Improving Economic and Operational Viability, Energy Efficiency, and Environmental Impact of Medium- and Heavy-Duty Electric Delivery Fleets via Optimal Routing, Vehicle-to-Grid Integration, and Peak Shaving

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Motivation

- Transportation sector accounts for **28% of the total U.S. GHG emissions**, of which **23%** comes from Medium- and Heavy-Duty Trucks (MHDV) (EPA 2018).[1]

Transportation electrification is driven by plug-in electric vehicle (PEV) policies:

- CARB's Advanced Clean Trucks (ACT) program requires truck manufacturers to transition from diesel to electric trucks beginning in 2024, with **all new truck sales** having **zero tailpipe emissions by 2045**.
- Biden's Climate Day executive orders highlight a **$2T plan** to achieve a carbon-free electricity sector by 2035 and **nationwide net-zero emissions** by **2050**.
- Amazon committed to The Climate Pledge to achieve **net-zero carbon** across operations by **2040**, switching to an all-electric delivery fleet.
- Battery-electric trucks are more expensive to purchase, have limited range and payload capacity, and take longer to refuel, requiring **additional logistical planning** for **charging**, **operations**, and **fleet sizing**. However, PEVs also have unique potential for fleet owners, offering **lower operating and maintenance costs** and the possibility for **additional revenue** via electric grid services, such as **vehicle-to-grid (V2G)** energy arbitrage and peak-shaving at facilities.

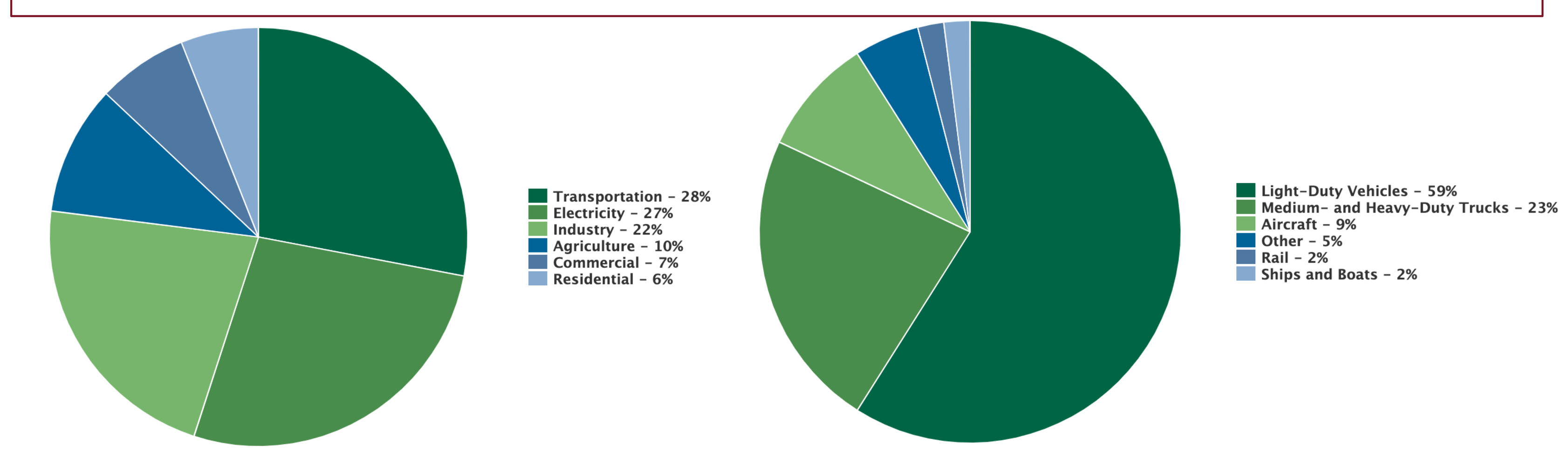

Figure 1. 2018 U.S. emissions by sector (left) and transportation sector GHG emissions by source (right).[1]

Research Question

How can **fleet operators** evaluate **MHDPEV delivery fleets** to **(1) improve economic competitiveness with diesel vehicles**; **(2) coordinate operational decisions**, accounting for the reduced payload and increased refueling (charging) requirements of PEV trucks; **(3) leverage the revenue potential of grid services** using controlled charging and V2G operations; and **(4) leverage the EV potential of using EV trucks to shave peak power demand** at operator facilities to reduce the electric demand charge costs?

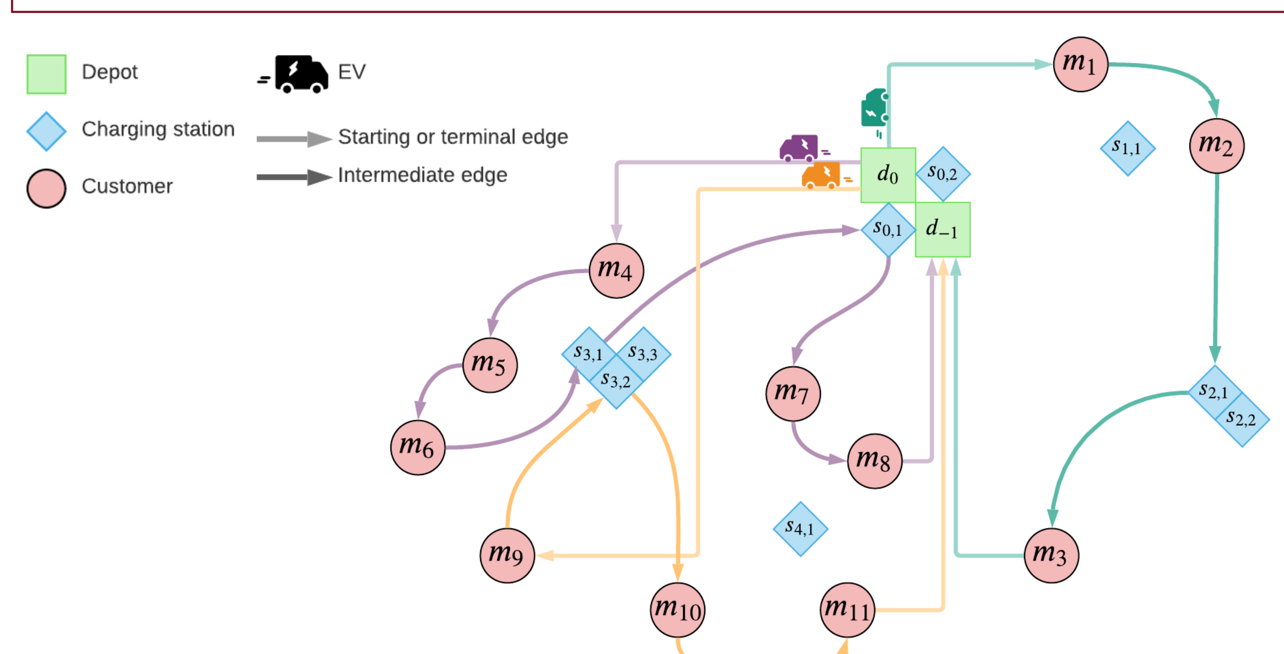

Figure 2. Representation of the Electric Vehicle Routing Problem (EVRP) with duplicate charging station nodes and roundtrips to central depot.

Model & Methods

We leverage recent developments in vehicle routing and advance these models to capture PEV truck delivery, V2G, and peak shaving.[2,3] The resulting modeling and computational tool **(1) supports planning decisions** for EV acquisition and operational planning for fleet operators and policy analysts; **(2) determines the degree to which grid services may improve economic viability** of PEV trucks relative to diesel trucks and **(3) characterizes conditions under which PEV trucks are most competitive**, including delivery network characteristics, and cost and regulatory parameters.

$$\underset{\mathbf{x}}{\text{maximize}}\ \pi(\mathbf{x}) = R(\mathbf{x}) - C(\mathbf{x}) - O(\mathbf{x}) \qquad \text{Net amortized profit}$$

$$\mathit{Profit} = \mathit{Revenues} - \mathit{CapEx} - \mathit{OpEx}$$

with respect to:

$$\mathbf{x} = \begin{array}{llll} x^{\gamma}_{ij} & \in \{0,1\} & \forall i \in \mathcal{V}'_0,\ j \in \mathcal{V}'_{-1} & \text{Route decision of each edge for each vehicle} \\ x^{\kappa}_{it} & \in \{0,1\} & \forall i \in \mathcal{S}',\ t \in \mathcal{T} & \text{EV charge or discharge decision, 0=idle} \\ x^{\omega}_{i} & \in \mathbb{R} \geq 0 & \forall i \in \mathcal{V}'_{0,-1} & \text{Arrival time for each vehicle at each node} \\ x^{\mathrm{q}}_{i} & \in \mathbb{R} \geq 0 & \forall i \in \mathcal{V}'_{0,-1} & \text{Payload of each vehicle arriving at each node} \\ x^{\mathrm{a}}_{i} & \in \mathbb{R} \geq 0 & \forall i \in \mathcal{V}'_{0,-1} & \text{Energy of each EV arriving at each node} \\ x^{\mathrm{d}}_{i} & \in \mathbb{R} \geq 0 & \forall i \in \mathcal{S} & \text{Each station's net peak electric demand} \\ x^{\mathrm{p}}_{it} & \in \mathbb{R} & \forall i \in \mathcal{S}',\ t \in \mathcal{T} & \text{Charge or discharge rate of each EV} \end{array}$$

where:

$$O(\mathbf{x}) = O_L(\mathbf{x}) + O_M(\mathbf{x}) + O_Y(\mathbf{x}) \qquad R(\mathbf{x}) = R_G(\mathbf{x}) + R_E(\mathbf{x}) + R_L(\mathbf{x})$$

$$\mathit{OpEx} = \mathit{Wages} + \mathit{Maintenance} + \mathit{Cycling\ Costs} \qquad \mathit{Revenues} = \mathit{Peak\ Shaving} + \mathit{Energy\ Arbitrage} + \mathit{Delivery}$$

subject to:

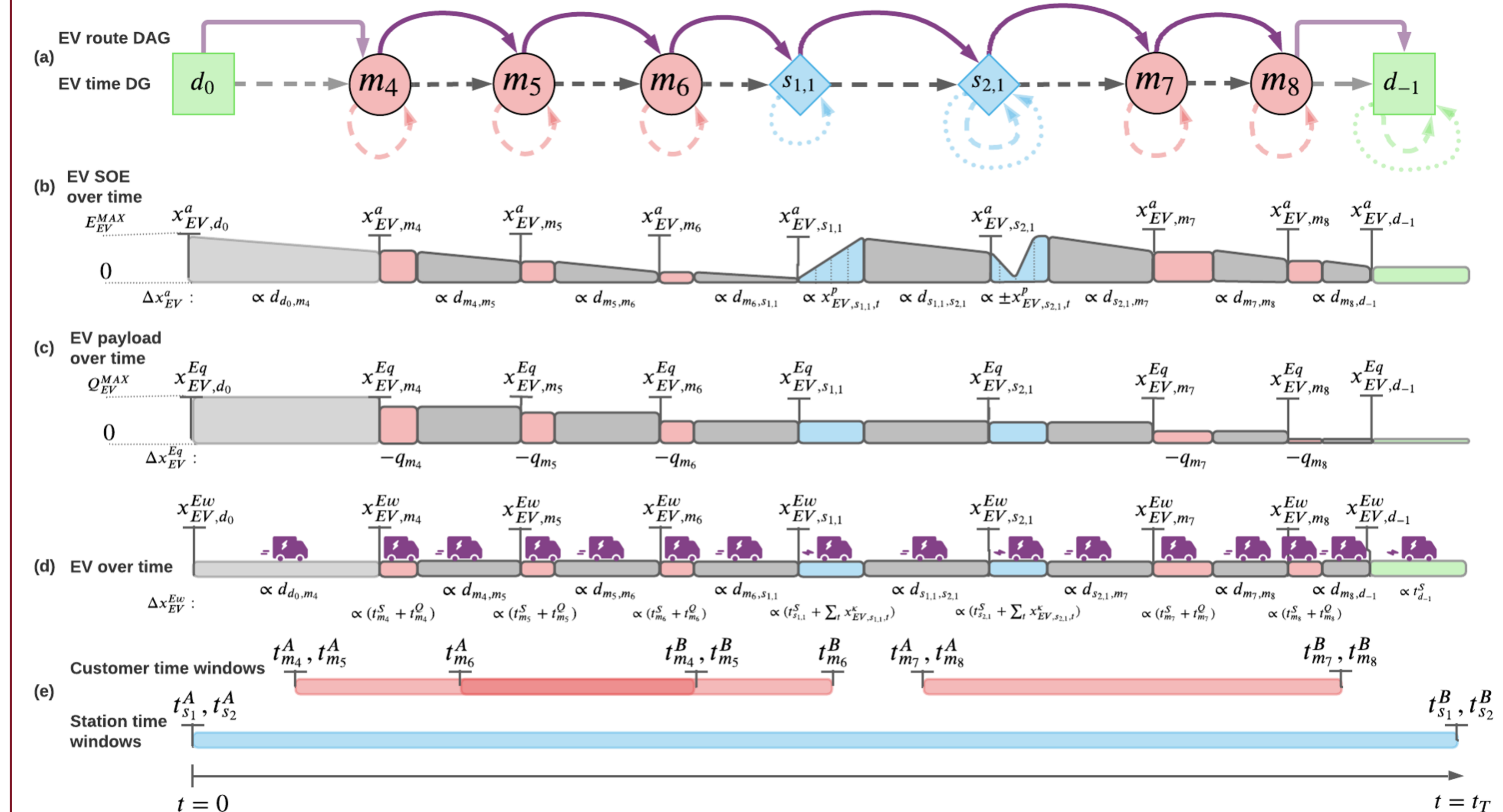

Figure 3. Graphical representations of (a) routing constraints; (b) energy constraints; (c) payload constraints; (d) time constraints; and (e) customer delivery time windows.

Table 1. Benchmarks of our model on seminal VRP test instances demonstrate our ability to reproduce and improve on fleet designs and optimal routes to minimize distance[2], though the problem scale due to our time-indexed decisions hits computational limits in achieving best known partial charging results.[3] Distance and fleet size results are produced using Gurobi's commercial MILP solver with a computational time limit of two hours on a 2015 Macbook Pro 2.8 GHz Quad-Core Intel Core i7.

Instances[2]	SSG[2]	KC[3]	Our Model (Gap %)
C103-5	176.05 // 1 EV	175.37 // 1 EV	175.37 // 1 EV (0.0%)
R103-10	207.05 // 2 EV	206.12 // 2 EV	206.12 // 2 EV (0.0%)
C101-10	393.76 // 3 EV	388.25 // 3 EV	393.56 // 3 EV (1.3%)
RC105-5	241.30 // 2 EV	233.77 // 2 EV	241.30 // 2 EV (3.1%)

Case Study: California Tesla Semi Fleet

We demonstrate our model capabilities on a **realistic MHDPEV fleet scenario** for intrastate transport in CA using current vehicle specifications and prices (Tesla Semi, 500 mile range), current utility EV electricity rates (see Table 2), actual estimated travel distances, and approximations of wages and maintenance costs. Four scenarios are presented:

- **(A) Baseline**: Minimize distance; no V2G in objective; start and end SOE must be full
- **(B) Charge Only**: Maximize net profit; V2G in objective; charge only; start and end SOE must be full
- **(C) V2G**: Maximize net profit; V2G in objective; charge and discharge; start and end SOE must be full
- **(D) V2G Opt.**: Maximize net profit; V2G in objective; charge and discharge; optimize start/end SOE

Table 2. CA case study graph data.

Location	Los Angeles	Irvine	San Diego	Fresno	Bakersfield	San Jose	San Francisco
Nodes	D0, D1, S0	S1, M1	S2, M2	S3, M3	S4, M4	S5, M5	S6, M6
Tariff	SCE TOU-EV-8	SCE TOU-EV-8	SDG&E TOU-M	PG&E BEV-1	PG&E BEV-1	PG&E BEV-1	PG&E BEV-2
Charger	1MW HPCCV	60kW Level 3	1MW HPCCV	60kW Level 3	60kW Level 3	60kW Level 3	1MW HPCCV

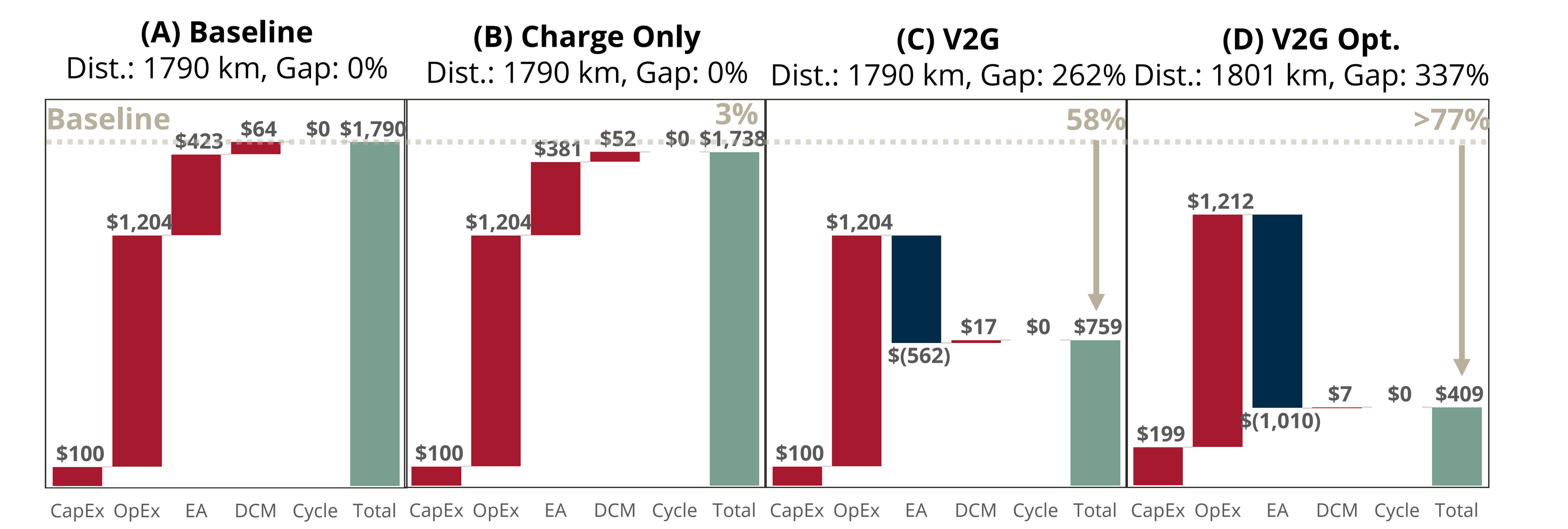

Chart 1. Waterfall of fleetwide **daily amortized profits** with **costs (+)** and **revenues (-)**, excluding delivery revenues. The total shown represents the daily amortized delivery revenue required for the fleet to breakeven. **Profit improvements (%)** are shown relative to the Baseline (A).

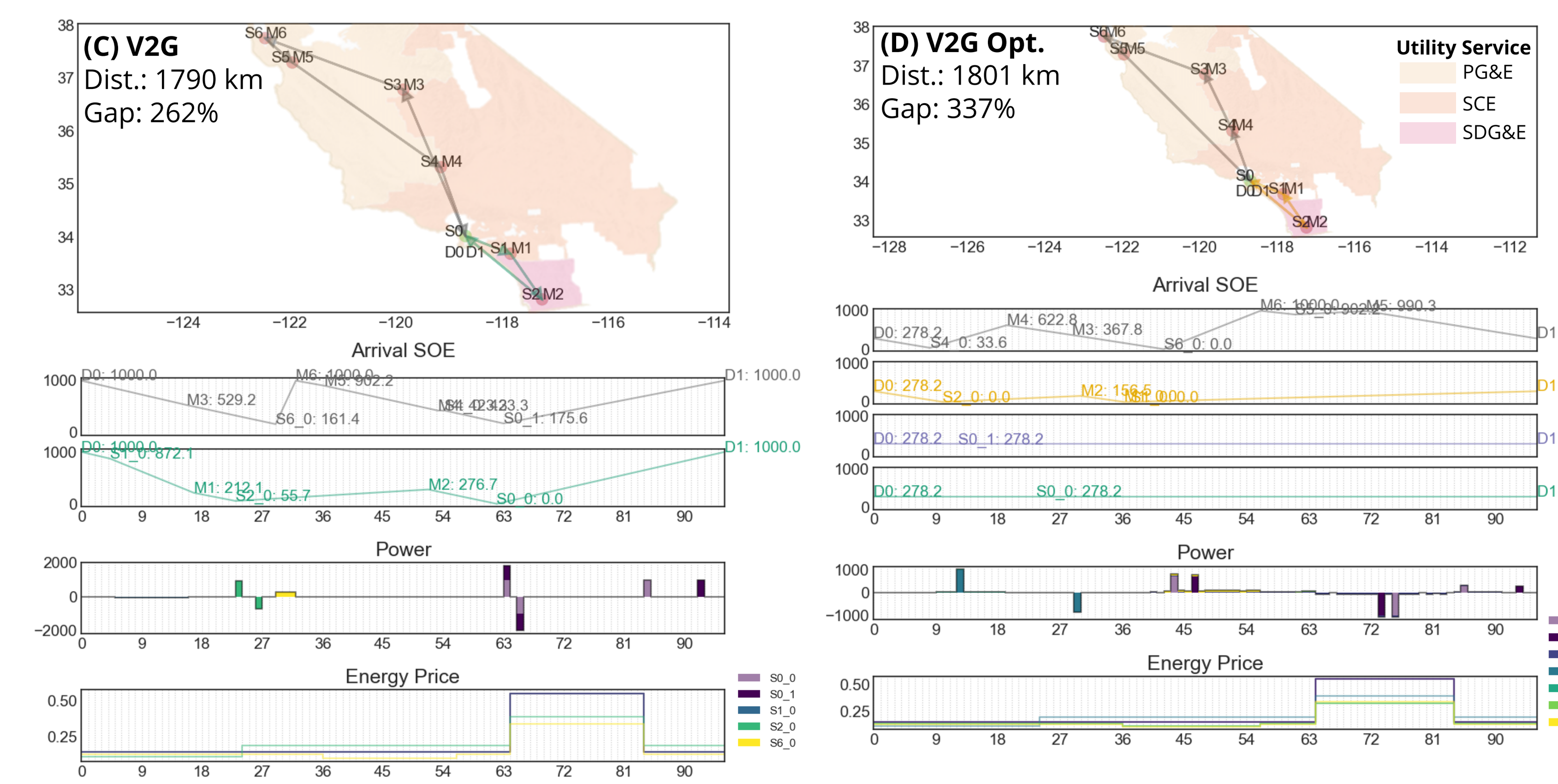

Figure 4. Results (A, B, C) demonstrate the same minimal distance—though different charging behaviors (power, kW)—with a fleet size (routes) of two Tesla Semis (only (C) is shown above). Result (D) optimally modifies routes and determines an optimal start and end SOE to take advantage of large energy arbitrage opportunities in SCE TOU-EV-8 (LA, Irvine) that justify "stationary storage". The optimal fleet size of four Tesla Semis is limited due to only two S0 node instances.

Conclusions

- Our model is a novel extension of the E-VRP, **co-optimizing routing, scheduling and V2G energy arbitrage and peak shaving** with a **net amortized profit objective**, enabling fleet operators or policymaker to plan the operation and design of MHDPEV fleets.
- Our CA case study shows **>77%** improvement in amortized profit from the standard E-VRP baseline methodology[2], primarily due to **significant energy arbitrage** opportunities on commercial electric retail EV tariffs.

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References

1. U.S. Environmental Protection Agency, *Fast Facts on Transportation Greenhouse Gas Emissions*. 5pp, 336 K, June 2020,EPA-420-F-20-037. https://www.epa.gov/greenvehicles/fast-facts-transportation-greenhouse-gas-emissions.
2. Michael Schneider, Andreas Stenger, and Dominik Goeke, Transportation Science 2014 48:4, 500-520.
3. Merve Keskin, Bülent Çatay, Transportation Research Part C: Emerging Technologies, Volume 65, 2016, Pages 111-127.