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GEORGIA TECH

# Smartphone-based Incentive Framework for Dynamic Network Level Traffic Congestion Management

*Viswa Sri Rupa Anne[1], Dr. Srinivas Peeta[1,2]*

*[1]School of Civil and Environmental Engineering, Georgia Institute of Technology*

*[2]H. Milton Stewart School of Industrial & Systems Engineering, Georgia Institute of Technology*

ACT lab — Georgia Tech Autonomous & Connected Transportation lab

## INTRODUCTION:

Traffic congestion and pollution are some of the major transportation related problems faced by urban areas. INRIX (1) study showed that a average American spends almost 100 hours in congestion, with $1350 in economic cost. Transportation sector and related pollution is also the largest contributor to the green house gas emissions (2).

Existing solutions:

| Supply Side solutions | Demand side solutions |
|---|---|
| Infrastructure changes<br>ITS solutions | Tolls<br>Congestion Pricing<br>Incentives |

- Supply side solutions such as infrastructure changes, traffic management devices or ITS solutions are expensive to implement, time-consuming and not sustainable.
- Demand side solutions use tools to target and influence individual's travel behavior. Incentive based solutions are more acceptable and equitable than tolls.

Literature review:

- Behavioral change strategies operate by motivating users to perform actions. Past studies on behavioral change typically targeted mode choice behavior to shift away from car usage towards transit usage.
- Tangible and in-tangible incentives were studied but often not all in the same context.
- Very few studies utilized a smartphone-based frameworks to deliver incentives
- Incentives when tested in real-life were often static and constant throughout the study period
- Real-time dynamic incentives that are reflective of the system congestion were not studied.

## OBJECTIVES:

1. List, categorize and classify behavioral change strategies that can be used to influence travel related decisions
2. Model the strategies in the context of dynamic traffic assignment

## INCENTIVES TYPES & CHARACTERISTICS:

Tangible Incentives:

- Motivates or drives user to behave a certain way
- Such incentives are monetary or value-based.
- Value-based incentives comprise of point systems that can be exchanged for goods and services.
- Incentives are positive quantities as opposed to tolls
- They are updated in real-time and are dependent on system congestion
- Incentives are appended to each choice

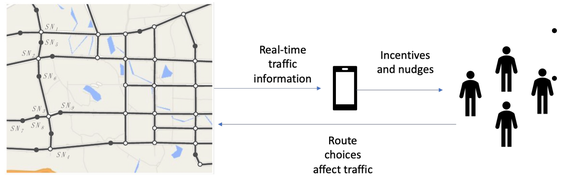
| | Tangible incentives | Nudges |
|---|---|---|
| Time-based | Yes | No |
| Dynamic | Yes | No |
| System level | Yes | No |
| Personalized | No | Yes |
| Geographical | Yes | No |

Nudges:

- Nudge theory: Any aspect of the choice architecture that alters people's behavior in a predictable way without significantly changing their economic incentives (3)
- Nudges do not have a tangible value
- Order of the trip options provided to the user affects their choice.

## METHODOLOGY:

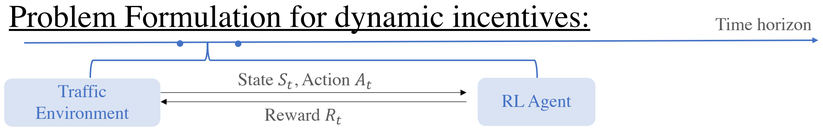
### Real-time smartphone-based incentive deployment framework:




- Mobile apps are ubiquitous in nature.

Real-time incentive deployment framework utilizes mobile apps to present the incentives and nudges to the users while tracking user choices and interpreting user preferences.

### Problem Formulation for dynamic incentives:




- The travel-time and incentives are analogous to the state-action pair in reinforcement learning (RL)
- RL agent generates the incentives.
- Incentives can be present on all arcs of the network based on congestion, as opposed to tolls.
- Consider a dynamic road network G(N, E) with nodes N and edges E.
- State $S_t = \{\dots, tt_{e,t}, \dots\} \forall\, e \in E, t \in T$
- Action $A_t = \{\dots, i_{e,t}, \dots\} \forall\, e \in E, t \in T$
- Reward $R_t = -\left(\sum_{e \in E} tt_{e,t}\right) - \beta * \left(\sum_{e \in E} i_{e,t}\right) \forall\, e \in E, t \in T$

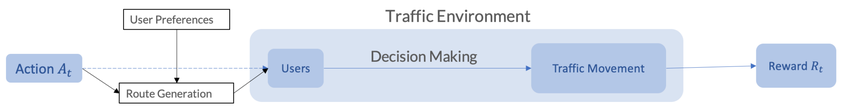
  $tt_{e,t}$ be the travel time on link $e$ at the end of time interval $t$

  $i_{a,t}$ is the incentive added on edge $a$ during RL step $t$

  where $i_t$ is the sum of all incentives added to the network RL step $t$

  $\beta$ is the scaling/weight factor

### Incentive usage and route generation:




Alternative routes $\eta = \{\dots, \eta_{u,t}, \dots\}$ are generated for users $u$ during every RL step $t$.

User preferences:

- Utility approach weighing both time and incentives
- Cost for user u on route is $c_\mu = \beta_{tt,u} * tt_\mu + \beta_{i,u} * i_\mu$

Let $\beta_{tt,u}$ and $\beta_{i,u}$ be the value of time and value of incentive for user u.

$tt_\mu$ and $i_\mu$ be the travel time and incentives on route $\mu$.

Decision Making:

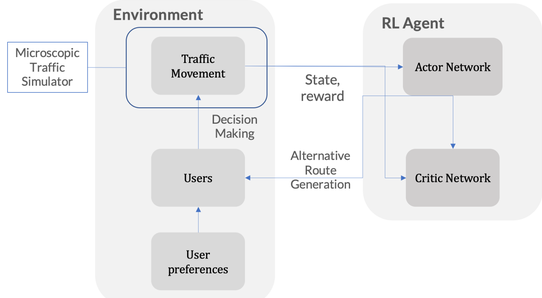
- Habitual users: even if the cost is lower, there is some resistance to changing the route
- Nudged users: even if the cost is higher, the user takes the route because he is nudged to do so

During simulation, the users are classified into nudged users or habitual users to model their corresponding behavior.

Upper limits on incentives are set to avoid negative costs.

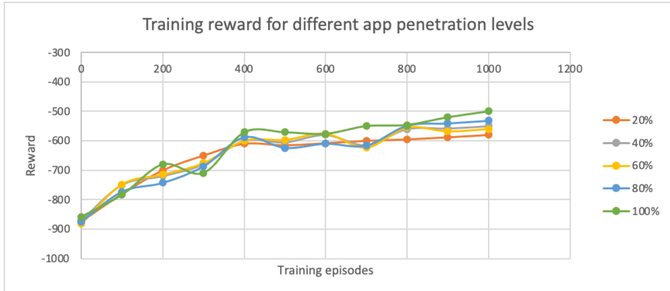
## TRAINING ENVIRONMENT:

- Due to the continuous nature of state and action pairs, the Deep Deterministic Policy Gradient (DDPG) algorithm (4) is utilized for training.
- DDPG is an actor-critic RL algorithm and uses deep learning approaches
  - Actor network generates action in every time step
  - Critic network evaluates the actions to update policy
- Model is trained on Hannover South City network with peak hours between 4PM - 5 PM.




- SUMO simulation platform is used as traffic simulator
- 6 levels of app penetration is tested

## RESULTS:




- App penetration line corresponds to % of the users equipped with incentives provisions app and can change their routes
- Reward value is the highest under 100% app penetration level.
  - Unrealistic but shows that the system is improving with increased app penetration levels
- All scenarios yielding similar training curves could mean that the RL framework needs more training episodes
- Training curves can be different based on overall system congestion levels
- Daily travel patterns data and socio-demographic data will help city managers and traffic operators develop and deploy this framework

## REFERENCES:

1. Inrix (2018) *Scorecard*, *Inrix*. Available at: https://inrix.com/scorecard/ (Accessed: December 12, 2022).
2. Mun, M., S. Reddy, K. Shilton, N. Yau, J. Burke, D. Estrin, M. Hansen, E. Howard, R. West, and P. Boda. PEIR, the Personal Environmental Impact Report, as a Platform for Participatory Sensing Systems Research.
3. Leonard, T. C. Richard H. Thaler, Cass R. Sunstein, Nudge: Improving Decisions about Health, Wealth, and Happiness. *Constitutional Political Economy 2008 19:4*, Vol. 19, No. 4, 2008, pp. 356–360. https://doi.org/10.1007/S10602-008-9056-2.
4. Lillicrap, T. P., J. J. Hunt, A. Pritzel, N. Heess, T. Erez, Y. Tassa, D. Silver, and D. Wierstra. Continuous Control with Deep Reinforcement Learning. 2016.