Congestion Reduction via Personalized Incentives

Ali Ghafelebashi, Meisam Razaviyayn, and Maged Dessouky

Daniel J. Epstein Department of Industrial & Systems Engineering
University of Southern California
Motivation and Background

- Longer traffic can worsen the air quality[^2]

Strategies to solve traffic congestion[^3]

1. Adding more capacity
2. Transportation System Management and Operation (TSM)
3. Demand management

Road pricing policy

- Pros: in theory and some cases work
- Cons: equity barriers

Rewarding policy (positive incentive)

- Three projects in the Netherlands[^4]
- CAPRI project[^5]
- This research project

# Incentive Offering Process

- **Personalized and Dynamic**

<table>
<thead>
<tr>
<th>Different individuals</th>
<th>Different times</th>
<th>Different routes</th>
</tr>
</thead>
<tbody>
<tr>
<td>7:00 AM Home $\times$ $\mathbf{\not\times}$ $\mathbf{\times}$ Office $\mathbf{\not\times}$</td>
<td>7:00 AM Home $\times$ $\mathbf{\not\times}$ Office $\mathbf{\not\times}$</td>
<td>7:00 AM Home $\mathbf{\not\times}$ Office $\mathbf{\not\times}$</td>
</tr>
<tr>
<td>7:00 AM Home $\checkmark$ $\mathbf{\not\times}$ $\mathbf{\times}$ Office $\mathbf{\not\times}$</td>
<td>4:30 PM Home $\checkmark$ $\mathbf{\not\times}$ Office $\mathbf{\not\times}$</td>
<td>7:00 AM Home $\mathbf{\not\times}$ Office $\mathbf{\not\times}$</td>
</tr>
</tbody>
</table>

- **Avoid creating new congestion**

Predicted Traffic Flow:

- **Scenario A**
  - a to b: 40
  - b to c: 25
  - c to d: 40

- **Scenario B**
  - a to b: 20
  - b to c: 5
  - c to d: 40

- **No congestion in the network**
- **New congestions in the network**
Incentivizing Process

High level process

Step 1: Sharing routes/preferences

Step 2: Offering incentives

Detailed process

Users send OD information

Users make decisions

Server receives user data and traffic data

Traffic prediction

Finding possible routes

Offering incentives to individual drivers
Modeling

What should be our objective/goal?

• Minimize incentivizing cost
• Maximize a utility of the drivers’ travel times
• Minimize Carbon emission footprint

A simple formulation

\[
\begin{align*}
\min_{\text{incentives}} & \quad \text{Cost of offering incentives} \\
\text{s.t.} & \quad \text{Volume}_t \leq \text{Capacity}, \quad \forall t
\end{align*}
\]

Drivers’ responses are random variables

\[
\begin{align*}
\min_{\text{incentives}} & \quad \text{Cost of offering incentives} \\
\text{s.t.} & \quad \mathbb{E} [\text{Volume}_t] \leq \text{Capacity}, \quad \forall t
\end{align*}
\]
First Model

\[
\begin{align*}
\text{min} & \quad \text{Cost of offering incentives} \\
\text{s.t.} & \quad \mathbb{E}[\text{Volume}_t] \leq \text{Capacity}, \ \forall t \\
& \quad \text{constraints on incentive offering mechanism}
\end{align*}
\]

- **Pros:** ILP → off-the-shelf solvers
- **Cons:**
  - Is it fair?
  - It assumes feasibility.

\[
\begin{align*}
\text{max} & \quad U(\text{Drivers’ travel time}) \\
\text{s.t.} & \quad \mathbb{E}[\text{Volume}_t] \leq \text{Capacity}, \ \forall t \\
& \quad \text{Cost of offering incentives} \leq \text{Budget} \\
& \quad \text{Other constraints incentives}
\end{align*}
\]

- **Major (limiting) assumption:**
  - We are operating below the system capacity (feasibility).
Operating in Congested Networks

Utility\( (\text{Speed, Volume, Routing}) \)

\[\text{Speed} \leftarrow R(-) \text{ borrowed from [2]}\]

\[\text{Routing information of drivers} \]

\[\text{Offered incentives (S)} \]

\[\text{BPR(-) [3]} \]

\[(\text{Expected) Volume} \hat{v}_t, t = 1, \ldots, T)\]

Example: Use the total carbon emission as the objective

\[
\begin{align*}
\min_S & \quad \sum_{\ell=1}^{|\mathcal{E}|} \sum_{t=1}^{|T|} \hat{v}_{\ell,t} f_{CE} (\hat{v}_{\ell,t}) L_{\ell} \\
\text{s.t.} & \quad \hat{v}_{\ell,t} = (RP)_\ell t S1 \\
& \quad S^T 1 = 1 \\
& \quad c^T S1 \leq \Omega \\
& \quad DS1 = q \\
& \quad S \in \{0, 1\}^{(|R|, |T|) \times |N|} 
\end{align*}
\]

\[\rightarrow \text{Total Carbon Emission [3,4]}\]
\[\rightarrow \text{Estimated volume [1,2]}\]
\[\rightarrow \text{One incentive per driver}\]
\[\rightarrow \text{Budget constraint}\]
\[\rightarrow \text{Aware of the # of drivers per O-D}\]

➢ Modular Design
  ➢ Can be changed if needed
  ➢ Can be learned
    ➢ Use preference learning
    ➢ Parameterize by a neural network and learn

➢ How to solve it? Large-scale and challenging


Efficient Algorithm

\[
\min_S \sum_{\ell=1}^{|\mathcal{E}|} \sum_{t=1}^{|\mathcal{T}|} \hat{v}_{\ell,t} f_{CE} (\delta(\hat{v}_{\ell,t})) L_\ell \quad \rightarrow \text{Total Carbon Emission } [3,4]
\]

s.t. \quad \hat{v}_{\ell,t} = (RP)_{\ell,t} S 1
\rightarrow \text{Estimated volume } [1,2]

\begin{align*}
S^T 1 &= 1 & \rightarrow \text{One incentive per driver} \\
c^T S 1 &\leq \Omega & \rightarrow \text{Budget constraint} \\
DS1 &= q & \rightarrow \text{Aware of the # of drivers per O-D}
\end{align*}

\[
f_{CE}(\delta) = 523.7 - (1654.4 \times 10^{-2})\delta - (2635.4 \times 10^{-4})\delta^2 - (1771.5 \times 10^{-6})\delta^3 - (442.9 \times 10^{-8})\delta^4. \quad [4]
\]

\[
\delta(v) = \frac{L}{t_0} \left( 1 + 0.15 \left( \frac{v}{w} \right)^4 \right)^{-1} \quad [3]
\]

**Theorem:** Relaxing the last constraint leads to a convex optimization problem!

➢ How should we solve this problem?
   • First order methods
   • Off-the-shelf solvers such as CVX and Gurobi

➢ It is still challenging due to massive scale of the problem.
➢ Can we use distributed/edge computation?
➢ Can we exploit the individual processing power of drivers’ smartphones?
➢ We use Alternating Direction Method of Multipliers (ADMM) to do distributed computation.

Alternating Direction Method of Multipliers (ADMM) - Background

Solving linearly constrained optimization problems in form:

$$\min_{w,z} h(w) + g(z) \quad \text{s.t.} \quad Aw + Bz = c$$

Augmented Lagrangian function

$$\mathcal{L}(w, z, \lambda) \triangleq h(w) + g(z) + \langle \lambda, Aw + Bz - c \rangle + \frac{\rho}{2} \|Aw + Bz - c\|^2_2$$

Augmented update rules

**Primal Update:**

$$w^{r+1} = \arg\min_w \mathcal{L}(w, z^r, \lambda^r),$$

$$z^{r+1} = \arg\min_z \mathcal{L}(w^{r+1}, z, \lambda^r)$$

**Dual Update:**

$$\lambda^{r+1} = \lambda^r + \rho \left( Aw^{r+1} + Bz^{r+1} - c \right)$$
Efficient Algorithm for Finding Optimal Incentives

\[ \min \sum_{\ell=1}^{|\mathcal{E}|} \sum_{t=1}^{|T|} \hat{v}_{\ell,t} f_{CE}(\delta(\hat{v}_{\ell,t})) L_\ell \]

s.t. \( \hat{v}_{\ell,t} = (RP)_{\ell,t} S1 \)

\( S^T 1 = 1 \)

\( c^T S1 \leq \Omega \)

\( DS1 = q \)

\( S \in \{0,1\}^{(|\mathcal{R}|,|\mathcal{I}|) \times |\mathcal{N}|} \)

The update rule of \( y_{\ell,t} \) can be done in parallel. Different columns of variables \( W, S, H \) can be updated in parallel (via edge computation).

**Theorem:** The above algorithm finds an \( \varepsilon \)-solution of the relaxed problem in \( O(1/\varepsilon) \) iterations.

How to do rounding? ADMM-Q algorithm (became popular recently for training binary neural networks)

Algorithm 1 ADMM

1. Input: Initial values: \( \gamma^0, S^0, \theta^0, z^0, \Pi^0, W^0, u^0, \beta^0, \lambda^0_1, \ldots, \lambda^0_\nu \), Dual update step: \( \rho \), Number of iterations: \( T \).
2. for \( t = 0,1,\ldots,T \) do
3. for \( \ell = 0,1,\ldots,|\mathcal{E}| \) do
4. for \( t = 0,1,\ldots,|T| \) do
5. \( y_{\ell,t}^{t+1} = \arg\min_{y_{\ell,t}} f_{CE}(y_{\ell,t}) L_\ell + \lambda_{\ell,t}^t (a_{\ell,t} u^t - y_{\ell,t}) + \frac{\rho}{2} (a_{\ell,t} u^t - y_{\ell,t})^2 \)
6. end for
7. end for
8. \( S^{t+1} = \frac{1}{\rho} (-\lambda^t_1 + \rho S^{t+1}) \)
9. \( \theta^{t+1} = \frac{1}{\rho} [(I + c^T e^T)^{-1} (-\lambda^t_0 + \lambda^t_1 e^T + \rho c^T e + \rho \Omega c)] \)
10. \( z^{t+1} = \frac{1}{\rho} (\lambda^t_0 + \rho u^t) \)
11. \( H^{t+1} = \Pi \left( \frac{1}{\rho} (-\lambda^t_0 + \rho S^{t+1}) \right) \)
12. \( W^{t+1} = \frac{1}{\rho} [(I + T 1)^{-1} (-\lambda^t_2 + \rho 1 1^T + \rho S^{t+1})] \)
13. \( u^{t+1} = \frac{1}{\rho} [(3I + D^T D + A^T A)^{-1} (-\lambda^t_1 + D^T 1^T - A^T 1^T + \lambda^t_1 + \lambda^t_2 - \rho S^{t+1} + \rho D^T q + \rho A^T \gamma^{t+1} + \rho \Delta^{t+1}) \]
14. \( \beta^{t+1} = \Pi \left( \frac{1}{\rho} (-\lambda^t_2 + \rho c^T \theta^t + \rho \Omega) \right) \)
15. \( \gamma^{t+1} = \lambda^t_1 + \rho (S^{t+1} 1 - u^{t+1}) \)
16. \( \lambda^{t+1}_2 = \lambda^t_2 + \rho (W^{t+1} 1 - 1) \)
17. \( \lambda^{t+1}_1 = \lambda^t_1 + \rho (D^T u^{t+1} - q) \)
18. \( \lambda^{t+1}_3 = \lambda^t_3 + \rho (A u^{t+1} + \gamma^{t+1}) \)
19. \( \lambda^{t+1}_4 = \lambda^t_4 + \rho (H^{t+1} - S^{t+1}) \)
20. \( \lambda^{t+1}_5 = \lambda^t_5 + \rho (T^t 1 - u^{t+1}) \)
21. \( \lambda^{t+1}_6 = \lambda^t_6 + \rho (c^T \theta^t + \beta^{t+1} - \Omega) \)
22. \( \lambda^{t+1}_7 = \lambda^t_7 + \rho (u^{t+1} - z^{t+1}) \)
23. \( \lambda^{t+1}_8 = \lambda^t_8 + \rho (W^{t+1} - S^{t+1}) \)
24. end for
25. Return: \( S^T \)
Network Construction

❖ How do we construct the network?

❖ How to estimate O-D pairs for drivers?
  • We do not have access to prior O-D as some works need [1-4]
  • We have a large-scale problem (some prior work cannot scale)
  • We use [5]

❖ Data:
  • ADMS (Archived Data Management System at USC)
    o Real-time traffic data such as volume and speed
    o Collected by loop sensors
    o Highway data → recorded every 30 seconds
    o Arterial road data → recorded every 1 minute
  • City: Los Angeles
    ➢ Why this region?
      1. Available detailed data
      2. Including both heavy and light traffic
  • Date: March, April, and May 2018
  • Only business days
  • Used features: speed and volume

Numerical Experiments - Small Region

- **Experiment I**:  
  - Region: USC neighborhood  
  - Only arterial roads  
  - Incentive Set: \{0, 1, 2, 5, 10, 1000\}

<table>
<thead>
<tr>
<th>Budget ($ \times 10^3$)</th>
<th>Percentage of drivers to whom we offered incentives</th>
<th>Average of the incentive amount ($)</th>
<th>Reduction in Carbon Emission</th>
</tr>
</thead>
<tbody>
<tr>
<td>7-8 AM exp. I</td>
<td>1</td>
<td>8.94%</td>
<td>4.33%</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>43.12%</td>
<td>17.79%</td>
</tr>
</tbody>
</table>
Numerical Experiments - Large Region

- **Experiment II:**
  - Region: Los Angeles
  - Only highways
  - Incentive Set: \{0, 1, 2, 5, 10, 1000\}

![Graph showing number of incoming drivers over time](image)

<table>
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<tr>
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<th>Reduction in Carbon Emission</th>
</tr>
</thead>
<tbody>
<tr>
<td>7-8 AM exp. II</td>
<td>1</td>
<td>3.78%</td>
<td>0.72%</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>21.91%</td>
<td>5.70%</td>
</tr>
</tbody>
</table>
Conclusion

• Offering personalized incentives to drivers to reduce congestion
• Efficient algorithms to solve the problem in large-scale
• Utilizing the computational power of individuals’ smartphones by distributed algorithm

❖ Future work:
• Considering different travel modes such as public transportation, carpooling, and biking in options
• Utilizing preference learning to learn the drivers’ acceptance probability
• More features such as income value and gender in computation the drivers’ acceptance probability
• Implementation and analysis of the algorithm in the real-world
• Combining the data of highways and arterial ways
Thank you
Theory of congestion pricing has been widely studied (de Palma and Lindsey 2011, Tsekeris and Voß 2009)
  • Time or area dependent pricing (Zheng et al 2016)
  • Distance dependent (Daganzo and Lehe 2015)
  • Based on vehicle characteristics (Zhang et al 2018)

Limitations:
  • Political barriers, social barriers such as equity, and unpopularity of taxation (Knockaert et al 2012, Levinson 2010, Martens et al 2012)

  • Design and technological complexities (Azevedo et al 2018)

Offering rewards
  • Psychologically more effective than penalizing (Brehm 1966)
  • More popular (Knockaert et al 2012)
  • Some studies on offering rewards:
    o Context of safe driving (Mazureck and Hattem 2006, Bolderdijk et al 2011)
A Simple Model

$$\begin{align*}
\min_{\{s_i^n\}} & \sum_{n \in \mathcal{N}} \sum_{i \in \mathcal{I}_n} s_i^n c_i^n \\
\text{s.t.} & \sum_{n \in \mathcal{N}} \sum_{i \in \mathcal{I}_n} \sum_{r \in \mathcal{R}_n} s_i^n p_i^{r,n} \beta_{r,t} \leq v_0, \quad \forall t \in T \\
& \sum_{i \in \mathcal{I}_n} s_i^n = 1, \quad \forall n \in \mathcal{N}, \\
& s_i^n \in \{0, 1\}, \quad \forall n \in \mathcal{N}, \forall i \in \mathcal{I}_n
\end{align*}$$

\[\mathcal{N} = \{1, \ldots, N\} \quad \text{Set of drivers}\]

\[\mathcal{I}_n = \{\text{money amount, route}\} \quad \text{Set of incentives for driver } n\]

\[s_i^n \in \{0,1\}, \quad i \in \mathcal{I}_n \quad \text{Decision variable: Offer incentive } i \text{ or not}\]

\[c_i^n \quad \text{Cost of offering incentive } i \text{ to driver } n\]

\[p_i^{r,n} \quad [1] \quad \text{Prob of selecting route } r \text{ after offering incentive } i\]

\[\beta_{r,t} \quad [2] \quad \text{Location of driver on route } r \text{ at time } t (\text{Probability vector})\]


Modifying the Simple Model

\[ \min \text{ cost of offering incentives} \]
\[ \text{s.t. } \mathbb{E}[\text{Volume}_t] \leq \text{Capacity, } \forall t \]
\[ \max \text{ } U(\text{Drivers' travel time}) \]
\[ \text{s.t. } \text{Volume}_t \leq \text{Capacity, } \forall t \]
\[ \text{Cost of offering incentives } \leq \text{Budget} \]
\[ \text{Decision variable: Offer incentive } i \text{ or not} \]
\[ \text{Cost of offering incentive } i \text{ to driver } n \]
\[ \text{Prob of selecting route } r \text{ after offering incentive } i \]
\[ \text{Location of driver on route } r \text{ at time } t \text{ (Probability vector)} \]

\[ \mathcal{N} = \{1, \ldots, N\} \]
\[ \mathcal{I}_n = \{(\text{money amount}, \text{route})\} \]
\[ s_i^n \in \{0,1\}, \quad i \in \mathcal{I}_n \]
\[ c_i^n \]
\[ p_i^{r,n} \]
\[ \beta_{r,t} \]

Expected travel time of driver \( n \) after offering incentive \( i \)

\[ \sum_{n \in \mathcal{N}} \sum_{i \in \mathcal{I}_n} s_i^n \sum_{r \in \mathcal{R}_n} p_i^{r,n} \delta_{r} \]
\[ \sum_{n \in \mathcal{N}} \sum_{i \in \mathcal{I}_n} \sum_{r \in \mathcal{R}_n} s_i^n p_i^{r,n} \beta_{r,t} \leq v_0, \quad \forall t \in \mathcal{T} \]
\[ \sum_{n \in \mathcal{N}} \sum_{i \in \mathcal{I}_n} s_i^n c_i^n \leq \text{Budget} = \Omega \]
\[ \sum_{n \in \mathcal{N}} s_i^n = 1, \quad \forall n \in \mathcal{N}, \]
\[ \sum_{i \in \mathcal{I}_n} s_i^n = 1, \quad \forall n \in \mathcal{N}, \forall i \in \mathcal{I}_n \]

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ODDS Research Group

University of Southern California
References

- Jia Shuo Yue, Chinmoy V Mandayam, Deepak Merugu, Hossein Karkeh Abadi, and Balaji Prabhakar. Reducing road congestion through incentives: a case study. 2015.