Follow the Sun and Go with the Wind: Carbon-Footprint Optimized Timely E-Truck Transportation

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US Trucking Industry: A Top-20 Economy with High Environmental Impact

- U.S. Trucking Industry is a top-20 economy
  - Freight revenue: **$875.5B** in 2021
    - ranks **18th** against countries' GDP worldwide
  - Freight tonnage: **11B** (72% of all freight), 2021

Rank	Country	GDP (USD billion)
1	United States	23,315
2	China	17,734
3	Japan	4,940
…	….	…
18	**Saudi Arabia**	**833**
19	Turkey	815
20	Switzerland	812

- Carbon emission: **456.6M** tons, 2019
  - **25%** in the transportation sector.
  - **8.8%** of all carbon emissions.

E-Truck: A Future Direction for Better Environment

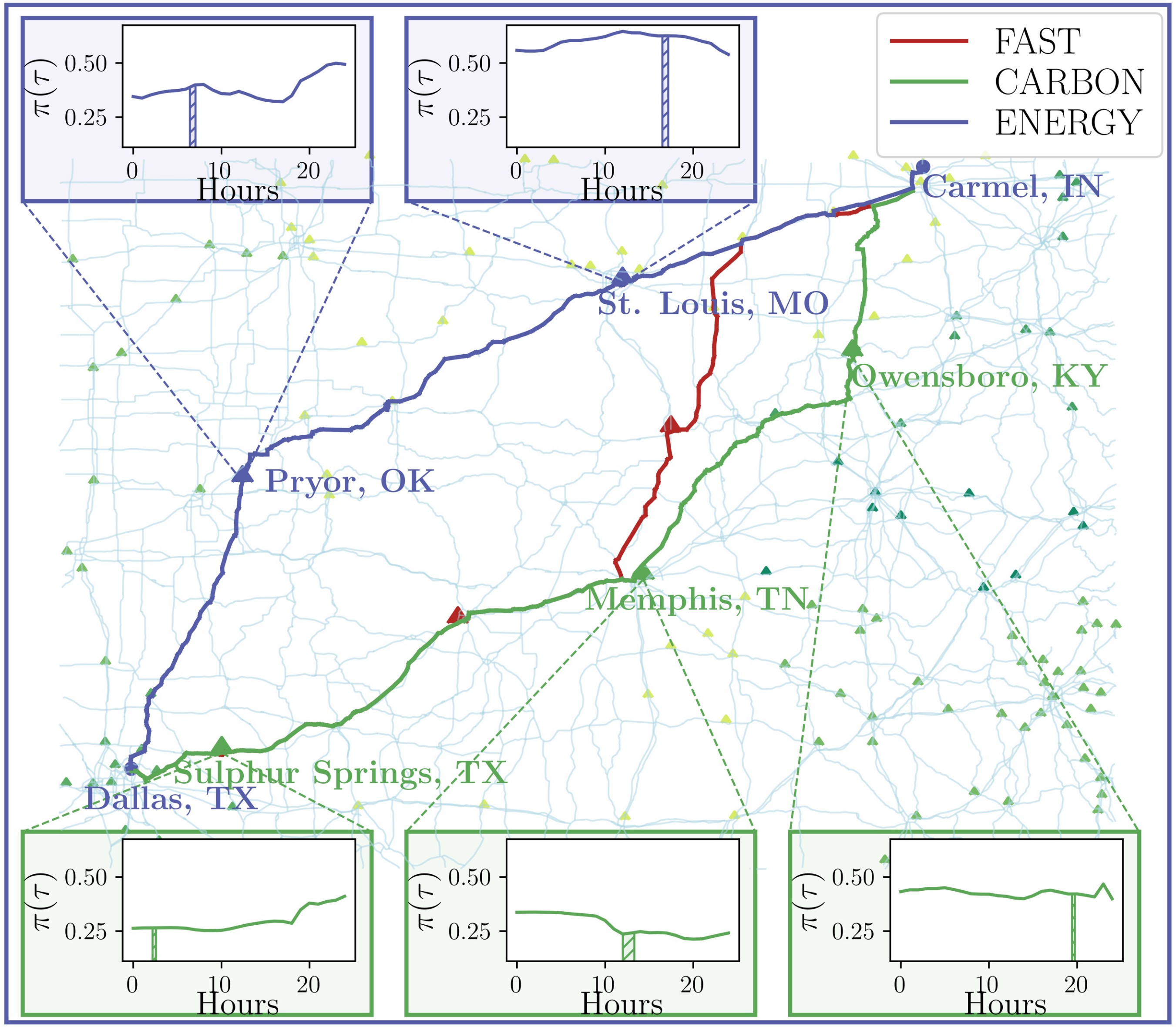
- High energy efficiency
  - Electric motor: ~95%, 1.8 kWh/mile
  - Internal combustion engine (ICE): ~35%, 4.7 kWh/mile
- Electric trucks have zero direct emissions.

- However, the **carbon footprint** of an electric truck is non-zero.
  - E-truck: 1.8 kg/mile (if electricity all from coal)
  - E-truck: 0.7 kg/mile (if electricity all from natural gas)
  - ICE truck: 1.3 kg/mile

- We use the **carbon intensity** (kg/kWh) to measure the cleanness of the electricity.

	Coal	Natural gas	Petroleum	Renewable
Carbon Intensity (kg/kWh)	1.02	0.39	0.91	0
Total emission (tons)	7.86×10^{8}	6.35×10^{8}	1.6×10^{7}	0
Electricity (kWh)	7.73×10^{11}	1.62×10^{12}	1.75×10^{10}	7.92×10^{11}

Carbon Footprint Optimization (CFO) Problem



	Carbon footprint (kg)	Energy (kWh)	Distance (miles)	Time (hours)
FAST	1022.0	1633.7	919.9	19.3
ENERGY	637.3	1239.7	879.8	24.0
CARBON	413.6	1487.5	946.9	24.0

- **Objective:**
  - Carbon footprint incurred at each charging station.
- **Decisions:**
  - Path planning
  - Speed planning
  - Charge planning
- **Constraints:**
  - State of Charge (SoC) constraints
  - Deadline constraint.

Fundamental Challenges

- □ The problem is **NP-hard** even just to find a feasible solution.

- □ Positive battery State of Charge (SoC) constraints.

- □ **Non-convex** carbon footprint objective.

- □ **Enormous** geographical and temporal charging options with diverse carbon intensity.

Contribution

- **Important and Challenging Problem**
  - We identify and study an important and challenging problem Carbon Footprint Optimization (CFO).

- **Novel Formulation**
  - We provide a novel problem formulation based on a stage-expanded graph.
  - It reveals a special problem structure and has a low model complexity.

- **Efficient Approach with Performance Guarantee**
  - (i) convergence rate, (ii) polynomial time complexity, and (iii) performance bound.

- **Insights:**
  - Carbon-optimized solutions save up to **28%** carbon as compared to baselines.

Comparison with Conceivable Alternatives

Graph Model in Formulation	Problem	Model Complexity	Algorithm	Complexity	Optimality
Original graph	MIP	$O(\lvert\mathcal{V}\rvert + \lvert\mathcal{E}\rvert)$	Branch and bound	Exponential to $\lvert\mathcal{V}\rvert$ and $\lvert\mathcal{E}\rvert$	Optimal
Battery-expanded graph	MILP†	$O(B/\epsilon(\lvert\mathcal{V}\rvert + \lvert\mathcal{E}\rvert))$	Branch and cut	Exponential to $\lvert\mathcal{V}\rvert$, $\lvert\mathcal{E}\rvert$, and B/ϵ	$O(\epsilon)$ to optimal
Time-expanded and battery-expanded graph	Shortest Path	$((T \cdot B)/\epsilon^2)(\lvert\mathcal{V}\rvert + \lvert\mathcal{E}\rvert)$	Bellman-Ford	Polynomial to $\lvert\mathcal{V}\rvert$, $\lvert\mathcal{E}\rvert$, T/ϵ and B/ϵ	$O(\epsilon)$ to optimal
Our stage-expanded graph	Generalized RSP‡	$O(N(\lvert\mathcal{E}\rvert + \lvert\mathcal{V}\rvert))$ 1	Dual subgradient	Polynomial to $\lvert\mathcal{V}\rvert$, $\lvert\mathcal{E}\rvert$, and N	Posterior bound

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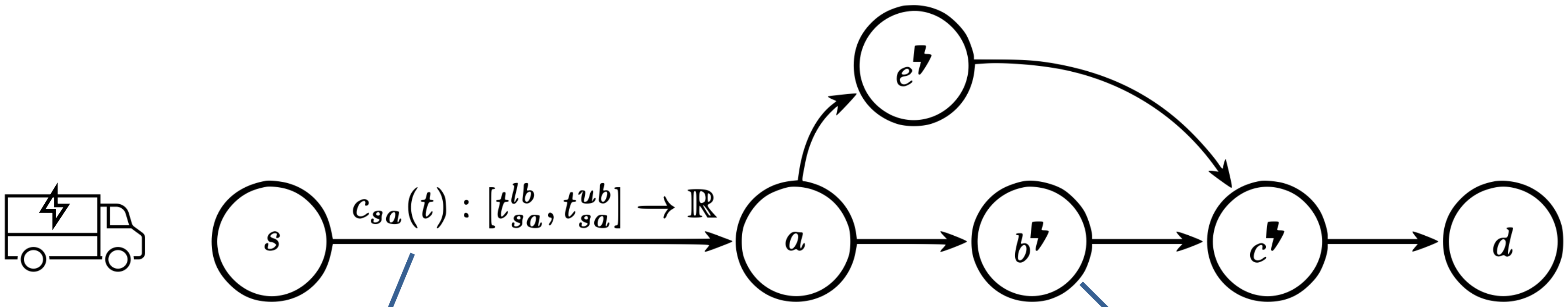
†: Provided that the carbon intensity function is approximated by a piecewise linear function. ‡: RSP stands for restricted shortest path.

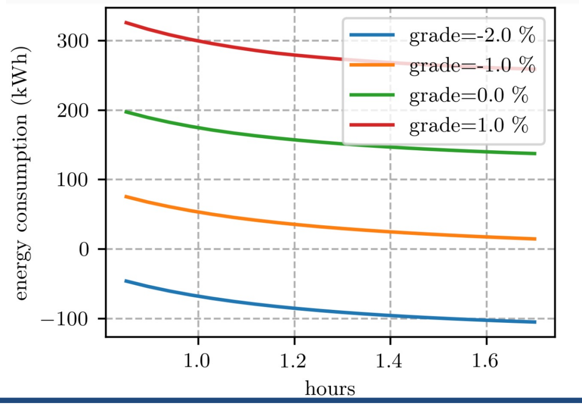
Message 1: Our stage-expanded graph has a **low model complexity** as compared to battery-expanded graphs. Because the number of charging stops N ≤ 10 in practice.

Message 2: Our formulation reveals an **elegant problem structure** that leads to an efficient algorithm with favorable performance in both theory and experiments.

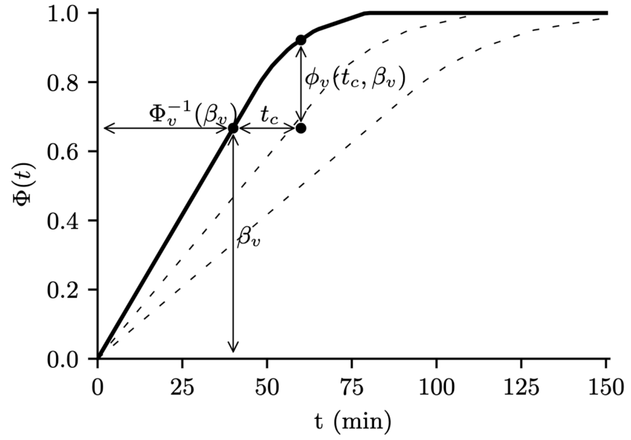
System Model: Graph and Charging Station



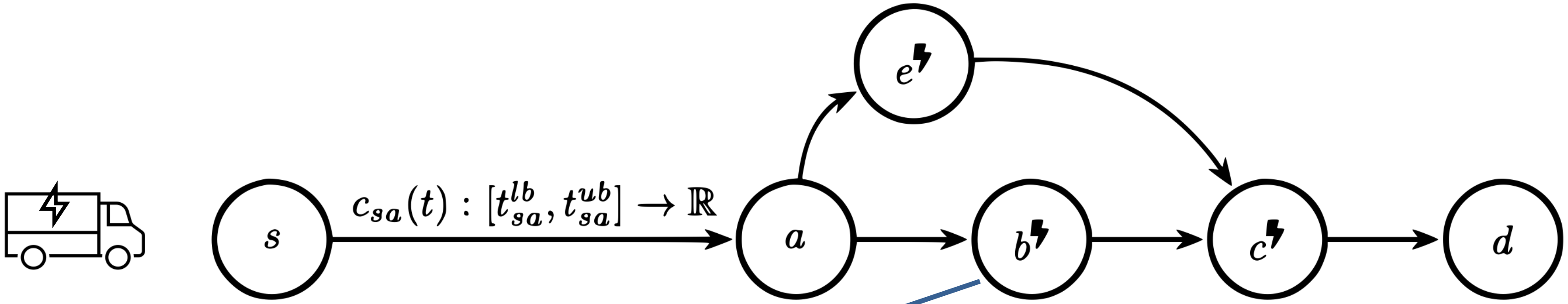
- □ $G = (V, E)$:
  - V: the set of nodes, E: the set of edges
- □ $c_e(t_e)$: $[t_e^{lb}, t_e^{ub}] \to \mathcal{R}$: the (convex) energy consumption function
- □ **Decision**: travel time $t_e \in [t_e^{lb}, t_e^{ub}]$.



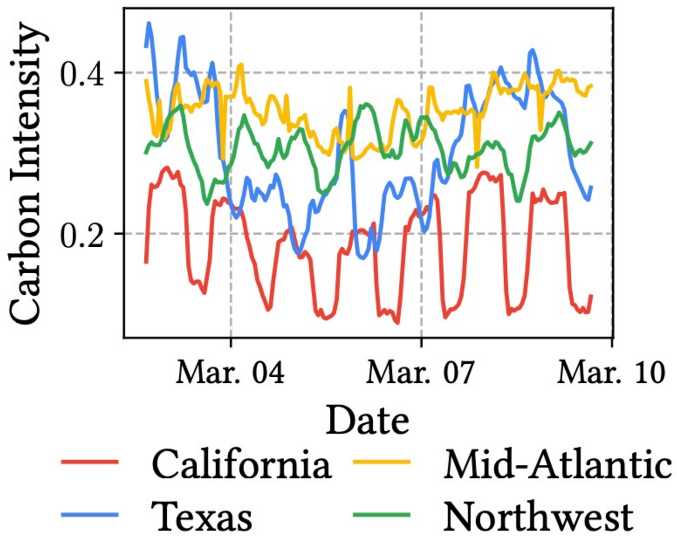
- □ $V_c \subset V$ the set of charging stations
- □ $\Phi_v(t)$: the (concave) charge function
- □ **Decisions:** Wait time $t_w \in [t_w^{lb}, t_w^{ub}]$ and charge time $t_c \in [0, t_c^{ub}]$



System Model: Carbon Intensity and Objective

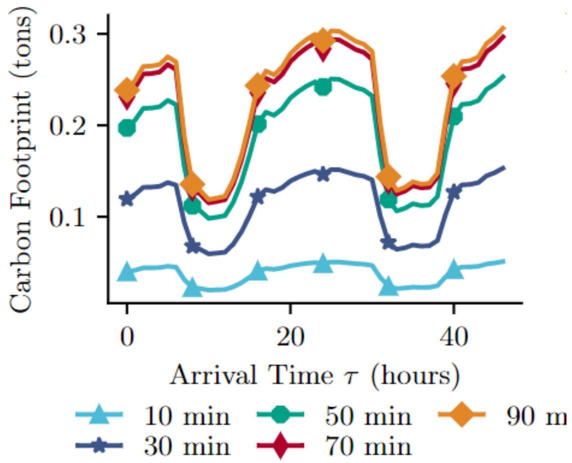


- $\pi_v(\tau)$: the carbon intensity function (unit: kg/kWh).

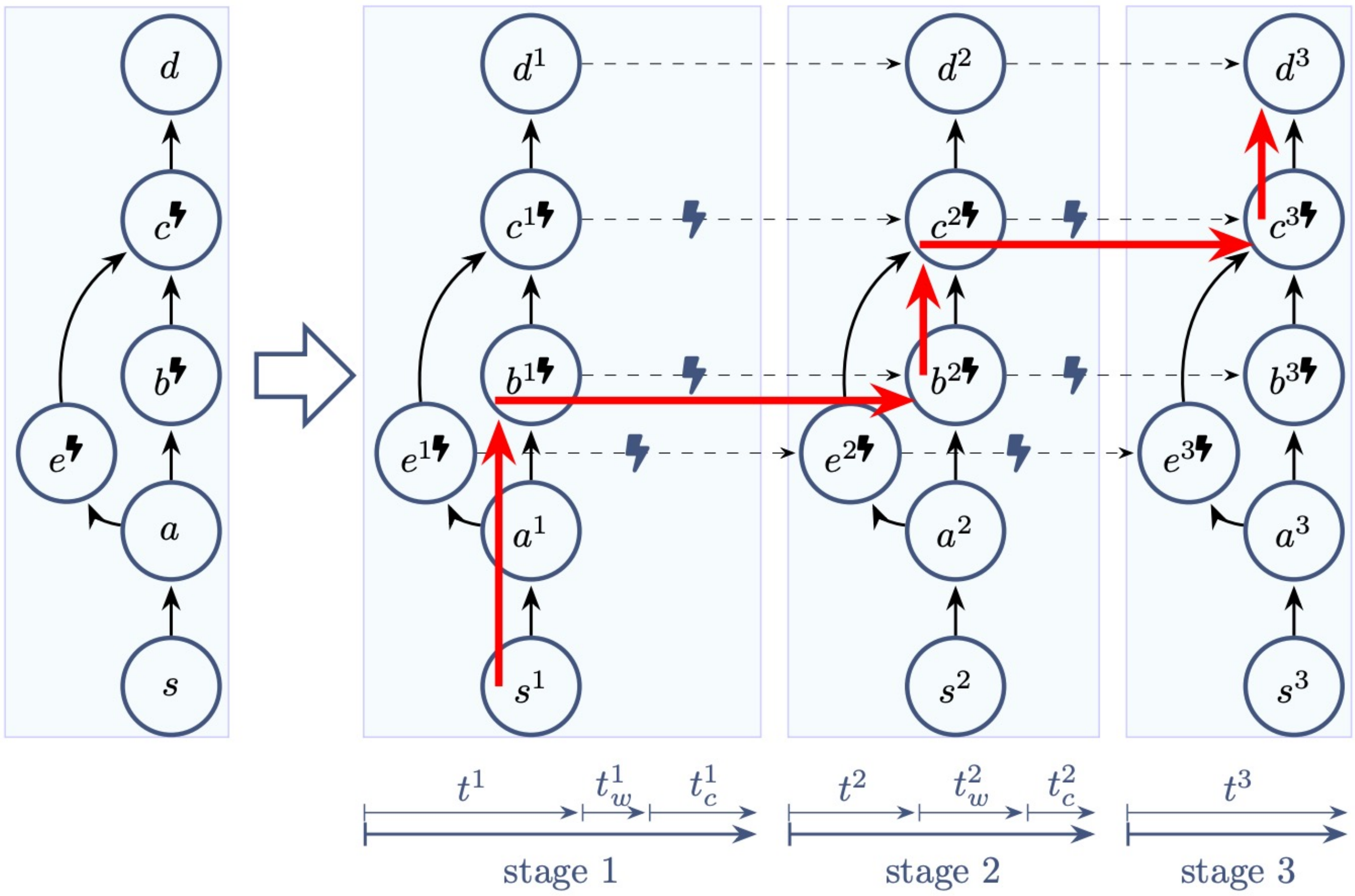


- The carbon footprint objective function

$$F_v(t_c, t_w, \beta, \tau) = \int_0^{t_c} \pi_v(\tau + t_w + \xi)\,\frac{\partial \phi_v}{\partial t}(\beta, \xi)\, d\xi$$



Problem Formulation: A Stage-expanded Graph



Property 1: The stages are connected by virtual charging edges.
Property 2: The time duration of each stage is variable.

- N: we allow e-truck to charge at most N times.
- s, d: the source and the destination.

- **Benefits:**
  - Incorporates arrival time and SoC information.
  - Low model complexity.
  - Reveals problem structure.

Problem Formulation

$$\text{CFO}: \min \sum_{i=1}^{N} \sum_{v \in \mathcal{V}_c} y_v^i F_v(t_c^{i,v}, t_w^{i,v}, \beta_v^i, \tau_v^i) \tag{10a}$$

$$\text{s.t.} \ \delta_i^\tau(\vec{x}, \vec{y}, \vec{t}, \vec{\tau}) \le 0, \forall i \in \{1, \ldots, N+1\} \tag{10b}$$

$$\delta_i^\beta(\vec{x}, \vec{y}, \vec{t}, \vec{\beta}) \le 0, \forall i \in \{1, \ldots, N+1\} \tag{10c}$$

$$\text{var.} \ (\vec{x}, \vec{y}) \in \mathcal{P}, \vec{\beta} \in \mathcal{S}_\alpha, \vec{\tau} \in \mathcal{T}_\tau, \vec{t} \in \mathcal{T}. \tag{10d}$$

The carbon footprint objective

Deadline and scheduling Constraint with dual λ_i^τ

SoC lower bound constraint with dual λ_i^β

x: the path selection variable
y: the charge location selection variable
$\mathcal{P}$: the path selection set.

β_i: the arrival SoC at stage i.
τ_i: the arrival time at stage i.

t^i: the travel time at stage i.
t_w^i: the wait time at stage i.
t_c^i: the charge time at stage i.

Dual Based Method: High Level Idea

- We aim to solve the dual problem:

$$\max_{\vec{\lambda}\geq 0} D(\vec{\lambda}) = \max_{\lambda \vec{\geq} 0} \min_{(\vec{x},\vec{y})\in\mathcal{P}, \vec{t}\in\mathcal{T}} L(\vec{x}, \vec{y}, \vec{t}, \vec{\lambda})$$

- Given $\vec{\lambda}$, we can compute $D(\vec{\lambda})$ by decompose the problem.
  - we can assign cost to each road segment and charging station with $\vec{\lambda}$
  - λ_i^{β} is the cost for battery underflow at stop i.
  - λ_i^{τ} is the delay cost for the charging scheduling at stop i.

- We can then update $\vec{\lambda}$ by checking its corresponding constraints and re-solve $D(\vec{\lambda})$ with less constraint violation.

Dual Based Method: The Dual Problem

$$\max_{\vec{\lambda}\geq 0} D(\vec{\lambda}) = \max_{\lambda \geq 0} \min_{(\vec{x},\vec{y})\in\mathcal{P}, \vec{t}\in\mathcal{T}} L(\vec{x},\vec{y},\vec{t},\vec{\lambda})$$

$$D(\vec{\lambda}) = D_1(\vec{\lambda}) + \min_{(\vec{x},\vec{y})\in\mathcal{P}} \left(\sum_{i=1}^{N+1} \sum_{e\in\mathcal{E}} x_e^i \boxed{\min_{t_e^i\in[t_e^{lb}, t_e^{ub}]} g_e^i(\vec{\lambda}, t_e^i)} + \sum_{i=1}^{N} \sum_{v\in\mathcal{V}_c} y_v^i \boxed{\min_{\substack{t_c^{i,v}\geq 0, t_w^{i,v}\geq t_w^0,\\ \beta_v^i\in[0,B], \tau_v^i\in[0,T]}} h_v^i(\vec{\lambda}, t_c^{i,v}, t_w^{i,v}, \beta_v^i, \tau_v^i)} \right)$$

$$= D_1(\vec{\lambda}) + \min_{(\vec{x},\vec{y})\in\mathcal{P}} \sum_{i=1}^{N+1} \sum_{e\in\mathcal{E}} w_e^i(\vec{\lambda}) x_e^i + \sum_{i=1}^{N} \sum_{v\in\mathcal{V}_c} \sigma_v^i(\vec{\lambda}) y_v^i$$

Single-variable convex optimization for speed planning

4-variable non-convex optimization for charge planning

Weight for each road segment

Cost for each charging station

$\mathcal{P}$: Find N charging stops and $N+1$ sub-paths such that the overall cost is minimized.

$$\text{CFO}: \ \min \sum_{i=1}^{N} \sum_{v\in\mathcal{V}_c} y_v^i F_v(t_c^{i,v}, t_w^{i,v}, \beta_v^i, \tau_v^i) \quad (10a)$$

$$\text{s.t.} \ \delta_i^{\tau}(\vec{x},\vec{y},\vec{t},\vec{\tau}) \leq 0, \ \forall i \in \{1,...,N+1\} \quad (10b)$$

$$\delta_i^{\beta}(\vec{x},\vec{y},\vec{t},\vec{\beta}) \leq 0, \ \forall i \in \{1,...,N+1\} \quad (10c)$$

$$\text{var.} \ (\vec{x},\vec{y}) \in \mathcal{P}, \vec{\beta} \in \mathcal{S}_{\alpha}, \vec{\tau} \in \mathcal{T}_{\tau}, \vec{t} \in \mathcal{T}. \quad (10d)$$

Solving the Path Selection Problem

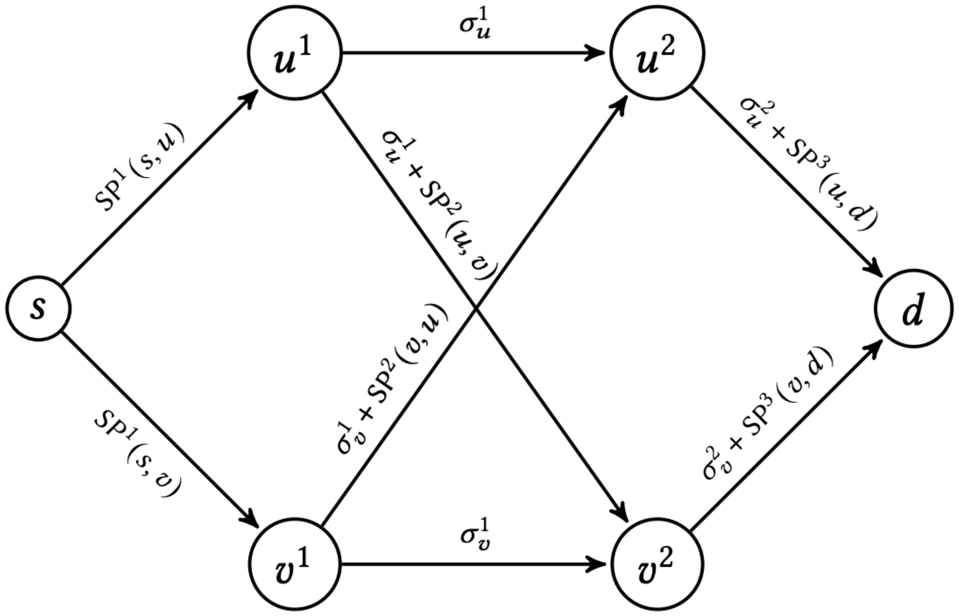
- We consider an extended graph $\tilde{G} = (\tilde{V}, \tilde{E})$ which contains N copies of charging stations and $\{s, d\}$
  $$\tilde{V} = \{v^i : v \in V_c, i \in \{1, \dots N\}\} \cup \{s, d\}$$

$$\min_{(\vec{x},\vec{y})\in\mathcal{P}} \sum_{i=1}^{N+1} \sum_{e\in\mathcal{E}} w_e^i(\vec{\lambda}) x_e^i + \sum_{i=1}^{N} \sum_{v\in\mathcal{V}_c} \sigma_v^i(\vec{\lambda}) y_v^i$$

Weight for each road segment

Cost for each charging station

- For each pair (u^i, v^{i+1}), we construct an edge between them with the cost: $\sigma_u^i + SP^{i+1}(u, v)$
  - $SP^{i+1}(u, v)$ denotes the cost of shortest path between u, v with weight w_e^{i+1} on the original graph.
  - Similarly, we construct an edge between (s, u^1) and (u^N, d) for all $u \in V_c$.



- Then we can apply the shortest path from s to d to the extended graph.

The Dual Subgradient Method

$$\max_{\vec{\lambda} \geq 0} D(\vec{\lambda}) = \max_{\lambda \vec{\geq} 0} \min_{(\vec{x},\vec{y}) \in \mathcal{P}, \vec{t} \in \mathcal{T}} L(\vec{x}, \vec{y}, \vec{t}, \vec{\lambda})$$

□ We know how to compute $D(\vec{\lambda})$, the next thing is to update $\vec{\lambda}$

□ We update $\vec{\lambda}$ based on the subgradient of $D(\vec{\lambda})$ at iteration k.

$$\lambda_i^{\tau}[k+1] = [\lambda_i^{\tau}[k] + \alpha_k \boxed{\delta_i^{\tau}[k]}]^{+}$$

$$\lambda_i^{\beta}[k+1] = \left[\lambda_i^{\beta}[k] + \alpha_k \boxed{\delta_i^{\beta}[k]}\right]^{+}$$

Constraint violations

– Here α_k is the step size.

□ Basically, we increase constraint penalty if there is a constraint violation.

Performance Analysis

- □ **Convergence rate** of $O(\frac{1}{\sqrt{k}})$ to the dual optimal $D(\lambda^*)$.
  - where k is the number of iterations.

- □ **Time complexity** per iteration is

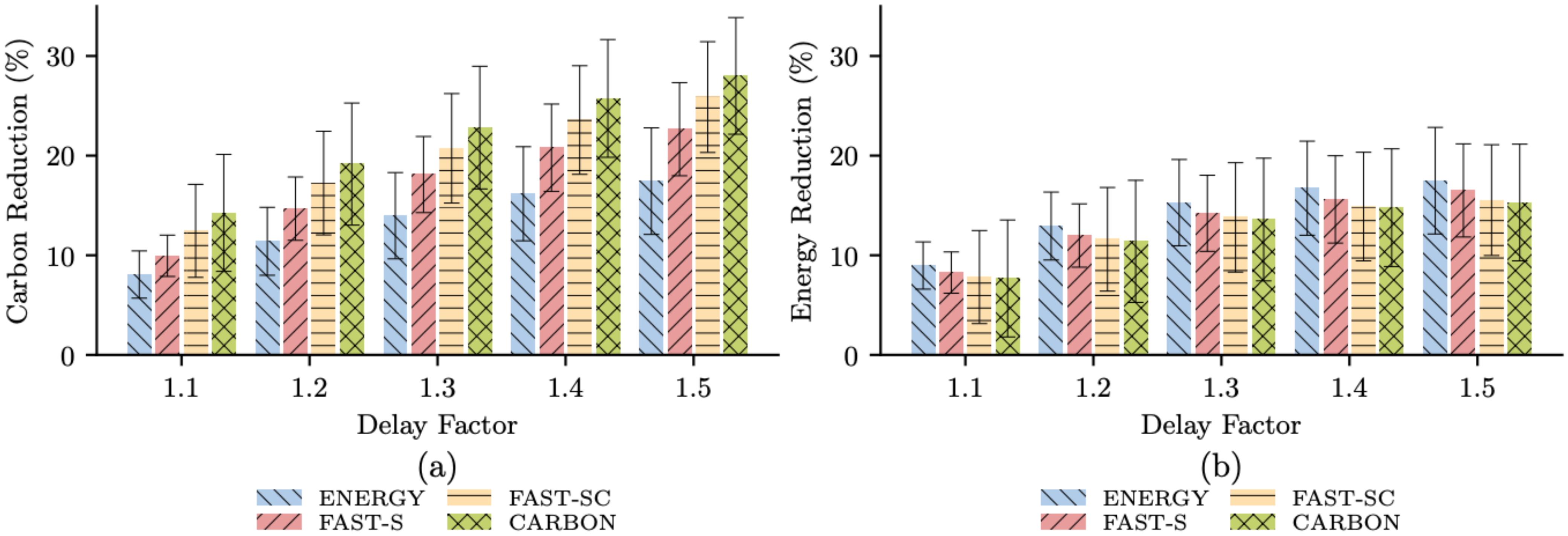
$$O(N|V_c||V||E| + N|V_c|\frac{M^4}{\epsilon_1^4})$$

  - Here, $M = \{t_c^{ub}, t_w^{ub}, B, T\}$ and ϵ_1 is the required accuracy for the subproblems

- □ Bound on **optimality gap**.

$$ALG - OPT \leq -\sum_{i=1}^{N+1}\left(\lambda_i^{\beta}\delta_i^{\beta} + \lambda_i^{\tau}\delta_i^{\tau}\right)$$

Simulation Results



- **Message 1**: The carbon-optimized solutions save up to **28%** carbon as compared to FAST, and **9%** as compared to ENERGY.
- **Message 2:** Carbon-optimized solutions are also energy-efficient.

Concluding Remarks

- **Important and Challenging Problem**
  - We identify and study an important and challenging problem Carbon Footprint Optimization (CFO).
- **Novel Formulation**
  - We provide a novel problem formulation based on a novel stage-expanded graph.
- **Efficient Approach with Performance Guarantee**
  - We provide an efficient dual-based method for solving the challenging CFO problem with favorable performance
  - It is applicable to many other applications.
- **Insights:** carbon-optimized solutions are necessary.