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Sensitivity Analysis of the Fleet Charging Impact on Feeder Load

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SUMMARY

Fleet vehicles account for a small proportion (~5%) of the total vehicles and yet represent more than 25% of the overall greenhouse gas emissions from the transportation sector. Motivated by the policies and incentives to de-carbonize the transportation sectors, major fleet operators are aiming for the 100% electrification of their fleets. The electrification of fleets, especially in industrial zones, would significantly increase the loading on the electric distribution feeders. 51 fleet owners connected to 19 distribution feeders were identified in a US metro area served by the National Grid. This paper identifies seven factors impacting the charging load peak. These factors are - dwell time, charger capacity, operating temperature, energy requirement, charging strategy, charger ratio, and time of use rates. A detailed sensitivity analysis over 19 feeders is performed to evaluate the contributions of these factors on the feeder load.

KEYWORDS

Fleet Electrification, Electric Vehicles, Medium- and Heavy-Duty Vehicles, MHDV, Charging Strategy, Battery Performance, Grid Impacts, System Planning

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Introduction: Fleet Electrification

The transportation sector has overtaken electric generation as the United States' largest source of greenhouse gas emissions. Movement to more sustainable fuel sources, such as electricity, is one path forward in mitigating transportation emissions. The electrification of fleets presents a major opportunity: medium- and heavy-duty vehicles (MHDVs) accounted for almost a quarter of U.S. transportation emissions in 2019 [2]. Addressing transportation emissions will be critical to meeting climate, environmental, and equitable access goals.

Policymakers are adopting strong targets to decarbonize fleets, and for good reason: fleets offer a substantial return on investment when it comes to decarbonization. While cargo trucks and buses account for a small proportion of total vehicles and miles traveled, they represent a far greater share of fuel use and emissions [2]. Converting fleets will take heavier polluters off the road – and when fleets make bulk purchases of electric vehicles, this conversion can have large, immediate benefits for pollution and health [2][4]. The shift to electric fleets may appear slow compared to passenger vehicles, but commercial EV adoption is expected to accelerate quickly [1]. This could result in step-changes in electric load at operators' sites, compared to steadier growth in residential and other commercial areas. Quantifying how and where fully electric fleets might impact the grid will be critical to enable fleet electrification at scale while minimizing costs for fleet planners and operators [5][6].

This paper examines seven key factors affecting fleet system planning and operations as these factors affect fleet charging needs, infrastructure investments, ongoing costs, and utility system requirements. These factors are 1) Dwell Time, 2) Charger Capacity, 3) Operating Temperature, 4) Energy Requirement, 5) Charging Strategy, 6) Charger Ratio, and 7) Time of Use Rates.

Preliminaries: Factors impacting the charging profile

1. ***Dwell Time***
   Dwell time is the total time a fleet vehicle is parked at the depot. For the fleet vehicles charging at the depot, the dwell time is critical in deciding the ratings of the charging infrastructure. A higher rated charger (kW) is required to accommodate the charging requirements during a shorter dwell time. Figure 1 illustrates the charging load peaks for the vehicles with different dwell times and similar charging kWh requirements. The fleets with lower average dwell times would need chargers with higher rated capacity (kW) to charge the fleet, thereby increasing the peak load on the system.

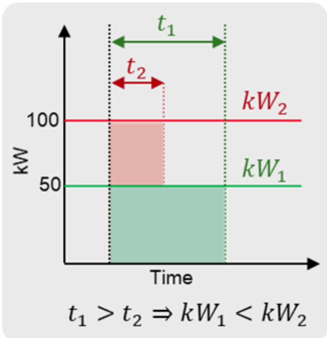


Figure 1: Effect of dwell time on the charging load

2. ***Charger Capacity***
   Figure 2 shows the charging load for 50 kW and 100 kW chargers meeting similar charging requirements during the dwell time of the vehicle. Here, the dwell time for a 50 kW charger is twice the time required to charge the vehicle at 100 kW. If managed charging strategies are not employed for higher-capacity chargers, the system could experience significant loading. On the other hand, if the charging

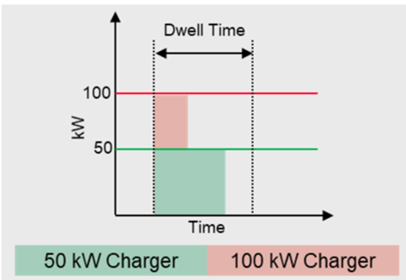


Figure 2: Impact of the charger rating on the potential charging peak load.

requirements can be met using the lower charger capacities (ex. 50 kW in the Figure 2), the system loading is constrained by the charger limits.

3. ***Operating Temperature***
   Driving efficiency decreases significantly during colder weather conditions. Almost a 40% reduction in battery efficiency can be observed in electric vehicles when the operating temperature is at -4°F for a lithium-ion battery [7][8]. Lower driving efficiency leads to higher energy usage and charging requirements during the lower operating temperature, hence the charging duration would increase during winter operating conditions (Figure 3).

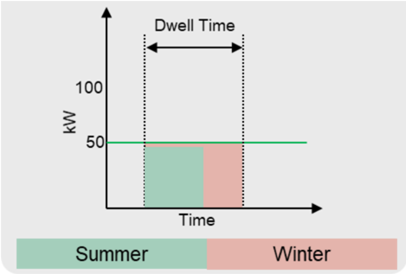


Figure 3: Effect of the temperature on the total charging requirements.

4. ***Energy Requirement***
   The energy requirement for class 8 freight trucks (Gross Vehicle Weight Rating over 33,000 pounds) would be significantly higher compared to the class 4 box truck (GVWR around 15,000 pounds). Typically, a class 8 freight truck travels about 0.45 mile/kWh vs a class 4 box truck at 0.72 mile/kWh [7]. To accommodate the different charging requirements (kWh) within the dwell time (H) of the vehicle types, appropriately rated chargers (kW) are required. Hence, the system loading varies based on the vehicle class and distance traveled by the vehicle in the fleet (Figure 4). For example, a fleet of class 8 freight trucks would need a significantly higher capacity charger to meet the charging demand.

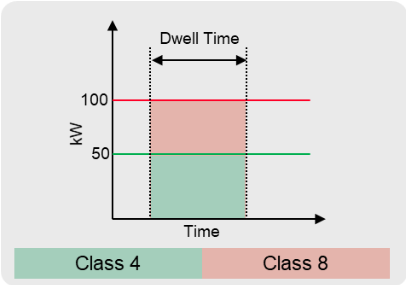


Figure 4: Difference in the charging requirements of a class 4 and class 8 vehicle.

5. ***Charging strategy***
   The charging strategy is essential in controlling the peaks of the charging load. A "Managed Charging" strategy is often considered an effective way to control the peak of charging load. For this analysis, a constant minimum charging profile, based on dwell time, is used as an indicator of managed charging benefits. As shown in Figure 5, the minimum charging strategy spreads out the charging requirement over the dwell time of the vehicle. More substantial peak reduction is observed when compared to the peak of high capacity charging infrastructure.

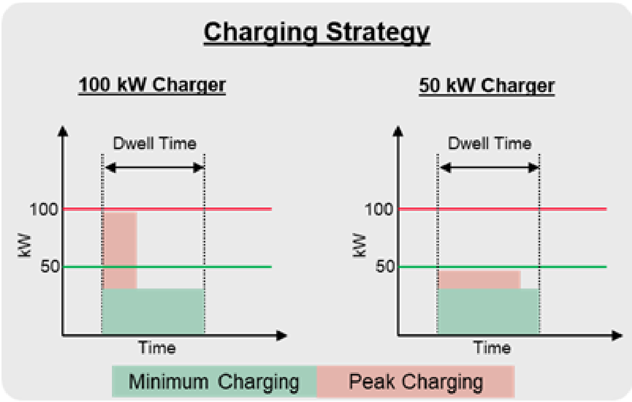


Figure 5: Impact of charging strategy on the peak charging load.

6. ***EV to Charger Ratio***

The EV to Charger ratio represents the number of electric vehicles charging from one port of Electric Vehicle Supply Equipment (EVSE)[9]. The ratio also represents the total number of EVSE for each fleet. Figure 6 compares charging scenarios for two vehicles with different EV to Charger ratios. When EV to Charger ratio is 2:1, two vehicles would be sharing one charger and charging consecutively. Here the total charging peak is limited by the charger rating. However, when each vehicle has a dedicated EVSE and they are charging simultaneously, the charging peak would be higher. Any "unnecessary" simultaneous charging can be avoided by appropriately determining the EV to charger ratio or by adopting managed charging schedules and strategies.

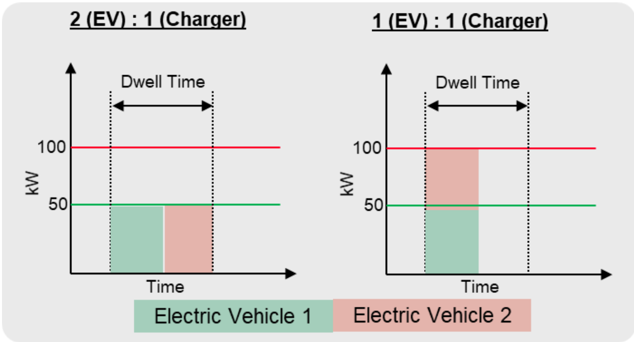


Figure 6: Potential of simultaneous charging and higher charging peak for lower EV to charger ratio.

7. ***Time of Use (TOU) Rates***

Utilities often offer lower rates to shift the EV charging load to off-peak periods. By shifting the charging of vehicles to off-peak periods, fleet owners can substantially save on electricity costs. Figure 7 shows the variations in the charging peak based on the TOU rates ($p_1 and\ p_2$).

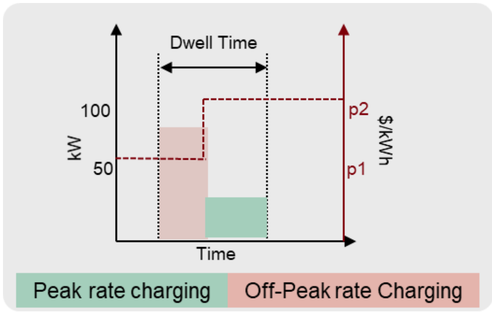


Figure 7: Shifting of the charging load based on the TOU rates.

Framework for the Analysis

The fleet schedule depends on the fleet type and the service provided by the fleet, and fleet charging patterns are based on the individual vehicle class, operation requirement, and charging infrastructure. To accommodate the uncertainties associated with fleet charging, a Monte-Carlo framework was developed. A fleet schedule is generated, for each hour of each day, determining when each vehicle is at the depot. Then, a range of charging loads is computed for each hour of each day, using the generated schedules. Lastly, each charging load is allocated to a feeder to determine the aggregate impact, considering charging sensitivities associated with the seven key factors described above. The following discussion details the major components of the framework.

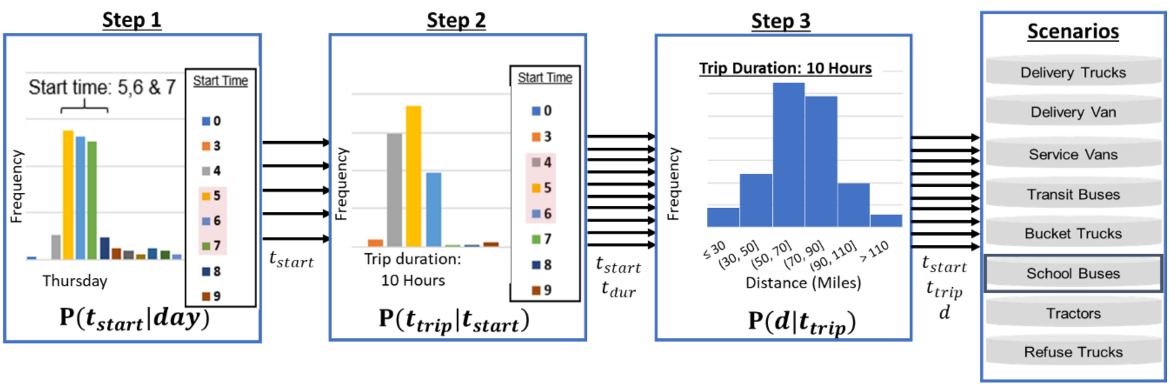


Figure 8: Monte-Carlo based framework for fleet schedule generation

Monte Carlo-Based Fleet Schedule Generation

Monte Carlo is a scenario generation technique, often used to model scenarios based on the probability of their occurrence. The approach has been widely used to identify the risks due to events that cannot be accurately forecasted due to unknown variables' intervention and contribution. In the current framework, the Monte-Carlo-based approach is used to generate scenarios for the start time, duration, and the distance covered for the trip. Based on the statistical analysis of the NREL's Fleet DNA data, the probabilistic interdependencies of these variables were identified and leveraged to generate the additional randomized scenarios. The Monte Carlo-based framework for fleet schedule generation is shown in Figure 8. Three steps are performed to generate probabilistic scenarios for fleet schedules. Using school buses as an example, illustrated below are the probabilistic relations in each step.

Step 1: Generating start time for a given fleet type on a given day.

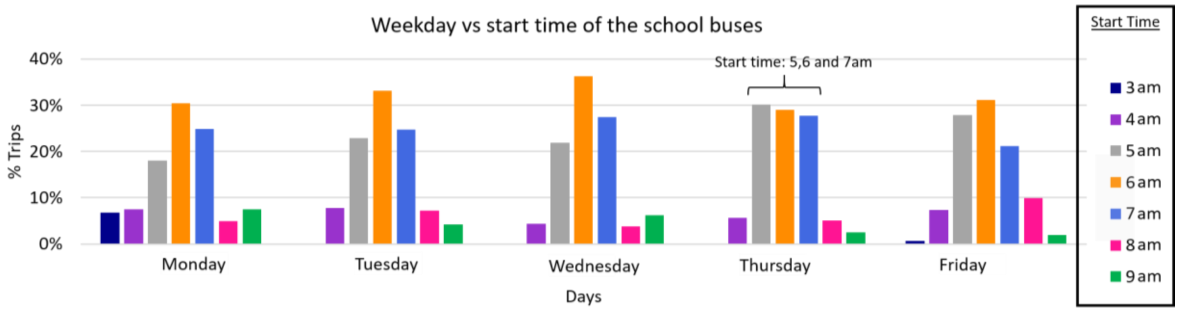


Figure 9: Probability of a trip starting at a specific hour of the day..(Fleet Type: School Bus)

Figure 9 shows the probability of school buses starting their trips at a specific hour of the day. Most school bus trips start between 5:00 am and 7:00 am, though some can begin as late as 8:00 am or 9:00 am, with more variation on Friday. This step generates *n* scenarios of trip start-time for a given day.

Step 2: Generating trip length information for a given start time and day

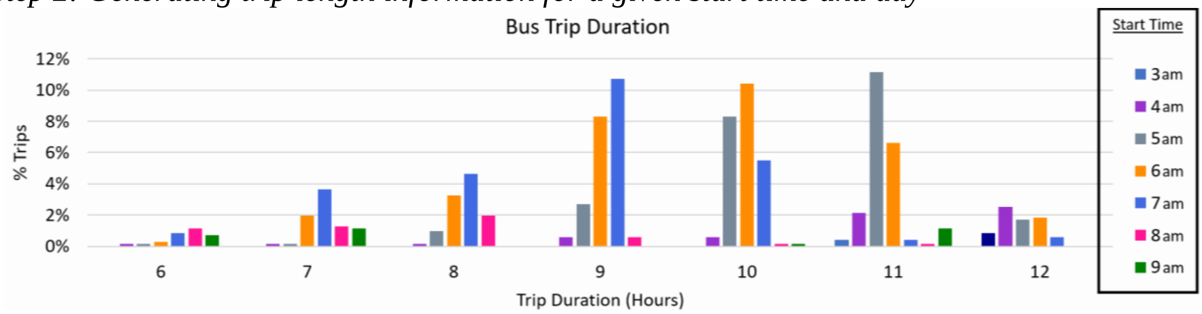


Figure 10: Distribution of the trip duration based on the start time of the trip

Figure 10 shows the distribution of the trips based on the trip start time and the trip length. Figure 10 supports the observation from Step 1 with regard to the majority trips starting between 5 am and 7 am. Moreover, it also provides information regarding the probable trip end-times. Most school bus trips in the Fleet DNA database tend to last from 8 to 11 hours.

This step generates additional *n* scenarios of trip duration for each of the *n* start time instances; by the end of this step, n^2 trip schedules are generated. Hence, each vehicle's start-time and end-time provide the information regarding the dwell-time of the vehicle at the depot. The vehicle charging needs to be accommodated during the vehicle's dwell time.

Step 3: Generating distance travelled for a given trip duration.
The distance traveled during the trip is required to identify each vehicle's energy consumption and charging requirement. The miles covered by fleet vehicles vary based on the trip duration. Figure 11 shows the distribution of the distance traveled by school buses as a function of trip durations, ranging up to 12 hours.

At the end of Step 3, n^2 scenarios are generated (based on probability of occurrence with sample data from the Fleet DNA) with the following variables:

- Day of week
- Trip start time (hour)
- Total duration of the trip in hours
- Distance traveled during the trip

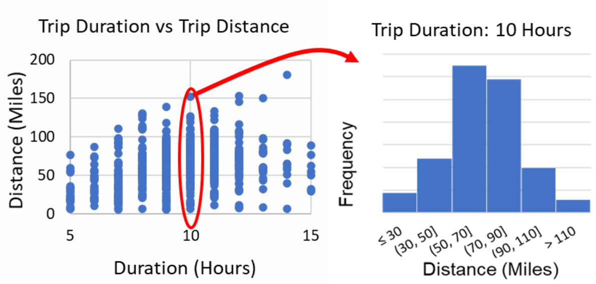


Figure 11: Distribution of the distance traveled by the school bus during a 10-hour long trip

A database is created for every class and category of fleet vehicle, with n^2 different scenarios developed for every working day. These scenarios are used to determine the potential charging load for each major fleet within the study area.

Charging Load Calculation

This Monte Carlo-based scenario generation approach develops an extensive database for each vehicle category. For a fleet, if the number (N) and type of vehicle are known, $C(N,\ n^2)$ combinations can be randomly extracted from the database to represent the fleet schedule for a typical day. Since the vehicle is assumed to charge only at the depot, the vehicle dwell-time information or parking schedule is used to determine the charging profile for a fleet. The fleet charging scenario generation process is summarized in Figure 12. A least squares-based optimization is used to approximate the aggregated charging requirements.

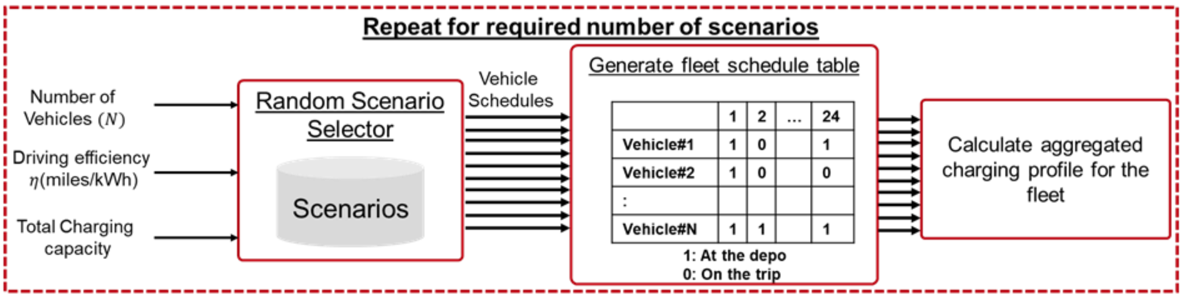


Figure 12: Aggregated fleet charging profile generation

The overall charging requirement is limited by the number of vehicles available for every hour, aggregated charging requirement for all vehicles based on the vehicle usage, charging efficiency, vehicle battery efficiency, individual charger kW limit, and the number of chargers available for every fleet vehicle. Additional constraints are added to determine the total and hourly charging requirements for a fleet. GEKKO, a python-based machine learning and optimization suite, was used to estimate the individual fleets' charging requirements at every hour.

Feeder Impact

In this study, the geographical location of the individual fleets and the distribution feeders is known and taken into account. The Nearest Neighbour Join (NN-Join) approach assigns the nearest feeder to the respective fleets that it would serve. The impact of the fleet charging load is estimated by aggregating the seasonal (summer and winter) maximum load on the feeder and the charging load from all fleets supported by the same feeder.

Implementation of the Framework

The framework was implemented to identify the impact of 100% fleet electrification in a top-100 metro area in National Grid's U.S. service territory. The analysis considers six factors to generate charging scenarios for the fleets in the study area:

1. **Fleet location:** 51 major fleet operators were manually identified in the study area through online map services and satellite imagery. The analysis assumes that fleet vehicles would only be charging at the depot, irrespective of any temporary stops during trips. The current study focuses on larger fleet operators with easily identifiable fleets. As such, small commercial sites and geographically dispersed fleets are not included in this study. Figure 13 shows all of the fleets supported by each of the 19 feeders in the study area.
2. **Fleet vehicle count:** The number of vehicles in individual fleets was estimated based on facility and parking lot sizes, the number of parking spots available, and visible vehicles at fleet locations. Figure 14 shows the total number of vehicles being supported by each of the 19 feeders in the study area.
3. **Fleet vehicle class:** Eight categories of fleet vehicles were identified based on 1) the type of service provided by the fleet operators (e.g., transit or freight) and 2) satellite images of the parked vehicles. The vehicles at each site were assigned to one or two vehicle classes, depending on available data.

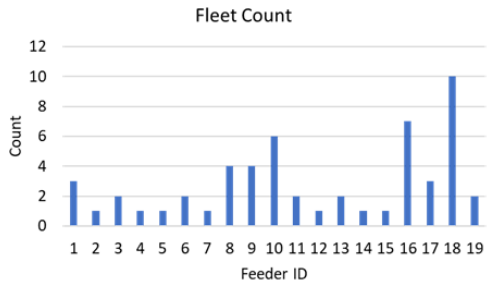


Figure 13 Fleet Count at Each Feeder

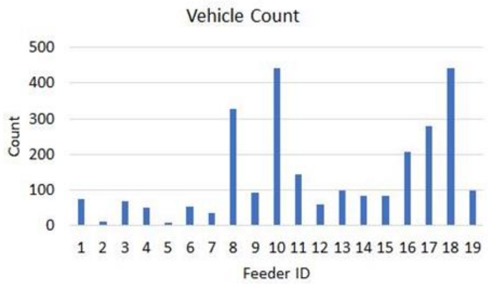


Figure 14 Vehicle Count at Each Feeder

4. **Electric vehicle characteristics:** Extensive literature review was performed based on the projected EV models available for each EV fleet vehicle category. The study area experiences cold winters, with low temperatures in January averaging 15 degrees Fahrenheit. Extremely cold ambient temperatures can significantly affect battery capacity, so the impact of temperature on battery efficiency (that is, total miles/kWh) was separately considered under winter and summer conditions for each vehicle type [1]. The total battery charging requirement is determined from the trip mileage and battery efficiency of each vehicle category.
5. **Driving pattern:** The National Renewable Energy Laboratory's (NREL) Fleet DNA dataset informed assumptions for the driving patterns of the fleet operators (Fleet DNA,

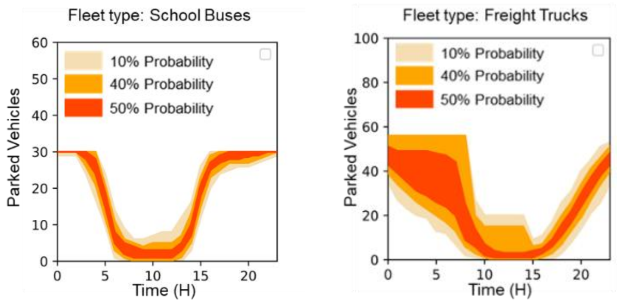
2021). The Fleet DNA dataset is an open-source real-world dataset of MHDVs and provides comprehensive information on fleet vehicles' driving patterns.

6. **Charging infrastructure ("Right Sized"):** Charger ratings are determined from 1) the average dwell time of the vehicles (time at the depot between trips) and 2) the vehicle's total energy demand for its operating profile. Charger ratings were determined such that a vehicle's battery could fully charge during its dwell time. All charging is assumed to be performed at the depot, with no opportunistic or on-route charging. This "right-sized" infrastructure also assumes two vehicles per charger for every fleet.

19 feeders were identified supporting the major fleet locations. The peak load for every hour for summer and winter was extracted from the dataset and used as a base (non-EV) load for each feeder.

Results and Discussion

This section analyzes the impact of the factors listed in earlier section on charging load. Unless specified, the study uses the full charging strategy with "right-sized" charger capacities as the reference to the base case to identify the sensitivities of the factors. The EV:EVSE ratio is 2:1 for the base case. The variable's sensitivity to the charging load is illustrated through a fleet of 30 school buses and a separate fleet of 56 freight trucks. Figure 15 shows the parking schedule of the school buses and the freight trucks. The use case of the school bus and freight truck is interchangeably used based on the relevancy of the variable studied.



(a) 30 School Buses (b) 56 Freight Trucks

Figure 15: Vehicle parking schedule

1. ***Dwell Time:***

Vehicles charging at full capacity on arrival will not be significantly sensitive to the dwell time since the vehicle's charging is independent of the vehicle's dwell time. However, the magnitude of the peak with a minimum charging strategy is dependent on the vehicle's dwell time. An incremental analysis identifies the sensitivity of the fleet's peak charging load to the average dwell time of the vehicles. Figure 16 shows a reduction in the peak charging load with increasing dwell time for the fleet of 30 school buses. The fleet shows the reduction at the rate of ~31 kW for an additional hour of the average dwell time. Since the fleet consists of 30 school buses, the charging peak to the dwell time sensitivity for each vehicle can be estimated as ~1.26kW/hour.

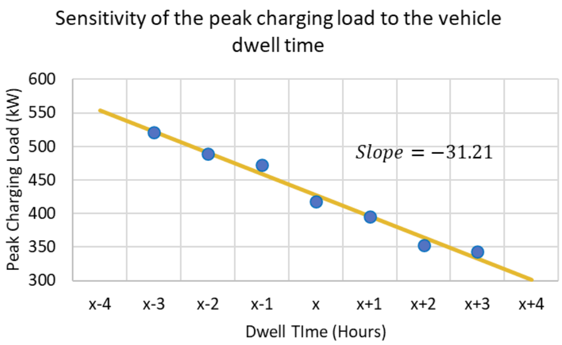


Figure 16: Sensitivity of charging load to the dwell time of the studied 30 school buses case.

2. ***Charger Capacity:***
The charger capacity, or charger rating, significantly impacts the peak load, especially if the vehicles charge at the rated charger capacity on arrival. An incremental analysis identifies the sensitivity of the peak charging load to the charger capacity for the fleet of 30 school buses. The base case rating for the school bus chargers is 19.2 kW (Right Sized). The parking schedule of the school buses is shown in Figure 15. Most school buses arrive at the depot between 3-4 pm. Since the arrival time for all vehicles is not distributed over a broader time duration, all the depot chargers are occupied by the fleet vehicles at 4 pm, and simultaneous charging of the vehicles increases the fleet's charging peak linearly with the charger capacity (Figure 17). In other words, for a 1 kW increase in charger capacity, the charging peak increases by 15 kW since there are 15 operational chargers for the fleet. Figure 18 relates the impact of increased charging load aggregated at the feeder level with the increased charging capacity (by two times) against the base case with right-sized charger ratings. The slope of the regression line indicates a 68% increase in the peak of the charging load aggregated at the feeder level.

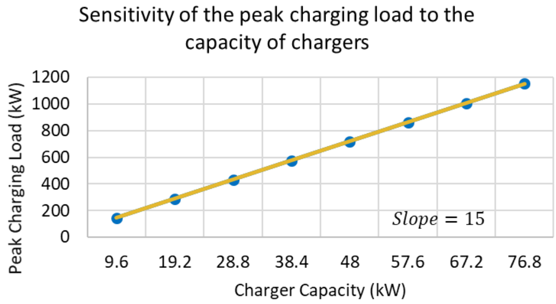


Figure 17: Variation in the charging load with the charger rated capacity of the studied 30 school buses case.

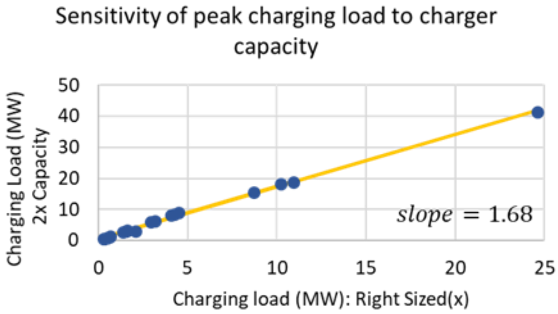


Figure 18: Sensitivity of the charging load aggregated to the rated charger capacity at feeder level.

3. ***Operational Temperature***
The battery efficiency of electric vehicles varies based on the operational temperature. The charging requirements are almost 40% higher during severe winter conditions. A comparative study for severe winter and moderate summer conditions analyzes the impact of temperature on the charging peak. Figure 19 shows the difference in the total charging requirements for the fleet of 30 school buses. The charging efficiency is assumed to be 85% for both winter and summer conditions. Hence, the charging requirements for the

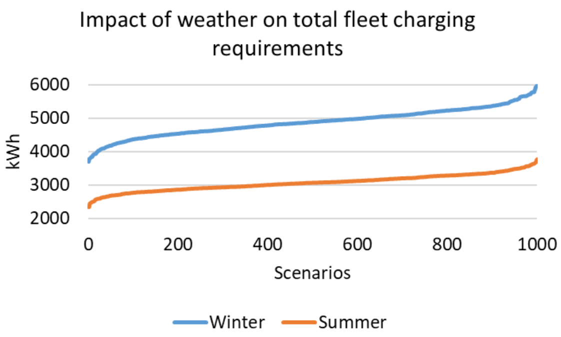


Figure 19: Total charging requirements during summer and winter operating conditions for a fleet of 30 school buses.

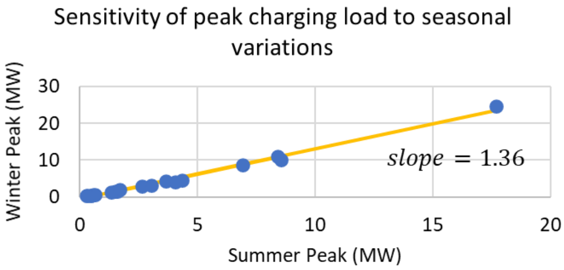


Figure 20 Sensitivity of the charging load aggregated at feeder level to the operational temperature.

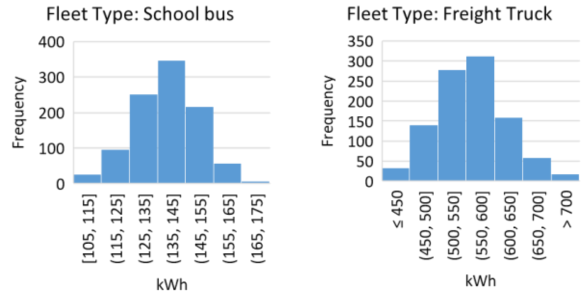
school bus fleet increases by 56% during winter. The peak charging load depends on both the charging requirement and fleet arrival time. Since the arrival time and mix of vehicle types is different for all feeders, the peak reduction varies for all feeders. Figure 20 shows the comparison in the charging peak for all 19 feeders. The slope of the regression plot suggests a 36% increase in the peak load among the 19 feeders during winter.

4. ***Energy Requirements***

Depending on the application of the fleet vehicle, the manufacturer sizes up the battery storage capacity of the fleet vehicle. Factors like vehicle class, average distance covered by the vehicle, and many more are considered while determining the size of the battery. Hence, the charging requirement varies based on the fleet's targeted service. Figure 21 shows the charging demand from 1,000 trips of school buses and freight trucks. The average charging requirement of a school bus is 138 kWh, whereas the average charging requirement for a freight truck is 557 kWh. Higher capacity chargers would be needed to accommodate the high energy needs of the freight trucks within the dwell time of the vehicle. Hence, the charging peak is higher for the feeders supporting heavy-duty fleets like freight trucks. Figure 22 represents the linear rise charging peak based on energy requirement. For every 1 MWh increase in the energy needs, there is a 0.1 MW increase in peak demand on the feeders.

5. ***EV to Charger Ratio:***

An increased number of chargers lowers the wait time of the incoming vehicle for charging. However, simultaneous charging of vehicles increases the charging load peak. Figure 23 shows the variation of charging peak load with the charger count for a fleet of 56 freight trucks. Since the chargers are rated at 150 kW, the load increases at 150 kW per charger until the charger count reaches



(a) School bus (b) Freight truck

Figure 21: Distribution of energy requirements of school buses and freight trucks

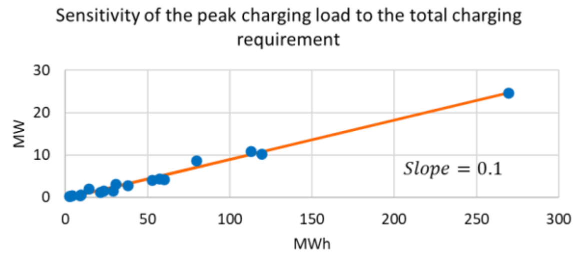


Figure 22 Sensitivity of the charging load to the charging requirements aggregated at feeder level.

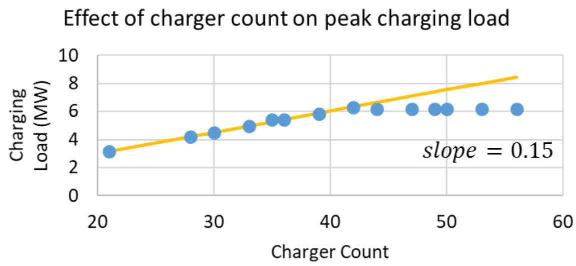


Figure 23 Sensitivity of the charging peak to the charger count.

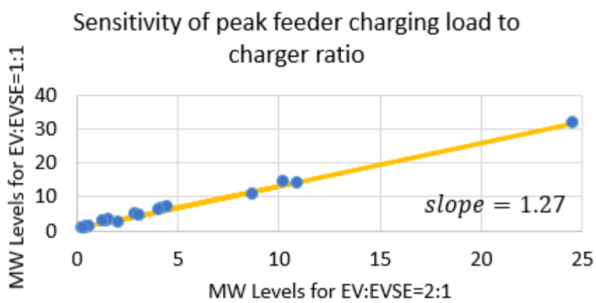


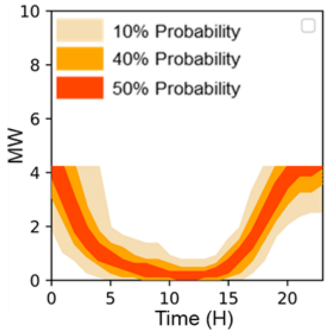
Figure 24 Sensitivity of the charging load to the charger ratio.

42. Beyond 42 chargers, the growth in charging load is not observed, indicating that there is never simultaneous charging of more than 42 freight trucks. The elbow point varies for all fleets based on their driving and depot parking schedules. Figure 24 compares the peak charging load of two different charger ratios for 19 feeders. The slope of the fitting line is 1.27, indicating approximately a 27% increase in the charging peak load for a higher charger ratio (1 EV per charger).

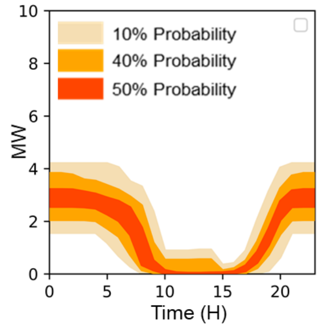
6. ***Charging Strategy:***
As discussed in the previous sections, the impact of full charging and minimum charging strategies are analyzed in the current paper.

- **Full Charging Strategy:** This is the base case presented in the paper. This strategy assumes that the fleet vehicles charge at the full charger nameplate rating immediately upon returning to the facility (or upon a charger becoming available). Therefore, if a vehicle is using a 150 kW-rated charger, it will charge at 150 kW until the battery is fully charged.
- **Minimum Charging Strategy:** This strategy assumes that fleet vehicles charge at the minimum rate possible to fully charge during the vehicles' dwell time. That is, even if a vehicle is using a 150 kW-rated charger, it may charge at less than 150 kW, as long as that lower rate allows it to fully charge before it departs the depot. The optimization routine manages the charging schedule of the parked vehicles and adjusts the rate of charging of the fleet to meet vehicles' overall charging requirement during their dwell time at the lowest charging peak at the facility. Vehicles could charge at their full nameplate rating for a period of time and then a lower rating as more vehicles return to the depot.

Figure 25 shows the fleet charging profiles for 56 freight trucks supplied by 28 150 kW chargers. The charging infrastructure sets the hard upper limit of 4.2 MW. The peak charging limit is reached by >75% scenarios when a full charging strategy is implemented. However, <5% of scenarios reach the charging limit when a minimum charging strategy is implemented. The charging peak is approximately 3.5 MW for >75% of scenarios with minimum charging. The full charging and minimum charging strategies were analyzed on the 19 feeders with 51 fleets observed in the study area. The linear regression plot (Figure 26) quantifies the reduction in the peak load through a minimum charging strategy. The slope of the fitted line indicates a 16% reduction in the peak through minimum charging for the right-sized infrastructure.



(a) Full Charging Strategy



(b) Minimum Charging Strategy

Figure 25 Charging load profile for a fleet of 56 freight trucks

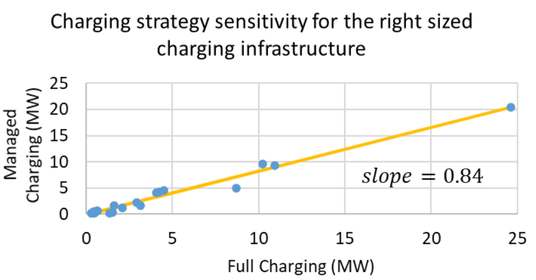


Figure 26 Sensitivity of the charging load peak to the charging strategy for 19 feeders.

The slope would decrease further for any additions to the charging capacity (such as lower EV:EVSE ratio or higher charger capacity).

7. ***Time of Use (TOU) Rates***
TOU rates with low off-peak prices may motivate fleet owners to shift the charging to off-peak hours. Further study is required, along with the modeling of consumer behavior, to understand the impact of TOU rates on shifting charging load peak. The shifting charging load would provide sensitivity/elasticity coefficients relating to the consumer's response to the TOU price difference.

Cross Interaction of the Sensitivity Factors and Their Impact on the Feeder Load

Figure 27 captures the effects on the overall feeder load from the interaction between charging infrastructure and charging strategy. The analysis assumes that all of the charging requirements and schedules are constant for all the use cases. However, the peak load significantly differs between use cases, indicating the sensitivity of the charging load to changes in the charging strategy and charging infrastructure. For the full charging strategy, the ranking of the sensitivities of the feeder peak load to the charging infrastructure correlates for all feeders. The base case with "Right-Sized" charging infrastructure has the lowest peak for all feeders under "full charging" assumptions, and the scenario with oversized charging infrastructure has the highest peak loads. Managed/minimum charging strategies should be encouraged to reduce feeder loading. In the case of the minimum charging strategy, the peak charging load is similar regardless of the charging capacity and the number of chargers, as fleets charge at the minimum even if they have faster charging methods available.

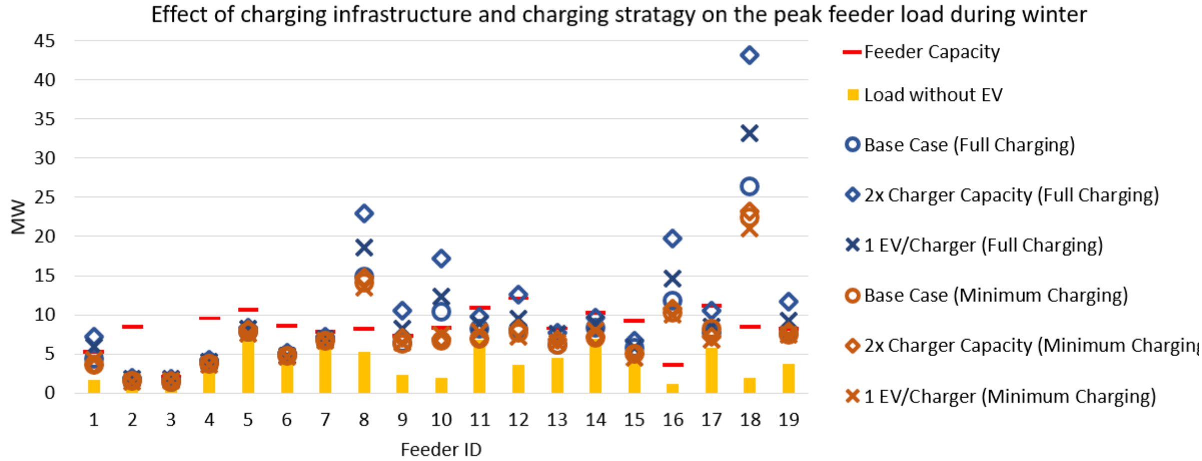


Figure 27 Impact of the charging strategy and infrastructure on the feeder peak load during winter

Conclusion

This paper identifies and evaluates seven key factors impacting EV demand and electric loads. Table 1 summarizes the observations of the charging load to each of the seven factors. The capacity of the charging infrastructure can be increased by both increasing the charger count and increasing the charger capacities. The sensitivity of charger capacity to charging load is higher for charger rating (68%) compared to the higher charger count (27%) based on our case study. Further, charging strategies are effective (>16%) in reducing the peak of charging load in this case. Future work could include the modelling of fleet owners' responses in shifting the charging peak based on the TOU rates.

Table 1: Summary

Factor	Observations
Dwell Time:	Varies for every fleet based on the schedule. The decrease of dwell time will increase the charging demand to ensure the fleet are fully charged. Understanding available dwell time for vehicle operations will be a useful input to estimating the opportunities for reducing peak charging needs.
Charging Capacity	Higher charging capacity facilitates faster charging of vehicles. Simultaneous operation of higher capacity chargers increases the total charging load of the fleet.
Operational Temperature	Driving efficiency is lower during winter. Hence, the charging requirements and charging load increases during cold operating conditions. Reliable business operations will require consideration of seasonal temperature impacts such that installed chargers can meet greater energy needs in winter. Feeders with many fleet vehicles may see a shift in annual peak from summer to winter due to the higher charging load.
Energy Requirements	Fleets with heavy duty vehicles need high-capacity chargers to meet the higher charging requirements. Hence, the charging load is higher for feeders supporting heavy duty fleets.
EV to charger ratio	The wait time of vehicles is reduced with a lower EV to charger ratio, but the simultaneous charging of more vehicles increases the charging load of the fleet. This could increase ongoing energy costs and the upfront cost to procure and install the additional EVSE.
Charging Strategy	Chargers are utilized at the rated capacity under full charging strategy. The minimum charging strategy distributes the charging load over the available dwell time, hence the charging peak is lower with minimum charging strategy. Understanding operational schedules and the ability for vehicles to charge at lower rates throughout their dwell times could allow greater participation in managed charging programs, reduce system needs for EV charging, and reduce energy costs for fleet operators.
Time of Use Rates	TOU rates may motivate the fleet operators to shift the vehicle charging to off-peak periods which would decrease the loading on the feeder peak.

Acknowledgements

This paper was developed from a more detailed study by National Grid and Hitachi ABB Power Grids titled "The Road to Transportation Decarbonization: Understanding Grid Impacts of Electric Fleets," available on National Grid[1] and Hitachi ABB Power Grids[2] websites.

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