A mixed equilibrium simulation-based dynamic traffic assignment model for network planning with mixed autonomous and human-driven vehicles

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-Introduction: Autonomous vehicle (AV) technology along with dynamic traffic assignment (DTA) models have the potential to shed light on identifying and addressing the inefficient traffic network routing attributed with human-driven vehicles (HVs). While user equilibrium (UE) condition is known to prevail in urban networks, traffic controllers often wish to establish system optimum (SO) because of lower total system travel time. With the advent of self-driving vehicle technologies that are centrally controlled and dispatched in the network, SO can be followed in the network to mitigate the impact of selfish routing of users. Two approaches are investigated in this context including uniform-ratio and optimal-ratio control scheme (URCS and ORCS) of SO users in a time-dependent traffic assignment setup. In the uniform-ratio approach, a fraction of controllable vehicles is predefined and identically distributed over all OD pairs at different times while in the dynamic ORCS, the optimum ratio of the SO users is determined considering the central agent potential in controlling existing AVs. The objective of the ORCS is that to maximize the total travel time savings by controlling as few AVs as possible between each OD pair at different time intervals.

-Objectives: This research aims to estimate the dynamic mixed traffic flow pattern in an urban network in the presence of AVs and HVs that follow different route choice behaviors. The problem is formulated as a bi-level optimization problem and seeks a trade-off between the system travel time reduction and the ratio of the under-control vehicles. A simulation-based algorithm for mixed equilibrium dynamic traffic assignment problem is presented in the lower level that predicts time dependent traffic flow patterns based on the optimal SO ratio obtained from the upper level problem.

-ORCS formulation as a bi-level optimization:

min $\omega \|\tilde{q}\|_1 + (1-\omega) z(x^*)$

s. t. upper level: $0 \le \tilde{q}_d^\tau \le C_{max} . q_d^\tau$

lower level: Algorithm 1: mixed equilibrium DTA(x^*)

-Solution algorithm for <u>upper level</u>:

-Input: Network G (N, A, T), demand vectors q^τ, $\forall\ \tau \in$ T, control coefficient **ω**, penalty parameter ρ, maximum control potential Cmax, gap tolerances ε3, ε4,

-Output: Optimal shift flow in assignment intervals $\tau \in$ T $(\tilde{q}^{\tau *})$

-Initialize:

Set n = 0, g3 = ∞, $\tilde{q}^{\tau,n} = 0$,$q_1^{\tau,n} = q^\tau$, $q_2^{\tau,n} = 0$. Derive the mixed equilibrium flow pattern $x_1^{\tau,n}$, $x_2^{\tau,n}$ using Algorithm 1 with the initial demand and calculate $t^{\tau,n}$, $mt^{\tau,n}$ and $mc^{\tau,n}$.

-Main Loop:

while n < N3 and g3 > ε3:

Calculate the approximation of $\nabla z^{\tau,n}$:

-Find the shortest and the least marginal travel time path between each OD pair for all assignment intervals $(\tau \in$ T)

-Calculate the vector form of $\nabla z^n = (\cdots, \nabla z^{\tau,n}, \cdots)$

Solve the optimal control problem using ADMM:

-Initialize: Set k = 0, e1 = ∞, e2 = ∞, $c^k = u^k = 0$.

while (k < N4 and (e1 > ε4 or e2 > ε4):

Update $\tilde{q}^{\tau,k+1}, c_d^{\tau,k+1}, u^{\tau,k+1}$ with iterative subproblems as follows:

$$\tilde{q}^{\tau,k+1} = c^{\tau,k} - u^{\tau,k} - \frac{(1-\omega)}{\rho} \nabla z^{\tau,n}$$

$$c_d^{\tau,k+1} = \begin{cases} \min\{q_d^+, \tilde{q}_d^{\tau,k+1} + u_d^{\tau,k} - \omega/\rho\}, & \tilde{q}_d^{\tau,k+1} + u_d^{\tau,k} > \omega/\rho; \\ 0, & \tilde{q}_d^{\tau,k+1} + u_d^{\tau,k} \in [-\omega/\rho, \omega/\rho]; \\ \max\{0, \tilde{q}_d^{\tau,k+1} + u_d^{\tau,k} + \omega/\rho\}, & \tilde{q}_d^{\tau,k+1} + u_d^{\tau,k} < -\omega/\rho. \end{cases}$$

$$u^{\tau,k+1} = u^{\tau,k} + \tilde{q}^{\tau,k+1} - c^{\tau,k+1}$$

Update errors e1 $= \|\tilde{q}^{\tau,k+1} - c^{\tau,k+1}\|_1$, e2 $= \|c^{\tau,k+1} - c^{\tau,k}\|_1$, Set k = k + 1.

end while

check demand flow shift not to exceed from Cmax

Solve the new mixed traffic equilibrium

Update demand vectors $q_1^{\tau,n+1} = q_1^{\tau,n} - \tilde{q}^{\tau,k}$, $q_2^{\tau,n+1} = q_2^{\tau,n} + \tilde{q}^{\tau,k}$. Derive the equilibrium flow pattern x_1^{n+1}, x_2^{n+1} using Algorithm 1 with updated demand $q_1^{n+1} = (\dots, q_1^{\tau,n+1}, \dots)$ and $q_2^{n+1} = (\dots, q_2^{\tau,n+1}, \dots)$.

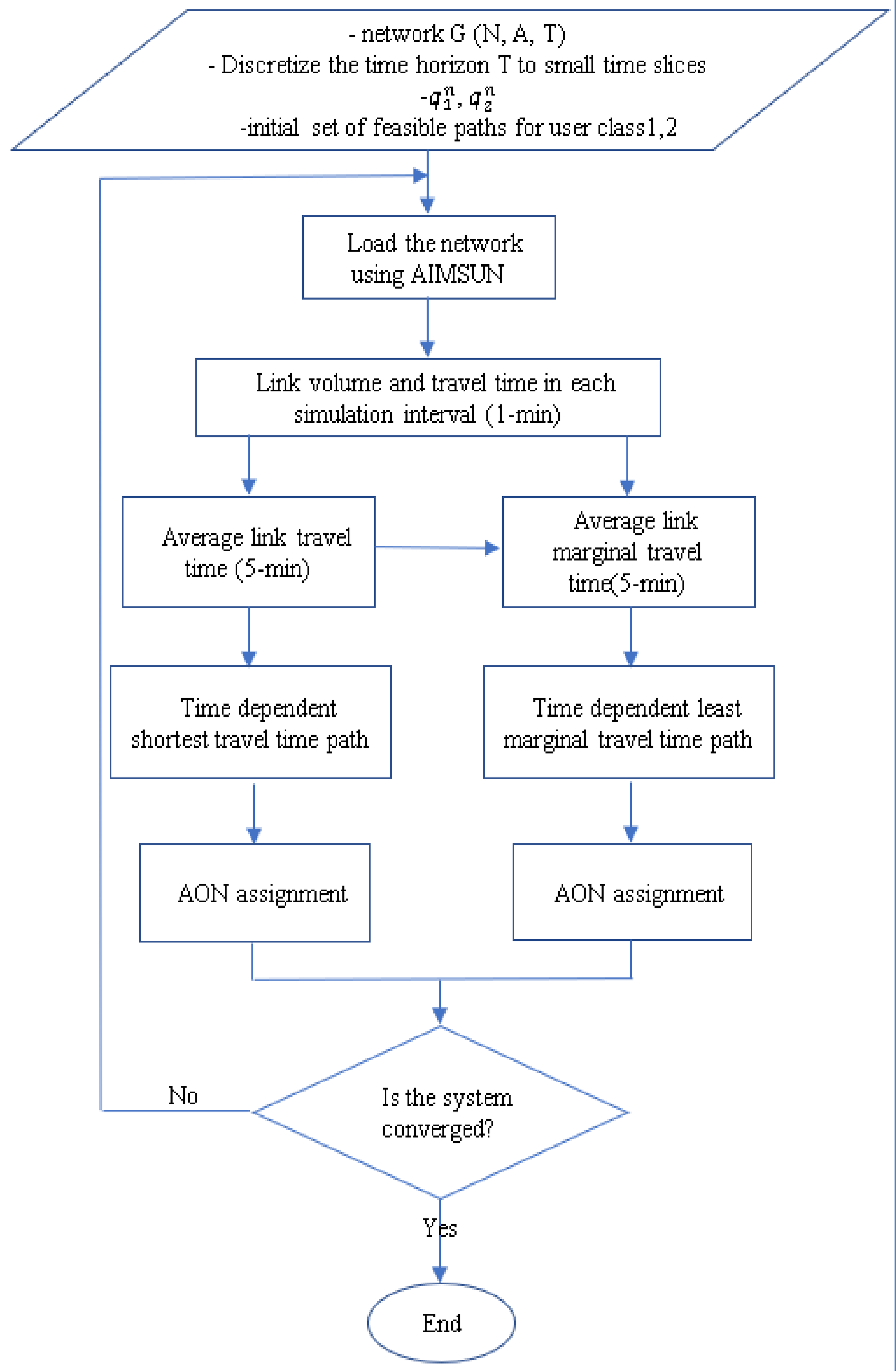
-Compute gap g 3= $\|\tilde{q}^k\|_1$.

-Set $\tilde{q}^{\tau,n+1} = \tilde{q}^{\tau,n} + \tilde{q}^{\tau,k}$; n = n + 1.

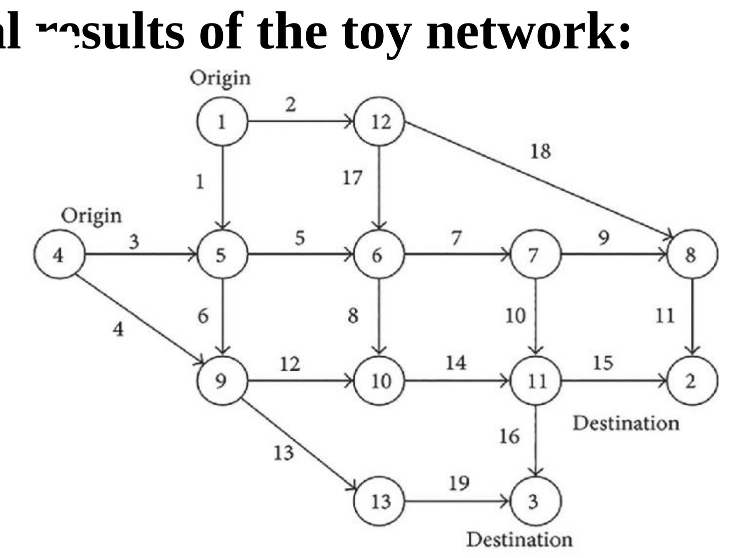
end while

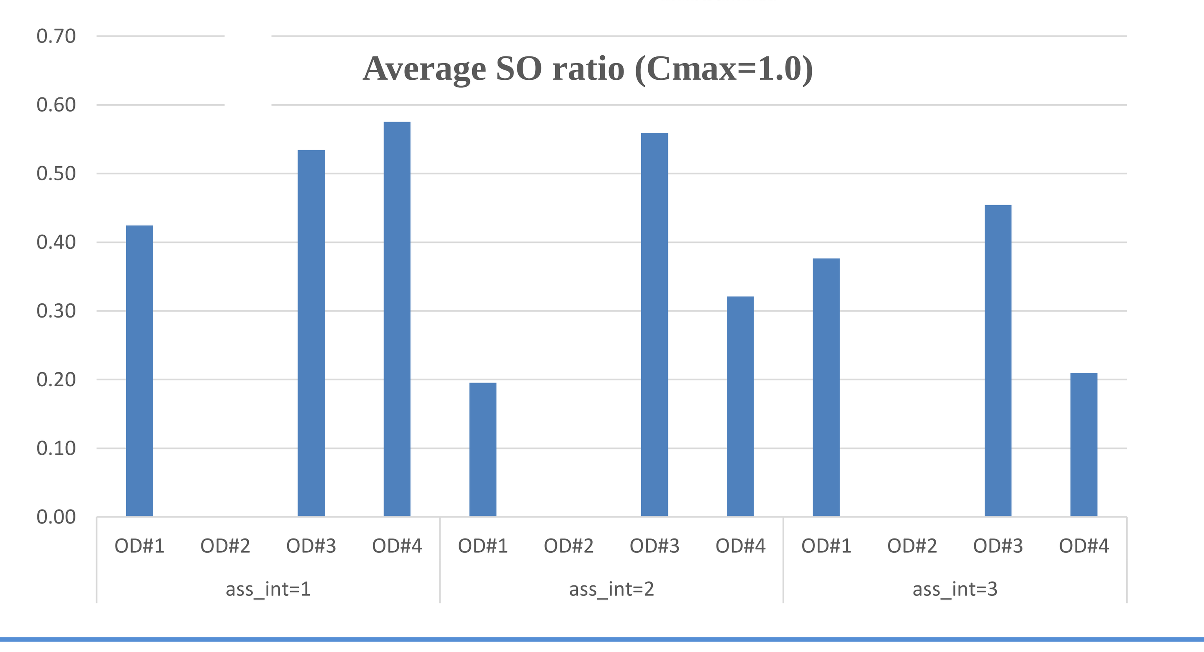
-Set $\tilde{q}^{\tau *} = \tilde{q}^{\tau,n}$.

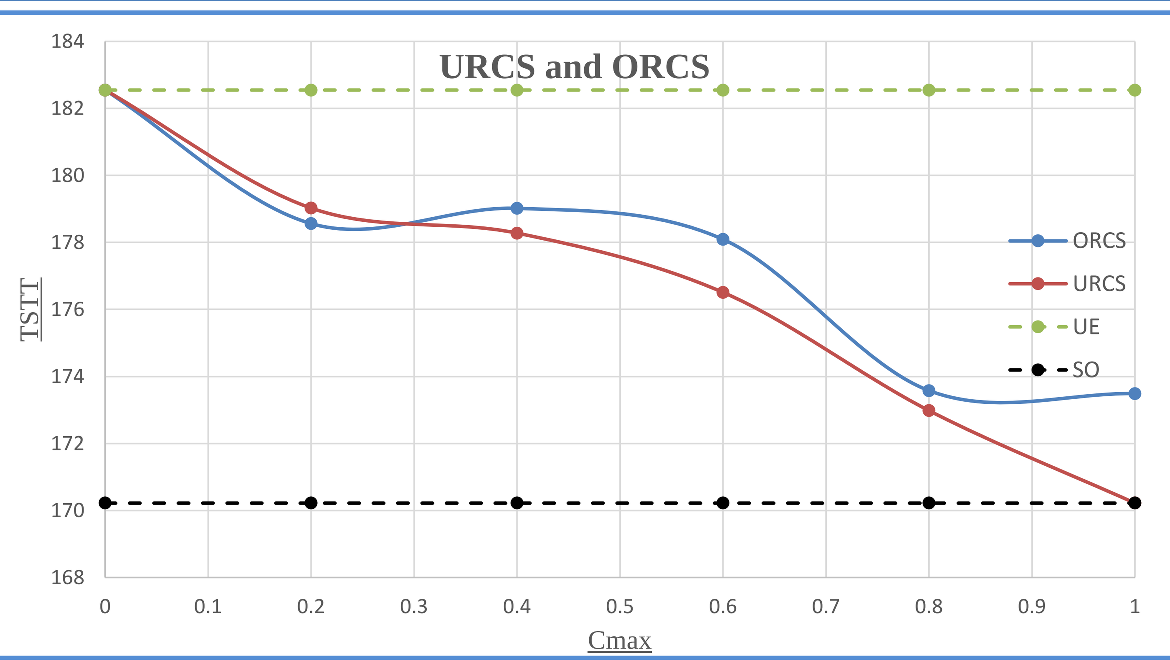
-Algorithm1 (mixed equilibrium DTA) in <u>lower level</u>:

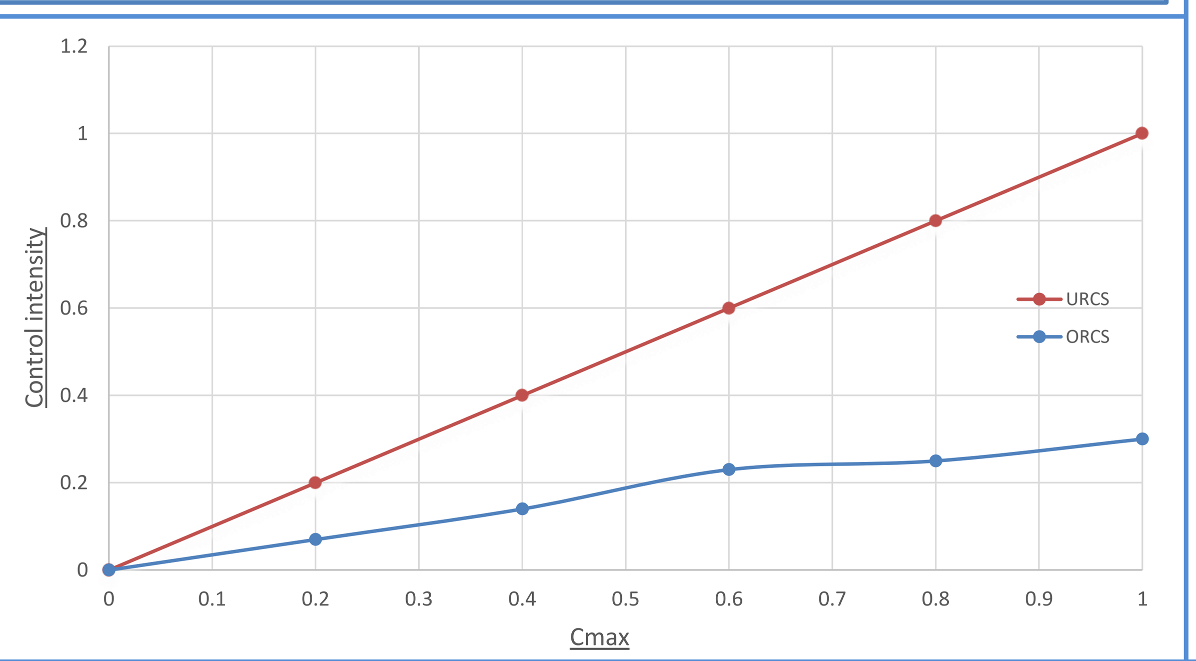


Numerical results of the toy network:









Reference:

-ZHANG, K. & NIE, Y. M. 2018. Mitigating the impact of selfish routing: An optimal-ratio control scheme (ORCS) inspired by autonomous driving. *Transportation Research Part C: Emerging Technologies*, 87, 75-90.

-HU, T.-Y., TONG, C.-C., LIAO, T.-Y. & CHEN, L.-W. 2018. Dynamic route choice behaviour and simulation-based dynamic traffic assignment model for mixed traffic flows. *KSCE Journal of Civil Engineering*, 22, 813-822.

-MAHMASSANI, H. S. 1994. Development and testing of dynamic traffic assignment and simulation procedures for ATIS/ATMS applications.

-PEETA, S. & MAHMASSANI, H. S. 1995. System optimal and user equilibrium time-dependent traffic assignment in congested networks. *Annals of Operations Research*, 60, 81-113.