# Mixed Information Routing Framework Using Competing Equilibrium Strategy

Niharika Deshpande, Hyoshin (John) Park, Ph.D., Gyugeun Yoon, Ph.D.
Department of Computational Data Science and Engineering

Venktesh Pandey, Ph.D.
Department of Civil, Architectural and Environmental Engineering
North Carolina A&T State University, Greensboro 27411, USA

---

**Introduction** Drivers traveling on the road usually choose the route which will reduce their own travel time without giving a thought about how this decision will affect other users in the traffic network. Their behaviours leads to problem of oscillating congestion on the roads in the event of traffic disruption. This paper addresses this issue by adopting a competing optimal approach for informed and uninformed drivers. Informed drivers are proposed with alternate routes that reduce the system cost while uninformed drivers continue their journey on originally proposed routes. This strategy of dispersing traffic can reduce congestion significantly. The framework is implemented using Transmodeler, a traffic simulation by experimenting with varying percentage of informed drivers in the network.

**Literature review** Most of the Dynamic Traffic Assignment (DTA) studies did the assignment which push the system towards either Dynamic User Equilibrium (DUE) (Han, Eve, and Friesz 2018) or Dynamic System Optimal (DSO) (Samaranayake et al. 2018) Equilibrium. Peeta and Mahmassani (1995) compared performance of both approaches in DTA while Morandi (2021) used mixed DTA-DSO framework to route vehicles but in static assignment. These studies do not consider mixed framework in dynamic traffic assignment and, therefore, cannot effectively circulate congestion in real time. Folsom, Park, and Pandey (2022) used competitive equilibrium strategy of dynamic traffic assignment to overcome limitations in previous literature stated above. This study extends the utility function for informed drivers by considering information gain about previously unexplored route. This study implemented a mixed information framework by leveraging manipulative capability of traffic simulator.

**Methodology** Some drivers in a random driver group are selected with a predefined ratio and designated as informed drivers, given an alternative route with travel time a little longer compared to the shortest path. The algorithm ensures that the increment of travel time is always within a predefined threshold time $\theta$. It is assumed to be constant for each traveler. It is defined such that it does not significantly affect the driver in terms of its total travel time but it is optimal for the system. The possible alternate routes satisfy the following equation.

$$\frac{TT_k^t - TT_{shortest}^t}{TT_{shortest}^t} < \theta \tag{1}$$

$TT_k^t$ is the travel time on path $k$ at departure time $t$, and $TT_{shortest}^t$ is the shortest among $TT_k^t$.

Dynamic Traffic Assignment (DTA) algorithm runs iteratively. The delays in previous iterations are used to change routes and departure times for the informed driver group. This study develops a utility function to update the link travel times in each iteration of DTA. The utility function accounts for link marginal cost (LMC) and information gain of exploring unvisited roads for other users. For every iteration of DTA, the study period is divided into 2 minute-time intervals, and LMC for each link is calculated for each interval.

$LMC_{i,t}$, LMC of link $i$ within time interval $t$ consists of two components. The first one is link perceived cost (LPC) which takes into consideration $TT_{i,t}$, the travel time of $i$ within time interval $t$, and $SCD_{i,t}$, the scheduled delay cost of $i$ within $t$ which accounts for the difference between expected and actual travel time on $i$ for $t$. All these parameters are calculated using results of previous iteration of DTA.

$$LPC_{i,t} = TT_{i,t} + SCD_{i,t} \tag{2}$$

The total link marginal cost is calculated using following equation.

$$LMC_{i,t} = LPC_{i,t} + LMC_{i,t}^{TT} + LMC_{i,t}^{SCD} \tag{3}$$

where, $LMC_{i,t}^{TT}$ is the change in travel time cost for all other users caused by additional flow on link $i$ within time interval $t$, $LMC_{i,t}^{SCD}$ is the change in schedule delay cost for all other traffic caused by the additional flow on link $i$ within time interval $t$, and $LPC_{i,t}$ is the perceived link cost given by above Eq.(2). Above Eq.(3) is the utility function used to update the travel times of all links in network for all time intervals. When updated, travel times are provided to the informed travel group for the next iteration of DTA to calculate new routes while the uninformed group of drivers keep using the historical travel times of links for their route choices. The total travel time of path $k$ is calculated as the sum of the travel time of all links belonging to the path. For informed drivers, travel times of all possible paths satisfying Eq.(1) is determined and, the one with the least travel time is provided as a route suggestion. The built-in feature in the simulator is used for changing the distribution of departure time over time to work the system toward convergence.

$$\begin{aligned}&P = min(\textstyle\sum_{i\epsilon k^*} LMC_{i,t})\\ &where, k^*\text{is all canonical routes between given OD pair}\\ &\text{P is presented route choice to informed driver.}\end{aligned} \tag{4}$$

This study also takes into consideration the information gain for other drivers when a driver chooses to explore a certain path. Even though the travel time through that route is not optimum for the driver himself, the exploration of the unknown route decreases the uncertainty of the path for others in the network. The following modified utility function is used to accommodate the information gain factor.

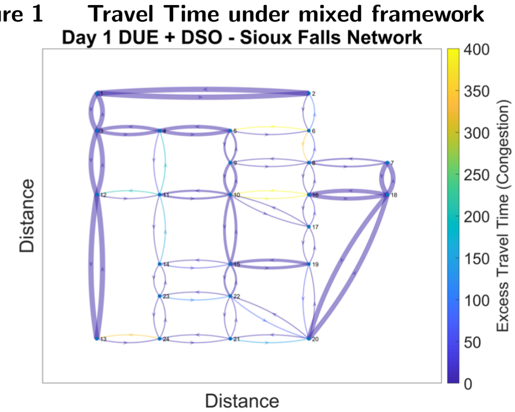
$$U_{k,t} = \sum_{i\epsilon k} LMC_{i,t} - (\alpha/K) \sum_{b\epsilon x^a(t)} \delta\sigma(k_a, k^*_{b\epsilon x^a(t)}|Y, \psi) \tag{5}$$

where, $k_a$ is a route for driver $a$, $k^*_a$ is a canonical route for driver $a$, and $\delta\sigma(k_a, k^*_{b\epsilon x^a(t)}|Y, \psi)$ is the variance reduction (information gain) of $k^*$ for driver $b\epsilon x^a(t)$ on link $a$ when driver $a$ runs some other route $k$ given observations Y and $\psi$. The above utility function is used to strategically alter the behavior of informed drivers by considering the trade-off of exploration and exploitation. The route with minimum utility is presented to the informed driver through a route suggestion app as being the most preferable route.

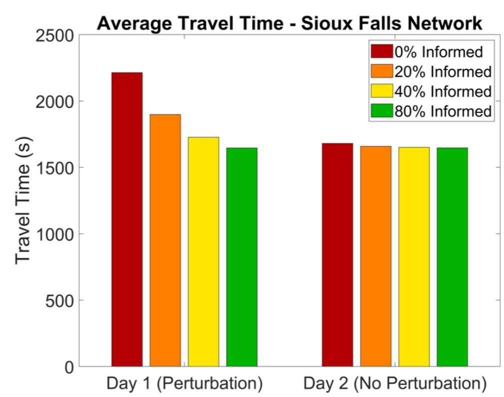
**Results & Conclusion** The congestion results are calculated by changing the percentage of informed drivers in the simulation. The percent is changed from 0% to 100% in the interval of 20%P with 0% being no driver is informed and 100% being all drivers are informed. It has been found that the optimal level of reduction in congestion is achieved for 80% of drivers informed. fig. 1b shows the average travel time of day 1 and day 2 with varying percent of informed drivers.

On day 1 of disruption, the congestion reduces most for 80% informed drivers while on day 2, less improvement occurs because uninformed drivers have accustomed to disruption. fig. 1a represents

**Figure 1** **Travel Time under mixed framework**




(a) Average Excess TT on Day 1 with 20% informed drivers.




(b) Average Travel Time under varying fractions of informed drivers congestion on road network on day 1 of when 20% drivers are informed. The thickness of edges indicates the link capacity. Therefore, thicker ones have higher capacity. The maximum number of iterations for the simulation is 100. The route choices of informed drivers push the system towards dynamic system optimal while that of uninformed drivers push towards dynamic user equilibrium. This framework uses the competing strategies to alleviate congestion in traffic network.

This research develops a novel framework that utilizes link marginal cost to provide updated route choices to informed driver group. It also accounts for uncertainty reduction for other drivers caused by exploration of unknown route. This study presents the route choice to informed drivers which is a trade off between exploration and exploitation. After 100 iterations of DTA are complete, the congestion in the network is reduced by 60% for the 80% informed drivers.

## Acknowledgments

This study is the results of the research project funded by NSF Grant No. 2106989, 2200590, and 1910397, NCDOT Grant No. TCE2020-01, and NASA JPL RSA 1625294.

## References

Folsom L, Park H, Pandey V, 2022 *Dynamic routing of heterogeneous users after traffic disruptions under a mixed information framework. Frontiers in Future Transportation* 3, URL `http://dx.doi.org/10.3389/ffutr.2022.851069`.

Han K, Eve G, Friesz T, 2018 *Computing dynamic user equilibria on large-scale networks: From theory to software implementation.*

Morandi V, 2021 *Bridging the user equilibrium and the system optimum in static traffic assignment: how the cooperation among drivers can solve the congestion problem in city networks.*

Peeta S, Mahmassani H, 1995 *System optimal and user equilibrium time-dependent traffic assignment in congested networks. Annals of Operations Research* 60:81–113, URL `http://dx.doi.org/10.1007/BF02031941`.

Samaranayake S, Krichene W, Reilly J, Delle Monache ML, Goatin P, Bayen A, 2018 *Discrete-time system optimal dynamic traffic assignment (so-dta) with partial control for physical queuing networks. Transportation Science* 52, URL `http://dx.doi.org/10.1287/trsc.2017.0800`.