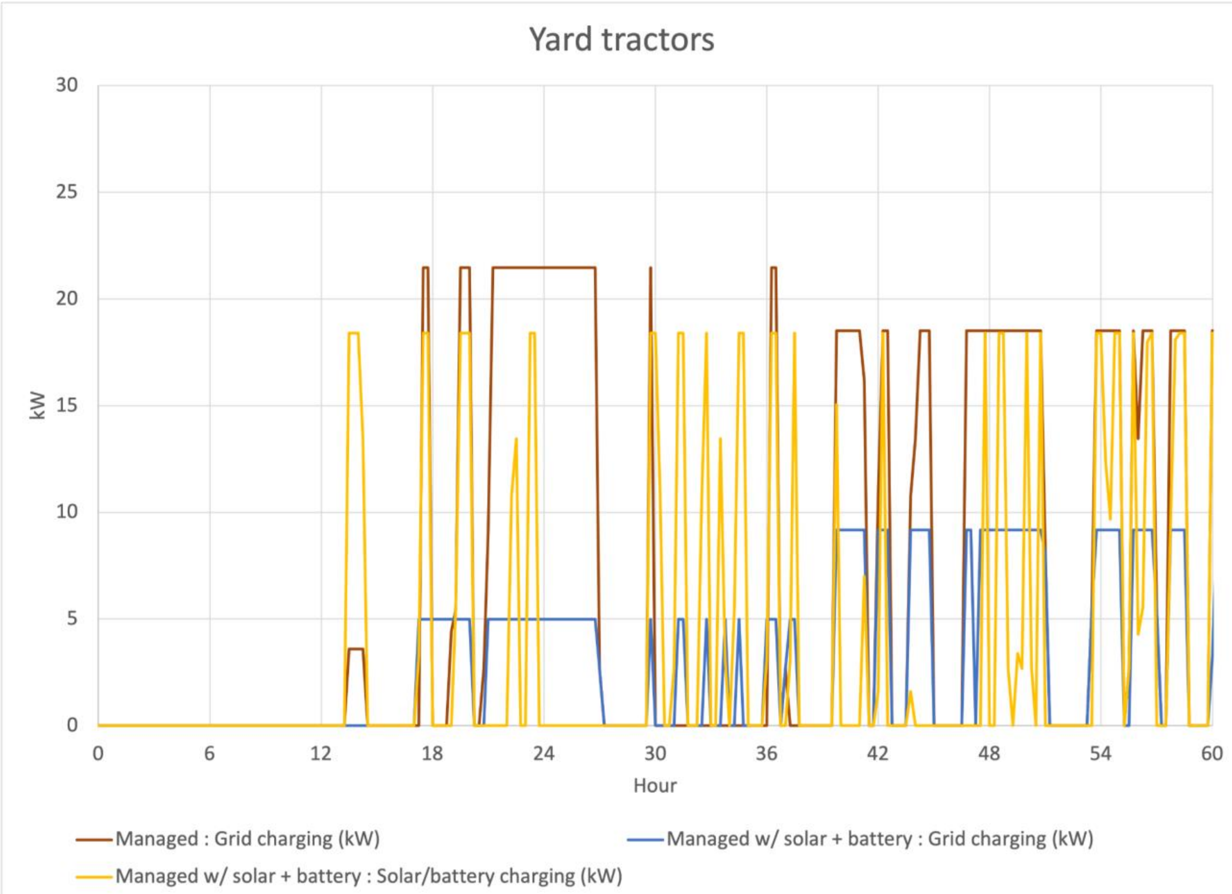


Figure 12 shows a comparison for managed charging for yard tractors with vs. without solar + battery, which shows a reduction in maximum grid charging from 26.8 kW to 9.2 kW for the two-vehicle fleet, again supplemented by power from stored solar energy. However, due to the more frequent opportunities for charging throughout the day, charging is split up into multiple periods each day.

Figure 12
Comparison of managed charging profiles with vs. without solar + battery for yard tractors



Result 6: Fuel cost comparison

We calculated avoided fuel costs for vehicle classes 3-7 using actual costs paid for fuel; see Table 10. Depending on vehicle class, number of days per week that vehicles operate, and depot size, annual fuel costs vary from ~$3,400/yr (class 7) to ~$64,000/yr (class 5). By comparison, as discussed earlier, electricity costs vary widely depending on optimization type and rate. In the best case (managed charging, AC RTP rate), electricity cost is between 22% and 62% of fuel costs, whereas in the worst case (unmanaged charging, PSEG RTP rate) the cost is between 3.2 and 14.6 times higher.

Table 10

Fuel vs. electricity annual costs for depot

				Scaled to year and depot:			Electricity cost ($/yr)	
Vehicle use case	Vehicle class	Days per week	Depot size	Distance (mi/yr)	Fuel used (gal/yr)	Fuel cost ($/yr)	Best (Managed, AC RTP)	Worst (Unmanaged, PSEG RTP)
Landscaping	3	4	2	27,096	2,031	$5,385	$1,321	$38,918
Food service	4	5	4	68,255	6,038	$15,959	$3,670	$52,722
Wired telecom	5	6	11	180,213	23,945	$63,841	$13,839	$203,192
Armored car	6	5	7	84,542	14,776	$41,084	$11,650	$151,353
Yard tractors	7	5	2	7,476	1,236	$3,440	$2,141	$50,144

Note: Fuel use for yard tractors was inferred based on an average fuel efficiency for class 7 and 8 trucks in New Jersey from Geotab.

Table 11 shows fuel cost relative to the total cost of ownership, which can be higher or lower than fuel costs depending on vehicle use case in the best case (managed charging, AC RTP rate). For all but wired telecom, it is more expensive to operate the depot using electricity, but as annual fuel cost increases, this difference becomes smaller, approaching 10% for armored cars - and for wired telecom, it is 15% cheaper to use electricity.

Table 11

Total cost of ownership relative to estimated fuel costs, annual costs for depot

		Best (Managed, AC RTP)		
Vehicle use case	Fuel cost ($/yr)	Total cost of ownership ($/yr)	Savings relative to fuel costs ($/yr)	Savings relative to fuel costs (%)
Landscaping (Class 3)	$5,385	$13,653	-$8,268	-154%
Food service (Class 4)	$15,959	$22,616	-$6,657	-42%
Wired telecom (Class 5)	$63,841	$54,408	$9,433	15%
Armored car (Class 6)	$41,084	$45,009	-$3,924	-10%
Yard tractors (Class 7)	$3,440	$14,473	-$11,033	-321%

While Table 7 showed that electricity costs can be lower than fuel costs for all vehicle uses cases if using a favorable rate, when infrastructure costs are included, there are only savings over fuel costs for one use case (wired telecom). Put another way, without financial support for fleet infrastructure, these additional costs make it difficult to breakeven for most use cases.

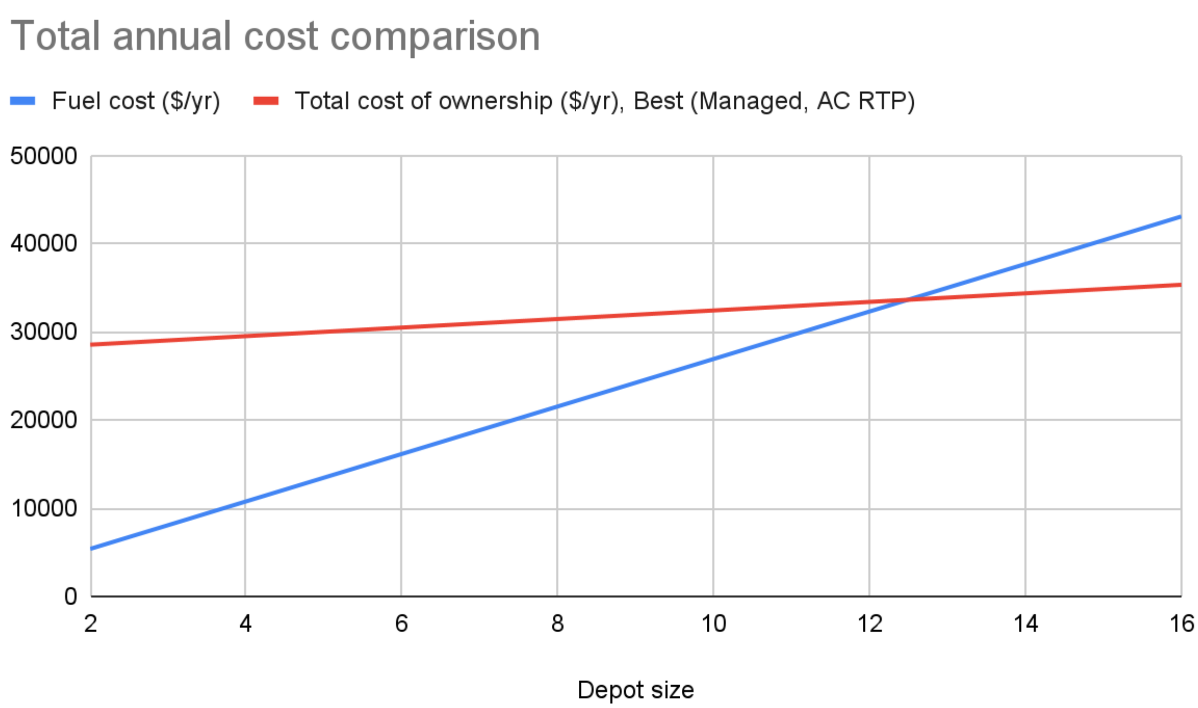
To shed light on why these results appear to vary strongly with vehicle use case, we extrapolated costs from our simulated scenarios to estimate the total cost of ownership when the number of vehicles per depot increased, along with additional charging infrastructure. Such a situation is plausible whenever the number of hours needed to charge is less than the available charging time across all available chargers (see Table 5).

As an example, consider landscaping. With an average daily energy demand of 85 kWh per vehicle, a single 20 kW charger with 13.0 h of charging time can recharge just over 3 vehicles on average. While the total cost of ownership is much higher than the fuel costs at the default depot size of two, a cost breakeven point is reached at a depot size of just over 15 vehicles with five chargers, and with higher-powered chargers, the breakeven point is reached with fewer vehicles and fewer chargers. This is because the fuel cost increases linearly with depot size, whereas the total cost of ownership increases much more gradually because the cost is dominated by capital cost, which is unchanged; only electricity cost increases with depot size.

Figure 13 gives an example of a single 100 kW charger able to support 15.3 landscaping vehicles on average; the cost breakeven depot size occurs at 12.5 vehicles. Note, however, that the breakeven point would change depending on operating conditions of the fleet (shorter time windows, driver shift constraints, etc.).

Figure 13

Total cost of ownership vs. depot size for landscaping for 100 kW charger case



For other vehicle uses cases, we observe similar crossover points around ~8 to ~10 vehicles, suggesting that, in general, charging depots with ~8 to ~15 vehicles have the potential to have a lower total cost of ownership than traditional fueling costs. This shows that smaller fleets with depot sizes of less than 15 trucks are the most challenged to see fuel cost savings, and infrastructure support for these fleets should be prioritized.

Part 2: Grid Impacts

In this section of the study, we scaled our estimated depot-level costs and impacts to all of New Jersey, focusing on the impact of charging on the grid, and the impact on grid costs of using managed charging with solar + storage.

Result 7: Avoided infrastructure costs of managed charging

Avoided peak load

Figure 14 shows the estimated New Jersey peak load by optimization type, obtained by scaling up the numbers of vehicles in each simulated vehicle class to equal state totals based on vehicle registrations (see section on Scaling results to New Jersey in Appendix A: Data). Total avoided peak loads relative to unmanaged charging, with breakdown by vehicle class, are shown in Table 12. Avoided peak load ranges from ~8,400 MW for managed charging, to ~10,000 MW for managed charging with solar + battery.

Figure 14

New Jersey peak load from electric vehicles by optimization type

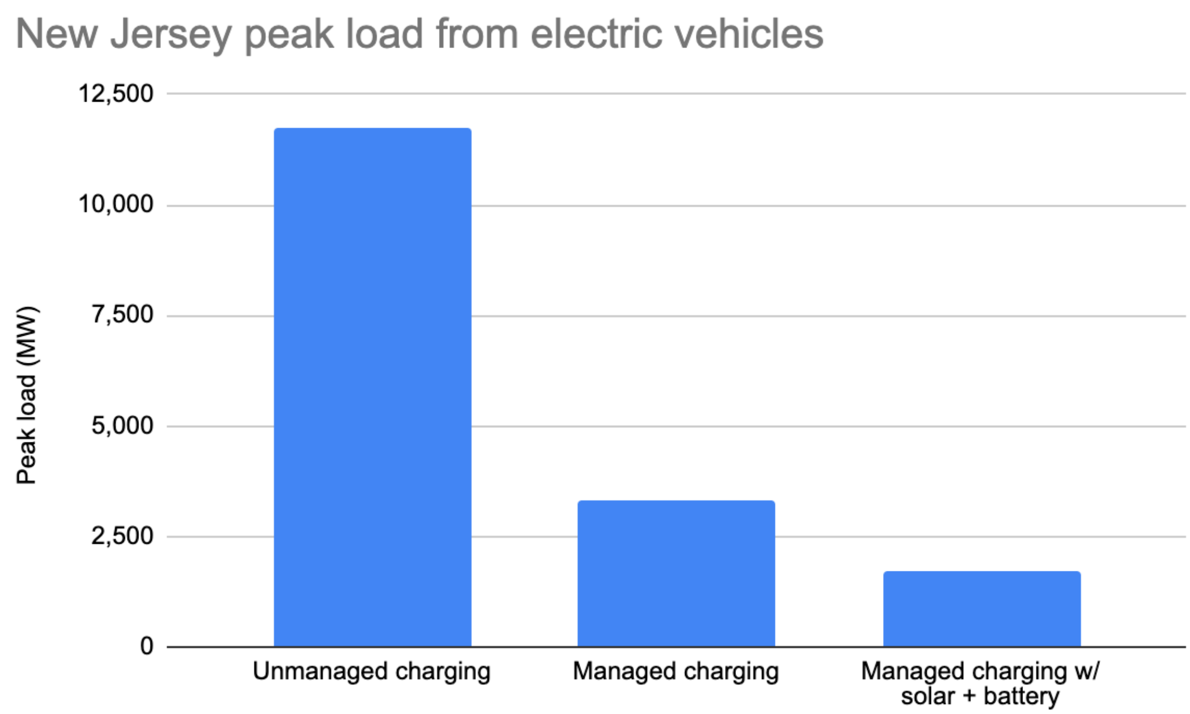


Table 12

Avoided New Jersey peak load (relative to unmanaged charging) by vehicle class (MW)

Vehicle class	Managed charging	Managed charging w/ solar + battery	Number of vehicles
Landscaping (Class 3)	1,435	1,589	37,758
Food service (Class 4)	1,112	1,380	44,870
Wired telecom (Class 5)	1,868	2,110	55,449
Armored car (Class 6)	2,145	2,570	48,018
Yard tractors (Class 7)	1,865	2,398	34,162
Sum	8,424	10,047	220,258

Avoided costs

Based on the estimated New Jersey avoided peak load depicted above, Table 13 shows our estimated ranges of avoided New Jersey infrastructure costs arising from these grid expansion savings, broken down by vehicle class. Savings per kW were estimated from two sources, detailed in the second on Grid expansion savings in Appendix A: Data. Note that these estimates of the cost of infrastructure may increase substantially in the future. Savings from managed charging with solar + battery included are higher from managed charging alone. Total (not annual) avoided infrastructure costs are between $320M and $1,803M for managed charging, and between $382M and $2,150M for managed charging with solar + battery.

Table 13
Avoided New Jersey infrastructure costs by vehicle class ($M)

Vehicle class/type	Managed charging (Minimum)	Managed charging (Maximum)	Managed charging w/ solar + battery (Minimum)	Managed charging w/ solar + battery (Maximum)
Landscaping (Class 3)	$55	$307	$60	$340
Food service (Class 4)	$42	$238	$52	$295
Wired telecom (Class 5)	$71	$400	$80	$452
Armored car (Class 6)	$82	$459	$98	$550
Yard tractors (Class 7)	$71	$399	$91	$513
Sum	$320	$1,803	$382	$2,150

Result 8: Aggregated New Jersey impacts

Figure 15 shows our estimated aggregated infrastructure costs if all class 3-7 registered trucks in New Jersey were electrified. Results are presented in aggregate for each rate in terms of annual cost, which includes amortized capital and electricity costs. Note there are no utility grid buildout costs (or cost savings) included in this cost estimate. One sees that, like the per-vehicle costs, managed charging is lowest for each rate, managed charging with solar is next highest, and unmanaged charging highest. Table 14 shows the breakdown by vehicle class.

Figure 15
New Jersey charging infrastructure total cost of ownership for all vehicle classes combined

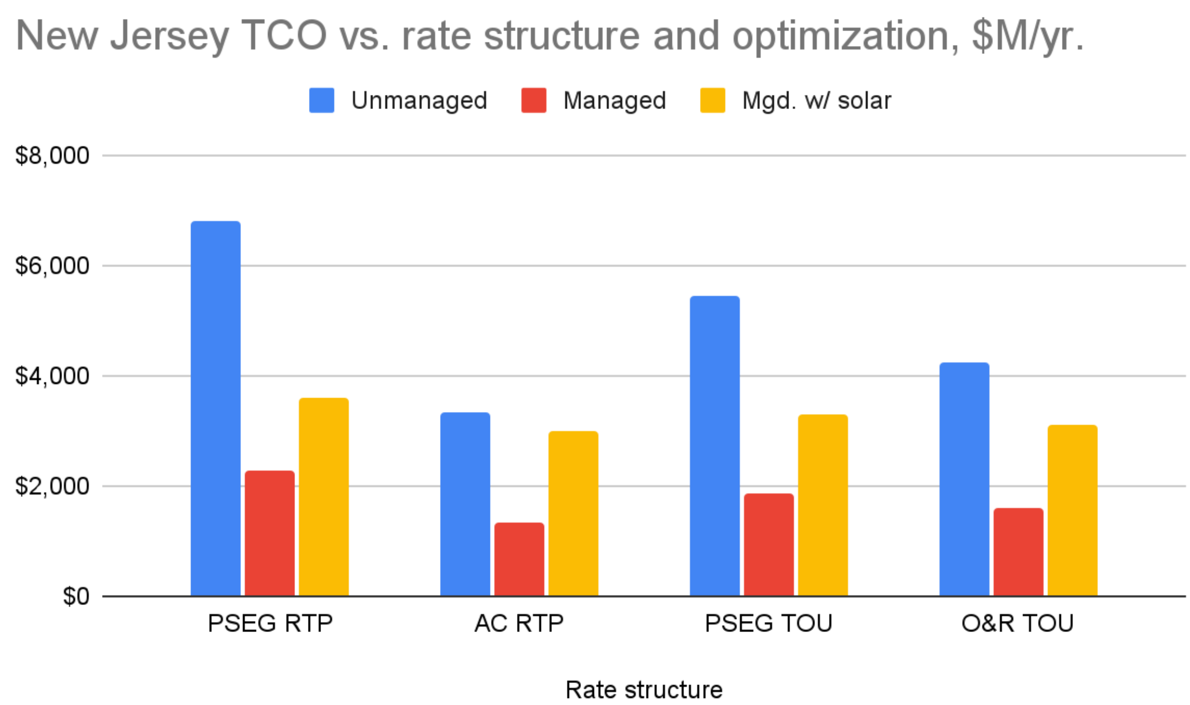


Table 14

New Jersey total cost of ownership by vehicle class, optimization, and rate structure

		New Jersey TCO ($M/yr.) by vehicle class				
Rate structure	Optimization type	3	4	5	6	7
1	Unmanaged	$1,217	$1,109	$1,533	$1,661	$1,293
1	Managed	$425	$422	$464	$526	$455
1	Mgd. w/ solar	$559	$640	$927	$994	$495
Rate structure	Optimization type	3	4	5	6	7
2	Unmanaged	$593	$631	$686	$839	$585
2	Managed	**$258**	**$254**	**$274**	**$309**	**$247**
2	Mgd. w/ solar	$419	$518	$820	$864	$379
Rate structure	Optimization type	3	4	5	6	7
3	Unmanaged	$924	$939	$1,152	$1,404	$1,041
3	Managed	$315	$337	$418	$465	$326
3	Mgd. w/ solar	$459	$570	$900	$962	$407
Rate	Optimization	3	4	5	6	7

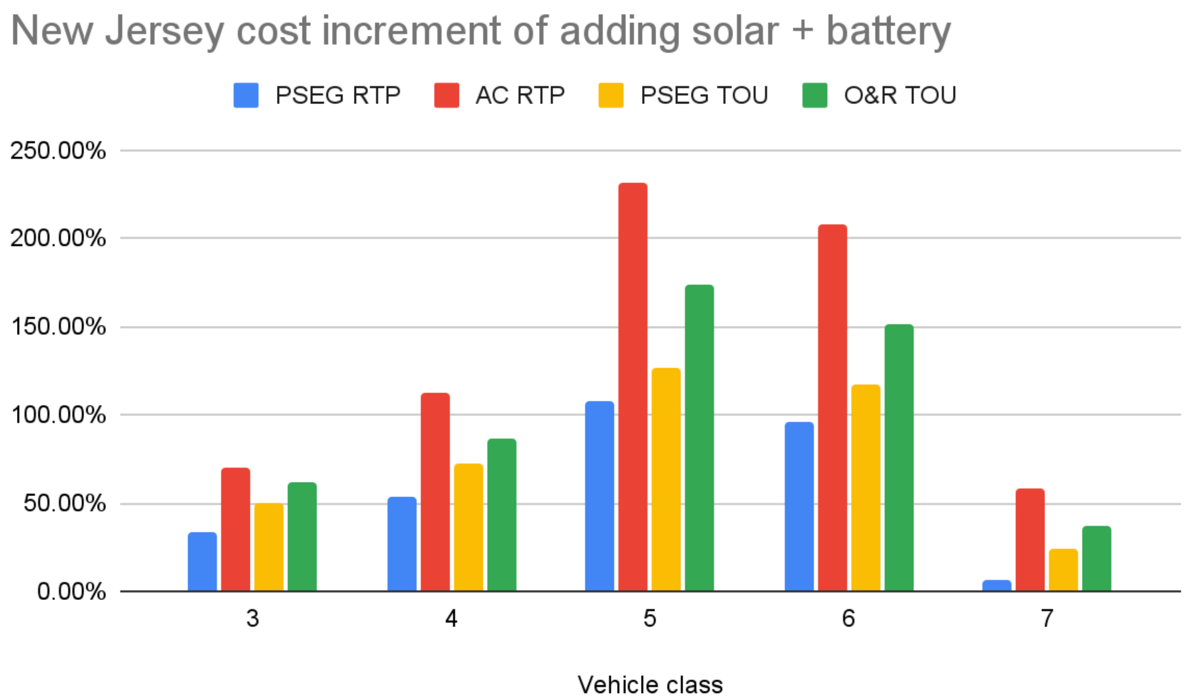
structure	type					
4	Unmanaged	$689	$779	$921	$1,135	$729
4	Managed	$277	$300	$333	$384	$291
4	Mgd. w/ solar	$433	$544	$847	$902	$396

Including infrastructure savings in total cost of ownership

While the results above indicate once again that managed charging is cheaper overall than when solar + battery infrastructure are included, the picture begins to change at the state level when infrastructure savings are included. While not true for most vehicle classes, the net incremental New Jersey-wide cost of adding solar + battery to managed charging approaches breakeven (<7% cost increment) for vehicle class 7 for the PSEG RTP rate, due to the high overall cost of electricity, and the high utilization and relatively modest capital costs of charging infrastructure for this vehicle class (this is also discussed in the GNA report). For other rate structures and vehicle classes, the cost differential is still very high. See Figure 16. However, grid costs in the future may be more expensive, which could improve the case for solar + battery which reduces grid upgrade and generation costs. This also does not consider the other revenue opportunities what onsite solar and battery could be exploiting through grid services.

Figure 16

New Jersey infrastructure cost increment from adding solar + battery, with infrastructure savings included


New Jersey cost increment of adding solar + battery
PSEG RTP
AC RTP
PSEG TOU
O&R TOU
250.00%
200.00%
150.00%
100.00%
50.00%
0.00%
3
4
5
6
7
Vehicle class

Conclusions

This study modeled the electrification of medium- and heavy-duty vehicles (MHDVs) in New Jersey using realistic case studies representing different vehicle classes 3 through 7. Two types of vehicle charging approaches were compared: unmanaged charging (when vehicles charge at full power as soon as trucks return to the depot) and managed charging (when fleets optimize their charging times and charging power to reduce the cost of charging). Scenarios with a solar photovoltaic (PV) + battery system at the depot were also modeled.

Study objectives were to determine depot electrification readiness by vehicle class, total cost of ownership and cost savings for depots under various assumptions, the impact of managed charging (both with and without solar + battery) on total charging infrastructure costs, and the avoided costs and other impacts to grid operators.

Firstly, we showed that using real fleet driving data of five representative MHDV fleets (classes 3-7), we were able to determine that using existing electric truck technology, all fleets were able to use electric trucks for over 80% of their needed routes on a single charge without having to change driving behavior and up to 98% if 2 to 3 charging sessions were incorporated into operations.. This would mean that these challenging fleets are able to meet NESCAUM and ACT electrification goals.

A large percentage of failed trips, or trips which could not be completed using existing battery technology, could easily be managed with enroute charging or modifying operations to allow for multiple charging sessions as the dwell time available was more than sufficient to meet charging needs. This would mean that installing shared charging at common stops, could enable more trucks to electrify and benefit electrification overall for this truck class.

Cost of charging infrastructure is still a major barrier for fleets in New Jersey, where the charging cost per vehicle ranges from $50k to $125k depending on the charging management and scenario. Up to 32% of these costs are attributed to make-ready, which shows a clear policy opportunity to reduce barriers and accelerate electrification of medium duty trucks in New Jersey. Programs that reduce make-ready costs would have the highest benefit to small fleets.

Rates in New Jersey are not tuned to accommodate MHDV electrification, with most having fixed demand charges that are non-coincidental to system peak. The demand charge (defined as the sum of capacity, generation, transmission, distribution, and delivery charges, where applicable, that scaled with power, e.g., $/kW) portion of the bill for each fleet, when unmanaged, was seen to be 58-94% of the cost (depending on rate structure). Approaches to minimize demand charges by distributing load across more hours of the day, rates designed to reduce the magnitude of demand charges on a $/kW basis, as well as short-term special rates as New Jersey transitions to electric vehicle charging, would all help reduce electricity costs.

The impact of managed charging for fleets lead to significant cost savings. These savings resulted in $66,739 lower capital costs (NPV per vehicle) for charging equipment, and between

$15,836 (AC RTP rate) and $83,500 (PSEG RTP rate) lower electricity costs (NPV per vehicle), mainly due to reduced demand charges. Therefore, states and utilities should be exploring fleets as part of their overall electrification plan.

When solar PV + battery is added to the charging infrastructure, there is a further savings in electricity cost, but this is more than offset by higher capital costs of the additional hardware. As fleet sizes increase, the utilization of charging infrastructure tends to become more efficient, leading to larger savings and an increased offset in capital costs. It is clear that financial support is needed to scale onsite solar and battery at depot sites. Given the high capital costs, breaking even in savings and additional hardware costs seems most viable with class 7-8 fleets or those with constrained operating cycles and higher power charging needs. Further work is needed to explore what is required to reach grid cost parity, including finding other sources of revenue for solar/battery such as demand response, spinning reserves, frequency regulation, and other grid services.

For all fleets, there was significant annual fuel cost savings from charging compared to gasoline/diesel vehicles, up to $50k (depending on vehicle class), but only in the case of managed charging. While this was excluding the cost of charging infrastructure, it does show there is a clear pathway to fuel cost savings for electrification of trucks once infrastructure installation costs are covered. There is a need for programs that encourage managed charging by helping to educate users, and providing technology to implement it.

When including the cost of charging, there was only savings for wired telecom of <$10k. It is clear that without financial support for fleet infrastructure, these additional costs make it difficult to break even for most use cases, and make a clear case for programs to reduce costs. This was particularly true for smaller fleets of less than 15 trucks. It was shown that as fleet sizes increase, and utilization of charging increased, fuel cost savings could be seen, making a clear case for focusing funding for small fleets and early adopters. In the short term, there is a need to support infrastructure to achieve cost parity, with a special focus on smaller fleets. Our studies showed that 8-15 vehicles were more likely to achieve cost parity, though this may change depending on operational characteristics. This clearly indicated that smaller fleets required additional support to overcome these barriers.

Further, when scaling the impact of managed charging and solar + battery New Jersey-wide, avoided peak load ranged from ~8,400 MW for managed charging to ~10,000 MW for managed charging with solar + battery. This could lead to potential avoided cost savings for the utility of between $320M and $1,803M for managed charging, and between $382M and $2,150M for managed charging with solar + battery. Significant savings will accrue to utilities implementing managed charging, as well as solar + battery, and managed charging will also benefit fleets, making this a win-win solution. Effort should be made to explore how solar + battery can be a win-win solution for fleets as well.

Appendix A: Data

Data sources

Emerging Futures utilized several data sources in putting together input data for this analysis. We divide sources into vehicle use data, electricity rate data, hardware cost data, and other data. Each is described in more detail below.

Vehicle use data

Two data sources were used to provide vehicle use data:

ARI

ARI, a Holman Enterprises company established in 1924 and located in Mount Laurel, NJ, manages 1.9 million fleet vehicles in Canada, United States, Mexico, the United Kingdom, and Germany. ARI provided vehicle use data for this analysis.

Dependable Highway Express (DHE)

DHE is a full-service logistics provider established in 1950 and headquartered in Los Angeles, CA. It operates a fleet of vehicles in California, for which use data were shared with Emerging Futures.

Electricity rate data

We used four sources of data to provide the electricity rate structures used in our simulations:

Atlantic City Electric Company

Located in Mays Landing, NJ, Atlantic City Electric Company delivers electric service to 560,000 customers in southern New Jersey. It was first incorporated in 1924 and is now a subsidiary of Exelon Corporation. Emerging Futures used Atlantic City Electric's tariff information dated July 1, 2021 to provide rate structure information for our Rate 3.

PJM

PJM is a regional transmission organization (RTO) that coordinates the movement of wholesale electricity in all or parts of 13 states (including New Jersey) and the District of Columbia. PJM publishes hourly real-time, day-ahead electricity prices through a public portal. Emerging Futures used this data as the basis for estimating real-time pricing for our Rates 1 and 2.

Public Service Enterprise Group (PSEG)

PSEG is a diversified energy company established in 1903 and headquartered in Newark, NJ. An important subsidiary of PSEG is the Public Service Electric and Gas Co. (PSE&G), which provides electricity to 2.3 million customers and natural gas to 1.9 million customers—the largest in New Jersey. PSEG tariff sheet data issued October 30, 2018 were used to provide rate structure information for our Rates 1 and 2.

Rockland Electric Company (RECO)

RECO is a wholly owned subsidiary of Orange and Rockland Utilities, Inc. (Orange & Rockland), which is located in the northwestern suburbs of New York City, and provides electricity and gas service to more than 300,000 households and businesses in six counties in New York and northern New Jersey. Founded as the Rockland Light & Power Co. in Nyack, NY in 1899, it became Orange & Rockland in 1958 when Rockland Light & Power merged with Orange and Rockland Electric Company. Orange & Rockland became wholly owned by Consolidated Edison, Inc. (ConEd) in 1999.

RECO rate case filing data, along with additional information on time-of-use rates, were used to provide rate structure information for our Rate 4.

Hardware cost data

Several sources provided us with hardware costs needed to estimate total cost of ownership:

ABB

ABB is a leading global technology company focused on providing software for “electrification, robotics, automation and motion.” ABB was created in 1988 by the merger of two older companies, Allmänna Svenska Elektriska Aktiebolaget (ASEA) established in 1890 in Sweden, and Brown, Boveri & Cie (BBC) established in 1891 in Switzerland. ASEA itself was formed from the merger of two smaller Swedish companies established in the 1880s. Both ABB and ASEA were involved in the early years of electricity production. ABB currently employs more than 100,000 people in over 100 countries.

Steve Bloch, the Western Regional Vice President for E-mobility at ABB, provided guidelines on “make ready” costs to connect a greenfield site to a utility as a function of kW DC fast charger capacity in kW. Bloch noted that there is a lot of variation based on what the utility is willing to provide, so the numbers provided represented rough averages.

International Council on Clean Transportation (ICCT)

The ICCT is a nonprofit organization founded in 2011 to provide high-quality unbiased research, and technical and scientific analysis, to environmental regulators, with a focus on environmental performance and energy efficiency of transportation. A 2019 ICCT paper (Michael Nichols, “Estimating electric vehicle charging infrastructure costs across major U.S. metropolitan areas,” Working Paper 2019-14, August, download here), was used to provide Level 3 (DC fast) charger capital and installation costs.

Rocky Mountain Institute (RMI)

RMI is an independent nonprofit founded in 1982 that is focused on transforming the way energy is produced and used globally, to create a clean, prosperous, and secure low-carbon future. It engages businesses, communities, institutions, and entrepreneurs to accelerate the adoption of market-based solutions that cost-effectively shift from fossil fuels to efficiency and renewables. RMI is headquartered in Boulder, CO with four additional U.S. offices as well as an office in Beijing, China.

We used the 2020 RMI EV report (Chris Nelder and Emily Rogers, *Reducing EV Charging Infrastructure Costs,* download here) to provide estimates of Level 3 charger capital costs, data and network contract costs, charger cable costs, warranty costs, and consumer and utility make-ready costs.

Smart Charge America

Smart Charge America has been installing electric car charging stations for homes, workplaces, and retail locations since 2007. We used their online marketplace to estimate costs of Level 3 charging stations.

Other data

Atlas Public Policy

Atlas Public Policy works in the areas of transportation and building electrification, climate policy, and disinformation tracking. According to its website, Atlas "equips businesses and policymakers to make strategic, informed decisions that serve the public interest. Atlas builds analytical tools and dashboards using powerful, accessible technology, and offers expert advisory services to tackle the pressing issues of the day."

Atlas furnished Emerging Futures with Class 3-8 truck registrations in 2019 in New Jersey, which was used to scale our simulation results to New Jersey.

ChargEVC/Gabel Associates

According to its website, ChargEVC.org is a not-for-profit trade and research organization comprised of a community of stakeholders to promote EV use in New Jersey and Pennsylvania. ChargEVC-NJ is managed by Gabel Associates, a trusted energy consulting firm located in New Jersey that has been providing economic, policy, and regulatory support for over 25 years. ChargEVC published the report, Full Market Vehicle Electrification in New Jersey: The Opportunities, Impacts, and Net Benefits For Light-, Medium-, and Heavy-Duty Electric Vehicles, in October 2020.

Energy Information Administration (EIA)

The EIA is an independent U.S. government agency physically located within the U.S. Department of Energy (DOE) and is charged with collecting, analyzing and disseminating unbiased energy information, and is considered an authoritative source by many in the energy industry. A table of conversion factors were used to calculate the heat content of gasoline and diesel fuel.

FuelEconomy.gov

FuelEconomy.gov is the U.S. government's official source for fuel economy information that is jointly operated by the DOE and the U.S. Environmental Protection Agency (EPA). Webpages on the energy efficiencies of gasoline and all-electric vehicles were used to provide conversion estimates from gasoline to electrical engine efficiencies, while information from ICCT was used to provide additional data to estimate the conversion from diesel to electrical engine efficiency.

Geotab

Geotab, Inc. was established in 2000, and has grown from a small, family business to a global leader in solutions for fleet management and vehicle tracking. It provides web-based analytics to help customers better manage their fleets. Geotab is headquartered in Ontario, Canada, with offices across the world, including its U.S. location in Las Vegas, NM. Geotab provided data on the relationship between electric vehicle driving range versus ambient temperature, due to heating and cooling loads, respectively, during cold and hot weather. Geotab was also used to provide estimated fuel efficiency of class 7 and 8 trucks in New Jersey.

Gladstein, Neandross & Associates (GNA)

GNA is a clean transportation and energy consultancy founded in 1993. GNA published a report for EDF in March 2021 called *California Heavy-Duty Fleet Electrification*: Summary Report. The report focused on electric vehicle simulations for class 7 and 8 trucks. Some of the parameters in this report, detailed below, were used for the current study.

ICCT

ICCT (described above) provided estimates of the loss in driving range of battery electric tractor-trailer as a function of temperature in their 2019 paper (Ben Sharpe, "Zero-emission tractor-trailers in Canada," Working Paper 2019-04, March, download link). This along with data from Geotab was used to estimate additional energy consumption from electric vehicles as a function of season.

A webpage on diesel engine efficiency was used to provide conversion estimates from diesel to electrical efficiency.

National Renewable Energy Laboratory (NREL)

NREL, located in Golden, CO, has developed solutions to transform the way the U.S. generates, consumes, stores, and distributes energy for more than 40 years. Its PVWatts energy estimation tool was used to provide estimated solar photovoltaic (PV) output for a generic location in northern New Jersey.

Snohomish County Public Utility District (SNOPUD)

SNOPUD published an up-to-date list of electric truck models including battery capacities for classes 1-8. We used this information to determine the maximum battery capacity for each vehicle class 3-6 for our simulations. (Class 7 battery capacities were already available from the data provider.)

U.S. Climate Data

U.S. Climate Data is a data aggregation site meant to inform people about the climate in the United States. Data originates from a variety of sources, such as The National Climatic Data Center at the National Oceanic and Atmospheric Administration (NOAA), but data are not guaranteed to be accurate. For this reason, we also consulted another data source, World Climate, described below. Data for New Jersey were gathered by month.

World Climate

World Climate is a data aggregation site that gathers worldwide climate data in one place in an easy-to-use format, using a variety of public sources. Like U.S. Climate Data above, data are not guaranteed accurate. Data for New Jersey were gathered by month.

Data preparation

Gasoline and diesel vehicle data

A data provider gave Emerging Futures access to refueling event data for commercial vehicles with operations in New Jersey and New York over a period from May 2020 through April 2021. A raw total of 171,475 New Jersey and 247,981 New York transactions were provided, spanning almost 100 different business types across vehicle classes 3-6.

Initial screening

An important goal of the project was to identify business types that were well-represented in the data, with a target of identifying 4-5 distinct business types. An initial screening identified 26 business types, each with >2,000 raw entries in New Jersey and/or New York. See Table A1 and Table A2.

Table A1

Initial count of New Jersey business types with >2,000 raw entries

	Raw counts by class					
Business type	3	4	5	6	Total	Fraction of total
ARMORED CAR SERVICES	6	5,832	2,977	1,905	10,720	6.25%
CONSTR/MINING EQUIP.	411	26	5,853	956	7,246	4.23%

ELECTR/PLUMB/WHOLSLRS	26	0	1,871	2,950	4,847	2.83%
ENGINEERING SERVICES	3,004	0	0	2	3,006	1.75%
EQUIPMENT RENTALS	995	585	3,754	114	5,448	3.18%
FOOD SERVICE CONTRACT.	0	958	1,052	54	2,064	1.20%
FOOD VENDOR	78	2,199	172	292	2,741	1.60%
LANDSCAPING SERVICES	3,323	40,187	5,723	3,755	52,988	30.90%
MEMBERSHIP ORGANIZATIO	9,380	0	684	732	10,796	6.30%
MUNICIPAL GOVERNMENT	1,705	24	300	10	2,039	1.19%
TELECOMMUNICATIONS	1,925	98	4,945	0	6,968	4.06%
TRANSPORTATION SERVICE	862	335	639	497	2,333	1.36%
WASTE MGMT SERVICES	319	540	1,498	421	2,778	1.62%
WATER	3,591	155	37	770	4,553	2.66%
WIRED TELECOMMUNICATIONS	403	1,895	13,795	44	16,137	9.41%
Others	6,026	5,524	17,883	7,378	36,811	21.47%
All	32,054	58,358	61,183	19,880	171,475	100.00%

Table A2

Initial count of New York business types with >2,000 raw entries

	Raw counts by class					
Business type	3	4	5	6	Total	Fraction of total
ARMORED CAR SERVICES	2	8,978	3,702	6,693	19,375	7.81%
CABLE TV SYSTEMS	1,015	961	37,080	526	39,582	15.96%
ELECTR/PLUMB/WHOLSLRS	0	1	840	1,705	2,546	1.03%
EQUIPMENT RENTALS	404	1,476	4,764	365	7,009	2.83%
FOOD VENDOR	209	4,404	824	103	5,540	2.23%

FUEL OIL & LP GAS	1,594	206	7,279	6	9,085	3.66%
LANDSCAPING SERVICES	5,034	28,876	8,137	1,028	43,075	17.37%
LINE-HAUL RAILROADS	2,622	0	1,204	71	3,897	1.57%
LIQUEFIED PETROLEUM	90	0	3,707	2	3,799	1.53%
MACHINERY MFG	1,673	0	91	889	2,653	1.07%
MFG SANDWICHES	0	5,919	2,064	0	7,983	3.22%
NATURAL GAS DISTRIBUT	2,959	289	3,803	7,217	14,268	5.75%
RELIGIOUS ORGANIZATION	13	0	5,765	383	6,161	2.48%
STATE GOVERNMENT	14,796	754	10,625	503	26,678	10.76%
TELECOMMUNICATIONS	2,187	178	6,496	362	9,223	3.72%
TRANSIT SYSTEM	5,625	3,573	44	1	9,243	3.73%
WASTE MGMT SERVICES	1,063	827	455	180	2,525	1.02%
WHOL INDUSTRIAL EQUIP	208	0	2,372	1,453	4,033	1.63%
Others	7,826	5,787	13,105	4,588	31,306	12.62%
All	47,320	62,229	112,357	26,075	247,981	100.00%

From this initial list, further consultation with the data provider narrowed the list of eligible business types to five, governed mainly by the ability of the data provider to gather ancillary data such as operating hours, depot locations, etc. The final list of business types used is shown in Table A3.

Table A3

Final raw count of data entries by business type used

Business type	New Jersey	New York	Both
ARMORED CAR SERVICES	10,720	19,375	30,095
FOOD SERVICE CONTRACT.	2,064	0	2,064
FOOD VENDOR	2,741	5,540	8,281
LANDSCAPING SERVICES	52,988	43,075	96,063
WIRED TELECOMMUNICATIONS	16,137	0	16,137

Total	84,650	67,990	152,640

Initial data review

An initial data review was performed on a data sample in order to determine how the entire data set could be used in more in-depth analyses. While there were 28 fields included in the raw data, the fields that were most applicable to the project were the following:

- Vehicle Number (unique ID)
- Transaction Date and Time
- Vehicle Current Odometer (miles) — not used in analysis
- Amount of Transaction ($) — not used in analysis
- WEX Odometer (miles)
- Gallons (of fuel purchased)
- Product Name (type of fuel purchased)
- Gvwr (gross vehicle weight class)
- Business Type

Other fields were not used in the analysis as the vehicles used were similar in manufacture and were performing similar operational functions.

The intended use of the data was to estimate daily miles traveled by a group of vehicles used for a specific business activity. As a result, the focus was on understanding the validity of odometer readings. As a secondary goal, the gallons of fuel purchased was to be used to estimate, along with a valid odometer increment between adjacent refueling events, the average fuel efficiency of a particular vehicle.

Several findings were discovered during the initial data review:

1. Initially, there seemed to be duplicate transactions but were later found to be discounts or non-fuel related transactions.
2. The Vehicle Current Odometer field contained the latest odometer reading as of the date the data was prepared. This meant that Vehicle Current Odometer was not useful to the analysis.
3. The WEX Odometer field was generally useful, and as described by the data provider, was a manually entered odometer reading at the time of the refueling event. However, it did not always appear to be increasing in value with time. For example, the reading for a transaction date was sometimes lower than the reading on the previous date, which indicated an error in data entry. Also, “123456” was a common entry, indicating an error in data entry.
4. The Product Name (type of fuel purchased) sometimes listed multiple products for the same vehicle in adjacent transactions. This suggested that some vehicles were using both diesel and gasoline. Since this is generally not possible in most vehicle engines, this indicated that some fuel was being purchased for other consumption (e.g., lawn mower).

The project team elected to perform a two-stage cleaning process to highlight the WEX Odometer errors described in (3), and to follow that process with a second round of cleaning. The pre-cleaning process is described below.

First stage data cleaning process

First, the data's Transaction Date and Time parameter was modified. The time stamps associated with this parameter were not organized sequentially, due to the data format being a character string. A simple conversion from the character string format to the date format was performed. As a result, the WEX Odometer readings were ordered sequentially for each Vehicle Number. This step was important to accomplish, as the subsequent step filters the data based on the WEX Odometer readings for each Vehicle Number.

Filtering the data involved removing outliers from the WEX Odometer readings and analyzing whether the data trends exceeded a goodness-of-fit threshold and contained at least a minimum number of data points, for each Vehicle Number. The outliers were removed by performing a boxplot analysis of the WEX Odometer readings for each Vehicle Number, then removing any values outside of interquartile range. Three combinations of a goodness-of-fit threshold and a minimum number of data points were then tried: A minimum R^2 and a minimum number of data points of (1) 0.90 and 50, (2) 0.97 and 25, and (3) 0.98 and 10, respectively.

Once this was performed, the data was finally filtered so that the trends were monotonically increasing with the WEX Odometer readings, while removing the least amount of data and maximizing the increase in R^2.

Last, all remaining trends were analyzed by eye, and few trends were further removed as they were deemed insufficient for further, feasible use.

Second stage data cleaning process

The initial, pre-cleaned vehicle data file was received. Using the cleaning process described below, we were able to produce a set of daily miles traveled and gallons consumed by vehicle while eliminating unusable, or suspect data.

Two data files, pre-cleaned in R, were imported into Microsoft Excel, separately:

- Vehicle_data_sample_ordered_filtered_combined_NY
- Vehicle_data_sample_ordered_filtered_combined_NJ

In Excel Power Query, the data was transformed by copying and converting the transaction.date.time into transactiondateNUM, a new field that would allow mathematical operations on the date.

The WEX Odometer values were filtered to remove 'NA' values, which were entries defined as data entry errors. Any remaining non-increasing WEX values not labeled as 'NA' were to be removed in the final steps. They were kept in the data to maximize the number of data values available.

All non-fuel transactions (e.g., Product = “OTHER”) were filtered out and the data was sorted by Vehicle Number, Transaction Date.

Columns not needed for the analysis were removed, leaving only the applicable columns: *Index, Vehicle.number, Transaction.date.and.time, transactiondateNUM, Vehicle.Current.Odometer WEX.Odometer, Amount, Gallons, Cumulative Gallons, Product.Code, Product.Name, Business.Type*

The Vehicle Class was added back later, during a final step.

After the initial filtering was complete, the data was exported to an Excel table. Calculated columns were inserted for the following purposes:

- Check for change in vehicle. This indicated when one vehicle’s data ended in the list, and another’s began.
- Check for same day transactions. This was necessary to later ensure that the last transaction of the day was used in capturing the WEX Odometer reading and to ensure that the calculation of “days since last fuel transaction” would be calculated correctly.
- Reference a single WEX Odometer reading for each transaction date. This was required when there was more than one fuel transaction on a single date.
- Calculate number of days since last fuel transaction. This was necessary to determine the daily rate of fuel use and miles driven.
- Calculate difference in WEX Odometer reading since previous transaction date.
- Calculate number of gallons since last transaction.
- Calculate the Average WEX Odometer Miles per day (difference in amount of miles/difference in dates)
- Calculate the Average Gallons per day (difference in cumulative gallons/difference in dates)

In the final step of cleaning, data was filtered to remove:

- All first day transactions. These are dates for which there is no previous transaction data to compare to, meaning the calculation of difference in gallons and difference in miles could not be performed.
- Remaining rows for which WEX Odometer readings were not increasing values. As noted previously, this would be completed in the final stage.

The vehicle class field was added back to the data. The files were formatted according to the class (Armored Car, Food Vendor, etc.) and exported to csv.

Figure A1 and Figure A2 illustrate a typical vehicle’s gallons and WEX Odometer mile profile after cleaning. Note that there are gaps in the data, removed during the cleaning processes, or not available in the original data set.

Figure A1
Vehicle 14S023 Cumulative Gallons by date

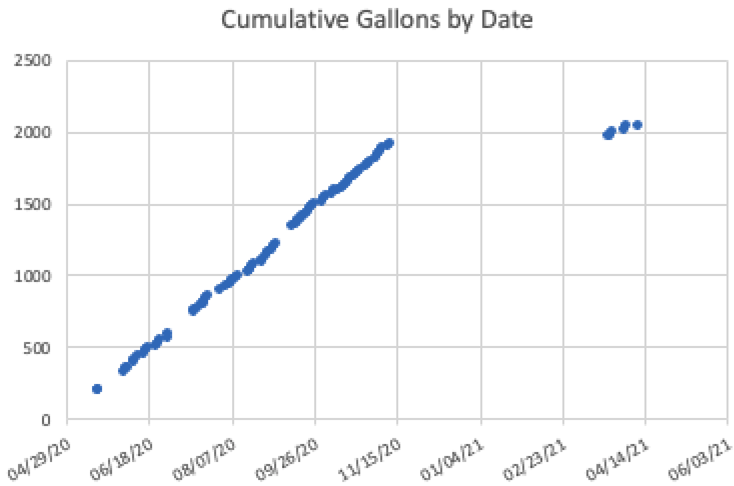
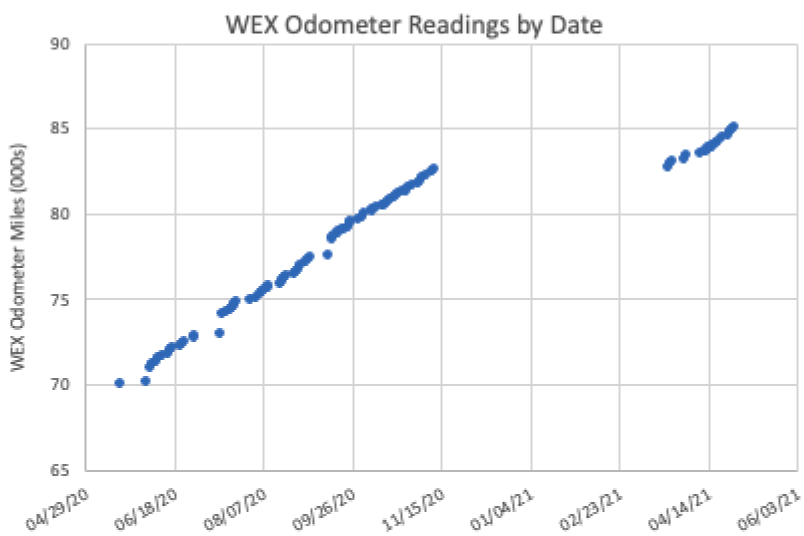


Figure A2

Vehicle 14S023 WEX Odometer reading by date



In total, 33,987 processed data points, or 22.3% of the initial raw data sample, were obtained. The percentage of raw data by business type varied between 10.3% (Armored car services) and 64.0% (Wired telecommunications). See Table A4.

Table A4

Final processed data counts by business type and class

	Processed data by class:					
Business type	3	4	5	6	Total	Fraction of raw
ARMORED CAR SERVICES	0	2,262	608	232	3,102	10.31%

FOOD SERVICE CONTRACT.	0	502	363	3	868	42.05%
FOOD VENDOR	85	2,966	182	157	3,390	40.94%
LANDSCAPING SERVICES	1,086	12,237	2,458	524	16,305	16.97%
WIRED TELECOMMUNICATIONS	231	958	9,106	27	10,322	63.96%
Total	1,402	18,925	12,717	943	33,987	22.27%

The range of dates over which the data were available was generally from the beginning of May 2020 to the end of April 2021, with the exception of Armored car services, which were only available from December 2, 2020 to May 1, 2021.

Electric yard tractor data

We obtained high-resolution (≤15 min. interval) charging data for yard trucks between December 6, 2019 through June 30, 2021. Since vehicles were already electric, no conversions from equivalent fuel energy use were required.

A total of 7,292 yard truck charging cycles (sum of two vehicles) were available over these time periods. Thus, each yard truck experienced an average of 6.4 cycles/day.

Real-time pricing data

PJM hourly day-ahead pricing data were available with locational marginal prices (LMPs) for more than 13,000 nodes. In order to simplify our analysis, we downloaded data from all nodes for a two-day mid-week period (August 4-5, 2020) and calculated the average LMP for each hour across the entire region. We then compared each node’s hourly LMP to the hourly average and calculated sums of squared differences to find the node with the lowest value, which would come closest to being “representative” for the entire region. This node was determined to be Hadley (pnode_id: 1183223784). An entire year’s worth of day-ahead real-time hourly price data for Hadley node was then downloaded for August 5, 2020 to August 4, 2021. This dataset was used to provide our estimated day-ahead real-time prices, including LMP, in our analysis for Rates 1 and 2.

Look-ahead time period

Day-ahead RTPs are settled in the PJM market by 2:45 pm the day before the rates take effect. As a result, our model performed simulations in 24-hour time intervals starting at 3 pm and continuing until 2:45 pm the next day. This allowed us to simulate the optimization approach as closely as possible to how it might be implemented in the real world.

This starting time was actually convenient to the modeling, as all of the class 3-6 vehicles were assumed to be driving and unavailable to charge at this time; the earliest vehicle type to return to the depot for charging was Food service (class 4), which returns at 4:30 pm. For yard tractors (class 7), which operate around the clock, this starting time was expected to have little impact on the optimization, as some vehicles will always be driving while others will be available to charge.

Vehicle characteristics

Vehicle classes

An important goal of the project was to represent a range of vehicle classes in the simulations. While the vehicle class 7 data was for a single use case (yard trucks), classes 3-6 each contained many vehicle use cases ("business type"). As a result, we made a determination of the most common vehicle class associated with each business type, and used only a portion of the full dataset assigned to that vehicle class in our analysis. Based on the breakdown of refueling transactions by business type and vehicle class, we were able to make a decision that spanned the full range of vehicle classes while including sufficient numbers of data points (>200) per representative business type for reasonably large sample sizes in the simulations. Data spanned the period between December 6, 2019 and June 30, 2021. See Table A5.

Table A5

Fraction of clean transactions by business type and vehicle class

	Processed data by class:						
Business type	3	4	5	6	Total	Class used	Data points used
ARMORED CAR SERVICES	0.00%	72.92%	19.60%	7.48%	100.00%	6	232
FOOD SERVICE CONTRACT. + FOOD VENDOR (combined)	2.00%	81.45%	12.80%	3.76%	100.00%	4	3,468
LANDSCAPING SERVICES	6.66%	75.05%	15.08%	3.21%	100.00%	3	1,086
WIRED TELECOMMUNICATIONS	2.24%	9.28%	88.22%	0.26%	100.00%	5	9,106
Total	4.13%	55.68%	37.42%	2.77%	100.00%		13,892

Table A6 shows the number of unique vehicles represented by the clean transactions in each business type and vehicle class. When downselected to only a single vehicle class, the number of unique vehicles ranged from 13 (Armored car services) to 140 (Wired telecommunications). Overall, 35% of the total unique vehicles in the clean transaction data were retained in the final input dataset for the simulations.

Table A6

Number of unique vehicles in clean transactions by business type and vehicle class

Business type	3	4	5	6	Total	Class used	Data points used
ARMORED CAR SERVICES	0	49	23	13	85	6	13
FOOD SERVICE CONTRACT. + FOOD VENDOR (combined)	5	95	23	6	129	4	95
LANDSCAPING SERVICES	40	324	53	16	433	3	40
WIRED TELECOMMUNICATIONS	8	25	140	1	174	5	140
Total	53	493	239	36	821		288

Depot size

We worked with an industry stakeholder to obtain estimates of the depot size (number of vehicles) by vehicle class for individual vehicle depots in New Jersey. While in some cases such counts were not available individually by class, we obtained separate counts for classes 3-5 for all business types, classes 3-6 for Armored cars and Food service, and class 4 for Landscaping. We estimated the depot sizes for each business type as follows:

- For Landscaping (class 3), we subtracted the class 4 depot sizes from classes 3-5 to obtain vehicle counts for classes 3 and 5 only. We then scaled this average depot size by the fraction of class 3 vehicles (43%) to obtain our estimate of 2.1 vehicles per depot, which we rounded to 2.
- For Food service (class 4), we scaled the depot sizes for classes 3-6 by the fraction of class 4 vehicles (74%) to obtain our estimate of 3.9 vehicles per depot, which we rounded to 4.

- For Wired telecommunications (class 5), we estimated depot sizes for class 5 by scaling the depot sizes for classes 3-5 by the fraction of class 5 vehicles (81%) to obtain our estimate of 10.8 vehicles per depot, which we rounded to 11.
- For Armored cars (class 6), we subtracted the classes 3-5 depot sizes from classes 3-6 to obtain vehicle counts for class 6 only. We then used this information to obtain our estimate of 6.9 vehicles per depot, which we rounded to 7.

For yard tractors (class 7), we used the actual depot size (2) associated with the data.

Daily driving schedules

The class 3-6 vehicle fleets operated on a regular weekly schedule that varied by business type, with four to six days of activity, and the balance of the week idle. Each active day, vehicles had daytime operations lasting between 12 and 14 hours, with the balance of the time spent idle at the depot, providing plenty of time for charging if converted to electricity.

The yard tractor (class 7) fleet operated on a 24-hour, five days/week schedule, so vehicles were never idle for more than a few minutes at a time during the active part of the week. Between the two yard trucks, the median driving duration was between 82 and 99 min., and the median charging duration was between 17 and 29 min.Given the estimated number of daily charging cycles derived earlier, this implies an average charging times of 2.49 hrs./day for yard tractors during the active workweek.

Table A7 summarizes this schedule information for all business types modeled.

Table A7
Daily driving schedules by business type

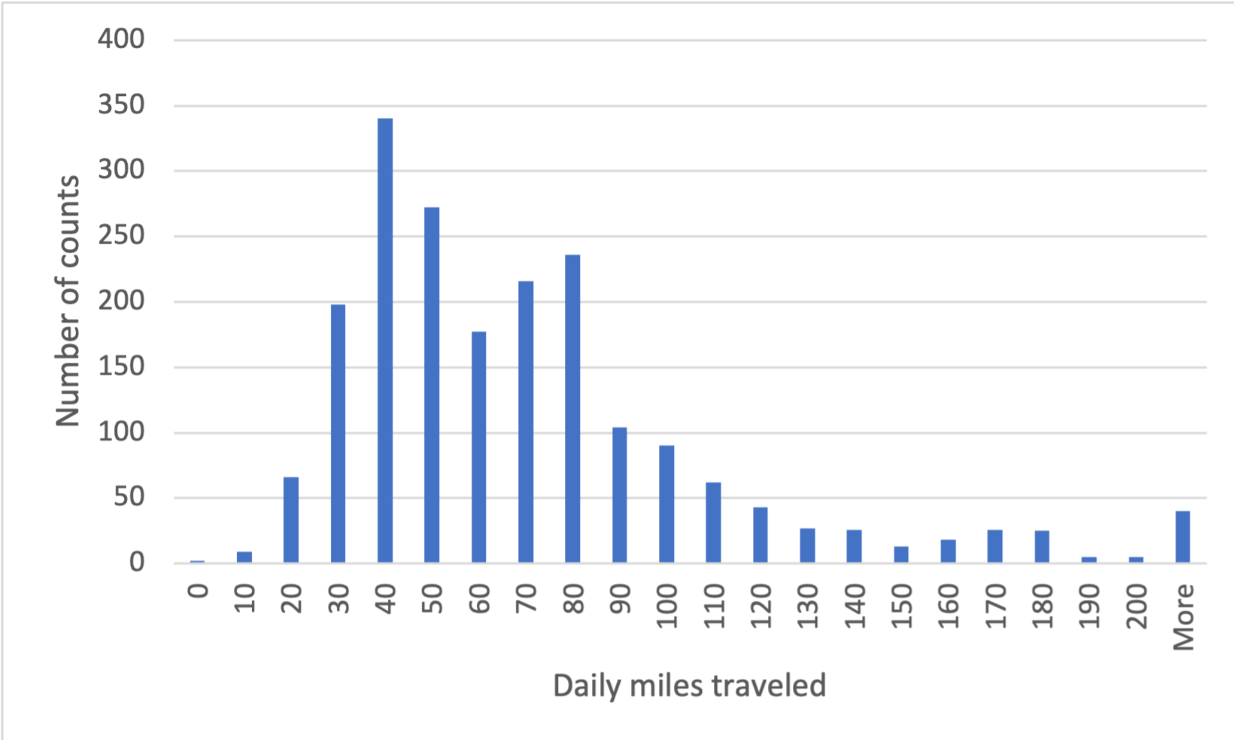
Business type	Vehicle class	Days of week	Days per week	Hours	No. of charging hours
Landscaping	3	Mon-Thu	4	7 am - 6 pm	13
Food service	4	Mon-Fri	5	5 am - 4:30 pm	12.5
Wired telecom	5	Mon-Sat	6	6 am - 6 pm	12
Armored car	6	Mon-Fri	5	7 am - 5 pm	14
Yard tractors	7	Mon-Fri	5	24 hrs./day	2.49

Daily travel ranges

Analysis of daily mileages for each business type indicated skewed distributions with average values ranging between 63 and 80 miles/day, but with maximum mileages exceeding 200 miles in some cases. For an example, see Figure A3; all business types examined exhibited similarly-shaped skewed distributions.

Figure A3

Daily driving distances for New York Food Vendors, class 4



In [Table A8](#), the average daily miles traveled by business type (filtered on a single vehicle class) is shown separately for diesel and gasoline vehicles, as well as the weighted average.

Table A8

Average daily driving distances and fuel efficiencies by business type

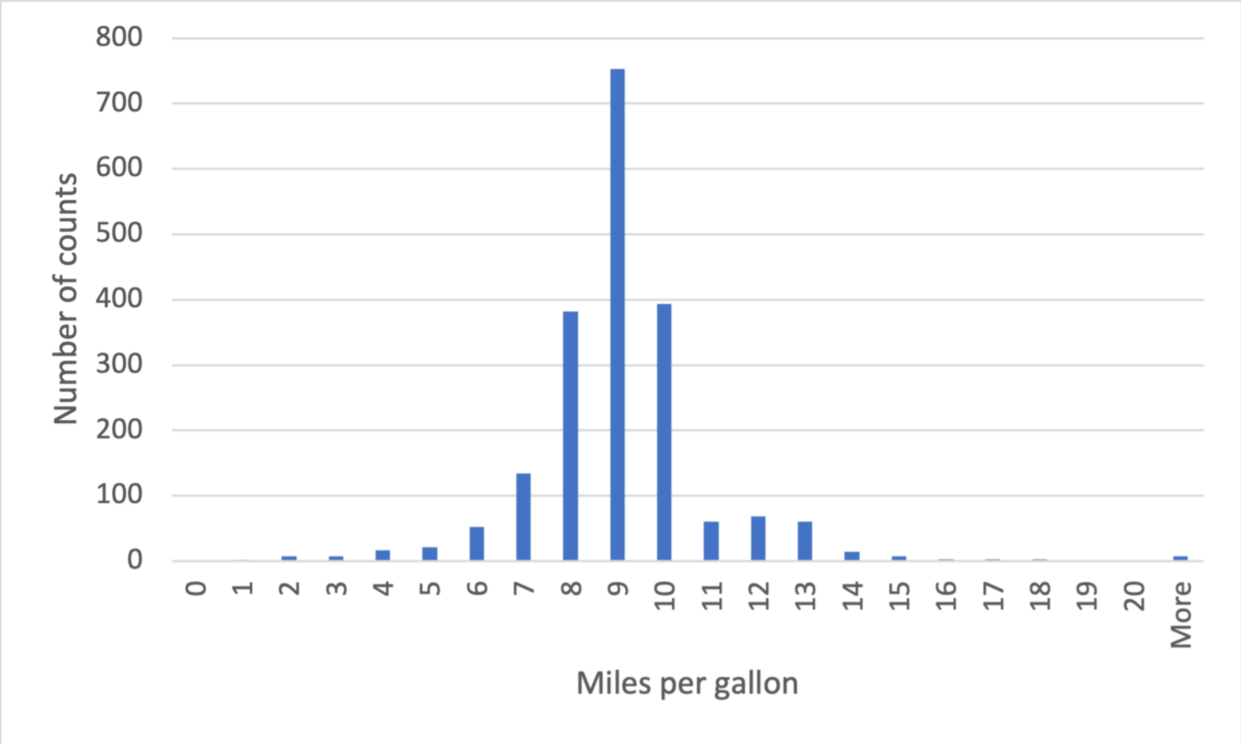
		Daily driving distance (mi/day)		
Business type	Vehicle class	Diesel	Gasoline	Combined
Landscaping	3	54.0	79.6	78.3
Food service	4	94.4	80.0	80.0
Wired telecom	5	79.8	60.7	63.2
Armored car	6	73.4	90.6	77.2

Energy use estimates

For class 3-6 vehicle data, we also needed to estimate average fuel efficiencies by business type/vehicle class, in order to convert average fuel consumption into an equivalent average electrical energy consumption. To do this, we began by examining distributions of fuel efficiencies for each business type/vehicle class; an example in shown in Figure A4 below. Again, all business types examined exhibited similarly-shaped distributions.

Figure A4

Average gasoline fuel efficiency for New York Food Vendors, class 4



Average diesel and gasoline fuel efficiencies by business type is shown in Table A9. We used standard values for the energy content of diesel and gasoline from FuelEconomy.gov and ICCT to convert each efficiency into an average energy efficiency, and then applied estimated diesel and gasoline engine efficiencies to convert to the equivalent electrical efficiency.

Table A9

Average energy efficiencies by energy type and business type

		Average energy efficiency		
Business type	Vehicle class	Diesel (mi/gal)	Gasoline (mi/gal)	Equivalent electricity (kWh/mi)
Landscaping	3	9.14	13.55	1.04
Food service	4	11.88	12.12	1.11
Wired telecom	5	8.76	7.35	1.93
Armored car	6	5.85	5.18	3.36
Yard tractors	7	6.05	N/A	3.50

Battery capacity estimates

We used the maximum listed battery capacity on the market by vehicle class from SNOPUD. Table A10 summarizes these values, along with our calculated average daily electricity demand by class. We found that the ratio between the maximum and average battery capacity varied between 1.51 and 1.85 depending on vehicle class.

Table A10

Vehicle battery size by vehicle class

Class	Max. capacity (kWh)	Average daily kWh	Ratio
3	140	82	1.72
4	156	89	1.75
5	226	122	1.85
6	343	259	1.32

Seasonal energy demand multipliers

We compared average monthly temperatures for New Jersey from U.S. Climate Data and World Climate, which agreed almost exactly, and used their average to estimate energy correction factors for the months of January, April, July, and October. The energy correction factor used was from Geotab for January, and from ICCT for other months. Table A11 summarizes these results. The average annual energy demand multiplier of 1.115 was applied to the required solar battery and solar PV capacities to achieve the appropriate scalings.

Table A11

Energy correction factor by month

Month	Average temperature (°F)	Driving range multiplier	Energy demand multiplier
January	31.5	0.7725	1.294
April	53.0	0.914	1.094
July	77.5	1.000	1.000
October	56.5	0.934	1.071
Average			1.115

Rate structures

A total of four rate structures were used for our analysis, summarized below.

Rate 1: PSEG service with real-time pricing (PSEG RTP)

This rate was actually composed of two closely-related PSEG rates, which differed depending on the total peak power consumption. The General Lighting and Power (GLP) service (PSEG tariff sheet no. 129) is applicable for users with <150 kW peak power in all months, whereas the Large Power and Lighting service for secondary distribution voltages (LPL-Secondary) (PSEG tariff sheet no. 142) is applicable for users with ≥150 kW peak power in any month. Both rates are modified to include a RTP component that is added to the base cost per kWh; RTP data was provided by PJM (see Real-time pricing data section for details). For unmanaged charging, where the maximum depot power was ≥150 kW for vehicle classes 4-7, we used the LPL-S rate, and for vehicle class 3, where the maximum depot power was 100 kW, we used the GLP rate. For managed charging, although the maximum depot power was <150 kW in all cases, we used the GLP rate for vehicle classes 5 and 6 only, and the LPL-S rate for other vehicle classes (which tended to result in a lower electricity cost). See Table A12 and Table A13.

Table A12

Rate 1 details for <150 kW peak power (GLP)

Parameter	Value	Units	Time period	Comments
Service charge	4.91	$/mo.	All	
Total energy charge - winter	0.027115	$/kWh	Oct.-May	plus real-time prices
Total energy charge - summer	0.022071	$/kWh	June-Sept.	plus real-time prices
Total demand charge - winter	26.06395	$/kW	Oct.-May	
Total demand charge - summer on-peak	31.07055	$/kW	June-Sept., 8 am to 8 pm Mon.-Fri.	
Total demand charge - summer off-peak	14.67065	$/kW	June-Sept., off-peak	

Table A13

Rate 1 details for ≥150 kW peak power (LPL-S)

Parameter	Value	Units	Time period	Comments
Service charge	370.81	$/mo.	All	
Total energy charge	0.019559	$/kWh	All	plus real-time prices
Total demand charge - winter and summer off-peak	23.11385	$/kW	Oct.-May, and June-Sept. off-peak	

Total demand charge - summer on-peak	27.6726	$/kW	June-Sept., 8 am to 10 pm, Mon.-Fri.	

Note that both rates include a partial “demand holiday” which is applicable in years 3+ of a new service contract. This is a 50% discount off the regular demand charge rate ($/kW). In years 1-2, this discount is 75%, but we did not apply that larger discount here in order to capture longer-term impacts.

Rate 2: Atlantic City Monthly General Service with RTP (AC RTP)

This rate is based on Atlantic City Electric’s Monthly General Service for secondary distribution voltages (MGS-Secondary) (Atlantic City tariff sheet 11). Like Rate 1 above, the rate is modified to include a RTP component (supplied by PJM) that is added to the base cost per kWh. See Table A14.

Table A14
Rate 2 details

Parameter	Value	Units	Time period	Comments
Total service charge	11.59	$/mo.	All	Three Phase
Energy charge	0	$/kWh	All	plus real-time prices
Total demand charge - first 3 kW - winter	0	$/kW	Oct.-May	Amount up to 3 kW
Total demand charge - first 3 kW - summer	0	$/kW	June-Sept.	Amount up to 3 kW
Total demand charge - amount over 3 kW - winter	3.83	$/kW	Oct.-May	Amount above 3 kW
Total demand charge - amount over 3 kW - summer	4.21	$/kW	June-Sept.	Amount above 3 kW

Note that, like Rate 1 above, there is an effective demand holiday owing to the very low cost per kW for peak power (and zero costs below 3 kW).

Rate 3: PSEG time-of-use (PSEG TOU) Basic Generation Service - Residential Small Commercial Pricing (BGS-RSCP)

This rate is based on PSE&G’s BGS-RSCP rate applicable to LPL-Secondary voltage distributions under 500 kW, which covers all simulated vehicle depots in this study. There is no RTP component, but there is an on- and off-peak price that varies monthly (note that no data were available for December 2021). See Table A15.

Table A15
Rate 3 details

Parameter	Value	Units	Time period*	Comments
Total service charge	0	$/mo.		
Total energy charge - on-peak Jan.	0.057466	$/kWh	Jan 2021 only	
Total energy charge - on-peak Feb.	0.055275	$/kWh	Feb 2021 only	
Total energy charge - on-peak Mar.	0.048816	$/kWh	Mar 2021 only	
Total energy charge - on-peak Apr.	0.0566317	$/kWh	Apr 2021 only	
Total energy charge - on-peak May.	0.053361	$/kWh	May 2021 only	
Total energy charge - on-peak Jun.	0.054837	$/kWh	Jun 2021 only	
Total energy charge - on-peak Jul.	0.054837	$/kWh	Jul 2021 only	
Total energy charge - on-peak Aug.	0.054837	$/kWh	Aug 2021 only'	
Total energy charge - on-peak Sep.	0.043881	$/kWh	Sept 2021 only	
Total energy charge - on-peak Oct.	0.043831	$/kWh	Oct 2021 only	
Total energy charge - on-peak Nov.	0.043831	$/kWh	Nov 2021 only	
Total energy charge - on-peak Dec.	N/A	$/kWh	Dec 2021 only	
Total energy charge - off-peak Jan.	0.050391	$/kWh	Jan 2021 only	
Total energy charge - off-peak Feb.	0.0482	$/kWh	Feb 2021 only	
Total energy charge - off-peak Mar.	0.041741	$/kWh	Mar 2021 only	
Total energy charge - off-peak Apr.	0.0495567	$/kWh	Apr 2021 only	
Total energy charge - off-peak May.	0.046286	$/kWh	May 2021 only	
Total energy charge - off-peak Jun.	0.042796	$/kWh	Jun 2021 only	
Total energy charge - off-peak Jul.	0.042796	$/kWh	Jul 2021 only	
Total energy charge - off-peak Aug.	0.042796	$/kWh	Aug 2021 only'	

Total energy charge - off-peak Sep.	0.03184	$/kWh	Sept 2021 only	
Total energy charge - off-peak Oct.	0.036756	$/kWh	Oct 2021 only	
Total energy charge - off-peak Nov.	0.036756	$/kWh	Nov 2021 only	
Total energy charge - off-peak Dec.	N/A	$/kWh	Dec 2021 only	
Total demand charge	18.3217	$/kW	All	Monthly peak

*on- peak hours are 9am to 7pm weekdays

Rate 4: Orange & Rockland time-of-use (O&R TOU) BGS-RSCP

This rate was based on Orange & Rockland's BGS-RSCP, time-of-use (TOU) rate applicable to service classification 2. As for Rate 3, there is no RTP component, but there is a more structured, five-tiered TOU structure. See Table A16.

Table A16
Rate 4 details

Parameter	Value	Units	Time period
Total service charge	32	$/mo.	
Energy delivery charge - summer peak	0.32012	$/kWh	June-Sept peak: 12pm-7pm, Mon-Fri, except holidays*
Energy delivery charge - summer shoulder	0.1145	$/kWh	June-Sept. Shoulder peak: 10am-12pm and 7pm-9pm, Mon-Fri, except holidays*
Energy delivery charge - summer off-peak	0.02061	$/kWh	June-Sept. Off-peak: 9pm-10am, Mon-Fri, holidays* and weekends
Energy delivery charge - winter peak	0.11454	$/kWh	Oct-May peak: 10am-9pm, Mon-Fri, except holidays*
Energy delivery charge - winter off-peak	0.02061	$/kWh	Oct-May off-peak: 9pm-10am, Mon-Fri, holidays* and weekends
Demand charge - first 5 kW, summer	1.69	$/kW	June-Sept., first 5 kW
Demand charge - amount over 5 kW, summer	5.82	$/kW	June-Sept., over 5 kW
Demand charge - first 5 kW, winter	1.44	$/kW	Oct.-May, first 5 kW
Demand charge - amount over 5 kW, winter	5.07	$/kW	Oct.-May, over 5 kW

**Holidays are: New Year's Day, Memorial Day, Independence Day, Labor Day, Thanksgiving Day, and Christmas Day*

Also, like Rates 1 and 2 above, there is an effective demand holiday due to the very low cost per kW for peak power, and a lower cost below 5 kW.

Solar PV generation

Hourly data

A year's worth of hourly data from PVWatts was provided for Roxbury Township, New Jersey, at 40.85°N, 74.66°W (northern central New Jersey). Table A17 lists the assumptions used. The annual maximum DC system output for this simulation was 3.378 kW, while the maximum AC system output was 3.244 kW. This dataset was scaled as appropriate to the solar PV array sizes specified in the simulations.

Table A17
Solar PV generation parameter assumptions

Parameter	Value
Location	40.85°N, 74.66°W
DC System Size	4 kW
Module Type	Standard
Array Type	Fixed (open rack)
Array Tilt	20°
Array Azimuth	180°
System Losses	14.08%
Inverter Efficiency	96%
DC to AC Size Ratio	1.2
Capacity Factor	14.7%

Demand scaling

For the 4 kW DC system described above, the average annual output is 15.31% (DC) or 14.65% (AC) of maximum theoretical output. In order to determine how large of a solar PV system to simulate for each vehicle type, we deferred to the GNA report, which indicated the preferred solar PV size should provide 80% of annual vehicle demand (in kWh). Thus, the solar PV size should be 80% / 14.65% = 5.46 times the rated DC power.

Table A18 below summarizes the solar PV sizes and solar battery capacities by vehicle type.

Table A18

Solar PV size and solar battery capacity by vehicle type

Business type	Vehicle class	Solar PV (rated DC kW)	Solar battery capacity (kWh)
Landscaping	3	23	100
Food service	4	64	280
Wired telecom	5	294	1,290
Armored car	6	220	960
Yard tractors	7	18	80

Selection of representative weeks per season

Total cost of ownership

The total cost of ownership, C_{total}, whether expressed in absolute or amortized (annual or monthly) terms, was calculated as the sum of the following components:

$$C_{total} = C_{solar\ PV} + C_{battery} + C_{charger\ capital} + C_{cable\ and\ contracts} + C_{charger\ install} + C_{charger\ warranty} + C_{customer\ make-ready} + C_{utility\ make-ready} + C_{electricity}$$

In the sections below, we detail how we estimated each of these parameters with the exception of the last one, which was an output of the model optimization.

Solar PV

We used data from EDF fleet partners to estimate the average cost of a solar PV system. The DHE system had a rated DC capacity of 864 kW and total cost of $2,307,000. We assumed a federal tax credit of 26%. Therefore, the normalized cost was $1,976/kW (raw DC) or $2,151/kW (final AC). We used the AC cost per kW for all sizes of solar PV systems in our analysis.

Solar battery

Similarly, we used data from EDF fleet partners to estimate the average cost of a solar battery system. The DHE system had an energy capacity of 130 kWh and 60 kW power capacity, and cost $93,822. We also assumed a federal 26% tax credit as for solar PV above. The normalized cost was $534/kWh, which we used without modification for estimating solar battery costs.

Charger capital

We used three different cost estimates (ICCT, RMI, and Smart Charge America) for Level 3 networked chargers to produce 12 different data points with capacities between 25 and 300 kW.

Figure A5 shows all data, fitted with a linear trendline ($R^2 = 0.913$). However, we find that a trendline with capacity exponent of 0.6 fits the data much better ($R^2 = 0.969$); this fit is shown in Figure A6. We subsequently used this fit to scale charger costs to any capacity. Table A19 shows the best-fit parameters, along with estimated costs for the capacity values used in the analysis.

Figure A5

Charger cost vs. power rating, with best-fit linear trendline

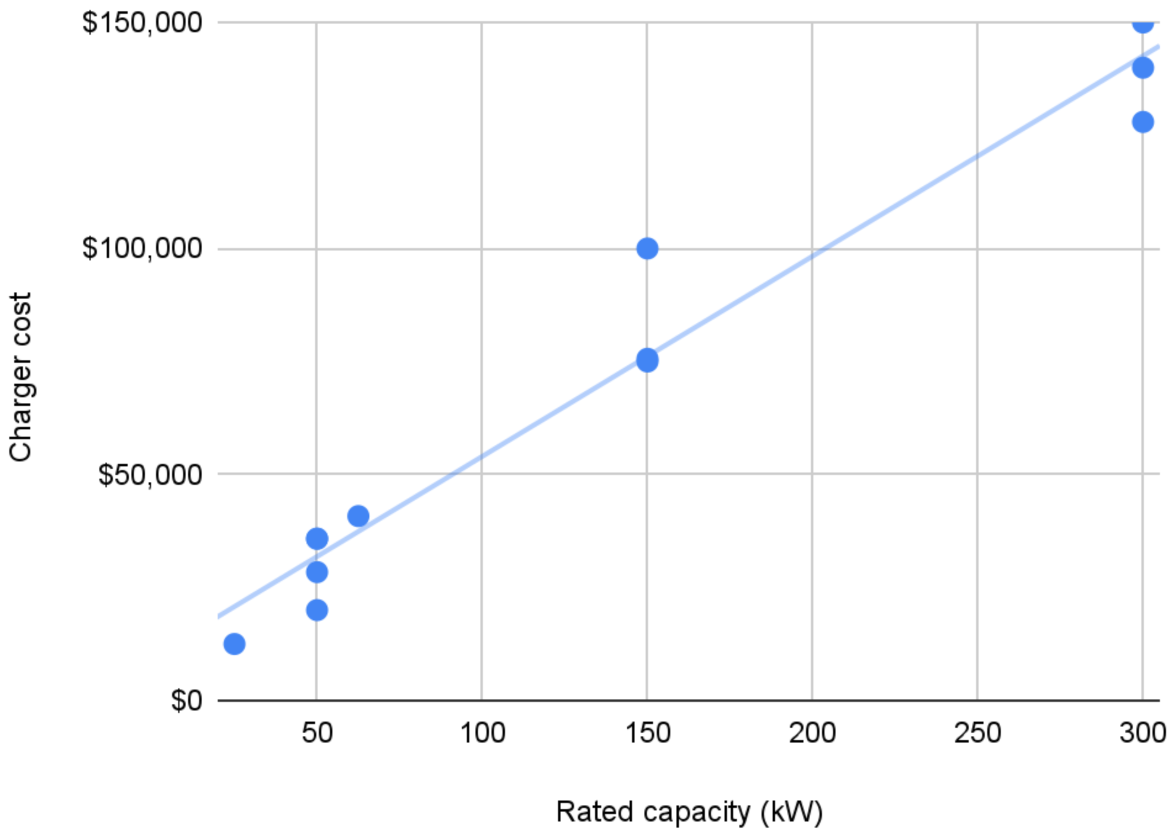


Figure A6

Charger cost vs. power rating^k, with best-fit linear trendline for k = 0.6

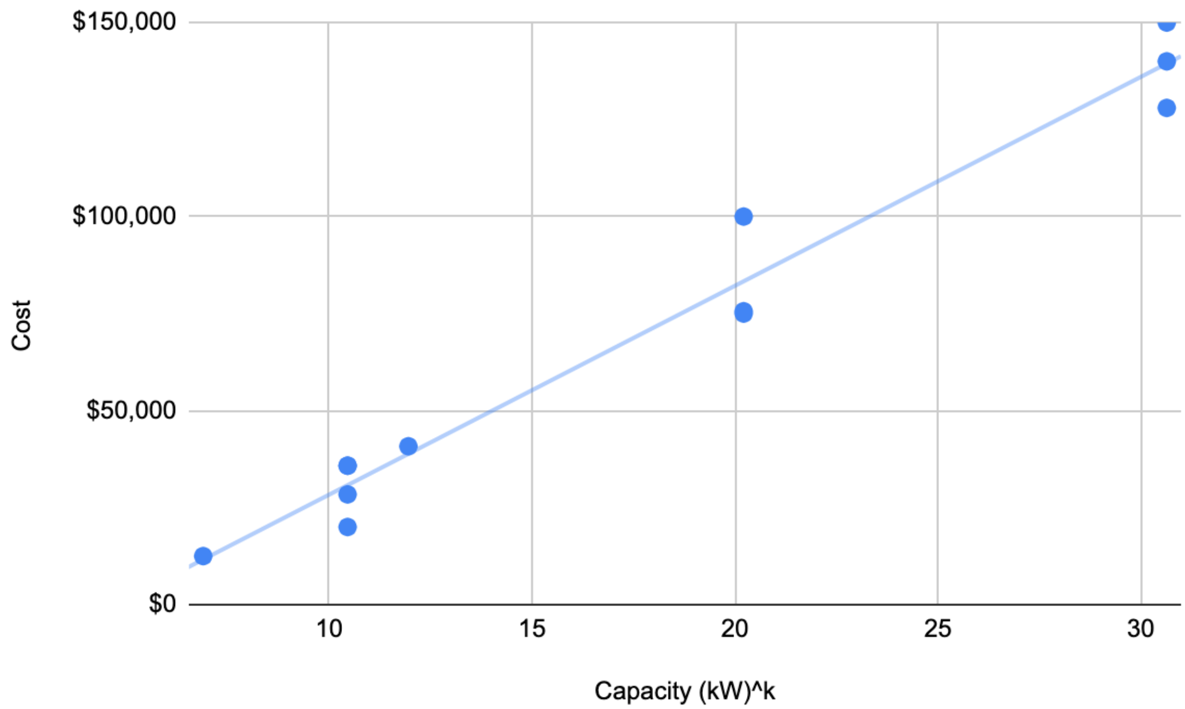


Table A19

Best-fit parameters to charger cost vs. capacity (kW)^k, and estimated cost vs. capacity

Parameter	Value
k	0.6
slope	5,383
intercept	-25,500
R^2	0.969
Capacity (kW)	Cost
20	$6,983
30	$15,930
50	$30,789
60	$37,296
100	$59,818
150	$83,317

Charger cable and contracts

The RMI report provided estimates of cable costs (average of $2,500) and annual costs (data plus network contracts, average of $387/yr. in total). These costs were added to the charger capital costs estimated above.

Charger installation

Installation costs were obtained from the ICCT report, which provided a breakdown of Level 3 charger costs by labor, materials, permits, and taxes per charger, broken out separately by power level (50, 150 or 350 kW) and number of chargers per site (1, 2, 3-5, and 6-20).

The sum of costs per charger followed a power law relationship with the number of chargers (where we approximated the number in each category from the average of ranges given, e.g., 1, 2, 4, and 13 chargers, respectively, corresponding to the four categories listed above); see Figure A7. We performed separate linear fits to ln-ln data for each power level ($R^2 > 0.9994$), and found that the slopes of these fits were virtually identical (standard deviation 0.0025%). The intercepts vs. capacity were fit to a linear function (Figure A8), which was used to estimate costs for different power levels. See Table A20 and Table A21.

Figure A7

Charger installation cost vs. number of chargers and charger capacity (kW), and power-law fits

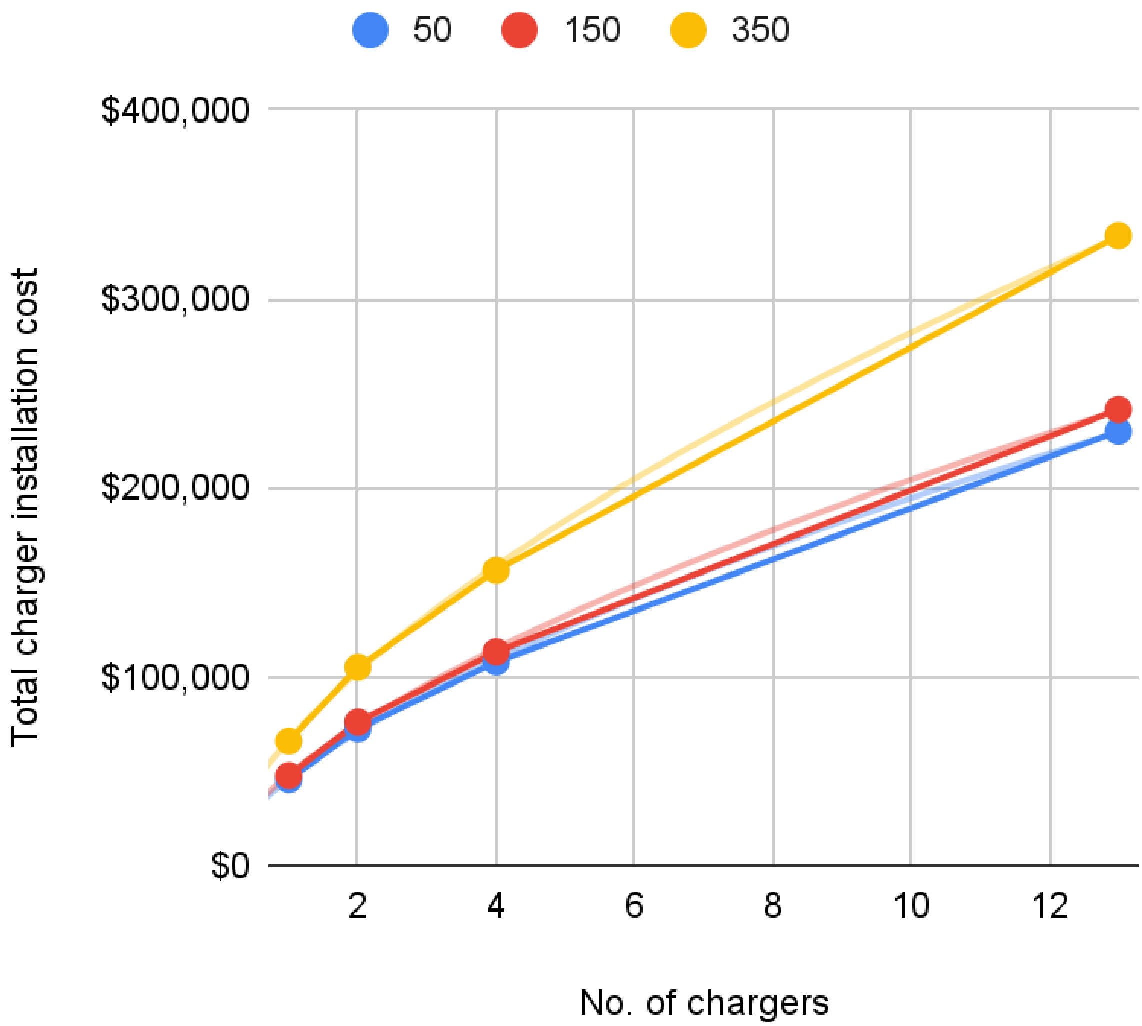


Figure A8
Ln-ln intercept vs. charger capacity and linear fit

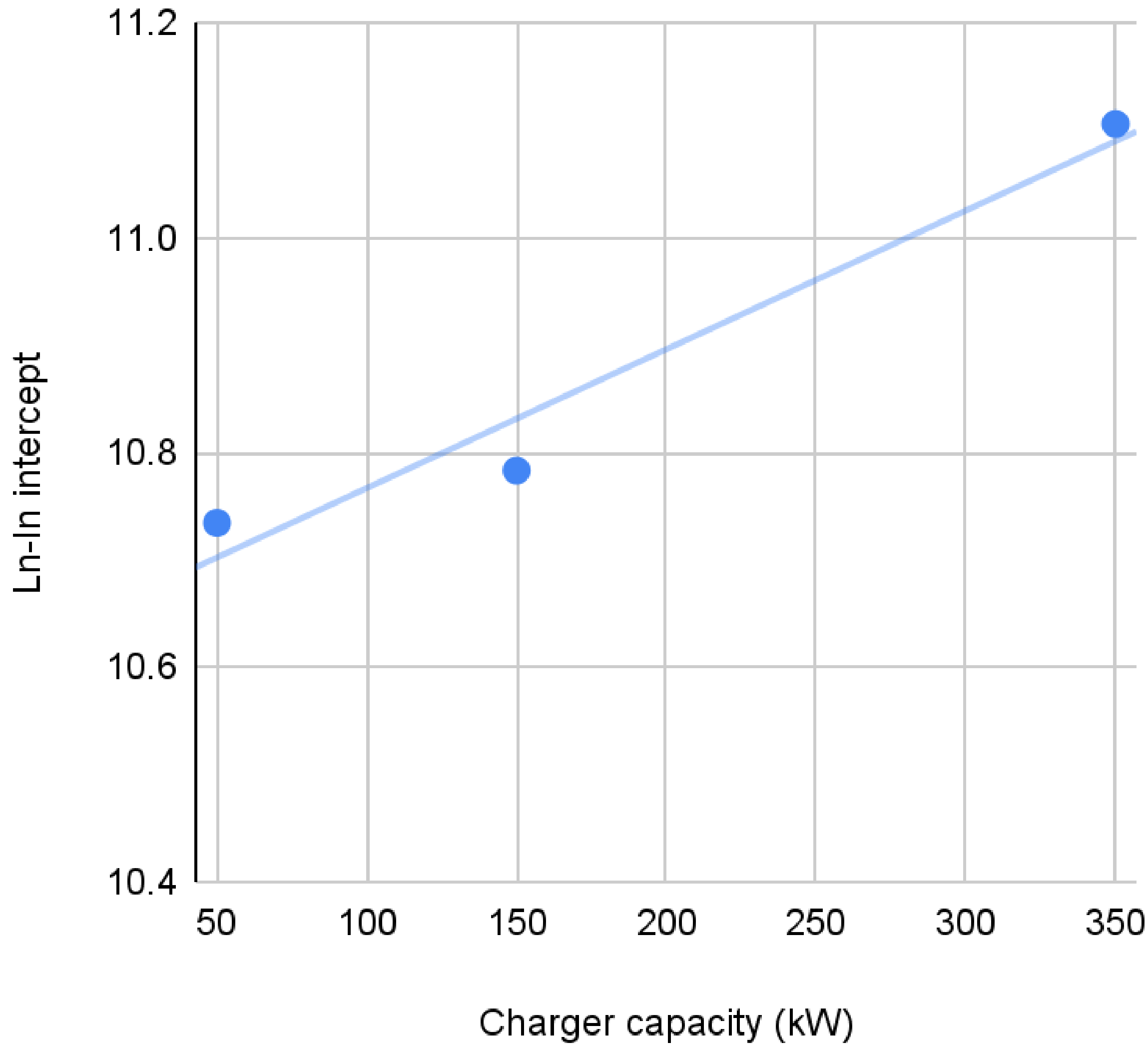


Table A20

Linear fitting parameters to ln-ln intercept vs. charger capacity (kW)

ln-ln slope:	0.627310
Linear fit to ln-ln intercept:	
slope	0.001292
intercept	10.6376
R^2	0.9556

Table A21

Estimated ln-ln intercept vs. charger capacity, and estimated total charger installation costs vs. charger capacity and number of chargers

	Charger capacity (kW):					
	20	30	50	60	100	150
In-In intercept:	10.6634	10.6764	10.7022	10.7151	10.7668	10.8314
No. of chargers	Total charger installation cost:					
1	$42,763	$43,319	$44,454	$45,032	$47,420	$50,585
2	$66,056	$66,915	$68,667	$69,560	$73,249	$78,138
3	$85,187	$86,295	$88,554	$89,706	$94,464	$100,769
4	$102,035	$103,362	$106,068	$107,447	$113,147	$120,698
5	$117,366	$118,892	$122,005	$123,592	$130,147	$138,833
6	$131,587	$133,298	$136,788	$138,567	$145,917	$155,656
7	$144,947	$146,832	$150,676	$152,636	$160,732	$171,459
8	$157,612	$159,662	$163,841	$165,972	$174,776	$186,441
9	$169,698	$171,905	$176,406	$178,700	$188,179	$200,738
10	$181,293	$183,651	$188,459	$190,910	$201,036	$214,453
11	$192,463	$194,966	$200,070	$202,672	$213,423	$227,666
12	$203,260	$205,904	$211,294	$214,042	$225,396	$240,439
13	$213,727	$216,506	$222,174	$225,064	$237,002	$252,820
14	$223,897	$226,809	$232,747	$235,774	$248,280	$264,850

Charger warranty

Charger warranties were estimated from three charger capacities reported in RMI's EV report. One was for a 7.7 kW Level 2 fleet charger, while the other two were DC fast chargers (50 and 62.5 kW capacity, respectively). Cost was presented as an up-front payment plus a per-year cost after year 3. We converted this information into a net present value (NPV) using an assumed 20-year charger lifetime and 8%/yr discount rate (see Financing section). Figure A9 shows the data with linear best-fit. Table A21 shows the best-fit parameters.

Figure A9

Charger warranty cost (NPV/kW) vs. capacity, with best-fit trendline

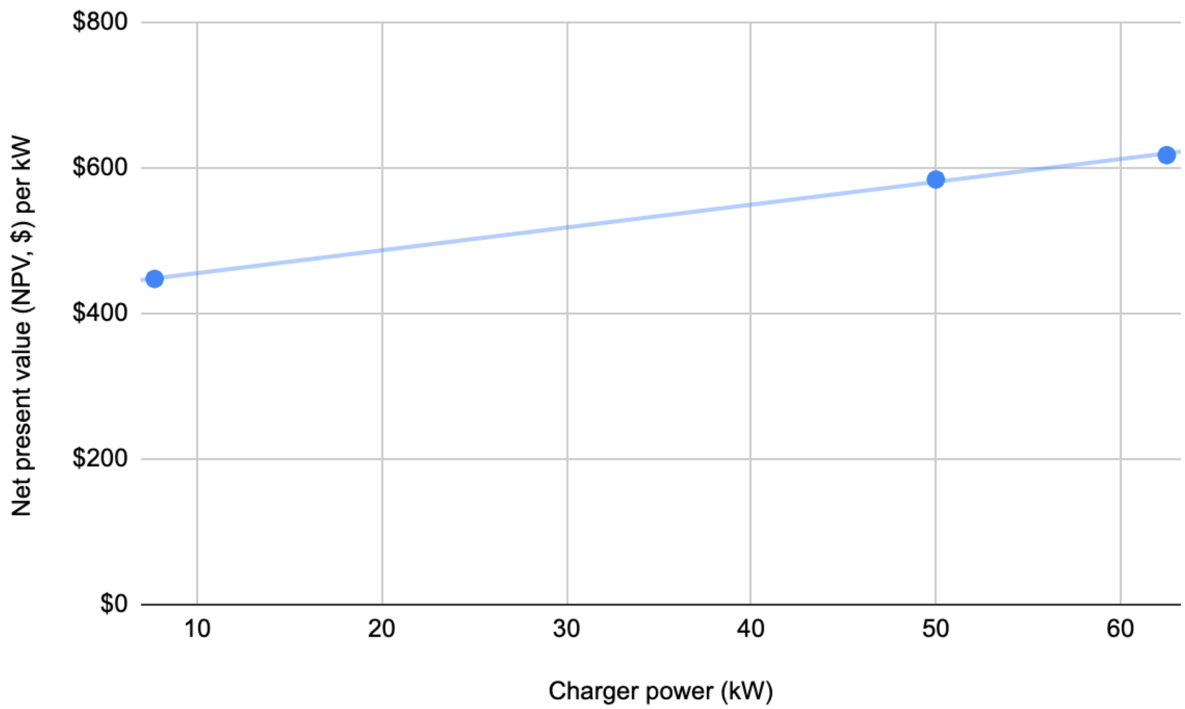


Table A21

Best fit parameters to warranty cost (NPV $/kW) vs. charger capacity (kW)

Slope	3.136
Intercept	424
R^2	0.9989

Customer make-ready

The cost of preparing the electrical system for EV charging ("make-ready") on the customer side was provided by estimates from RMI in their EV report that make-ready costs typically make up 30-40% of total charger installation costs. Using the average of this range (35%), this implies that make-ready costs alone constitute 35%/(1 - 35%) = 54% of other costs, which we assumed consisted of charger capital, cables, and installation. We applied this ratio in all charger configurations to estimate total customer make-ready costs.

Utility make-ready

Utility make-ready costs were provided by the RMI report for three ranges of transformer capacities, which we used as a proxy for all utility make-ready costs: 150-300 kVA (which is virtually identical to kW), 500-750 kW, and 1,000+ kW. Both high and low cost estimates were provided for each. We took the average cost and divided by the average kW capacity, where for the 1,000+ kW category, we assumed the average was 1,250 kW. The plotted data appeared to follow a roughly exponential curve of cost vs. capacity (Figure A10), so we performed a leastsquares fit to ln(cost) vs. capacity, obtaining an R^2 of 0.978. Fitting parameters and estimated costs are shown in Table A22.

Figure A10

Utility make-ready cost vs. capacity, with best-fit trendline to ln(cost) vs. capacity

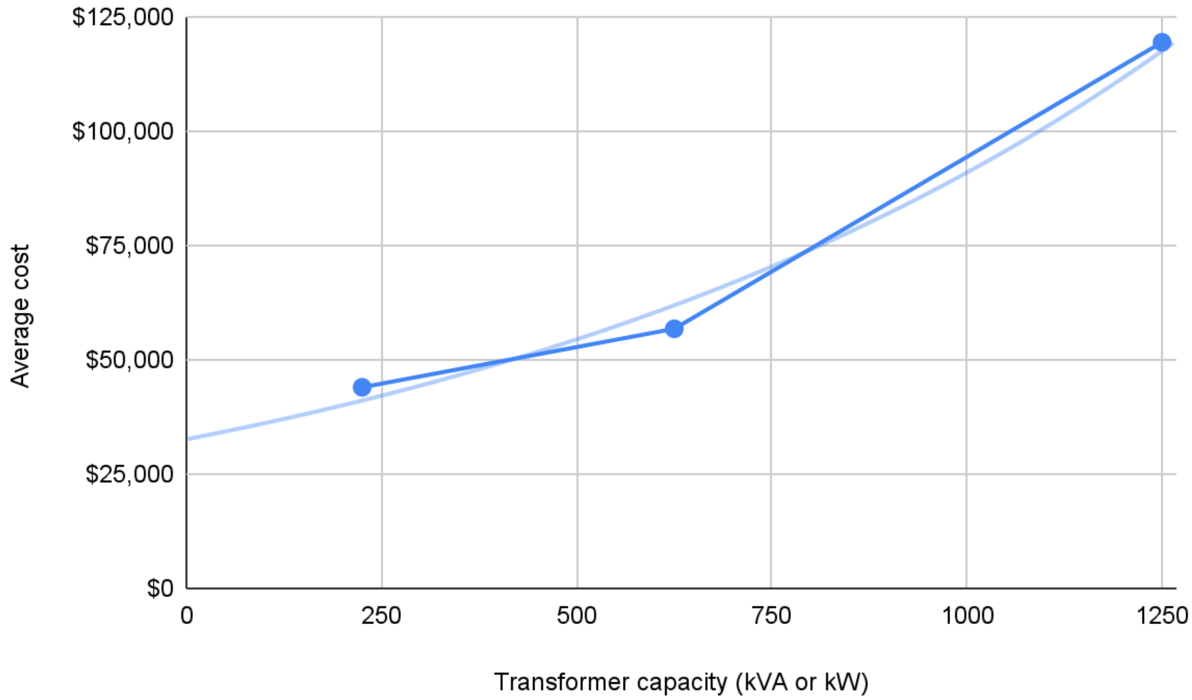


Table A22

Best fit parameters to ln(cost) vs. capacity, and estimated costs vs. capacity

Parameter	Value
Slope	0.00099367
Intercept	10.4145
R^2	0.9780
Capacity (kW)	Cost
50	$35,039
100	$36,824
150	$38,700
250	$42,743
500	$54,796
750	$70,248

1000	$90,057
1250	$115,453

Financing

We assumed financial parameters summarized in Table A23, and used these assumptions to convert among up-front (capital) costs, annual costs, and net present value costs.

Table A23

Financial parameter assumptions

Parameter	Value	Units
Solar PV lifetime	20	yrs
Solar battery lifetime	10	yrs
Charger, cables, contract, warranty lifetimes	20	yrs
Make-ready lifetime	50	yrs
Discount rate	8%	/yr

Scaling results to New Jersey

Atlas provided Class 3-8 new registrations in New Jersey for 2019 and January through March 2021, which were broken down by make, model, gross vehicle weight (GVWR), fuel type, and county. This data was mapped onto a list of counties in the PSE&G service territory, in order to determine how many vehicle registrations were associated with that territory. The energy savings estimates for the depot sizes simulated were then scaled to New Jersey-wide numbers, assuming 100% EV penetration levels. Scaling factors are presented in Table A24. Smaller penetration levels can be estimated by downscaling results as appropriate.

Table A24

New Jersey vehicle scalings by class

Vehicle class	Depot size	2019 NJ vehicle registrations	Fraction of total NJ registrations	Total scale-up factor
3	2	4,371	11.58%	18,879
4	4	1,739	3.88%	11,218
5	11	2,149	3.88%	5,041
6	7	1,861	3.88%	6,860
7	2	1,324	3.88%	17,081

Grid expansion savings

To estimate grid expansion costs, we examined two data sources: demand charges for the four rate structures modeled in this study, and the 2020 ChargEVC report. The highest demand charge among the four rate structures, $37.94/kW, was used as our minimum cost estimate, whereas the estimated NPV cost of NJ grid expansion between 2021 and 2050 presented in the ChargEVC report, implying $214/kW, was used as our maximum cost estimate. Input assumptions for this calculation are presented in Table A25. These two values were used to bracket our estimates for avoided costs when comparing unmanaged to managed charging, based on the reduction in peak loads.

Table A25

Parameters used to calculate average cost of 2021-2050 grid expansion in New Jersey

Parameter	Value	Units
Start year	2021	
Mid year	2035	
End year	2050	
Start year peak	0	GW
Mid year peak	1.2	GW
End year peak	2.8	GW
Discount rate	3%	/yr
NPV	$4,725	$M
Cost per GW	$214	$/kW

Source: ChargEVC, 2020, Full Market Vehicle Electrification in New Jersey: The Opportunities, Impacts, and Net Benefits For Light-, Medium-, and Heavy-Duty Electric Vehicles.

Appendix B: V2G-Sim modifications

Overview

V2G-Sim was developed at Lawrence Berkeley National Laboratory and built to couple models of vehicle powertrain dynamics, vehicle charging, and automated methods to rapidly initialize and execute large numbers of individual vehicle models. Users can also activate built-in models for automated trip-specific drive cycle generation, and electrochemical models to predict the internal dynamics and degradation of a vehicle battery. It is freely available on Github.

Much of this capability was not utilized for this project, as electricity demand was directly provided to the optimization part of the model using vehicle itineraries. The other component of V2G-Sim was to determine optimal charging based on minimizing or maximizing an objective function. Emerging Futures modified this objective function to reflect a total cost of electricity that was minimized for managed charging.

The model has been used successful in a number of previous studies including several peer-reviewed papers:

- Coignard, J., S. Saxena, J. Greenblatt, D. Wang, 2018. "Clean Vehicles as an Enabler for a Clean Electricity Grid," Environ. Res. Lett., 13: 054031. DOI: 10.1088/1748-9326/aabe97.
- Zhang, C., J. B. Greenblatt, P. MacDougall, S. Saxena, A. Jayam Prabhakar, 2020. "Quantifying the benefits of electric vehicles on the future electricity grid in the midwestern United States," Applied Energy, 270: 115174. DOI: 10.1016/j.apenergy.2020.115174.
- Greenblatt, J., M. McCall, 2021. Exploring enhanced load flexibility from grid-connected electric vehicles on the Midcontinent Independent System Operator grid, Final report to the Midcontinent Independent System Operator, Inc., February. https://cdn.misoenergy.org/Exploring%20enhanced%20load%20flexibility%20from%20grid%20connected%20EVs%20on%20MISO%20grid543291.pdf.

Modifications for project

The objective function, constructed to minimize the operational costs of the EVs, was modified to be convex in order to apply a mixed-linear integer program. This objective function is expressed as follows:

$$min\ (c^T x)$$

The x vector includes the variables of the simulation and the c^T vector includes the costs associated with these variables. These variables fall into six categories: (1) electricity consumption from the grid to the EVs, (2) electricity consumption from the solar PV battery to the EVs, (3) solar output obtained from the solar PV to the battery, (4) the maximum power consumed from the grid, (5) the number of ports being used at a time, and (6) the electricity consumption from the grid to the solar PV battery.

The following includes a list of constraints used for this simulation:

1. *EV Depot Minimum State-of-Charge:* This constraint ensures that the state-of-charge of each EV is greater than a set minimum value.
2. *EV Depot Maximum State-of-Charge:* This constraint ensures that the state-of-charge of each EV is less than a set maximum value.
3. *Infrastructure Limits:* The constraint ensures that the electricity consumption limit of each infrastructure component used is less than their set, corresponding value. These limits of the infrastructure components include the following: (1) the total energy which can be consumed by an EV, (2) the total amount of electricity which can be consumed by the grid, (3) the maximum solar output which can be obtained by the solar PV battery, (4) the total solar output which is produced for the solar PV battery, (5) the total electricity which can be consumed by the solar PV battery from the grid, and (6) the demand charge tier value for electric power. The one infrastructure component not included in this constraint involves the charging port system, which has its own charging ports.
4. *Demand Charge:* This constraint ensures that the superposition of the variables representing the maximum power consumed (to be used for the demand charge calculation) is equal to the total electricity consumption at the time when consumption is maximum.
5. *Positive Electricity Consumption:* This constraint ensures the electricity consumption is non-negative in all cases.
6. *Solar PV Battery Minimum State-of-Charge:* This constraint ensures that the state-of-charge of the solar PV battery is greater than a set minimum value.
7. *Solar PV Battery Maximum State-of-Charge:* This constraint ensures that the state-of-charge of the solar PV battery is less than a set maximum value.
8. *Singular Port Constraint:* This constraint ensures that for each port, the total charging which occurs is either that of half or the total charging station capacity. If two EVs are being charged at one station, each port can only provide half of the charging capacity of the charging station. If one EV is being charged, one port can provide the full charging capacity of the charging station.
9. *Total Port Constraint:* This constraint ensures that the number of ports being used to charge the EV depot never exceeds the number of ports available.
10. *Charging Port Capacity:* This constraint ensures that the electricity being consumed from a charging port never exceeds the maximum capacity of the charging station.

Modeling

In this section, we describe the model in which the EVs operate in our analysis and optimization.

First, this model contains modifications to V2G-Sim which grew out of work that Emerging Futures performed using V2G-Sim for the [Midcontinent Independent System Operator]() in 2019-2020. The modifications are associated with the development of a charging infrastructure system, driving-charging behaviors for the varying vehicle classes, and input parameters associated with the settings of interest. These variations were eventually tried and tested during the optimization.

Second, we also incorporate assumptions associated with the *operation* of the charging station infrastructure system to best capture the interests of the system operator when aiming to minimize costs. The objective in doing this involves aiming to implement a model as realistic as possible, predicated upon the point-of-view of those managing the charging station infrastructure system. These assumptions include the following: (1) the operators aim to minimize the costs, (2) forecasting electricity prices can only be done one day ahead, and (3) EV charging is subject to the constraints of the infrastructure system.

Modifications

As it pertains to the modifications that we applied to V2G-Sim, the following include those modifications as well as brief descriptions:

1. **Charging Infrastructure System:** We incorporate a system which contains an electric grid, a solar PV - battery configuration, and a system of charging stations, all of which are all linked to one another. This system has associated with it power ratings for all components to model a realistic power infrastructure system for when EVs charge.

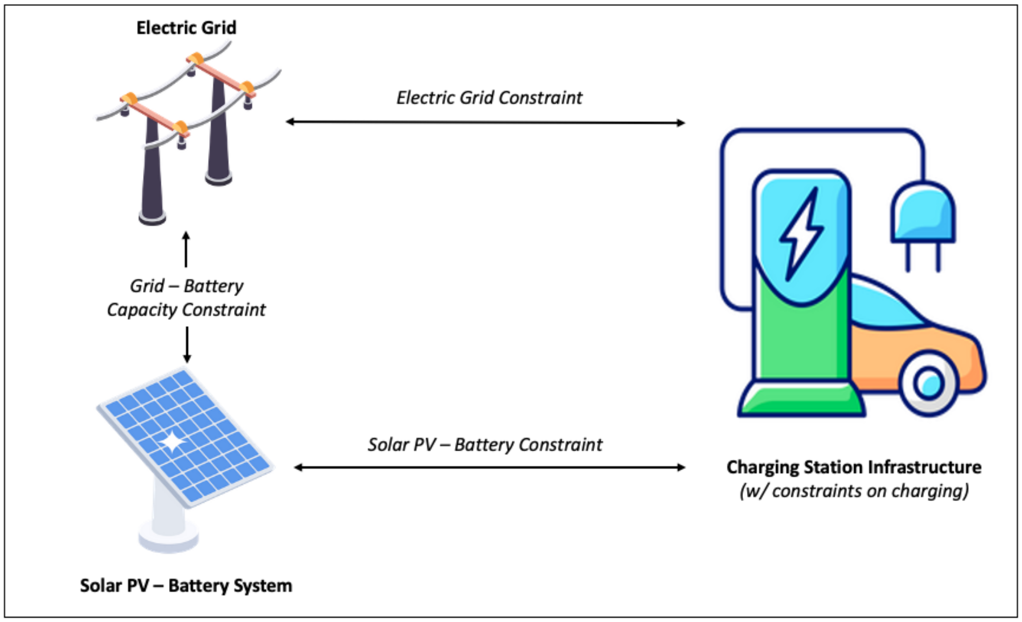
2. **Driving-Charging Behaviors:** Profiles for driving and charging were incorporated into the model. These windows of time for driving and charging were used later on for the optimization to signify when EVs could and could not be charged. Moreover, during driving, calculations of energy consumption took place to estimate the energy depreciation of the EVs' batteries.

3. **Input Parameters:** Various properties associated with the EV analysis and optimization are provided as inputs. First, the properties associated with the EV depot and the charging infrastructure system are provided, with no variation throughout the optimization. For pricing, four rate structures are used in the analysis. For parameters related to weather, solar production and efficiency are varied for four months of the year.

Charging Infrastructure System

A charging infrastructure system was developed to capture the limits in the demand of power associated with EV charging; in essence, this puts a physical bound on how much charging stations can power EVs from the grid and a solar PV - battery configuration. A schematic of this model is provided in Figure B1.

Figure B1
Layout of Charging Infrastructure System used for EV Modeling



The zone for which the power stations are contained is connected to the solar PV - battery configuration on one end and the electric grid on the other. The electric grid and the solar PV - battery configuration are connected to one another, as well. The significance of this lies in the links between each system component, where each link contains a physical limit in the amount of electricity that can be carried from one part of the system to another.

As it pertains to constraints on the system, three exist as follows: (1) the grid constraint on the charging station infrastructure, (2) the solar PV - battery constraint on the charging station infrastructure, and (3) the constraint associated with how much the solar PV - battery system is able to receive from the electric grid and vice versa. In essence, this system is put in place to ensure that the electricity consumption of the EV charging stations is bounded by a realistic infrastructure setting.

Driving-Charging Behaviors

EVs are modeled both during driving and charging. During driving, estimations of energy consumption are calculated beforehand and used to model the energy depreciation of the EVs' batteries. During charging, EVs are charged to completion either by the end of the day (for class 3-6 vehicles) or up to a point of sufficiency (for class 7 vehicles), subject to the bounds of the charging infrastructure system and batteries' energy capacities (discussed in depth in the Optimization - Constraints section).

For class 3-6 vehicles, these profiles simply consisted of one window for driving during typical business hours and one window for charging outside of typical business hours. The objective during charging involved ensuring that the EVs were 100% charged before the next day's operations.

For class 7 vehicles, these profiles were sporadic, where windows for driving and charging came about more-or-less arbitrarily throughout the day. The objective during charging involved ensuring that the EVs had a sufficient amount of energy within the batteries at all times during operation. Having 100% charge was irrelevant; rather, the objective involved maintaining enough charge at all times within sporadic settings.

Input Parameters

In essence, properties are input into the analysis and optimization to describe the EV depot and associated setting, the variation in price, and the variation in EV and solar PV performance with weather. These properties are described further, as follows:

1. **EV Depot & Infrastructure System Properties:** Each EV depot has an associated battery capacity, size (in terms of number of EVs), and charge-discharge schedule. Moreover, the components of the charging infrastructure system are rated for each EV depot, where the solar PV - battery configuration and the charging station infrastructure vary in design to examine differing capabilities during charging of the EV depot.

2. **Rate Structures:** The rate structures inputs vary with there being four differing rate structures for analysis described in Electricity rates in the main text.

3. **Weather:** Both the EV efficiency and the solar production vary with the weather. To capture this, the model was implemented across four months: January, April, July, and October. The variation for all months was captured during optimization.

Assumptions

Cost Minimization

The sole objective of the operators is to minimize the costs associated with operating the EV depot. This objective combines the contribution of both the energy charge and the demand charge. This assumption acts as the basis for the objective function used in the optimization, as described in Optimization - Objective Functions & Description - Objective Function.

Day-Ahead Charging

Having in hand information regarding the energy charge pricing is included in the modeling assumptions. In the modeling, the operators are assumed to know the information 24 hours ahead of the current time at 3 pm for every day of modeling. Therefore, the models start at 3 pm every day for the analysis.

Infrastructure Constraints

The system operators are assumed to only be able to charge the EVs subject to the constraints of the infrastructure system. The system is designed so that EVs at any time cannot charge more than what is available from the electric grid, the charging station infrastructure, and the solar PV - battery system. For the solar PV - battery system, it is assumed that the battery absorbs as much power from the solar PV as possible and that there are no constraints that the battery is filled by a certain amount at any particular time.

Optimization

The optimization can be classified into two categories: the minimization of an objective function and a set of systems of equations which pose as constraints. In this section, we describe the use of this optimization from a higher level (in the Optimization - Methods section) and in more depth for these two categories (in Optimization - Objective Function & Description section and Optimization - Constraints section).

Methods

A linear, mixed-integer program with linear constraints was determined as the right set of methods to develop a solution which optimizes for the operational cost of EV depot usage for all vehicle classes. The EV-charging problem was set up to be convex, allowing for optimal solutions for EV charging to be determined when minimizing operational costs.

Pertaining to the objective function, the calculation performed was linear, where every variable used for analysis is multiplied by a cost coefficient, and all products of cost coefficients with variables are superimposed. Each cost coefficient - variables pair represents a different cost, such as those associated with the rate structure and the demand charge, among others.

Pertaining to the constraints, these simply involve the implementation of linear sets of equations to bound our analysis and optimization to a *realistic*, physical scenario. This involves ensuring that the EV batteries' and the battery associated with the solar PV - battery system are charged between 0% and 100% of their capacities at all times, that the number of ports used during analysis does not exceed physical limits, and that the links of the Charging Infrastructure System do not transmit an amount of electricity which exceeds that of their capacities, among other physical bounds.

Objective Function & Description

Objective Function

As mentioned earlier, the objective function constructed to minimize the operational costs of the EVs is expressed as follows:

$$min\ (c^T x)$$

For each category representing the variable classes, the variables and their corresponding cost coefficients were ordered sequentially, as shown in Table B1. Descriptions for each category for the cost coefficients and variables are provided in the subsequent section.

The objective is defined as the costs and variables multiplied by one another and subsequently superimposed, providing the total cost of the electricity consumed during operation. We aim to minimize this objective with respect to the constraints of the system.

Table B1

Table of the Linear Cost Coefficients & Variables Used for Optimization

#	Cost Category	Cost Coefficient (c_n)	Cost Variables (x_n)
1	grid - EV electricity consumption	dependent on the rate structure values	one per vehicle and per time interval
2	solar PV - EV electricity consumption	zero cost or penalty value, dependent on optimization	one per vehicle and per time interval
3	solar PV - battery system solar insolation	zero cost; implemented for use in the constraint system	one per time interval
4	demand charges	values dependent on rate structure used	one per demand charge
5	# of charging station ports in use	zero cost; implemented for use in the constraint system	one per vehicle and per time interval
6	grid - battery (of solar - PV system) electricity consumption	dependent on the rate structure values	one per time interval

Description

These costs and variables represent the following in the model:

1. **grid - EV electricity consumption:** This cost category represents the electricity costs associated with the operational costs of the EVs, subject to the rate structure of use.

2. **solar PV - EV electricity consumption:** This cost category represents the costs of the EVs associated with the solar PV - battery system. This cost amounts to zero in all cases; however, this needs to be put in place to enhance the minimization of the operational costs and to incorporate later for the system of equations.

3. **solar PV - battery system solar insolation:** This cost category represents the cost of the solar insolation used to recover the battery state-of-charge. This cost amounts to zero in all cases; however, this needs to be put in place to incorporate later for the system of equations.

4. **demand charges:** This cost category represents the cost of the demand charges used during optimization.

5. **# of charging station ports in use:** This cost category represents the costs associated

with the charging station ports in use. This cost amounts to zero in all cases; however, this needs to be put in place to incorporate later for the system of equations. The association with any positive cost is that these variables limit the use of charging station ports in the system of equations, which are in turn used to dictate how much electricity can be consumed by the EVs from the electric grid and the solar PV - battery system.

6. **grid - battery (of solar - PV system) electricity consumption:** This cost category represents the electricity costs associated with the operational costs of the battery used in the solar PV - battery system, subject to the rate structure of use.

All variables are represented on a time-series basis over the course of a day in 15-minute intervals. For variables representing EV behavior, the number of variables amounts to 96 total intervals for the day multiplied by 'n' number of EVs. For other variables, the number of variables only amounts to 96, the total number of intervals for the day.

Constraints

Modeling of the constraints was the key part of this analysis. The main objective in the development of the constraints was to model the system as realistic as possible. This led to the diligent pursuit of developing and implementing the constraints provided in this section.

EV Minimum State-of-Charge

At all times the EVs must maintain a *minimum* state-of-charge. This state-of-charge is dependent on the electricity received by the EVs from the grid and the solar-PV battery, the energy consumed by the EVs during operation, and the initial charge at the start of the operation period for the EVs. The formulation is modeled as follows for each time step and EV:

$$EV_i : \sum_{t=0}^{j} x_{grid,j} + \sum_{t=0}^{j} x_{solar,j} - \sum_{t=0}^{j} e_{consumption,j} + charge_{init} \geq \alpha \cdot capacity_{battery}$$

… where the variables being represented are as follows:

- $x_{grid,j}$: electricity flow from the grid to the EV when parked, at a time *j*
- $x_{solar,j}$: electricity flow from the solar-PV battery to the EV when parked, at a time *j*
- $e_{solar,j}$: energy consumption of the EV during operation
- $charge_{init}$: initial energy capacity of the EV during window of analysis
- α: proportion for which the battery needs to remain at a minimum
- $\underline{capacity_{battery}}$: battery capacity of the EV being modeled

In this equation, the $\boldsymbol{\alpha}$ term dictates the proportion for which the battery needs to remain at a minimum. For the "daytime-operation" vehicles, this value is 0. For the "around-the-clock" vehicles, this value is 0.025.

For the “daytime-operation” vehicles, the minimum state-of-charge at the end-of-day is required to be 100%. For the “around-the-clock” vehicles, this value is 27.5%.

EV Maximum State-of-Charge

At all times the EVs must maintain a *maximum* state-of-charge. This state-of-charge is dependent on the electricity received by the EVs from the grid and the solar-PV battery, the energy consumed by the EVs during operation, and the initial charge at the start of the operation period for the EVs. The formulation is modeled as follows for each time step and EV:

$$EV_i : \sum_{t=0}^{j} x_{grid,j} + \sum_{t=0}^{j} x_{solar,j} - \sum_{t=0}^{j} e_{consumption,j} + charge_{init} \leq capacity_{battery}$$

… where the variables being represented are as follows:

- $x_{grid,j}$: electricity flow from the grid to the EV when parked, at a time *j*
- $x_{solar,j}$: electricity flow from the solar-PV battery to the EV when parked, at a time *j*
- $e_{solar,j}$: energy consumption of the EV during operation
- $charge_{init}$: initial energy capacity of the EV during window of analysis
- α: proportion for which the battery needs to remain at a minimum
- $capacity_{battery}$: battery capacity of the EV being modeled

Infrastructure Limits

For this set of constraints, six categories can be distinguished. Descriptions of these constraints as well as their representative equations are provides as follows:

1. *Charge Limits*: This set of constraints represents the limits for which charging station infrastructure can charge all EVs at any one time.

$$(x_{grid,i} + x_{solar,i})|_{i=1:(EV \cdot t)} \leq charge_{limit} \cdot e_i|_{i=1:(EV \cdot t)}$$

… where the variables being represented are as follows:

- $x_{grid,i}$: electricity flow from the grid to the EV, at time *t* and for a particular EV
- $x_{solar,i}$: electricity flow from the solar-PV battery to the EV, at time *t* and for a particular EV
- $charge_{limit}$: limit for total charge associated with the charging station infrastructure
- e_i: proportion of 15-min. interval for which charging can occur

2. *Grid Limits*: This set of constraints represents the limits for which electricity can be consumed from the electric grid.

$$(\sum_{i=0}^{EV} x_{grid,i})_t \quad |_{t=1:n} \leq grid_{limit}$$

… where the variables being represented are as follows:

- $x_{grid,i}$: electricity flow from the grid to all EVs, at time *t*
- $grid_{limit}$: limit for the total electricity consumption from the grid from all EVs, limited by the transformer

3. *Solar-PV Battery Limits*: This set of constraints represents the limits for which electricity can be consumed from solar PV - battery system.

$$(\sum_{i=0}^{EV} x_{solar,i})_t \,|_{t=1:n} \leq \frac{0.46 \cdot storage_{batt.}}{4}$$

… where the variables being represented are as follows:

- $x_{solar,i}$: electricity flow from the solar-PV battery to all EVs, for all EVs
- $storage_{batt.}$: total storage capacity (used to formulate the power demand limits)

4. *Battery - Solar Intake Limits*: This set of constraints represents the limits for which the battery of the solar PV - battery system can intake from the solar insolation.

$$x_{solar-batt,t}|_{t=1:n} \leq min.\,(solar_{limit,t}, \frac{0.46 \cdot storage_{batt.}}{4})|_{t=1:n}$$

… where the variables being represented are as follows:

- $x_{solar-batt,t}$: electricity flow from the solar-PV to the battery in the solar-PV battery system, at time *t*
- $solar_{limit,t}$: solar insolation, at time *t*
- $storage_{batt.}$: total storage capacity (used to formulate the power demand limits)

5. *Grid - Battery Intake Limits*: This set of constraints represents the limits for which the battery of the solar PV - battery system can intake from the electric grid.

$$x_{grid-batt,t}|_{t=1:n} \leq min.\,(grid_{limit}, \frac{0.46 \cdot storage_{batt.}}{4})|_{t=1:n}$$

… where the variables being represented are as follows:

- $x_{grid-batt,t}$: electricity flow from the electric grid to the battery of the solar-PV battery system, at time *t*
- $\underline{grid_{limit}}$: limit for the total electricity consumption from the grid from all EVs, limited by the transformer
- $\underline{storage_{batt}}$: total storage capacity (used to formulate the power demand limits)

6. *Demand Charge Lower Tier Limits*: This set of constraints represents the power limits for which the lower demand charge(s) cannot exceed.

In the typical case for which there is only one tiered demand structure, the bottom tier is limited as follows:

$$x_{demand,1} \le demand_{1,limit}$$

In the typical case for which there exists two tiered demand structures (for rate structure 1 during the summer), the second bottom tier is limited as follows:

$$x_{demand,3} \le demand_{3,limit}$$

… where the variables being represented are as follows:

- $x_{demand,1}$: demand charge for the rate structure's bottom tier
- $x_{demand,3}$: demand charge for the rate structure's second bottom tier (only for rate structure 1 during the summer)
- $\underline{demand_{1,limit}}$: demand charge limit for the rate structure's bottom tier
- $\underline{demand_{3,limit}}$: demand charge limit for the rate structure's second bottom tier (only for rate structure 1 during the summer)

Demand Charge

The variables for the demand charge are bound to be greater than the sum of all variables used for grid operation. Generally speaking, this is represented as follows:

$$x_{demand,1} + x_{demand,2} - \sum_{i=0}^{t} \quad x_{grid,i} \ge 0$$

… where the variables being represented are as follows:

- $x_{demand,i}$: variables for the maximum electricity demanded at any time
- $x_{grid,i}$: electricity flow from the grid to the EVs when parked, at a time *i*

Tier demand charges are minimized by the optimization to be exactly equated to the superposition of the grid charges.

For rate structures with dual-tiered demand charges, the lower tier is used first before the upper tier as it has a lower cost associated with it. For single-tier demand charges, the second variable is still present; however, it has a close-to-zero upper bound defined in the Constraints - Infrastructure Limits section, greatly limiting its contribution.

For the rate 1, summer season rate structure, two demand charges exist during the day for the weekdays, as follows:

$$x_{demand,1} + x_{demand,2} - \sum_{i=0}^{t0} x_{grid,i} \geq 0$$

$$x_{demand,3} + x_{demand,4} - \sum_{j=t0}^{t} x_{grid,j} \geq 0$$

The same rules and logic apply to this constraint; however, these two constraints exist during different parts of the day and are applied as so.

Positive Electricity Consumption

This constraint simply involves making certain that all variables in the analysis are greater than zero, to ensure that electricity use is always positive. This is shown simply as follows:

$$\sum_{j=0}^{t} x_j \geq 0$$

… where x_j represents all variables being used in the objective function.

Solar-PV Battery Minimum State-of-Charge

At all times the solar-PV battery must maintain a *minimum* state-of-charge. This state-of-charge is dependent on the electricity received from solar intake, electricity received from the grid, and the electricity consumed by the EVs from the solar-PV battery during operation. The formulation is modeled as follows for each time step and EV:

$$\sum_{j=0}^{t} x_{solar-batt,j} + \sum_{j=0}^{t} x_{grid-batt,j} - \sum_{j=0,n=0}^{t,EV} x_{batt-EVs,j,n} \geq 0$$

… where the variables being represented are as follows:

- $x_{solar-batt,j}$: variables representing the solar insolation consumed by battery, at time *i*
- $x_{grid-batt,j}$: variables representing grid electricity consumption from the battery, at time *i*
- $x_{batt-EVs,j,n}$: variables representing electricity consumption from the battery, from EV *n* and at time *i*

It should be mentioned that no upper bound was applied to the minimum state-of-charge at the end-of-day, unlike the EVs. The reason being is that this considerably increased operational costs without justification. When relaxing this constraint, the operational costs decreased with increasing battery size.

Solar-PV Battery Maximum State-of-Charge

At all times the solar-PV battery must maintain a *maximum* state-of-charge. This state-of-charge is dependent on the electricity received from solar intake, electricity received from the grid, and the electricity consumed by the EVs from the solar-PV battery during operation. The formulation is modeled as follows for each time step and EV:

$$\sum_{j=0}^{t} x_{solar-batt,j} + \sum_{j=0}^{t} x_{grid-batt,j} - \sum_{j=0,n=0}^{t,EV} x_{batt-EVs,j,n} \leq capacity_{battery}$$

… where the variables being represented are as follows:

- $x_{solar-batt,j}$: variables representing the solar insolation consumed by battery, at time *i*
- $x_{grid-batt,j}$: variables representing grid electricity consumption from the battery, at time *i*
- $x_{batt-EVs,j,n}$: variables representing electricity consumption from the battery, from EV *n* and at time *i*
- $capacity_{battery}$: constant representing the energy capacity of the battery in the solar PV - battery system

Singular Port Constraint

This constraint simply maintains that the variables representing charging from the ports to the EVs is always less than a value of two as follows:

$$\sum_{n=0,j=0}^{t,EV} x_{port,n,j} \leq 2$$

… where $x_{port,n,j}$ represents all port variables used in the optimization.

The reasoning for constraining these variables to two is that each port is assigned power associated with half of the capacity of the charging stations in use. In the case where $x_{port,n,j}$ is equal to two, an EV can be powered by the equivalent of one charging station at that particular time. The next constraint, *Total Port Constraint*, ensures that no more than ‘n’ number of charging stations dedicated to a vehicle depot is in use at any particular time.

This constraint does not apply to the yard tractors (Class 7). The variables for the port constraints are assigned as booleans, as each of the two yard tractors are assigned their own charging station.

Total Port Constraint

This constraint constrains the model so that at any particular time, the quantity of ports in use cannot be greater than the quantity of ports available, as follows:

$$\sum_{t=0}^{j} x_{port,t=j} \leq n_{ports}$$

… where the variables being represented are as follows:

- $x_{port,t}$: variables representing the use of ports at any particular time
- n_{ports}: total numbers of ports available in the optimization

Charging Port Capacity

This constraint constrains the model so that at any particular time, the quantity of power being demanded at one time cannot be greater than the power available, as follows:

$$-(x_{grid,i} + x_{solar,i})|_{i=1:(EV \cdot t)} + p_{cap} \cdot x_{port,i}|_{i=1:(EV \cdot t)} \leq 0$$

… where the variables being represented are as follows:

- $x_{grid,i}$: electricity flow from the grid to the EV, at time *t* and for a particular EV
- $x_{solar,i}$: electricity flow from the solar-PV battery to the EV, at time *t* and for a particular EV
- $x_{port,t}$: variables representing the use of ports at any particular time

This constraint goes hand-in-hand with the “Total Port Constraint,” which ensures that the total number of ports does not exceed those available. This constraint uses the results from the previous constraint to ensure that the EVs do not consume more power than possibly allotted.

Appendix C: Additional scenario results

Hardware and installation cost breakdown

Table C1 shows the hardware and installation cost breakdown by optimization type and vehicle class.

Table C1
Breakdown of non-electricity costs by vehicle class and optimization type

	Raw cost data ($/yr)								
Vehicle class/type and optimization type	Solar PV	Solar battery	Charger capital	Charger cables	Charger contracts	Charger install	Warranty	Utility make-ready	Customer make-ready
3 (Unmanaged)	$0	$0	$6,093	$509	$0	$4,830	$6,031	$4,940	$3,163
4 (Unmanaged)	$0	$0	$12,185	$1,019	$0	$7,461	$12,062	$8,930	$4,479
5 (Unmanaged)	$0	$0	$30,463	$2,546	$0	$13,256	$30,156	$19,993	$4,479
6 (Unmanaged)	$0	$0	$25,458	$1,528	$0	$10,264	$32,908	$16,097	$4,479
7 (Unmanaged)	$0	$0	$6,093	$509	$0	$4,830	$6,031	$4,940	$3,163
3 (Managed)	$0	$0	$711	$509	$387	$4,356	$796	$2,410	$3,163
4 (Managed)	$0	$0	$3,136	$509	$387	$4,528	$2,375	$3,532	$4,479
5 (Managed)	$0	$0	$9,408	$1,528	$387	$9,019	$7,124	$8,624	$4,479
6 (Managed)	$0	$0	$7,597	$1,019	$387	$7,085	$6,007	$6,785	$4,479
7 (Managed)	$0	$0	$711	$509	$387	$4,356	$796	$2,410	$3,163
3 (Mgd. w/ solar)	$4,996	$3,980	$711	$509	$387	$4,356	$796	$2,410	$3,163
4 (Mgd. w/ solar)	$13,958	$11,143	$3,136	$509	$387	$4,528	$2,375	$3,532	$4,479
5 (Mgd. w/ solar)	$64,419	$51,336	$9,408	$1,528	$387	$9,019	$7,124	$8,624	$4,479

6 (Mgd. w/ solar)	$48,205	$38,204	$7,597	$1,019	$387	$7,085	$6,007	$6,785	$4,479
7 (Mgd. w/ solar)	$4,996	$3,980	$711	$509	$387	$4,356	$796	$2,410	$3,163

Electricity cost breakdown

Table C2 through Table C6 show the electricity cost breakdown by optimization type and rate structure; each table shows these results for a different vehicle class. Results are expressed as both a net present value per vehicle, as well as an annual cost per depot.

Table C2

Electricity cost for landscaping (vehicle class 3) broken down by component and optimization type for the four rate structures simulated

	NPV/vehicle			Annual cost/depot		
Optimization and rate	Demand charge	Energy charge	Fixed charge	Demand charge	Energy charge	Fixed charge
Unmanaged, PSEG RTP	$160,913	$8,293	$21,844	$32,779	$1,689	$4,450
Unmanaged, AC RTP	$23,122	$4,764	$683	$4,710	$970	$139
Unmanaged, PSEG TOU	$107,931	$6,933	$0	$21,986	$1,412	$0
Unmanaged, O&R TOU	$30,971	$20,896	$1,885	$6,309	$4,257	$384
Managed, PSEG RTP	$22,438	$5,714	$21,844	$4,571	$1,164	$4,450
Managed, AC RTP	$2,549	$3,253	$683	$519	$663	$139
Managed, PSEG TOU	$15,113	$6,185	$0	$3,078	$1,260	$0
Managed, O&R TOU	$3,240	$6,492	$1,885	$660	$1,322	$384
Mgd. w/ solar, PSEG RTP	$15,878	$2,976	$21,844	$3,234	$606	$4,450
Mgd. w/ solar, AC RTP	$1,857	$1,779	$683	$378	$362	$139
Mgd. w/ solar, PSEG TOU	$11,553	$3,091	$0	$2,353	$630	$0
Mgd. w/ solar, O&R TOU	$2,085	$3,906	$1,885	$425	$796	$384

Table C3

Electricity cost for food service (vehicle class 4) broken down by component and optimization type for the four rate structures simulated

	NPV/vehicle			Annual cost/depot		
Optimization and rate	Demand charge	Energy charge	Fixed charge	Demand charge	Energy charge	Fixed charge
Unmanaged, PSEG RTP	$107,156	$11,331	$10,922	$43,656	$4,616	$4,450
Unmanaged, AC RTP	$17,341	$7,162	$341	$7,065	$2,918	$139
Unmanaged, PSEG TOU	$80,948	$11,293	$0	$32,979	$4,601	$0
Unmanaged, O&R TOU	$23,229	$33,074	$943	$9,464	$13,475	$384
Managed, PSEG RTP	$25,963	$9,025	$10,922	$10,577	$3,677	$4,450
Managed, AC RTP	$3,361	$5,306	$341	$1,369	$2,162	$139
Managed, PSEG TOU	$17,371	$9,961	$0	$7,077	$4,058	$0
Managed, O&R TOU	$4,405	$13,770	$943	$1,795	$5,610	$384
Mgd. w/ solar, PSEG RTP	$16,842	$4,154	$10,922	$6,862	$1,693	$4,450
Mgd. w/ solar, AC RTP	$2,576	$2,304	$341	$1,050	$939	$139
Mgd. w/ solar, PSEG TOU	$12,417	$4,260	$0	$5,059	$1,735	$0
Mgd. w/ solar, O&R TOU	$2,658	$7,408	$943	$1,083	$3,018	$384

Table C4

Electricity cost for wired telecom (vehicle class 5) broken down by component and optimization type for the four rate structures simulated

	NPV/vehicle			Annual cost/depot		
Optimization and rate	Demand charge	Energy charge	Fixed charge	Demand charge	Energy charge	Fixed charge
Unmanaged, PSEG RTP	$160,832	$16,557	$3,972	$180,192	$18,550	$4,450
Unmanaged, AC RTP	$21,020	$10,207	$124	$23,550	$11,435	$139
Unmanaged, PSEG TOU	$98,119	$15,736	$0	$109,930	$17,630	$0
Unmanaged, O&R TOU	$28,156	$44,494	$343	$31,545	$49,850	$384
Managed, PSEG RTP	$30,417	$15,447	$53	$34,079	$17,307	$59
Managed, AC RTP	$4,784	$7,444	$124	$5,359	$8,341	$139
Managed, PSEG TOU	$22,987	$14,792	$0	$25,754	$16,573	$0
Managed, O&R TOU	$6,366	$16,056	$343	$7,133	$17,989	$384
Mgd. w/ solar, PSEG RTP	$18,147	$6,485	$53	$20,332	$7,266	$59
Mgd. w/ solar, AC RTP	$2,614	$2,988	$124	$2,928	$3,347	$139
Mgd. w/ solar, PSEG TOU	$13,922	$5,995	$0	$15,598	$6,716	$0
Mgd. w/ solar, O&R TOU	$3,456	$6,589	$343	$3,872	$7,382	$384

Table C5

Electricity cost for armored cars (vehicle class 6) broken down by component and optimization type for the four rate structures simulated

	NPV/vehicle			Annual cost/depot		
Optimization and rate	Demand charge	Energy charge	Fixed charge	Demand charge	Energy charge	Fixed charge
Unmanaged, PSEG RTP	$183,696	$22,349	$6,241	$130,969	$15,934	$4,450
Unmanaged, AC RTP	$29,728	$14,276	$195	$21,195	$10,179	$139
Unmanaged, PSEG TOU	$138,769	$21,136	$0	$98,937	$15,069	$0
Unmanaged, O&R TOU	$39,820	$64,390	$539	$28,391	$45,908	$384
Managed, PSEG RTP	$40,765	$19,953	$83	$29,064	$14,226	$59
Managed, AC RTP	$6,092	$10,053	$195	$4,343	$7,167	$139
Managed, PSEG TOU	$29,348	$18,892	$0	$20,924	$13,469	$0
Managed, O&R TOU	$8,112	$23,113	$539	$5,783	$16,479	$384
Mgd. w/ solar, PSEG RTP	$25,367	$9,771	$83	$18,086	$6,966	$59
Mgd. w/ solar, AC RTP	$3,654	$4,806	$195	$2,605	$3,426	$139
Mgd. w/ solar, PSEG TOU	$19,305	$9,452	$0	$13,764	$6,739	$0
Mgd. w/ solar, O&R TOU	$4,844	$11,125	$539	$3,454	$7,932	$384

Table C6

Electricity cost for yard tractors (vehicle class 7) broken down by component and optimization type for the four rate structures simulated

	NPV/vehicle			Annual cost/depot		
Optimization and rate	Demand charge	Energy charge	Fixed charge	Demand charge	Energy charge	Fixed charge
Unmanaged, PSEG RTP	$214,312	$10,004	$21,844	$43,656	$2,038	$4,450
Unmanaged, AC RTP	$34,683	$7,321	$683	$7,065	$1,491	$139
Unmanaged, PSEG TOU	$161,897	$11,861	$0	$32,979	$2,416	$0
Unmanaged, O&R TOU	$46,457	$35,588	$1,885	$9,464	$7,250	$384
Managed, PSEG RTP	$38,505	$9,918	$21,844	$7,844	$2,020	$4,450
Managed, AC RTP	$4,113	$5,712	$683	$838	$1,164	$139
Managed, PSEG TOU	$22,576	$10,685	$0	$4,599	$2,177	$0
Managed, O&R TOU	$5,314	$15,934	$1,885	$1,083	$3,246	$384
Mgd. w/ solar, PSEG RTP	$13,330	$2,589	$21,844	$2,715	$527	$4,450
Mgd. w/ solar, AC RTP	$2,177	$1,423	$683	$443	$290	$139
Mgd. w/ solar, PSEG TOU	$9,535	$2,881	$0	$1,942	$587	$0
Mgd. w/ solar, O&R TOU	$3,608	$3,657	$1,885	$735	$745	$384

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