**Signal-Vehicle Coupled Control Demo in MCity 2.0**

*Proposer*: Jeff Ban, University of Washington

**Introduction**: Urban traffic control (UTC) is multiscale in both time and space domains, from fast/small vehicle control, to slow/large intersection and corridor control, and slower/larger regional control. Such a multiscale nature is more clearly revealed today with the rapid development of connected automated vehicles (CAVs) and the intelligent infrastructure. Methods and algorithms have been developed to formulate and solve multiscale UTC with CAVs [1]. This demo aims to test a two-scale signal-vehicle coupled control (SVCC) method using the MCity 2.0 testing platform, showcasing its ability to jointly optimize signal timing and vehicle trajectory control, with the benefits in mobility and energy savings.

**Specifics**: The proposal team has developed an SVCC model [1], implemented as a model predictive control (MPC) scheme with two main problems: a slow signal control optimization problem and a fast vehicle optimal control problem. Signal control runs every 5 seconds and optimizes for 6 time-steps (i.e., the next 30 seconds) to minimize the total travel time of all vehicles (mobility). The optimized signal timing plan for the next 2 time-steps (10 seconds) is passed to vehicle control (runs every half a second) to optimize the passing of each vehicle platoon to minimize the total energy use of the platoon (energy). State consistency and stability conditions of the MPC scheme can also be established for the proposed model and solution method [1]. The MPC scheme is currently implemented in Python and tested only in SUMO simulation. GAMS is also called in Python to solve large-size optimization problems.

**Testing Plan**: The team plans to test the SVCC model and the MPC solution method at one signalized intersection in MCity 2.0 with 1-2 real-world CAVs, and properly generated virtual testing vehicles (both CAVs and HDVs) in SUMO simulation. Specific testing scenarios are listed as follows:

1. SVCC with 100% CAVs. This will create a benchmark of the best-case performance.
2. SVCC with varying CAV penetration. CAV penetration will vary from 10% to 90% with 10% or 20% as the increment. This will help understand how SVCC works with the CAV penetration.
3. Learning-enhanced SVCC. A deep learning model will be trained using the optimization results from solving SVCC [2]. The trained learning model will then be applied to directly produce signal timing plans and vehicle platoon control methods. This can help reduce computation time [2].
4. Multimodal SVCC. Different vehicle types (internal combustion vehicles, electric vehicles, and hybrid vehicles; passenger cars, trucks, buses) and pedestrians/bicyclists will be generated, and the SVCC model will be tested to handle multimodal traffic flow.

The **metrics** to evaluate the SVCC performance include *mobility* (travel time/delay, queue), *sustainability* (energy use), *safety* (potential conflicts), and *equity* (disparity of the other metrics among different user groups). SVCC will also be compared with two **benchmark** signal control methods: *fixed-time signal control* and *actuated signal control*.

**Timeline** (tentative):

1. January 15, 2024 – March 15, 2024: Algorithm refinement and integration with MCity 2.0
2. March 15, 2024 – April 15, 2024: Testing, evaluation, and demo

**References**:

[1] Guo, Q., Ban, X., 2023. A Multi-scale control framework for urban traffic control with connected and automated vehicles. Transportation Research Part B 175, 102787.

[2] Guo, Q., Ban, X., 2024. Network Multiscale Urban Traffic Control with Mixed Traffic Flow. The 25th International Symposium on Transportation and Traffic Theory (ISTTT), under review.