Applied Energy 335 (2023) 120760

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Electrified autonomous freight benefit analysis on fleet, infrastructure and grid leveraging Grid-Electrified Mobility (GEM) model

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ARTICLE INFO

Keywords:
EV-grid integration
Freight electrification
Smart charging assignment
Benefit analysis

ABSTRACT

Fast-growing freight activities over the decades have become one of the major contributors to air pollution, leading to many efforts in freight decarbonization and electrification. However, the development of freight electrification is slow due to technological uncertainty, slow charging, high capital cost, etc. This paper analyzes the potential impact and benefit of heavy-duty vehicle (HDV) electrification and automation on fleet cost, infrastructure cost, the electricity grid, and environmental outcomes. In this work, we extended the vehicle electrification benefit analysis tool: Grid-Electrified Mobility (GEM) model, which had primarily been used to study light-duty passenger vehicles (LDVs), to analyze heavy-duty vehicle electrification. The extended model is derived for freight transportation electrification, and different freight electrification and automation adoption scenarios were analyzed. We find that the increased penetration of automated electric freight fleets within other types of electrified freight fleets from 1% to 99% will result in an overall cost reduction of 18.2%, fleet size reduction of 20.4%, and lower peak load reduction of 14.3%.

1. Introduction

The transportation sector is undergoing a transformation through the introduction of on-demand mobility and vehicle automation thanks to a variety of emerging mobility technologies [1]. These advances, combined with electrification, could create new synergies that would provide high-quality, low-cost, and energy-efficient mobility at scale [2]. However, the adoption of plug-in electric vehicles has been relatively slow for several reasons, including technological uncertainty, slow charging, range anxiety, and higher capital costs than other types of vehicles [3,4]. This is especially true in the freight industry, particularly around heavy-duty truck electrification and operation. As major truck fleet operators and truck manufacturers have announced plans to accelerate truck electrification, filling these gaps in system modeling capabilities will be crucial. For example, Walmart aims to electrify its entire truck fleet within a decade [5]. The uptake in the adoption of electric trucks is important in the context of rising freight demand, which is projected to grow by 52% from 397 billion miles in 2018 to 601 billion miles in 2050 projected by U.S. EIA [6]. While there is still a great deal of uncertainty around the exact impact that automated vehicles will have on the transportation system in the coming decades [7], many believe that they could soon become a substantial part of the transportation system, dramatically disrupting conventional modes of mobility.

Vehicle cost–benefit analysis has been widely studied in the past decades with the evolution of vehicle electrification/decarbonization technology. With the wide application of hybrid electric vehicles (HEVs), many studies have investigated the cost–benefit of HEVs. In [8,9], the team in NREL conducted a cost–benefit analysis to compare the costs (including vehicle purchase costs, energy costs, and battery costs) and the benefit of petroleum consumption reductions between plug-in hybrid electric vehicles (PHEVs) and conventional vehicles. They found that while PHEVs can result in over 45% of petroleum consumption reduction, the long-term projection cost of PHEVs can be over $8000 higher than conventional vehicles. Due to the great fuel-saving potential, governmental support is needed to accelerate the PHEV deployment. In [10], the authors presented a cost–benefit analysis of hybrid and electric buses in fleet operation. They found that PHEV and electric buses have a great potential to reduce energy consumption and emissions, and the cost efficiency also depends on the routing and scheduling of the buses. In [11], the authors introduced hybrid energy system modeling and conducted a cost–benefit analysis of hybrid energy systems for locomotives. In several other studies,

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https://doi.org/10.1016/j.apenergy.2023.120760
Received 26 September 2022; Received in revised form 7 January 2023; Accepted 22 January 2023
Available online 27 January 2023
0306-2619/

researchers have also examined the vehicle-level cost–benefit analysis for electric vehicles (EVs) compared to fuel-cell vehicles. In [12], the authors investigated the economic validity of fuel cell vehicles (FCVs) and (EVs). Their study found that the FCV diffusion is not economically beneficial until 2110, whereas EV diffusion might become beneficial by 2060, considering increasing gasoline pricing and emissions abatement costs. In [13], the authors studied the impact of EV energy storage with vehicle to grid (V2G), and identify the potential benefit of EV deployment to future energy pricing. In [14], the authors developed a case study to perform a cost–benefit analysis (including the energy sector, transportation sector, and household sector) to support the decarbonization scenario for 2030 in Italy. In this study, they found that public transport and electric mobility improvement have significant environmental and economic benefits. These studies mainly focused on the environmental and fuel consumption related cost–benefits for individual vehicles. Moreover, the primary focus of the above studies is on passenger vehicles, and freight vehicle electrification is seldom considered. In Hu et al. [15], the authors reviewed the EV fleet management in the smart grid from a control and optimization aspect. This review paper summarized state-of-the-art studies on EV fleet management control/optimization approaches taking into account the impact of the smart grids. However, the freight electrification studies are also not included in this review. In Tong et al. [16], the authors studied the GHG emissions for medium and heavy-duty vehicles based on an analysis of different natural gas pathways for MD/HDVs. This study identified the projection of natural gas usage to different freight fuel types and analyzed fuel consumption based on fuel usage, as well as the fuel consumption and GHG emissions originating from freight vehicles. They found that electric trucks reduce emissions significantly (31%–40%) compared to diesel or gasoline trucks. In Gao et al. [17], the authors conducted vehicle-level simulation and energy consumption analysis for plug-in hybrid electric trucks and battery electric trucks. Their results showed that electric trucks not only reduce energy consumption but also achieve significant energy cost savings (by 29% to 44%) compared with diesel fuel trucks. In Klauenberg et al. [18], the authors studied the potential users for vehicle electrification in commercial transport. They analyzed the economic sectors and conduct surveys with fleet managers to analyze the vehicle electrification potential. The above freight-related cost–benefit analysis considered the influence of freight electrification from multiple avenues. However, there is still a lack of comprehensive benefits analysis that studies the influence of freight electrification across environmental, economic, and grid impacts.

Overall, the urgent need to decarbonize the transportation sector combined with falling battery prices has spurred industry and policy interest in long-haul truck electrification. Understanding the charging behavior and resulting loads from freight electrification will be critical for the smooth operation of the electric grid and will have far-reaching impacts on the environment in the form of greenhouse gas (GHG) emissions and air pollution. As such, this work has aimed to assess the benefits of heavy-duty truck electrification and emerging vehicle electrification opportunities in micro-mobility markets using the Grid-Integrated Electric Mobility Model (GEM) and Medium and Heavy-Duty Electric Vehicle Infrastructure — Load Operations and Deployment (HEVI-LOAD) tool. This national model simultaneously optimizes the provision and operation of heavy-duty autonomous electric vehicles (HAEVs) to provide electrified goods mobility alongside an economic dispatch of power generation.

Our work examines a dynamic future where increasing levels of renewable energy are being added to the electric grid while vehicle electrification is simultaneously on the rise. The impacts of integrating these technologies require new analytical approaches that couple capabilities across the transportation and power sectors. This work has further developed the GEM model to explore these dynamics and the impacts of an integrated intelligent transportation-grid system in which mobility is served by either human-driven electrified trucks or autonomous electric trucks, charging is responsive to costs on the grid, and power resources are dispatched in merit order to serve electricity demand.

In previous works, the phase-one Grid-Integrated Electric Mobility model (GEM v1.0) was developed for passenger vehicle benefit analysis. This model can analyze the energy use, grid integration, and environmental and cost impacts for electrified mobility sectors including private light-duty EVs and shared automated light-duty EVs [19,20]. In this work, we extend the previous study to a broader electrified mobility sector which includes heavy-duty electrified vehicles. Moreover, we specify the electric fleets into more detailed component groups to consider the impact of human-assigned charging behavior versus smart-assigned behavior for human-driven trucks (HTs). The primary objectives of this work include:

- Development of a new method that can simulate the future electrified and automated freight transportation systems and quantify the national impact of electrified mobility-grid interactions.
- Analyze the impact of truck electrification, automation, and charging assignment on grid operation, charging infrastructure assignment, cost of trucks, fleet size, environmental benefits, etc.

The rest of the paper is organized as follows: Section 2 introduces the approaches used for this benefit analysis, Section 3 introduces the extended GEM modeling, Section 4 presents and discusses the results of our study, and finally, Section 5 provides a conclusion.

2. Approach

This work expands on the development of an optimization model that simultaneously solves the cost-minimizing dispatch of electrified heavy-duty vehicle fleets for operation and charging as well as the operation of the electricity system in the United States. Specifically, this optimization model can examine: (1) the allocation of heavy-duty autonomous and electric vehicles (HAEVs) to serve goods-delivery; (2) the investment and construction of a HAEV fleet and supporting charging infrastructure; and (3) the economic dispatch of electric power plants for the US bulk electricity grid. The power sector was included by coupling GEM to the Grid Operation Optimized Dispatch (GOOD) electricity model [21]. This combined model treats the size of the HAEV fleet and the amount of charging infrastructure as continuous decision variables (relaxing the problem from mixed-integer convex optimization to quadratic programming), allowing for heterogeneous vehicle ranges and charger levels. The model minimizes the total system costs (i.e., operating costs and capital costs) by choosing the timing of vehicle charging subject to several constraints: mobility demand is always served, energy is always conserved, and those generation assets on the grid are dispatched in merit order. Heavy-duty autonomous and electric vehicles (HAEVs) fleet planning costs are simultaneously minimized by amortizing the cost of the fleet and charging infrastructure to a daily period.

2.1. GEM

The Grid-integrated Electric Mobility (GEM) model is an open-source modeling platform developed by researchers at Lawrence Berkeley National Laboratory, UC Davis, and UC Berkeley [20]. This modeling system simulates mobility and electricity operations on a national scale. The framework of GEM is unique in that it optimizes a fully autonomous, electric, and shared mobility system while dynamically accounting for high-fidelity grid models. The first version GEM model mainly focuses on the operation of light-duty vehicles. In this work, we are extending this GEM model to a broader application that considers freight behaviors. The overall workflow of the expanded GEM model developed in this paper is summarized in Fig. 1 and the expanded GEM platform (GEM v2.0) can be found in [22]. This expanded GEM model co-optimizes the complete electrified mobility system and the

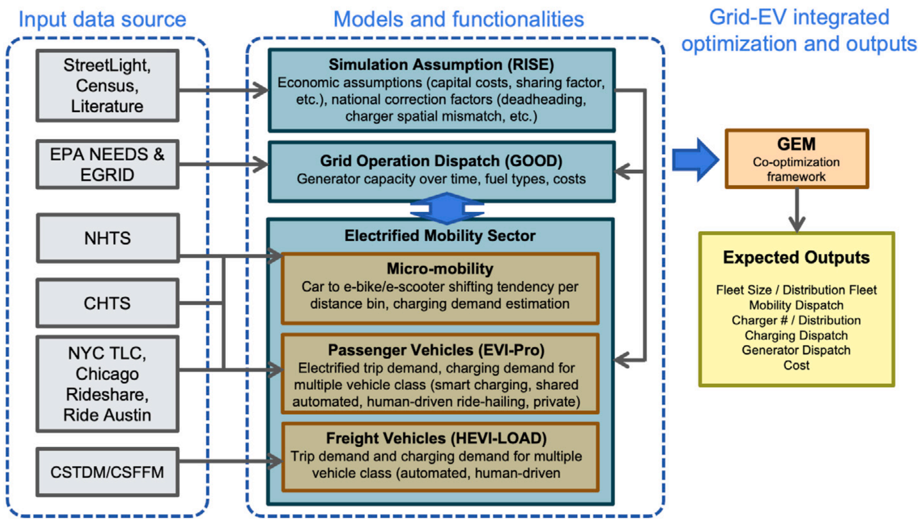


Fig. 1. Extended Grid-Integrated Electric Mobility (GEM) model processing workflow.

grid operation. The model consists of three types of modules: (1) Simulation assumption definition module, where we use the Routing and Infrastructure for Shared Electric vehicles (RISE) model to generate correction factors over a national scale and define the basic simulation assumptions for the GEM model based on data sources including StreetLight, Census, and other literature; (2) Grid optimization module, where we use the grid operation optimized dispatch (GOOD) model to calculate the power grid operation and the generator capacity, fuel types, grid costs, and other grid-related parameters using EPA NEEDs & EGRID data; (3) electrified mobility system, which is used for mobility sector charging and travel behavior modeling. This module is then divided into three mobility sectors: micro-mobility, passenger vehicles, and freight vehicles. For the micro-mobility sector, we use the national household travel survey (NHTS), the California household travel survey (CHTS), and ride-share data to estimate the car to e-bike shifting trip demand and charging demand. For passenger vehicles, we use the EVI-Pro tool with NHTS, CHTS, and ride share data to estimate the charging demand and trip demand for different vehicle classes (shared automated, shared human-driven, private automated, private human-driven). For freight vehicles, we use the Medium and Heavy-Duty Electric Vehicle Infrastructure — Load Operations and Deployment (HEVI-LOAD) tool with California Statewide Travel Demand Model (CSTDM/CSFFM) to estimate the charging demand and trip demand for freight vehicle classes (automated, human-driven). Using these three modules we can co-optimize the grid with the electrified mobility system under national scale assumptions and obtain the optimal mobility system and grid outputs including optimal fleet distribution, fleet mobility dispatch, charger distribution/dispatch, generator dispatch, overall costs, etc. Then these results are used for electrified mobility benefit analysis under different vehicle electrification scenarios. The novelty of this work compared to GEM v1.0 is that a more sophisticated mobility system is considered with multiple mobility sectors (including HDV, micro-mobility sector, human-driving LDV/HDVs, and ride-sharing). This expanded model will better summarize the electric mobility system operations and costs under a more comprehensive mobility electrification scenario. In this work we analyze the cost–benefit impact of HDVs under a joint operation/optimization scenario of all mobility sectors, whereas GEM v1.0 focused on the LDV-related cost–benefit analysis under a passenger vehicle only operation scenario.

2.2. HEVI-LOAD

HEVI-LOAD is a modeling tool developed by Lawrence Berkeley National Laboratory to project the state-wide charging infrastructure needed to accommodate the growing number of medium- and heavy-duty electric vehicles. To accelerate the decarbonization of medium and heavy-duty (MD/HD) vehicles in California and other states in the United States, HEVI-LOAD projects the number, type, and location of chargers and the related electric grid supply requirements to support the new charging stations. HEVI-LOAD consists of two analytical approaches to determine the load profiles and charging infrastructure needs: (1) the top-down approach that assesses the county-level charging load profile and infrastructure scenarios, and (2) the bottom-up approach that incorporates more granular (temporal, spatial, and duty-cycle-specific) behaviors of a variety of MDHD vehicles into the agent-based activity simulations for optimal charging infrastructure siting and sizing. Fig. 2 shows the preliminary charging load profile analysis for a variety of MDHDs in California, in 2030.

3. Problem formulation

In the previous GEM model, the light-duty vehicles (LDVs) were modeled and the optimization problem has been defined under an LDV framework [19]. In this work, we have extended the LDV GEM modeling to a more comprehensive optimization model that includes LDVs, and HDVs. The dimensions of the model include time, t, mobility region r, grid region i, LDV battery size b, HDV battery size b^H, LDV charger level l, HDV charger level l^H, LDV trip distance d, HDV trip distance d^H, and electricity generator g. The model is a quadratically constrained program and can be efficiently solved with a second-order cone programming solver (Cplex).

Note that the scale of the GEM framework is for the entire United States, where we divided the US into 13 mobility regions: East-South-Central (ESC), West-South-Central (WSC), Mountain (MTN), Pacific (PAC), New England (NE), Mid-Atlantic (MAT), South Atlantic (SAT), East-North-Central (ENC), West-North-Central (WNC), California (CA), Florida (FL), New York (NY), and Texas (TX). Each of these regions is divided into rural and urban, making an overall 26 regions. The modeling of each mobility sector and the grid sector are aggregated into these regions. On this scale of modeling, some detailed components are ignored for simplicity.

3.1. Objective function

As described in the main body of this article and previous work [19], the objective function minimizes the amortized daily cost of the fleet

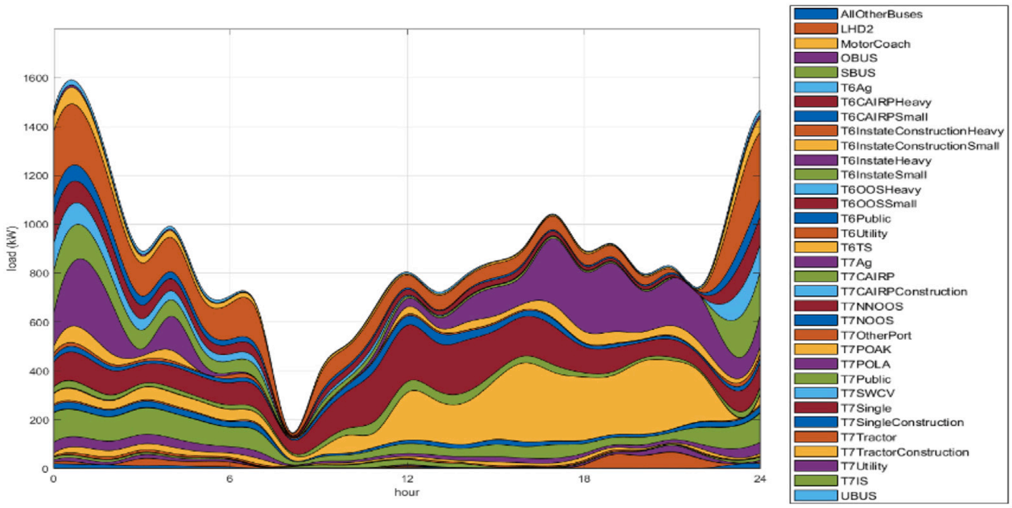


Fig. 2. Example Charging load profile of different types of electric trucks from HEVI-LOAD for California, 2030.

and infrastructure, fleet operation, and electricity grid operation.

$$\min Z = \sum_r \left[\sum_t \left(C^d_{tr} + C^m_{tr}\right) + nC^c_r + nC^v_r \right] + \sum_{g,t} \left(G_g C^g_g\right) + \sum_{i,t,i'} \left(T_{i,t,i'} C^t_{i,t,i'}\right) \tag{1}$$

where C^d_{tr} is the demand charge or capacity cost to use the grid and C^m_{tr} is vehicle maintenance cost in hour t and mobility region r, C^c_r is the amortized daily charging infrastructure cost, C^v_r is the amortized daily fleet cost, n is the number of days in the simulation time horizon, G_g is the electricity produced by generator g, C^g_g is the cost of producing a unit of energy by generator g, $T_{i,t,i'}$ is the electricity transmitted from grid region i to grid region i', and $C^t_{i,t,i'}$ are transmission wheeling costs.

The objective is subject to several constraints as described in the following section.

3.2. Constraints

Vehicle Maintenance Cost: mileage-dependent vehicle maintenance.

$$C^m_{tr} = \sum_{b,d} \beta_v V^m_{bdtr} v_{dtr} + \sum_{b^H,d^H} \beta^H_v V^{mH}_{b^H d^H tr} v^H_{d^H tr} \tag{2}$$

where β_v, β^H_v are the per-mile vehicle maintenance costs for LDVs and HDVs, $V^m_{bdtr}, V^{mH}_{b^H d^H tr}$ are the number of vehicles of types b, b^H serving mobility demand of trip length d, d^H in hour t and region r, and $v_{dtr}, v^H_{d^H tr}$ are the average speeds of the vehicles driving trips of length d, d^H. Costs associated with cleaning and service are included in maintenance. Note that all the terms with a superscript H are associated with the HDV components respectively in this section of the constraint expression.

Demand Charge Cost: cost of grid capacity.

$$C^d_{tr} = P^{max}_r \beta_r / 30.5/24 \tag{3}$$

P^{max}_r is the maximum power demand over the time horizon, β_r is the average demand charge for the region (\$/kW/month), and 30.5 and 24 convert the monthly demand charge into an hourly value which is summed over all hours in the simulation in the objective function.

Infrastructure Cost:

$$C^c_r = \sum_l N_{lr} \gamma_l \theta^c_l + \sum_{l^H} N^H_{lr} \gamma^H_{l^H} \theta^{cH}_l \tag{4}$$

where N_{lr}, N^H_{lr} are the number of chargers of power rating l, l^H in the region r, γ_l is the power capacity of the charger (kW), and $\theta^c_l, \theta^{cH}_l$ are the amortized daily charger cost (\$/kW):

$$\theta^c_l = \frac{\phi^c_l r(1+d_r)^{L^c}}{(1+d_r)^{L^c} - 1} \tag{5}$$

$$\theta^{cH}_l = \frac{\phi^{cH}_l r(1+d_r)^{L^{cH}}}{(1+d_r)^{L^{cH}} - 1} \tag{6}$$

where ϕ^c_l, ϕ^{cH}_l are the capital costs of the charger of levels l, l^H, L^c, L^{cH} are the lifetime of the charger in days, and d_r is the daily discount rate.

Fleet Cost: in this constraint, battery costs are considered separately from the rest of the vehicle.

$$C^v_r = \sum_b V^*_{br}(\theta^v + \theta^b B_b) + \sum_{b^H} V^{*H}_{b^H r}(\theta^{vH} + \theta^{bH} B^H_b) \tag{7}$$

where $V^*_{br}, V^{*H}_{b^H r}$ are the fleet size for LDVs and HDVs, θ^v, θ^{vH} are the amortized daily vehicle costs (without a battery), θ^b, θ^{bH} are the amortized daily battery costs (\$/kWh), B_b, B^H_b are the battery capacity (kWh), respectively.

$$\theta^v = \psi^f_r \left[\phi^v_{om} + \frac{\phi^v r(1+r)^{L^v}}{(1+r)^{L^v} - 1} \right] \tag{8}$$

$$\theta^{vH} = \psi^{fH}_r \left[\phi^{vH}_{om} + \frac{\phi^{vH} r(1+r)^{L^{vH}}}{(1+r)^{L^{vH}} - 1} \right] \tag{9}$$

$$\theta^b = \psi^b_r \left[\frac{\phi^b r(1+r)^{L^b}}{(1+r)^{L^b} - 1} \right] \tag{10}$$

$$\theta^{bH} = \psi^{bH}_r \left[\frac{\phi^{bH} r(1+r)^{L^{bH}}}{(1+r)^{L^{bH}} - 1} \right] \tag{11}$$

where ψ^f_r, ψ^{fH}_r are the fleet spatial mismatch correction factors (see Bauer et al. [23]), $\phi^v_{om}, \phi^{vH}_{om}$ are the daily fixed O&M costs for the vehicle, ϕ^v, ϕ^{vH} are the capital costs of the vehicles, and L^v, L^{vH} are the lifetimes of the vehicles in days. And where ψ^b_r, ψ^{bH}_r are the battery spatial mismatch correction factors (see Bauer et al. [23]), $\phi^b, \phi^{bH} r$ are the capital costs of the battery (\$/kWh) and L^b, L^{bH} are the lifetimes of the battery in days.

Demand Allocation: mobility demand must be served by some composition of vehicles.

$$\sum_b D_{bdtr} = DD_{dtr} \tag{12}$$

$$\sum_{b^H} D^H_{b^H d^H tr} = DD^H_{d^H tr} \tag{13}$$

where $DD_{dtr}, DD^H_{d^H tr}$ are exogenous demands in hour t for passenger vehicles (LDVs) and trucks (HDVs).

Energy to Meet Demand: the energy consumed by the fleet is a function of the number of trips served, and the conversion efficiency of the vehicles.

$$E_{bdtr} = \frac{D_{bdtr}\psi_r^{chdd}\psi_r^{cdd}\eta_b\rho_d}{\sigma_d} \tag{14}$$

$$E^H_{b^H d^H tr} = \frac{D^H_{b^H d^H tr}\psi_r^{chdd H}\eta^H_{b^H}\rho^H_{d^H}}{\sigma^H_{d^H}} \tag{15}$$

where $E_{bdtr}, E^H_{b^H d^H tr}$ are the energy consumed serving mobility of vehicle types b, b^H and trip length d, d^H in hour t and region r, $\sigma_d, \sigma^H_{d^H}$ are the sharing factor or the average number of passengers per vehicle trip, and the sharing factor for automated trucks mapped to per vehicle trip from human-driven trucks (HTs), $\psi_r^{chdd}, \psi_r^{chdd H}$ are the charge deadhead distance correction ratios (see [23]), ψ_r^{cdd} is the customer deadhead distance correction ratios, and $\eta_b, \eta^H_{b^H}$ is the conversion efficiency of the vehicle power trains of LDVs and HDVs (kWh/mile). Note that the sharing factor for trucks refers to the utilization of the truck under a multi-task scenario. Compared with human-driven electrified HDVs, the HAEVs fleet considers fewer human behavior constraints and is likely to take more tasks per vehicle per day.

Vehicles Moving: the number of vehicles actively serving trips is related to trip demand and the sharing factor. The terms $\frac{\rho_d}{\Delta t v_{dt}}, \frac{\rho^H_{d^H}}{\Delta t v^H_{d^H tr}}$ correct for the length of the time period, allowing, e.g. 1 vehicle to serve 2 trips in an hour if the distance to speed ratio is 1/2.

$$V^m_{bdtr} = \frac{D_{bdtr}\rho_d\psi_r^{cdt}}{\sigma_d \Delta t v_{dtr}} \tag{16}$$

$$V^{mH}_{b^H d^H tr} = \frac{D^H_{b^H d^H tr}\rho^H_{d^H}}{\sigma^H_{d^H}\Delta t v^H_{d^H tr}} \tag{17}$$

where ψ_r^{cdt} is the customer deadhead time correction ratio, and Δt is the length of the time period in hours.

Vehicles Charging: we relate the number of vehicles charging to the power consumed by the capacity of each charger type.

$$V^c_{btlr} = \frac{P_{btlr}}{\psi^{chdt}_{b,l,r}\gamma_l} \tag{18}$$

$$V^{cH}_{b^H t l^H r} = \frac{P^H_{b^H t l^H r}}{\psi^{chdtH}_{b^H, l^H, r}\gamma^H_{l^H}} \tag{19}$$

where V^c_t are the number of vehicles charging in hour t, $\psi^{chdt}_{b,l,r}, \psi^{chdtH}_{b^H, l^H, r}$ are the charger deadhead time correction ratios, and $\gamma_l, \gamma^H_{l^H}$ are the charging rates (kW/charger).

Charging Upper Bound: we assume the batteries in the fleet start full and therefore can only be replenished up to the cumulative amount consumed by the previous hour.

$$\sum_{\hat{t}=0}^{t}\sum_l P_{b\hat{t}lr} \le \sum_{\hat{t}=0}^{t-1}\sum_d E_{bd\hat{t}r}, \quad \forall btr \tag{20}$$

$$\sum_{\hat{t}=0}^{t}\sum_{l^H} P^H_{b^H\hat{t}l^H r} \le \sum_{\hat{t}=0}^{t-1}\sum_d E^H_{b^H d^H \hat{t}r}, \quad \forall b^H tr \tag{21}$$

Charging Lower Bound: charging must keep up with consumption as limited by the capacity of the batteries. Energy must be supplied by charging in the previous hour to be used in the next hour.

$$\sum_{\hat{t}=0}^{t-1}\sum_l P_{b\hat{t}lr} \ge \sum_{\hat{t}=0}^{t}\sum_d E_{bd\hat{t}r} - V^*_{br}B_b, \quad \forall btr \tag{22}$$

$$\sum_{\hat{t}=0}^{t-1}\sum_{l^H} P^H_{b^H\hat{t}l^H r} \ge \sum_{\hat{t}=0}^{t}\sum_{d^H} E^H_{b^H d^H \hat{t}r} - V^{*H}_{b^H r}B^H_{b^H}, \quad \forall b^H tr \tag{23}$$

No Charge At Start: the first hour of the day needs to have no charging to allow for the convention that charging can only occur after some energy is consumed by the fleet.

$$P_{btlr} = 0, t = 0, \quad \forall blr \tag{24}$$

$$P^H_{b^H t l^H r} = 0, t = 0, \quad \forall b^H l^H r \tag{25}$$

Terminal State of Charge: the aggregate state of charge of batteries must again be full at the end of the simulation.

$$\sum_t\sum_l P_{btlr} = \sum_t\sum_d E_{bdtr}, \quad \forall br \tag{26}$$

$$\sum_t\sum_{l^H} P^H_{b^H t l^H r} = \sum_t\sum_{d^H} E^H_{b^H d^H tr}, \quad \forall b^H r \tag{27}$$

Fleet Dispatch: together vehicles serving trips, charging, and idle cannot exceed the fleet size.

$$\sum_d V^m_{bdtr} + V^i_{btr} + \sum_l V^c_{btlr} \le V^*_{br} \tag{28}$$

$$\sum_{d^H} V^{mH}_{b^H d^H tr} + V^{iH}_{b^H tr} + \sum_l V^{cH}_{b^H t l^H r} \le V^{*H}_{b^H r} \tag{29}$$

Max Charging: vehicle charging cannot exceed the number of chargers.

$$\sum_{bd} V^c_{bdtl} \le N_{lr} \tag{30}$$

$$\sum_{b^H d^H} V^{cH}_{b^H d^H t l^H} \le N^H_{l^H r} \tag{31}$$

where N_{lr} is the number of chargers charging at power level l in the region r.

Max Demand: this constraint relates the maximum power consumed for each region to the power drawn in each time period. Because P_r^{max} is in the objective function, there will be no slack in the optimal solution, ensuring it will be equal to the maximum power demanded by the fleet.

$$P_r^{max} \ge \frac{\sum_{bl} P_{tblr}}{\Delta t} + \frac{\sum_{b^H l^H} P^H_{tb^H l^H r}}{\Delta t} - P^{private}_{t,r} - P^{Hs}_{t,r}, -P^{Hhdr}_{t,r} \quad \forall tr \tag{32}$$

where $P^{private}_{t,r}$ is the power demanded by the personally owned light-duty EV fleet, $P^{Hs}_{t,r}, P^{Hhdr}_{t,r}$ are the power demanded by the human-driven electric HDV fleet (smart/nonsmart charging)

Human-driven HDV Charging (smart assignment): The light-duty vehicle personal vehicle charging constraints are derived in our previous work [19]. The following four constraints represent the power and energy bounds on human-driven HDV with smart charging assignments.

$$P^{Hs}_{t,r} \ge \underline{P}^{Hs}_{t,r} \tag{33}$$

$$P^{Hs}_{t,r} \le \overline{P}^{Hs}_{t,r} \tag{34}$$

$$\sum_{t'=1}^{t} P^{Hs}_{t',r} \ge \underline{E}^{Hs}_{t,r} \tag{35}$$

$$\sum_{t'=1}^{t} P^{Hs}_{t',r} \le \overline{E}^{Hs}_{t,r} \tag{36}$$

where $\underline{P}_{t,r}^{Hs}$ and $\overline{P}_{t,r}^{Hs}$ are the min and max power constraints on EV charging, respectively; and $\underline{E}_{t,r}^{Hs}$ and $\overline{E}_{t,r}^{Hs}$ are the min and max cumulative energy constraints on EV charging, respectively.

Human-driven HDV Charging (come and charge): the following four constraints represent the power and energy bounds for the HDV human-driven charging behavior.

$$P_{t,r}^{Hhdr} \geq \underline{P}_{t,r}^{Hhdr} \tag{37}$$

$$P_{t,r}^{Hhdr} \leq \overline{P}_{t,r}^{Hhdr} \tag{38}$$

$$\sum_{t'=1}^{t} P_{t',r}^{Hhdr} \geq \underline{E}_{t,r}^{Hhdr} \tag{39}$$

$$\sum_{t'=1}^{t} P_{t',r}^{Hhdr} \leq \overline{E}_{t,r}^{Hhdr} \tag{40}$$

where $\underline{P}_{t,r}^{Hhdr}$ and $\overline{P}_{t,r}^{Hhdr}$ are the min and max power constraints on the human-driven HDV charging, respectively; and $\underline{E}_{t,r}^{Hhdr}$ and $\overline{E}_{t,r}^{Hhdr}$ are the min and max cumulative energy constraints on the human-driven HDV charging, respectively. Note that for these two human-driven fleet charging constraints, the upper and lower bounds of the energy and charging power are generated from the HEVI-LOAD tool introduced in Section 2.2.

Generation: The following three constraints represent power generation on the grid.

$$\sum_{g,i} G_{g,t} + \eta^{trans} \sum_{i'} T_{i',t,i} - \sum_{i'} T_{i,t,i'} \geq P_{i,t}^{other} + \sum_{r\epsilon i} P_{t,r}^{private} + \sum_{r\epsilon i,b,l} P_{tblr} \tag{41}$$
$$+ \sum_{r\epsilon i} P_{t,r}^{Hs} + \sum_{r\epsilon i} P_{t,r}^{Hhdr} + \sum_{r\epsilon i,b^H,l^H} P_{tb^H l^H r}^{H}$$

For all time steps t and grid regions i, where $P_{t,r}^{other}$ is electricity demand from non-mobility sources, and η^{trans} is the transmission loss factor associated with inter-regional transfers.

4. Results

In this section, the simulation results are presented and the benefit analysis is given based on the simulation study via the GEM model.

HDV charging load profile. Fig. 3 shows the overall charging load profile for a variety of scenarios of electrification and automation in the heavy-duty sector (with/without automated charging assignment) with the use of different charging levels. We assume for all the electrified trucks, S of them are HAEVs ($S = 1, 25, 50, 75, 99\%$), and $1 - S$ of them are human-driven fleets ($P = 1 - S$). Among the human-driven fleets, 50% of the fleets use smart charging assignments, and the rest 50% of the fleets simply charge when arriving at their destination. From Fig. 3, we observe that as the penetration of the HAEVs fleet increases, the overall charging load profile results in a smoother fluctuation. The peak daily charging load reduces by 47% with the penetration of HAEVs increasing from 1% to 99%. This reduction in fluctuation and peak load is due to the smart job assignment and charging assignment assumptions for HAEVs. Moreover, we also observe that for the human-driven electric HDV fleets, the smart charging assignment fleet will result in a lower charging demand in peak energy usage hours (we assumed the peak energy usage occurs from 5 pm to 10 pm). Whereas the human charging assignment (come and charge) will have a higher charging tendency during those times and a lower charging tendency during non-peak hours.

Number of chargers. Fig. 4(a) shows the number of chargers needed. As with fleet size, there are far more chargers when HAEVs are low (S = 1%) than in a counterfactual scenario of high penetration of HAEV fleet (S = 99%), reflecting much higher utilization among HAEV chargers. With the HAEV penetration increases from 1% to 99%, the overall number of chargers reduced from 396 million to 242 million, resulting in a reduction of 38%. The best number of HAEV chargers is decided from the GEM co-optimization framework in Eq. (4) with a higher sharing tendency to reduce overall operational cost, whereas the number of chargers of human-driven electric trucks is obtained based on human-driven electric truck charging demand and human charging behavior assumptions, indicating lower charging sharing factor. The reduction of the charger is primarily due to the reduction of human-driven electric HDV fleets-related chargers as those chargers have a lower sharing factor compared with HAEVs-related chargers.

Peak load. Fig. 4(b) shows the grid peak load, which also decreases substantially as the fraction of mobility demand met by HAEVs increases: Peak demand is 159 GW at S = 1% and is 135 GW when S = 99%. Based on this result, one can observe that with the increment of HAEV fleet size, the overall peak load will reduce. However, the peak load for individual fleet components may vary with different HAEV penetration. This is a result of the joint optimization of charging demand of all mobility sectors from Eq. (41). The relaxation of high truck charging demand during peak hours may encourage the charging for other fleet components in the electric mobility system to result in an overall minimum operational cost.

Fleet size. Fig. 4(c) shows the optimal fleet size of all types of vehicles in GEM modeling. We are particularly investigating the HAEVs and human-driven electrified HDVs in this study which decreases 47M total electric vehicles from the S = 1% case to the S = 99% case. This reduction in fleet size is primarily due to the higher utilization in job assignments for the HAEVs. The higher vehicle utilization is formulated as sharing factor $\sigma_{d^H}^{H}$ in Eq. (15). HAEVs are likely to complete more jobs per day compared with human-driven electric HDVs with the relaxation of human-driven constraints.

Total costs. Fig. 4(d) shows the overall cost changes with the fraction of HAEVs increases. We can observe that the fleet cost and infrastructure cost for the human-driven electrified HDVs are decreasing on a larger scale compared to the increment of fleet cost and infrastructure cost related to the increase of HAEV fleets. The overall mobility electrification related cost decreased from \$1085 billion to \$889 billion with the penetration of HAEVs increasing from 1% to 99%, resulting in a reduction of overall cost by 18%. The reduction in overall costs is a joint result of charging infrastructure reduction, peak load reduction, and fleet size reduction, which reduces the infrastructure cost, fleet cost, and power system operation cost, respectively.

4.1. Discussion

With the growing trend of freight electrification, there is an urgent need to understand the potential benefits of future electrified freight components. In this study, we analyzed the impact of freight electrification and studied the influence of different electrified freight fleet compositions. In our analysis, we gradually increased the percentage of HAEVs in electrified trucks and analyzed the potential impact on the grid, cost and fleet sizes, etc. Our findings could serve as suggestions for freight electrification development. With the simulation results, we find that: (1) The use of heavy-duty autonomous electric vehicles (HAEVs) with smart job assignment and charging assignment to provide goods delivery has substantial benefits over using human-driven electric trucks or gasoline trucks. The increased penetration of automated electric freight fleets within other types of electrified freight fleets from 1% to 99% will result in an overall cost reduction of 18.2%, fleet size reduction of 20.4%, and lower peak load reduction of 14.3%.; (2) Without charging time requirements, lower power charging stations and the use of smaller battery size trucks provide the benefit in terms of infrastructure and fleet cost reduction, and lower grid operational cost. The benefit of HAEV adoption in electrified truck fleets primarily comes from the following aspects: (1) a higher sharing tendency of charging infrastructure with optimized charger assignment; (2) optimal charging scheduling making the HAEV charging demand shifting away from peak energy hours; and (3) optimized job assignment and higher daily utilization of HAEVs.

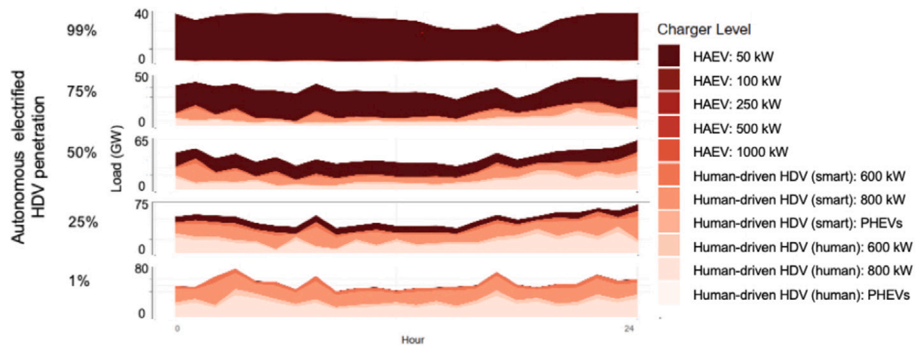
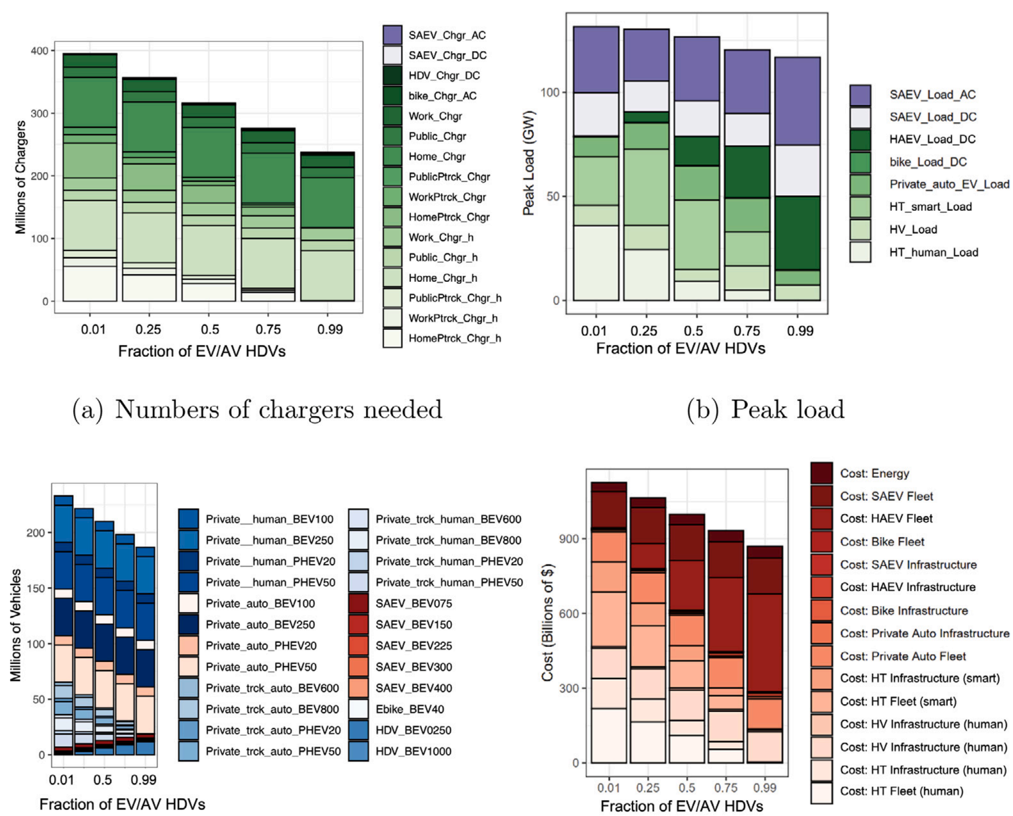


Fig. 3. Electrified HDV daily charging load profile across scenarios of AV/EV penetration.



(a) Numbers of chargers needed (b) Peak load

(c) Fleet size (d) Overall cost

Fig. 4. GEM system level outputs across scenarios of automation and electrification for HDVs.

5. Conclusion

The configuration of the freight system in which HAEVs serve goods delivery has substantial benefits over one that relies on human-driven electrified trucks or gasoline-powered vehicles. Overall, we demonstrate that electrified freight automation increases operating efficiency by reducing total costs and lowering emissions, which also increases goods delivery within the transportation system. From an economic standpoint, system costs are substantially reduced through higher vehicle utilization (smart job assignment) and automation, while fuel and operational costs remain much lower than those of gasoline/diesel vehicles today. From an electric power grid operator's perspective, HAEVs can smooth out large amounts of the variability in electricity generation, which substantially improves both the efficiency and emissions rate of fossil generation while simultaneously better utilizing solar and wind resources (thanks to the flexibility in charging times).

CRediT authorship contribution statement

Wanshi Hong: Conceptualization, Methodology, Formal analysis, Writing – original draft, Visualization. **Alan Jenn:** Methodology, Software, Resources. **Bin Wang:** Methodology, Resources, Project administration.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Wanshi Hong reports financial support was provided by US Department of Energy.

Data availability

The authors do not have permission to share data.

Acknowledgment

We would like to thank Cong Zhang, Fan Tong, and Srinath Ravulaparthy for their help with modeling development. This article and the work described were sponsored by the U.S. Department of Energy (DOE) Vehicle Technologies Office (VTO) under the Vehicle Technologies Analysis Program. The following DOE Office of Energy Efficiency and Renewable Energy (EERE) managers played important roles in establishing the project concept, advancing implementation, and providing ongoing guidance: Raphael Isaac, Rachael Nealer, Jake Ward, Katherine McMahon, Kelly Fleming, and Heather Croteau.

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