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# Deployment and Testing of Optimized Autonomous and Connected Vehicle Trajectories at a Closed-Course Signalized Intersection


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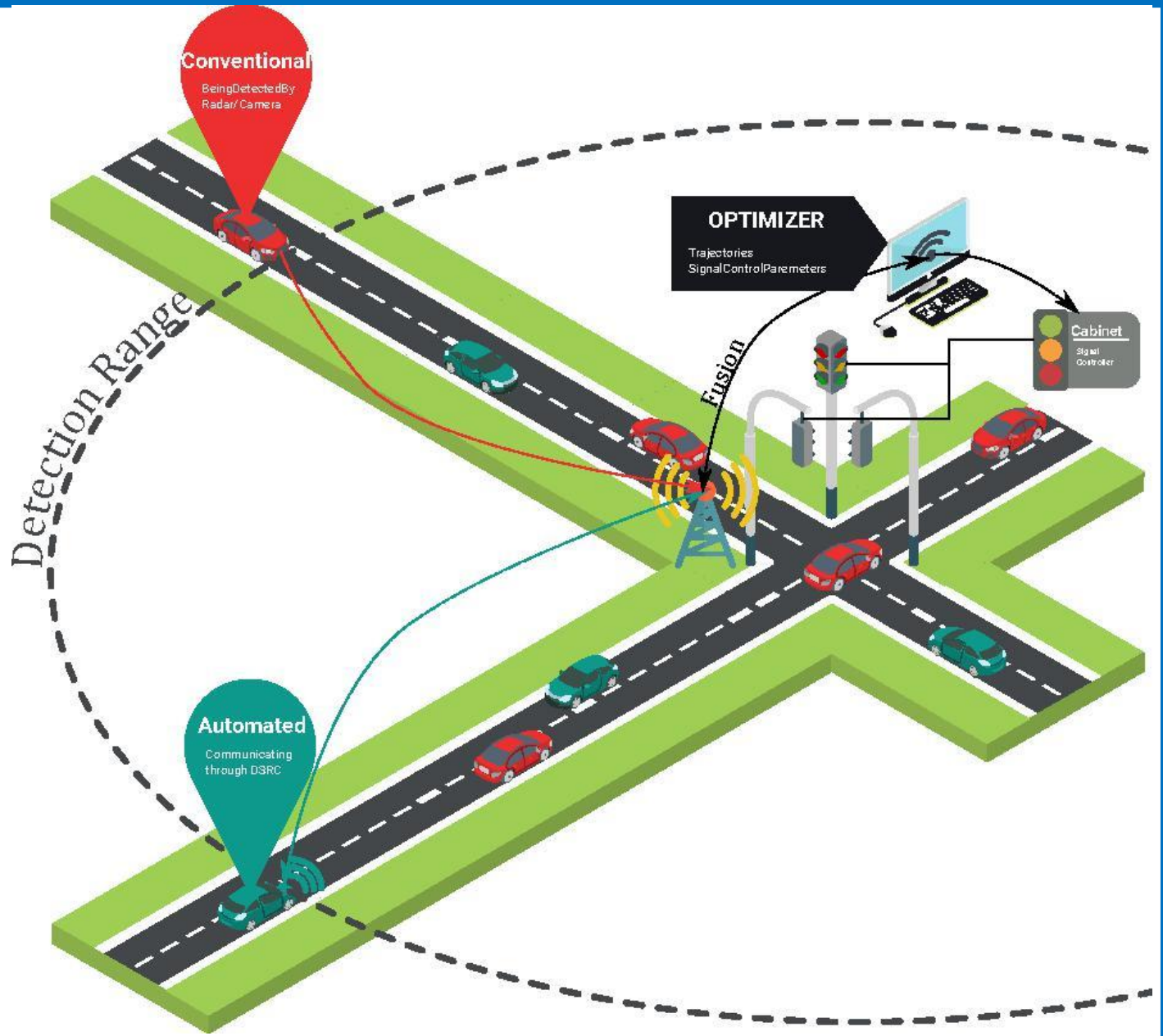
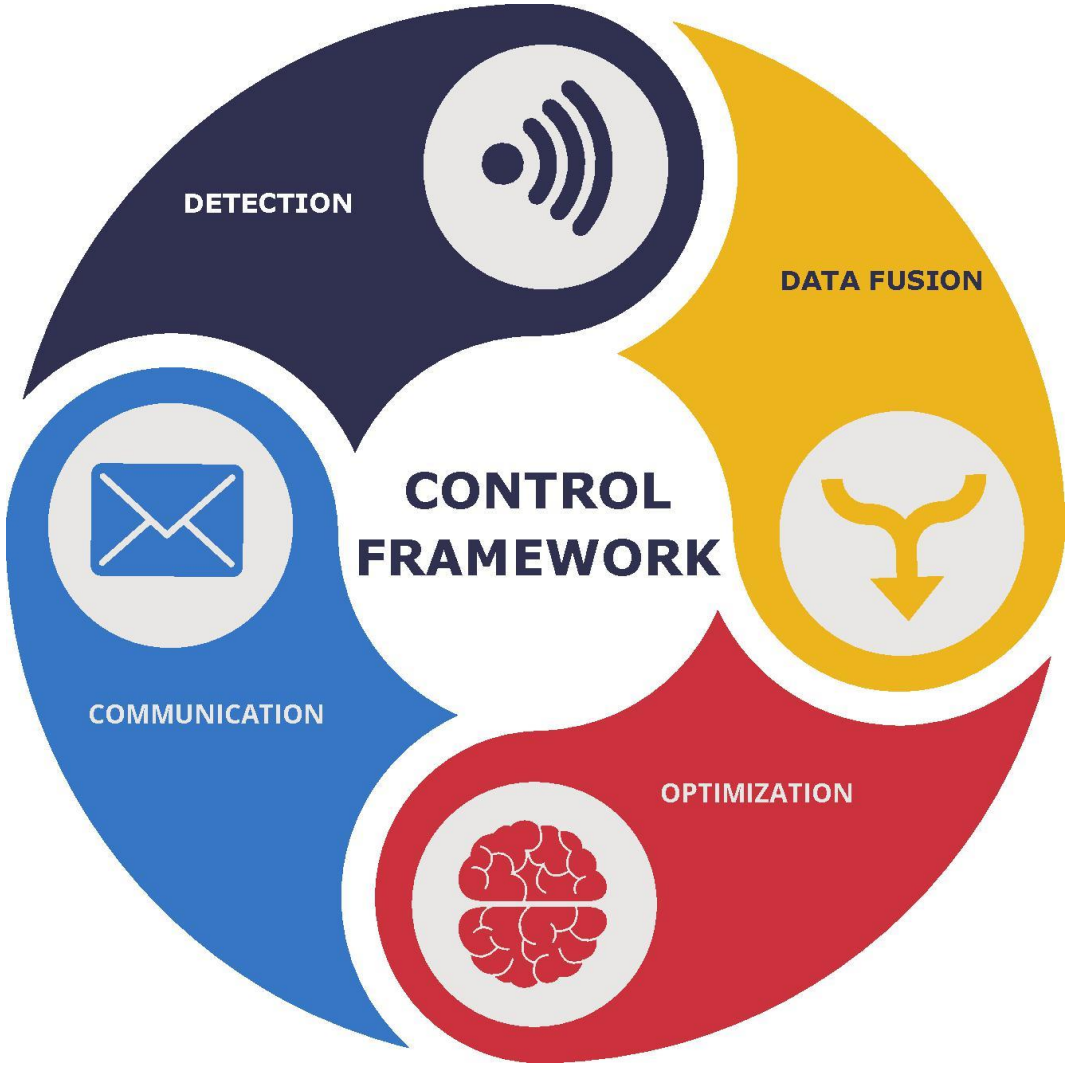
# Problem Description

Given: the arrival information of automated vehicles and conventional vehicles

Goal: to optimize the average delay by advising automated vehicles and controlling signal phase and timing



# The Real-time Framework




Involves Sensing technologies

- Dedicated Short Range Communication
- Radar
- (Camera, Lidar)

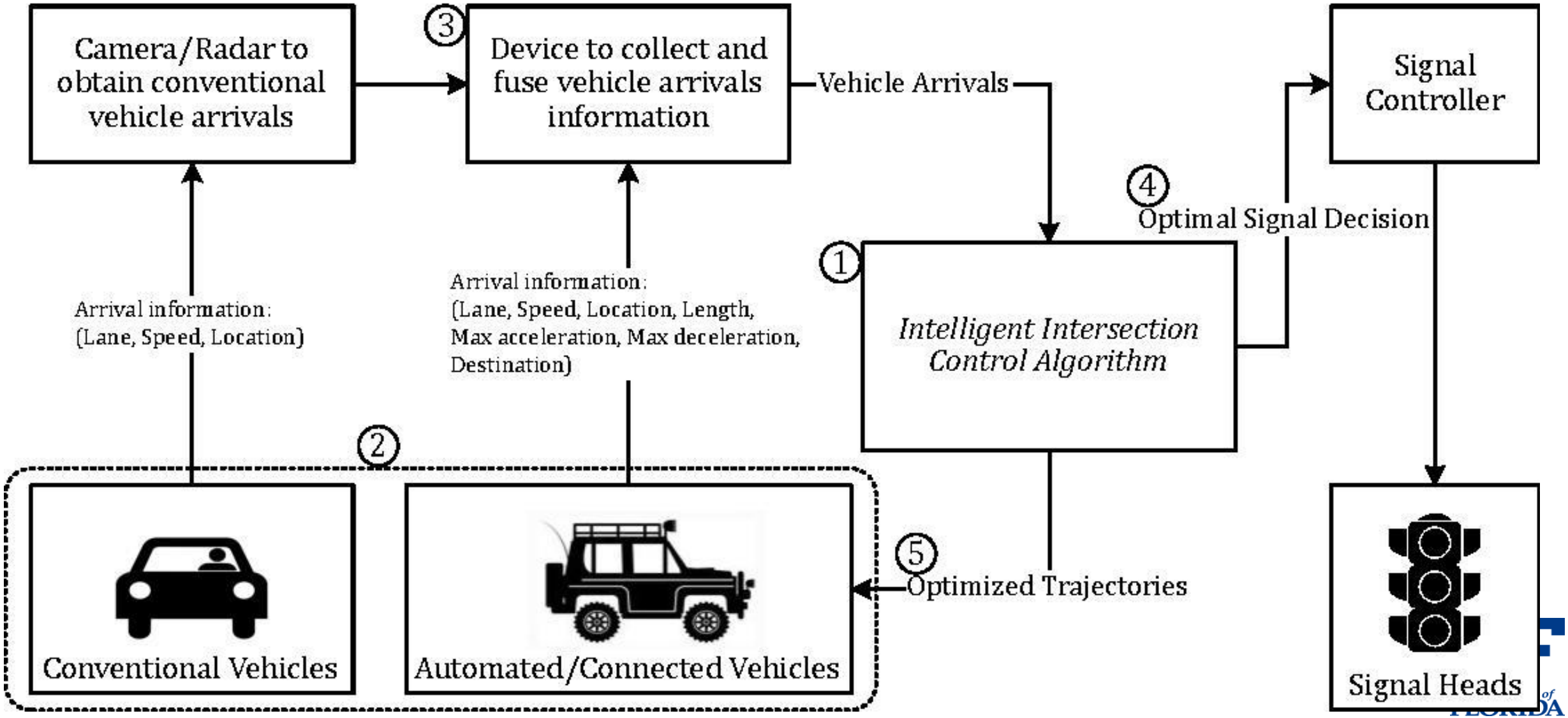
Autonomous Vehicle Technology

- Navigation and Localization algorithms

Optimization Algorithm

- Vehicle Path Optimizer
- Signal Status Optimizer

# Intelligent Intersection Control System

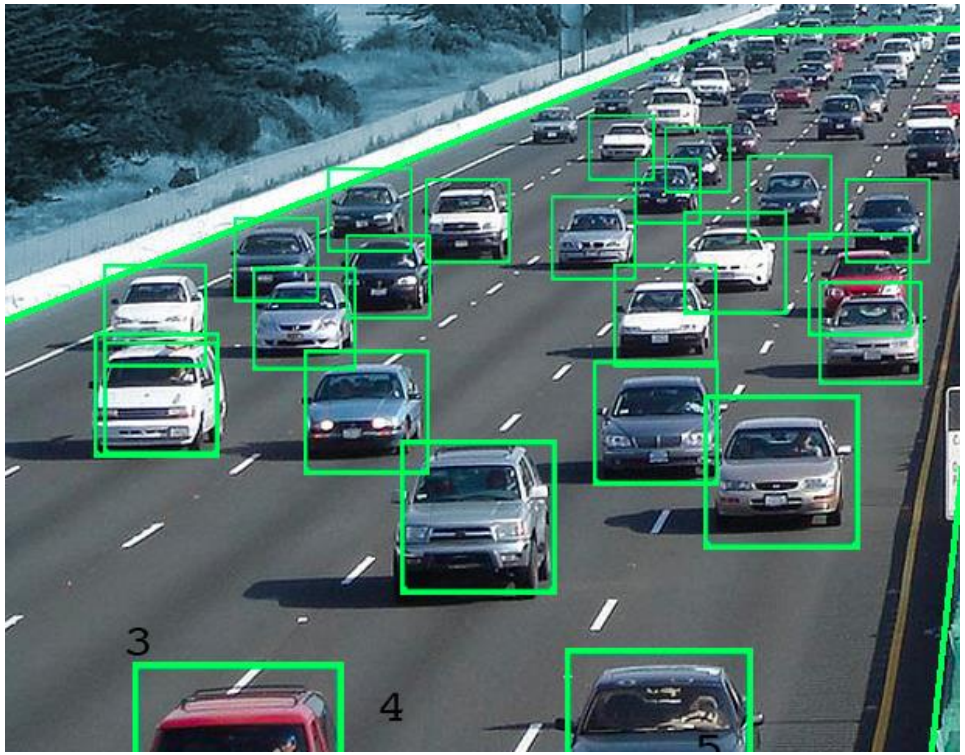


# Sensor Fusion for Intelligent Intersection Control

Goal: Classify and track all traffic participants up to ~600 feet away from the intersection

Challenging Multisensor-Multitarget problem

- Occlusion is common in medium-heavy traffic
- Need to synchronize and associate sensor data in real-time
- Need accurate models of uncertainty in sensor measurements and vehicle dynamics



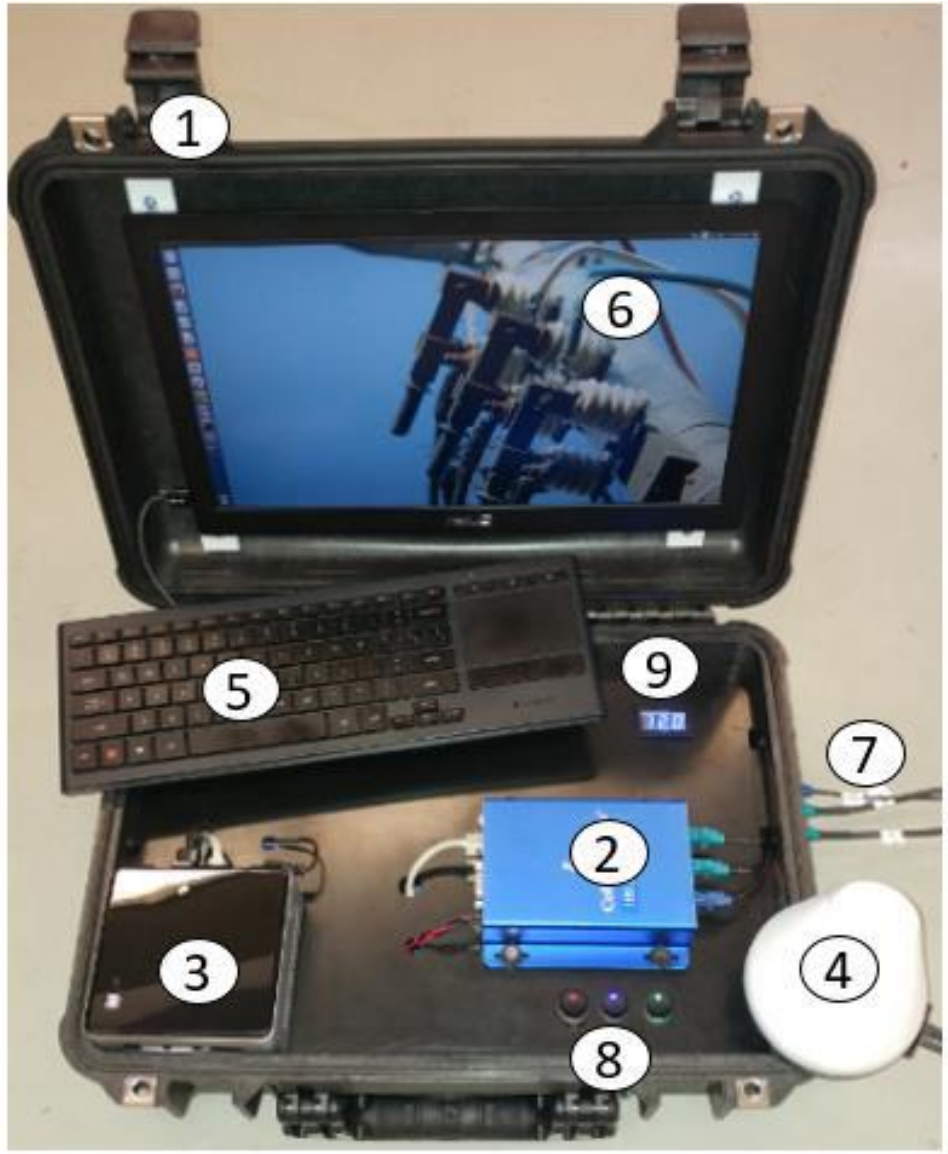
# Traditional Traffic Sensors + V2I

Doppler-based advanced detection traffic radar (range ~600 ft)


Dedicated Short Range Communication (DSRC) for Vehicle-to-Infrastructure (V2I) (range ~900 ft)

Video Camera (range ~300 ft)

# V2I Communication Infrastructure




Vehicles are equipped with On-Board Units (OBUs) containing a DSRC radio

In the image:

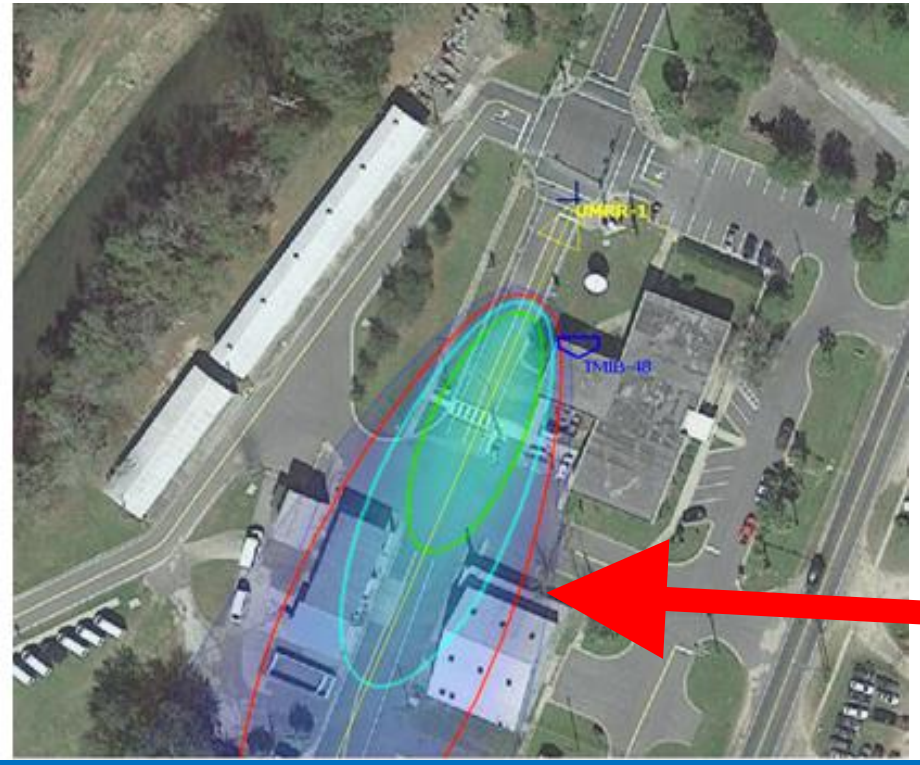
2. Cohda Wireless Mk5 DSRC radio
3. Small computer for developing OBU software
4. GPS antenna

# V2I Communication Infrastructure


A Cohda Wireless Mk5 is used as our Road-Side Unit (RSU), and is connected to a server running our sensor fusion and optimization algorithms at the intersection

Can receive Basic Safety Messages from multiple instrumented vehicles simultaneously over the 5 Ghz band

# Demonstration of Fusing DSRC and Radar




Tested proof of concept DSRC and radar sensor fusion system at isolated intersection

One Smartmicro radar and Five  Cohda Wireless DSRC units

Demonstrated ability to classify and track connected and conventional vehicles in isolated, low-traffic scenario

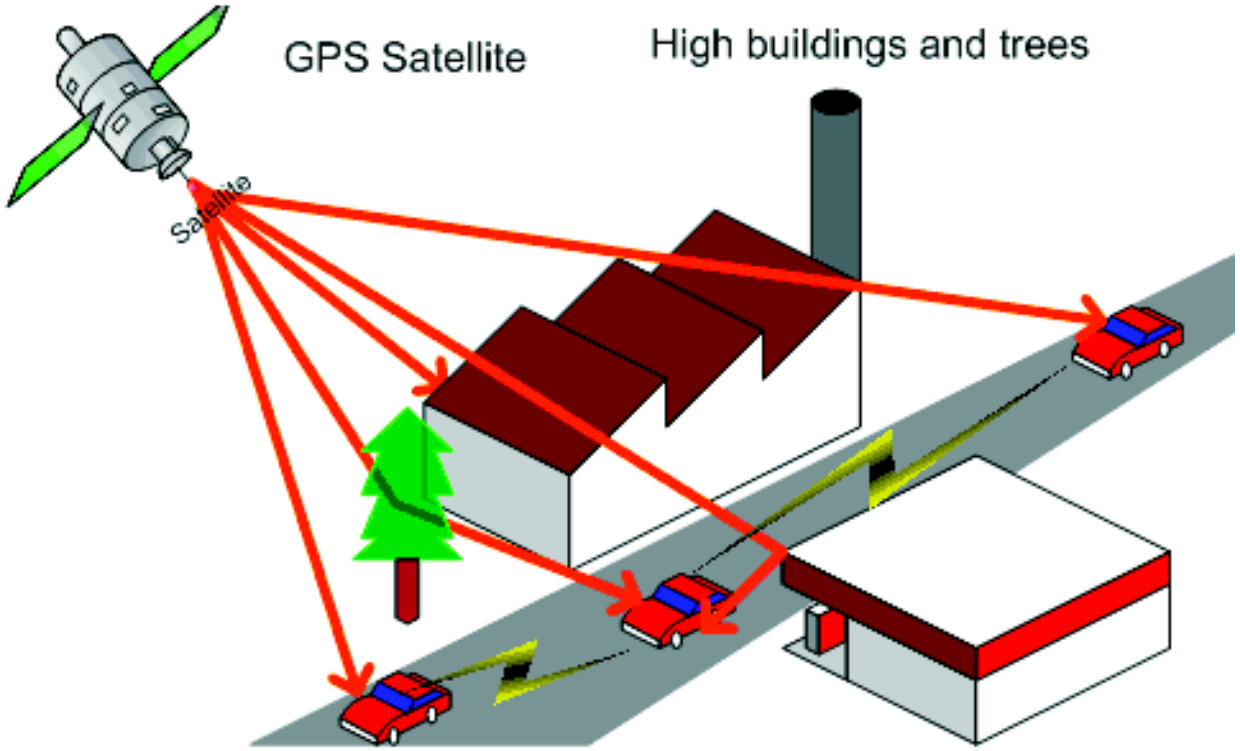
Emami P, Pourmehrab M, Elefteriadou L, Ranka S, Crane C. *A Demonstration of Fusing DSRC and Radar for Optimizing Intersection Performance*. Poster presented at: Automated Vehicle Symposium (AVS '17), 2017 July 11-13. San Francisco, CA.

# Uncertainty in GPS from off-the-shelf DSRC

Fusing data from DSRC with traffic radar and video camera data requires careful time synchronization and a probabilistic model for the uncertainty in the reported vehicle position.

Need sub-meter precision to ensure safety of traffic participants.

GPS can be affected by tall buildings, trees, and poor satellite coverage due to, e.g., cloudy skies



# DSRC GPS compared with high-precision GPS

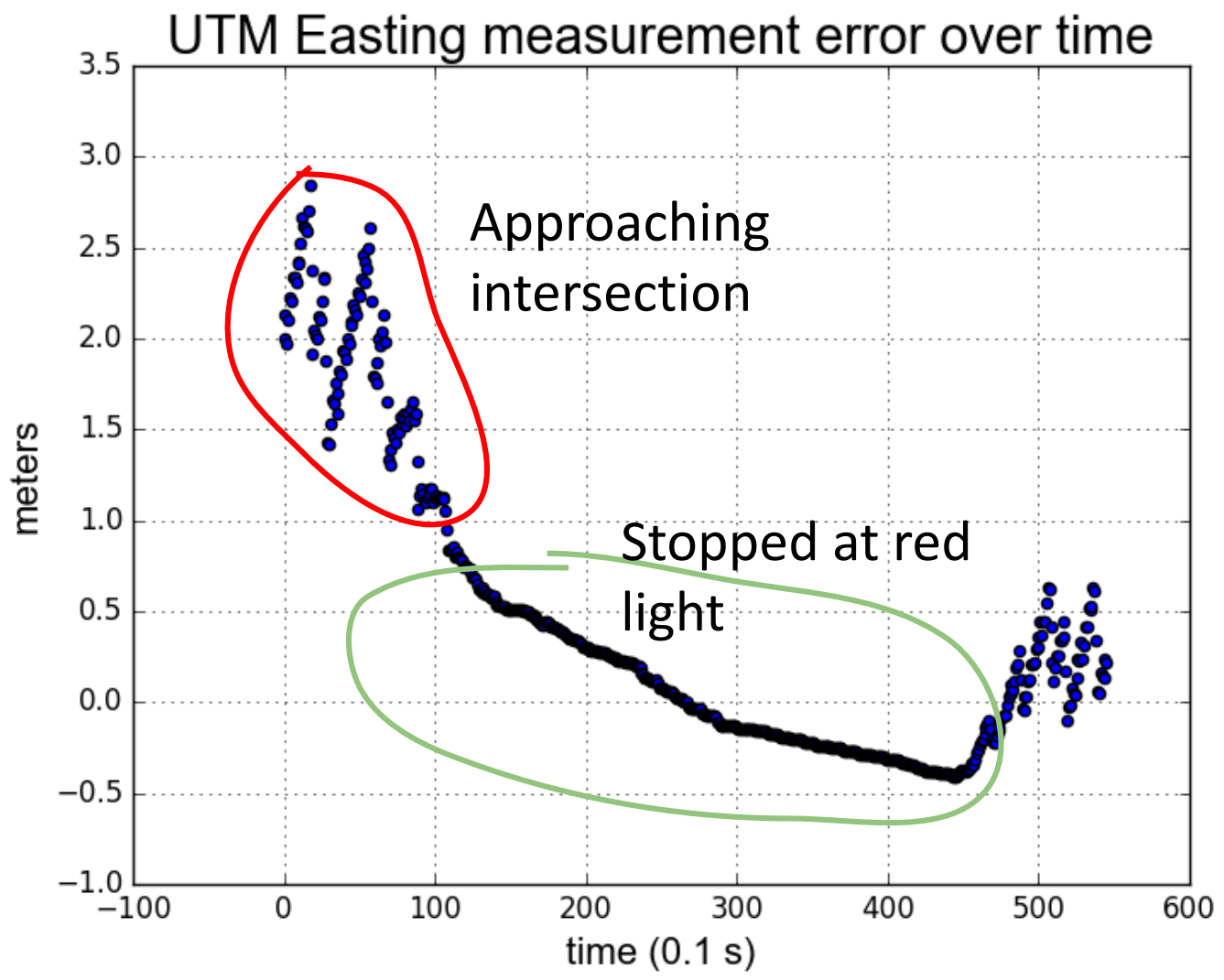



Figure at left shows spatial error in DSRC GPS for a vehicle slowing to a stop at a red light, compared to a high-precision GPS sensor

The DSRC GPS error is biased when vehicle is in motion (partly due to small clock synchronization error between GPS sensors)

Overall, measurement error appears to be non-Gaussian, and the bias (offset from 0) proves to be difficult to estimate and remove

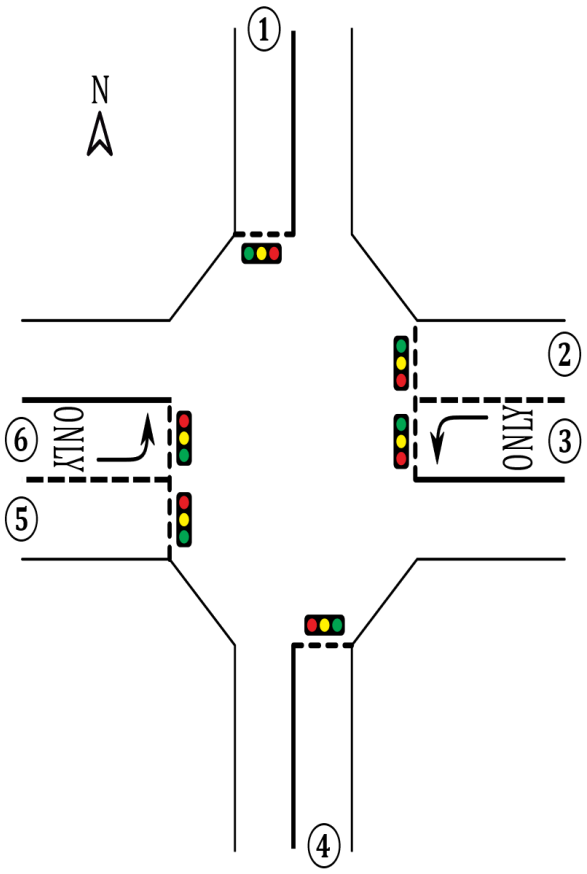
# Optimization Algorithm

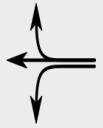
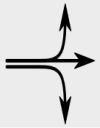
Objective: Minimize the Average Travel Time Delay experienced at the intersection

Approach: Mathematical Programming

Description:

- Automated Vehicles Shall receive a trajectory at the time they enter the detection range
- The Trajectories Shall comply with signal status and have no conflict with other vehicles
- The joint decision on Trajectories and Signal Phase and Timing yields the minimum average travel time delay




| Phase | Movement |
|---|---|
| 1 SB L,TH,R |  |
| 2 NB L,TH,R |  |
| 3 WB L/TH,R |  |
| 4 EB L/TH,R |  |

# Adaptive Signal Control with Trajectory Optimization

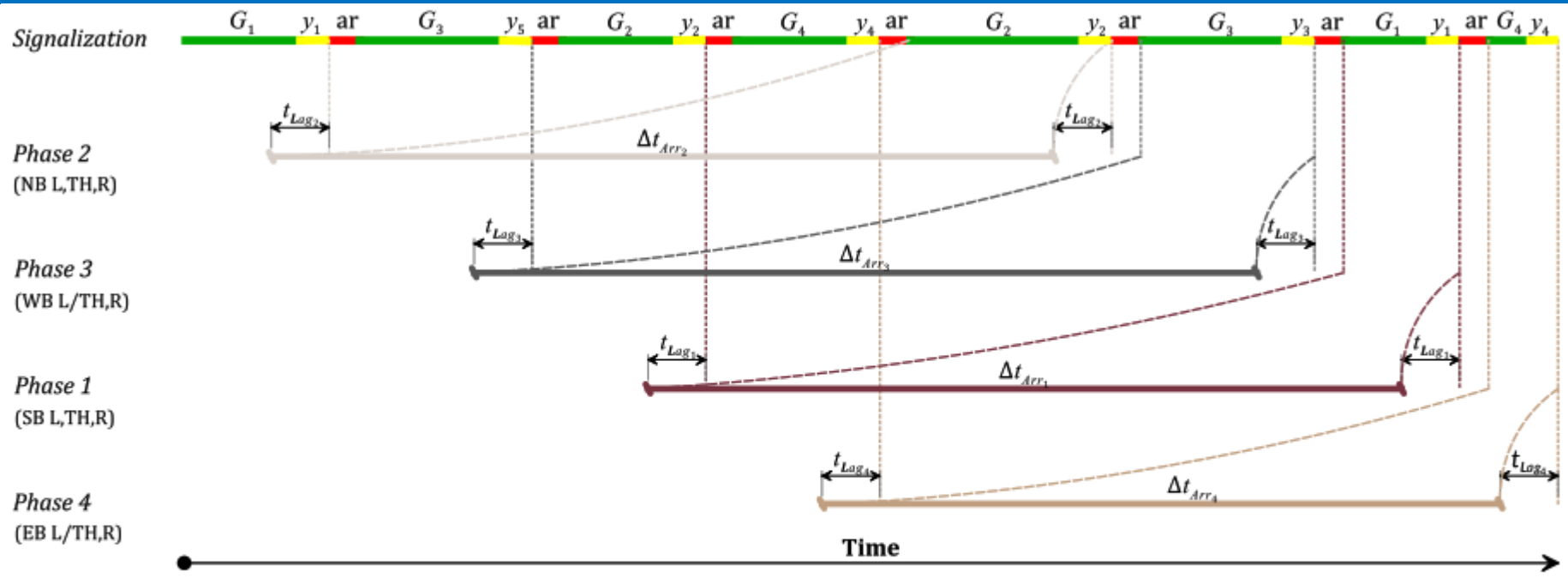
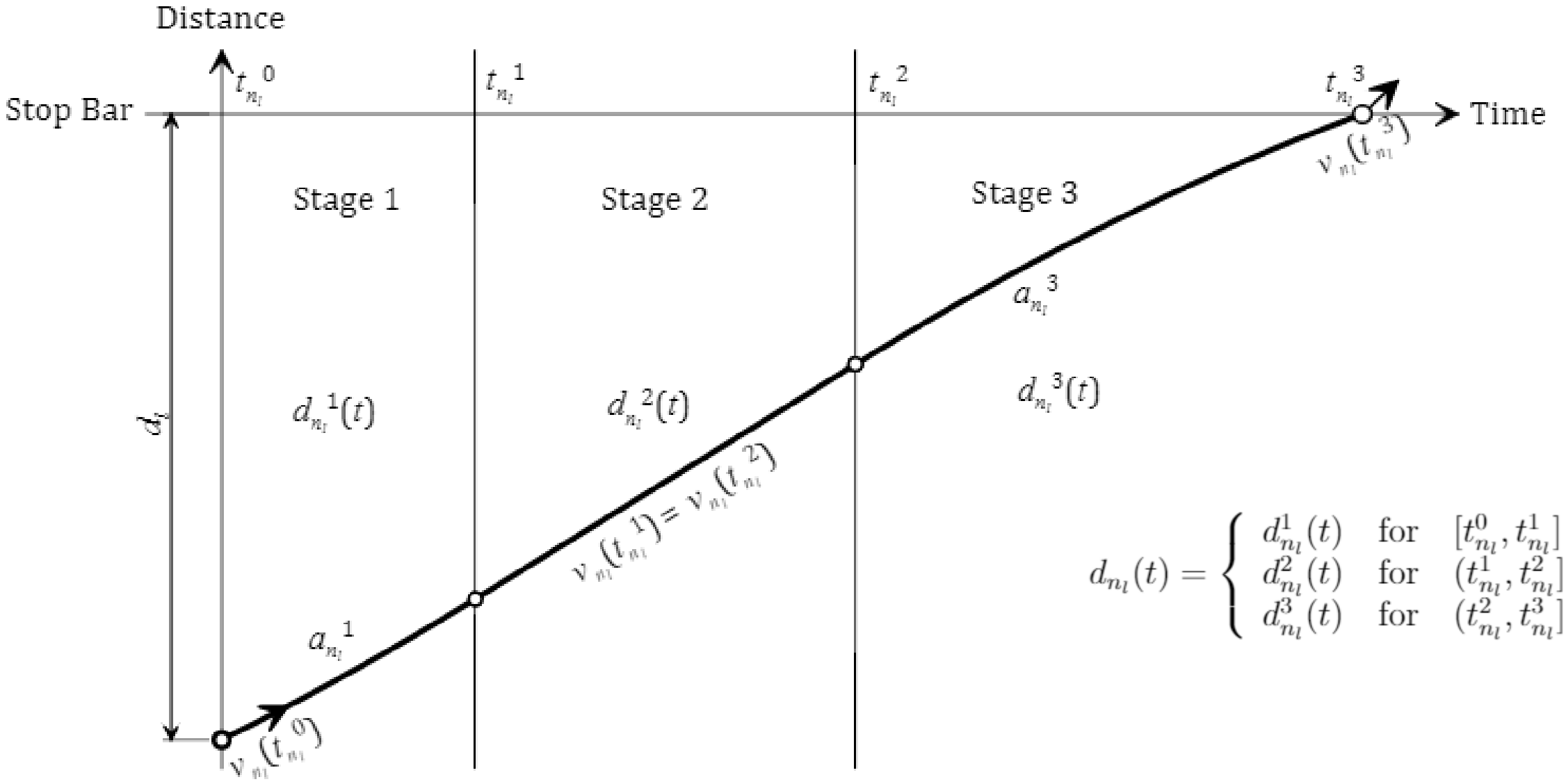



Figure 6: Schematic Signal Control Plan($G_i$ and $y_i$ are the green and yellow intervals for phase $i$; $\Delta Arr(i)$ indicates the arrival interval in phase $i$; $t_{Lag(i)}$ denotes the time before the end of yellow interval in phase $i$).

With information about trajectories, green intervals can be allocated to serve phases. The lag time accounts for the distance vehicles must travel to arrive at the stop bar.

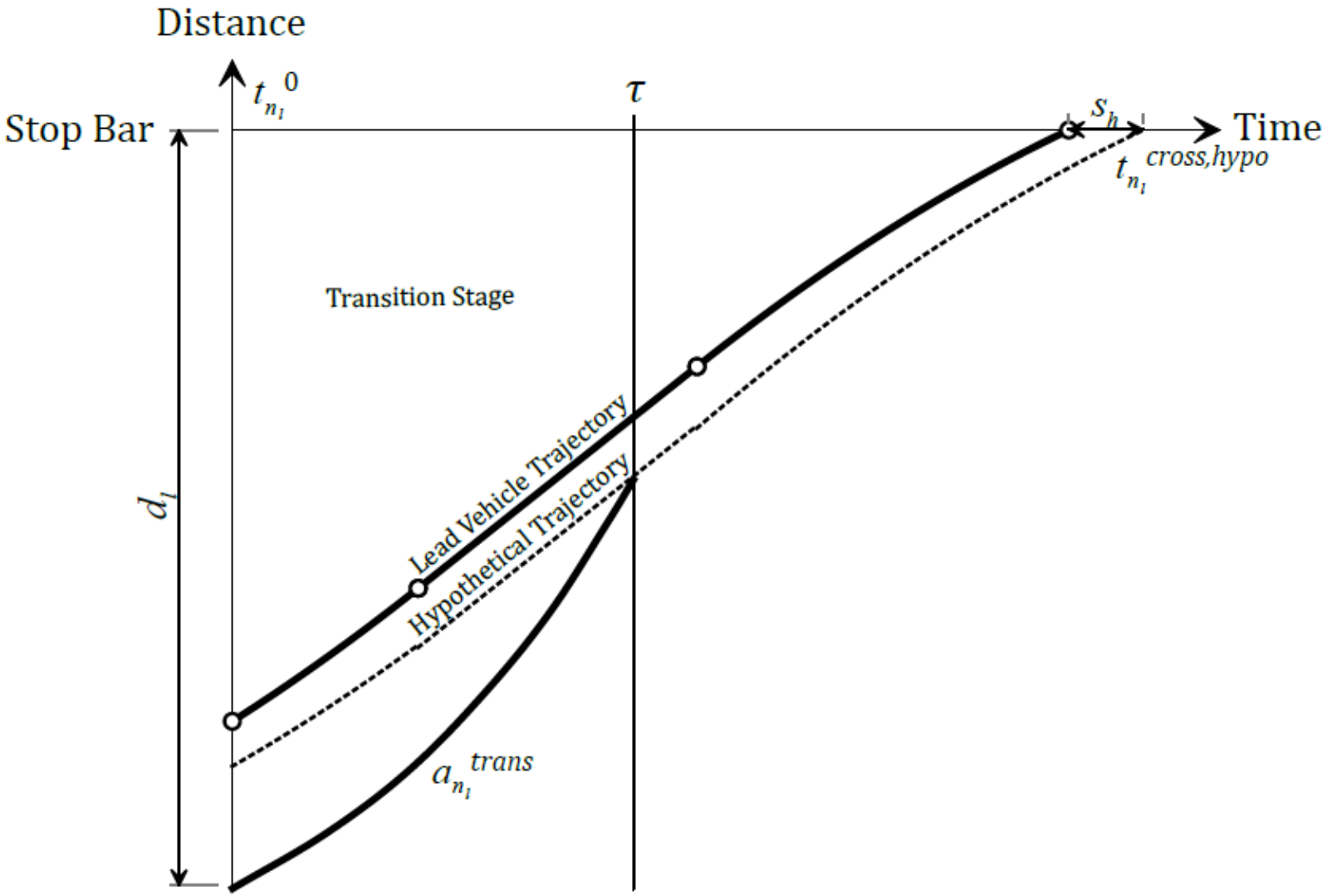
This image shows how green and yellow times that are assigned to each phase can cover arrivals (the ones with delta t) on a continuous basis.

# Three-stage Trajectory for Lead AV




$$d_{n_l}(t) = \begin{cases} d_{n_l}^1(t) & \text{for} \quad [t_{n_l}^0, t_{n_l}^1] \\ d_{n_l}^2(t) & \text{for} \quad (t_{n_l}^1, t_{n_l}^2] \\ d_{n_l}^3(t) & \text{for} \quad (t_{n_l}^2, t_{n_l}^3] \end{cases}$$

# Trajectory of a Follower Vehicle



# Automated Vehicle Trajectory Optimization

Recursive equation for Automated vehicle Trajectory Optimization (ATO):

$$d_{n_l}(t) = \begin{cases} LTO(\boldsymbol{s}(t), V_m^{max}, V_m^{cross}, a_{n_l}^{acc}, a_{n_l}^{dec}) & \text{for} \quad n_l = 1,\ \forall\, l \in L,\ c_{n_l} = AV \\ FTO(d_{(n-1)_l}(t), \boldsymbol{s}(t), V_m^{max}, V_m^{cross}, a_{n_l}^{dec}, a_{(n-1)_l}^{dec}) & \text{for} \quad n_l = 2, \ldots, N_l,\ \forall\, l \in L,\ c_{n_l} = AV \\ LTE(\boldsymbol{s}(t), v_{n_l}(t_{n_l}^0)) & \text{for} \quad n_l = 1,\ \forall\, l \in L,\ c_{n_l} = CV \\ FTE(d_{(n-1)_l}(t), \boldsymbol{s}(t), V_{n_l}^{des}, a_{n_l}^{acc}, a_{n_l}^{dec}) & \text{for} \quad n_l = 2, \ldots, N_l,\ \forall\, l \in L,\ c_{n_l} = CV \end{cases}$$

Depending on vehicle class and position:

- ❑ Lead automated vehicle Trajectory Optimization (LTO)
- ❑ Follower automated vehicle Trajectory Optimization (FTO)
- ❑ Lead conventional vehicle Trajectory Estimation (LTE)
- ❑ Follower conventional vehicle Trajectory Estimation (FTE)

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# Lead vehicle Trajectory Optimization

$$\text{(LTO)}\ del^*_{n_l} = \min_{v_{n_l}(t^1_{n_l}), v_{n_l}(t^3_{n_l}), a^1_{n_l}, a^3_{n_l}} \sum_{i=1}^{3} (t^i_{n_l} - t^{i-1}_{n_l}) - \frac{d_{n_l}(t^0_{n_l})}{V^{des}_{n_l}}$$

subject to

$$t^s_\phi(t) \leq \eta_{\phi l} \times (t^3_{n_l} - t^0_{n_l}) \leq t^s_\phi(t) + G_\phi(t) + Y_\phi(t) \quad \forall\ \phi \in \Phi$$

$$0 \leq v_{n_l}(t^1_{n_l}) \leq V^{max}_m$$

$$0 \leq v_{n_l}(t^3_{n_l}) \leq V^{cross}_m$$

$$a^{dec}_{n_l} \leq a^1_{n_l} \leq a^{acc}_{n_l}$$

$$a^{dec}_{n_l} \leq a^3_{n_l} \leq a^{acc}_{n_l}$$

The objective function: Travel Time Delay of vehicle *n* in lane *l*

The summation is over the travel time of all stages (which is equivalent to the total travel time of lead AV)

The fraction is the base travel time assuming vehicle would maintain its desired speed

Therefor, the travel time minus base travel time shows travel time delay (extra time vehicle spent to travel the detection distance)

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# Exact Heuristic Algorithm to Solve LTO

**Algorithm 1** AV Lead vehicle Trajectory Optimizer

**Require:** signal control status, vehicle arrival information, vehicle attributes, and speed limits

**Ensure:** valid trajectory with minimal delay for the lead AV

**procedure** LTO_EXACT_SOLVER($\boldsymbol{s}(t), V_m^{max}, V_m^{cross}, a_{n_l}^{acc}, a_{n_l}^{dec}$)
  $del_{n_l}^* \leftarrow M$ ▷ M to be a relatively large value
  $flag \leftarrow 0$
  $A \leftarrow \{v_{n_l}(t_{n_l}^1), v_{n_l}(t_{n_l}^3), a_{n_l}^1, a_{n_l}^3\}$
  **for** $counter = 1{:}4$ **do**
    Select a new variable $x$ from $A$
    Set variables in $A \setminus x$ to limit(s) using Eqs. (12-15)
    Correct the bounds based on Eq. (11)
    Obtain the range of variable $x$
    Solve the remaining single-variable constrained problem over $x$
    $del_{n_l} \leftarrow$ travel time delay at given the obtained solution
    **if** $del_{n_l} < del_{n_l}^*$ **then** ▷ current solution can be improved
      $del_{n_l}^* \leftarrow del_{n_l}$
      $flag \leftarrow 1$
    **end if**
  **end for**
  **if** $flag = 1$ **then**
    **return** $del_{n_l}^*$ ▷ the global optimal solution found
  **else**
    **return** LTO problem is infeasible
  **end if**
**end procedure**

We showed the optimal solution to LTO is on the boundary of its feasible region (constrains on previous slide)

Under the for loop we move on edges and search for optimal answer. It's done by setting all variables fix except one of them which is free to change between its bounds.

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# Follower Automated Vehicle Trajectory Optimization

**Algorithm 2** AV Follower vehicle Trajectory Optimizer

**Require:** trajectory of the lead vehicle, follower attributes, follower vehicle arrival information, and signal control status

**Ensure:** valid trajectory with minimal departure headway for automated follower

**procedure** FTO_SOLVER($d_{(n-1)_l}(t), \boldsymbol{s}(t), V_m^{max}, V_m^{cross}, a_{n_l}^{dec}, a_{(n-1)_l}^{dec}$)

  $t_{n_l}^{cross,hypo} \leftarrow \max\{t_\phi^s(t), t_{(n-1)_l}^{cross} + s_h\}$

  $d_{n_l}^{hypo}(t) \leftarrow d_{(n-1)_l}(t)$

  $[t_{n_l}^{0,hypo}, t_{n_l}^{cross,hypo}] \leftarrow [t_{(n-1)_l}^0 + t_{n_l}^{cross,hypo} - t_{(n-1)_l}^{cross}, t_{n_l}^{cross,hypo}]$

  $flag \leftarrow 0$

  **for** $\tau \in [t_{n_l}^{0,hypo}, t_{n_l}^{cross,hypo}]$ **do**

    $a_{n_l}^{trans} \leftarrow \frac{v_{n_l}^{hypo}(\tau)^2 - v_{n_l}(t_{n_l}^0)^2}{2\times(d_{n_l}(t_{n_l}^0) - d_{n_l}^{hypo}(\tau))}$

    **if** $a_{n_l}^{dec} \leq a_{n_l}^{trans} \leq a_{n_l}^{acc}$ **then**

$$d_{n_l}(t) = \begin{cases} d_{n_l}(t_{n_l}^0) - v_{n_l}(t_{n_l}^0) \times (t - t_{n_l}^0) - \frac{a_{n_l}^{trans}}{2} \times (t - t_{n_l}^0)^2 & \text{for} \quad [t_{n_l}^0, \tau] \\ d_{n_l}^{hypo}(t) \quad \text{for} \quad (\tau, t_{n_l}^{cross,hypo}] \end{cases} \tag{16}$$

      $flag \leftarrow 1$

    **end if**

  **end for**

  **if** $flag = 1$ **then**

    **return** $d_{n_l}(t)$

  **else**

    **return** LTO_Exact_Solver($\boldsymbol{s}(t), V_m^{max}, V_m^{cross}, a_{n_l}^{acc}, a_{n_l}^{dec}$) ▷ use Algorithm 1

  **end if**

**end procedure**

The hypothetical trajectory is the earlies imaginary path that vehicle can cross the stop bar right after the vehicle ahead of it. However the vehicle may not be able to catch up with the hypo trajectory all the times. The for loop looks for acceleration/deceleration to transition the vehicle to hypo trajectory.

If found, it construct the trajectory, otherwise we solve LTO for this vehicle.

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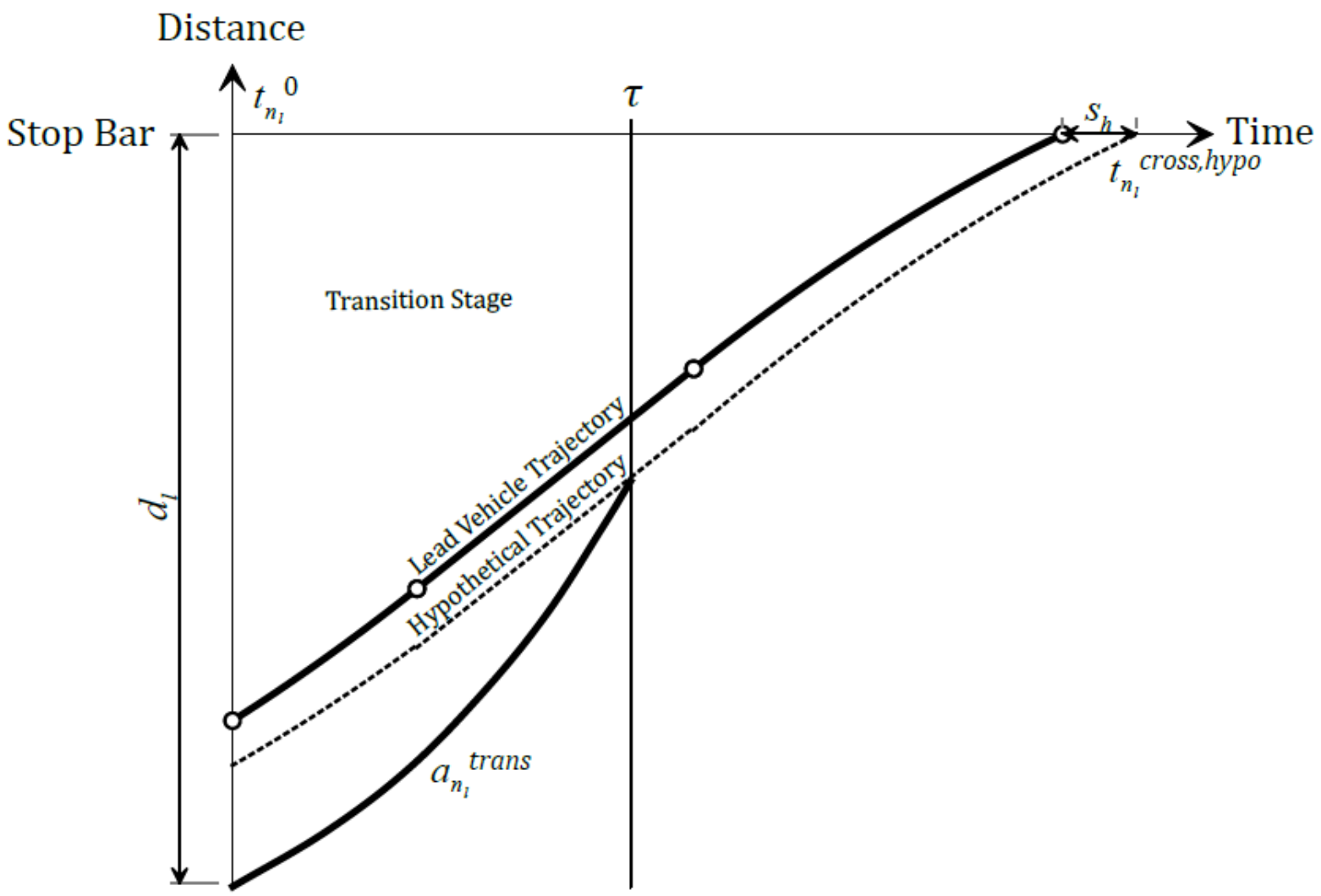
# Trajectory of a Follower Vehicle




This shows the result of previous slide's algorithm.

1. Hypothetical trajectory is ideal because it makes vehicle discharge at saturation headway.
2. The for loop in previous page searches for the transition stage to get the vehicle on hypothetical trajectory. This figure shows when such a transition is feasible.
3. The final trajectory will be the solid transition part followed by the dashed line on the hypothetical curve.

# Follower Conventional Vehicle Trajectory Estimator (Gipps Model)

**Algorithm 3** Conventional Follower vehicle Trajectory Estimator

**Require:** trajectory of lead vehicle, lead and follower's attributes, follower vehicle arrival information

**Ensure:** trajectory of conventional follower

**procedure** FTE_SOLVER($d_{(n-1)_l}(t), s(t), V^{des}_{n_l}, a^{acc}_{n_l}, a^{dec}_{n_l}$)
  $t \leftarrow t^0_{n_l}$
  **while** $d_{n_l}(t) > 0$ **do**
    Compute $v_{n_l}(t)$ using Eq. (17)
    $a_{n_l}(\tau) \leftarrow \frac{v_{n_l}(t+\Delta t) - v_{n_l}(t)}{\Delta t}$ for $\tau \in [t, t+\Delta t]$
    $d_{n_l}(\tau) \leftarrow d_{n_l}(t) - v_{n_l}(t) \times (\tau - t) - \frac{a_{n_l}(\tau)}{2} \times (\tau - t)^2$ for $\tau \in [t, t+\Delta t]$
    $t \leftarrow t + \Delta t$
  **end while**
  **return** $d_{n_l}(t)$
**end procedure**

$$v_{n_l}(t+\Delta t) = \min\{v_{n_l}(t) + 2.5 a^{acc}_{n_l} \times \Delta t (1 - \frac{v_{n_l}(t)}{v^{des}_{n_l}}) \times \sqrt{0.025 + \frac{v_{n_l}(t)}{v^{des}_{n_l}}}, \quad (17)$$

$$a^{dec}_{n_l} \times \Delta t + \sqrt{a^{dec}_{n_l} \times (2(d_{(n-1)_l}(t) + L_{n_l} - d_{n_l}(t)) + \Delta t \times (a^{dec}_{n_l} \times \Delta t + v_{n_l}(t)) + \frac{v_{(n-1)_l}(t)^2}{a^{dec}_{n_l}}}\}$$

where:

$\Delta t$ is the time steps to compute trajectory points

$v_{n_l}(t+\Delta t)$ is the speed of follower vehicle $\Delta t$ seconds after $t$

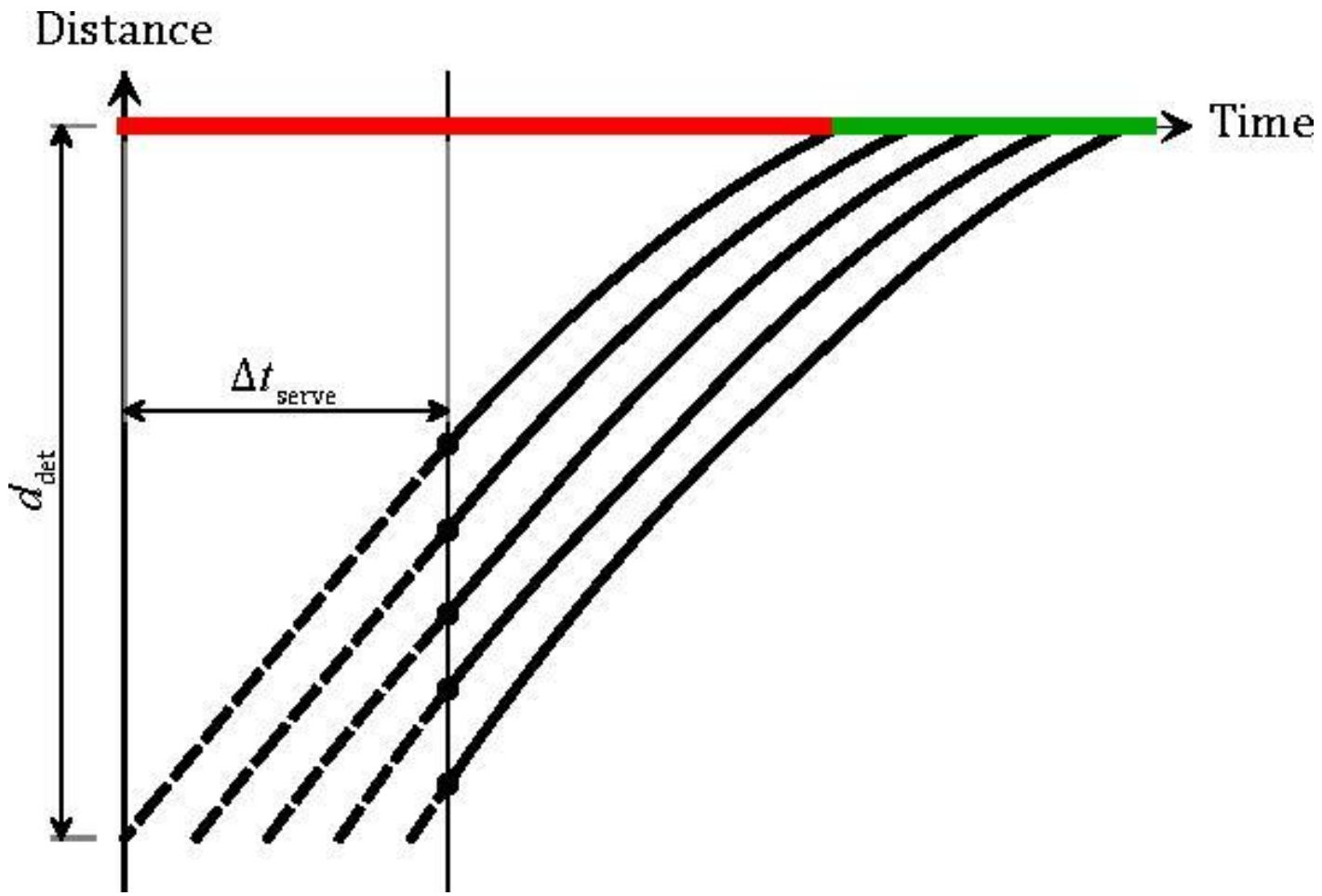
$L_{n_l}$ is the length of $n$th vehicle in lane $l$

Uses Gipps car following model to obtain the speed of follower vehicle

1. Assumes and finds constant acceleration during delta t. It uses the calculated speed at 4.
2. Gives the location of the follower vehicle using 4 and 5.
3. Trajectory is derived by using Gipps car following speed equation at every incremental time step.

Gipps, P. G. (1981). *A behavioural car-following model for computer simulation*. Transportation Research Part B: Methodological, 15(2), 105-111.

# Space-time diagram of controlled versus the uncontrolled portion




The dashed part is the part vehicle does not have any trajectory because the algorithm is not done computing.

The higher the delay, or the higher the initial speed, the bigger portion of detection distance is lost with no control.

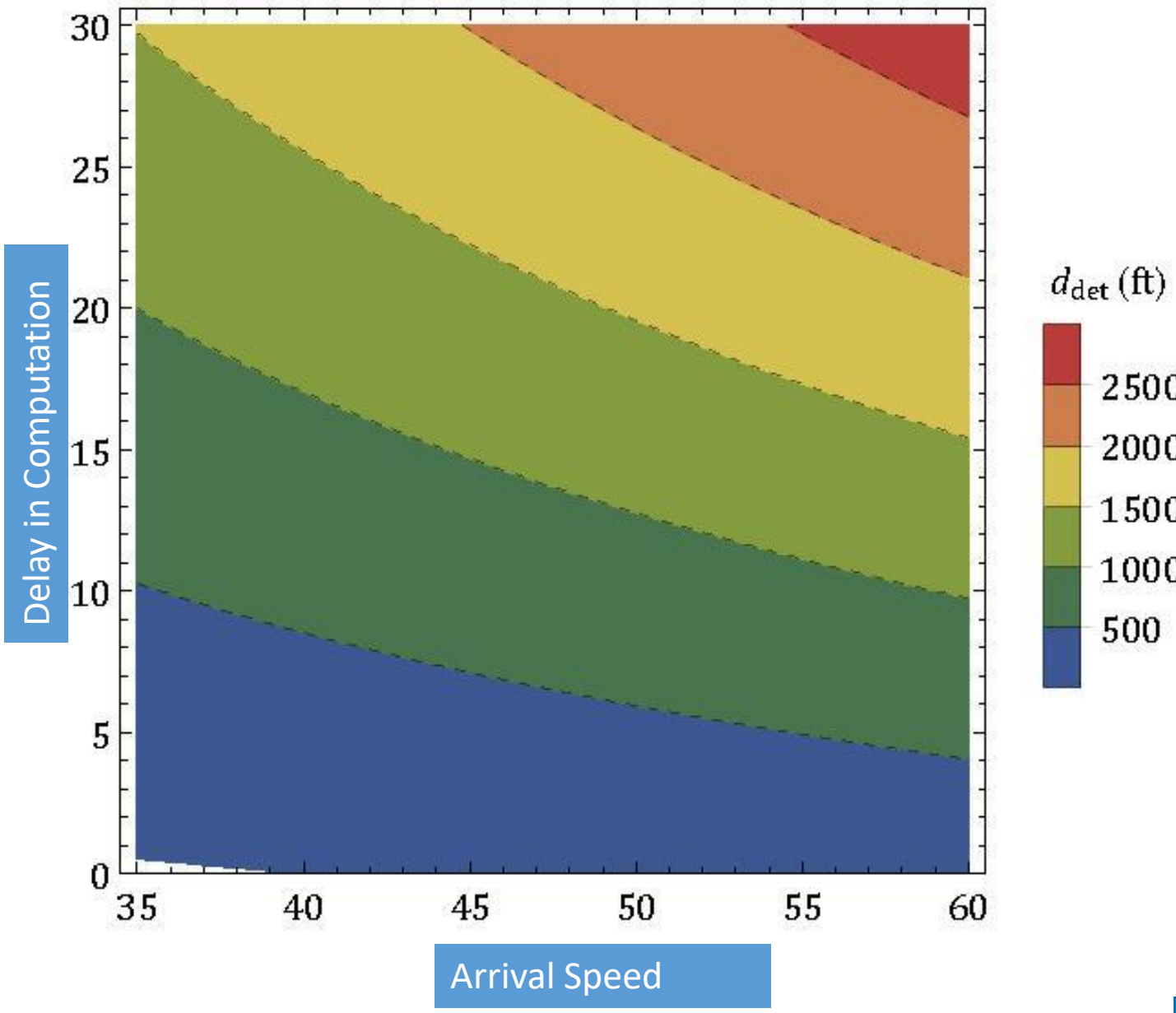
# Minimum Detection Range

The minimum detection range based on vehicle arrival information, deceleration capability, maximum crossing speed, and algorithms computation time.

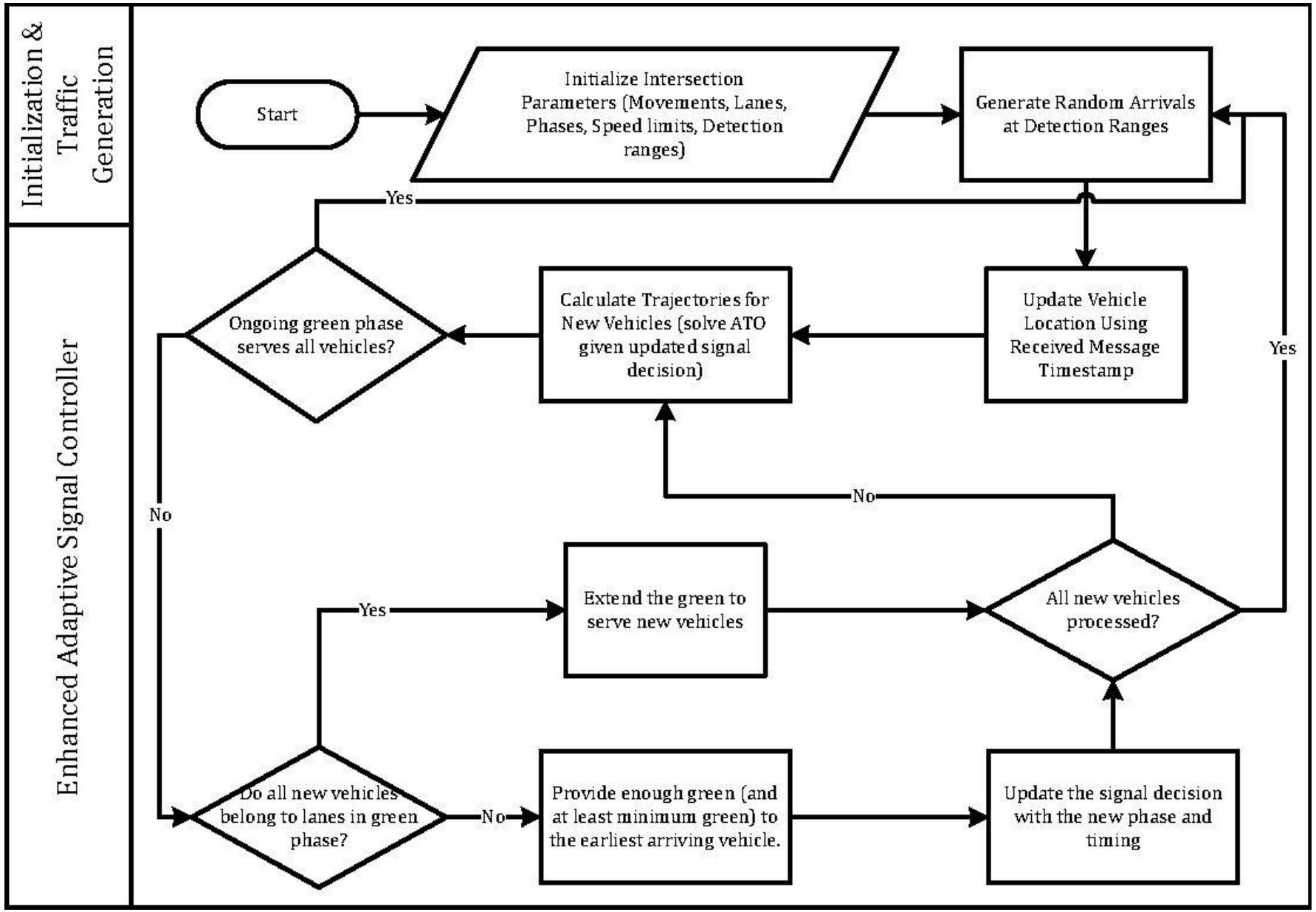
Observations:

1. For lower communication range with higher speed arrival of vehicles, the algorithm should perform faster.

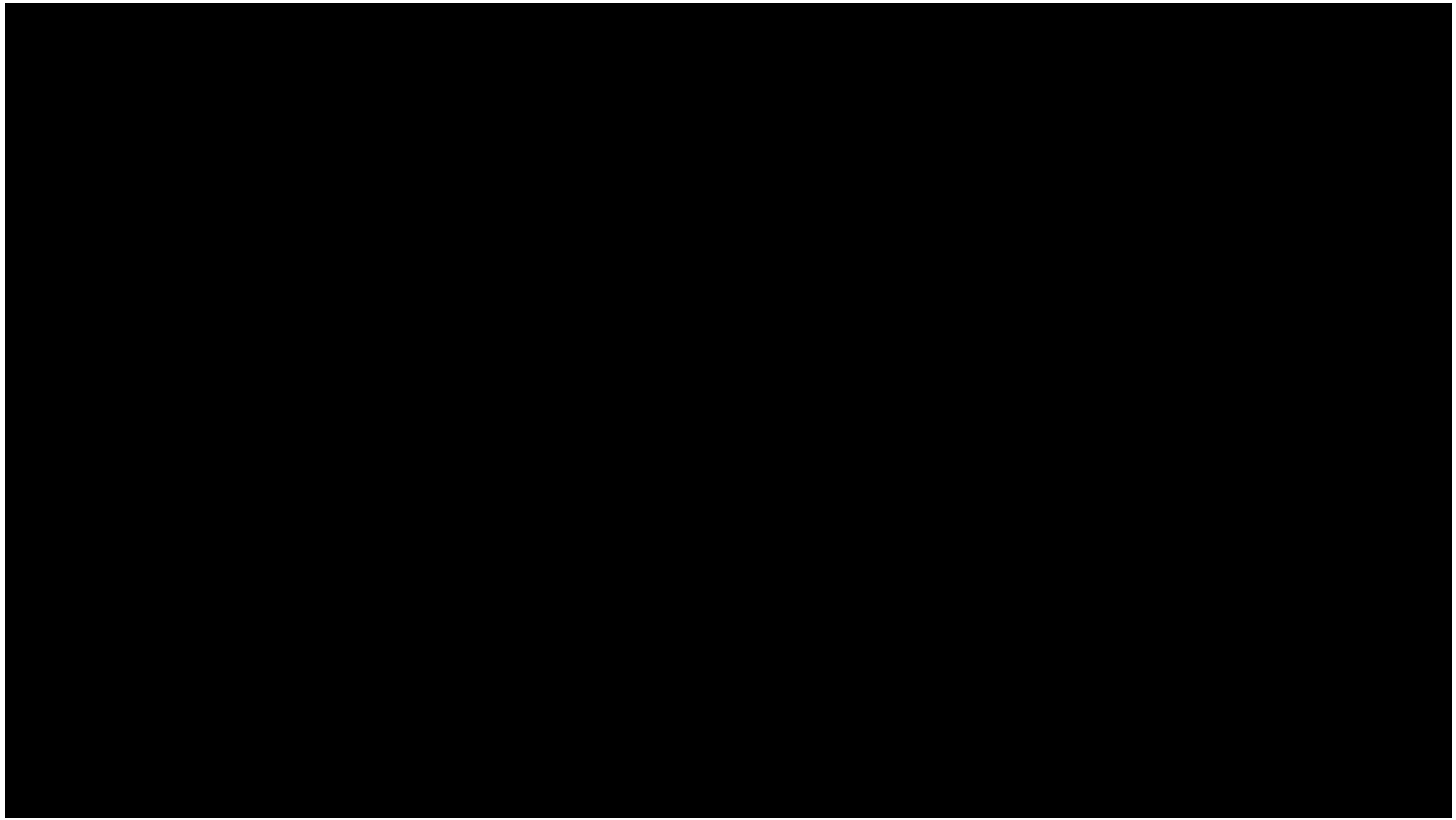
2. For a given delay (service time) in trajectory computation and initial vehicle's speed, a minimum detection range should be provided.



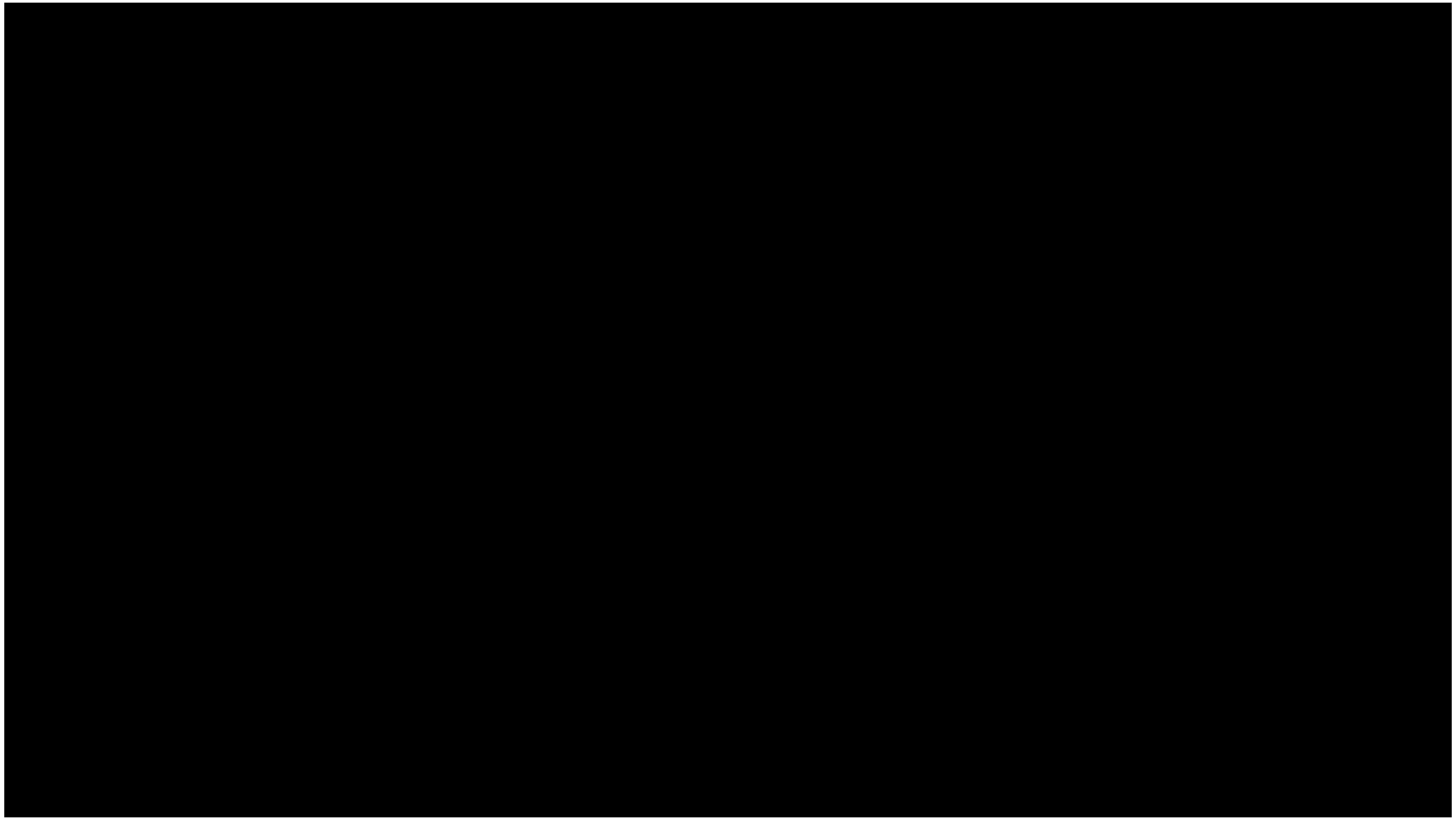
# Overall Algorithm



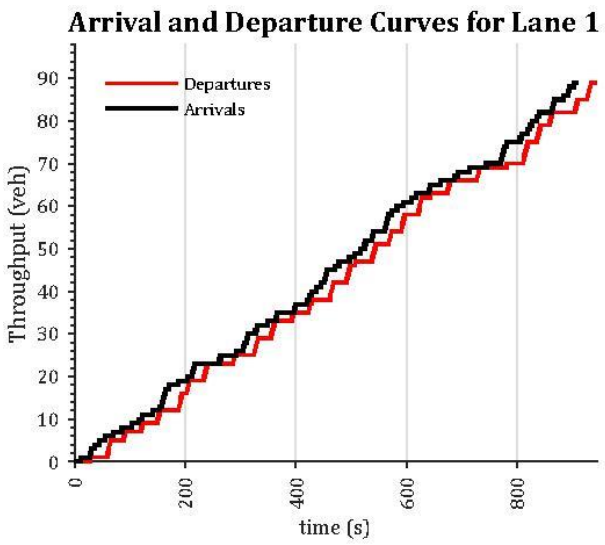
# Field Test of the System

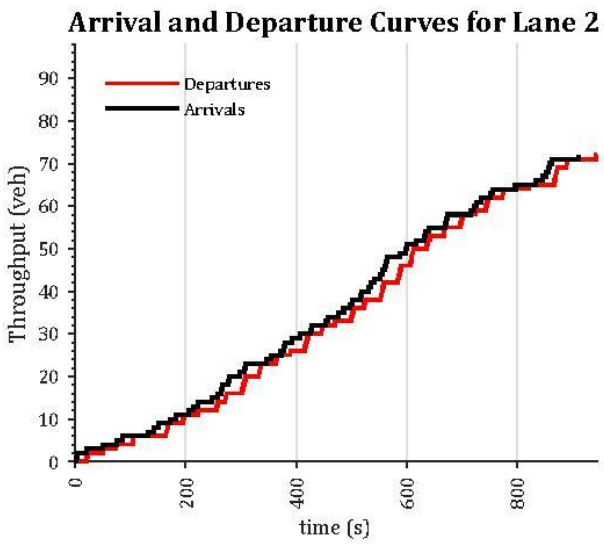


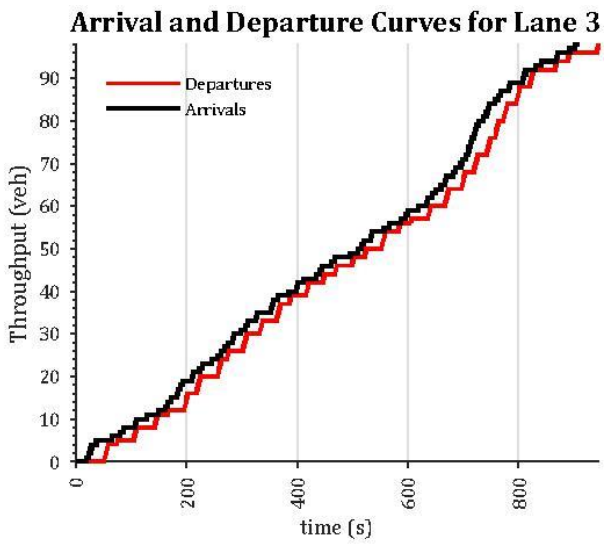
# Algorithm Logic and AV

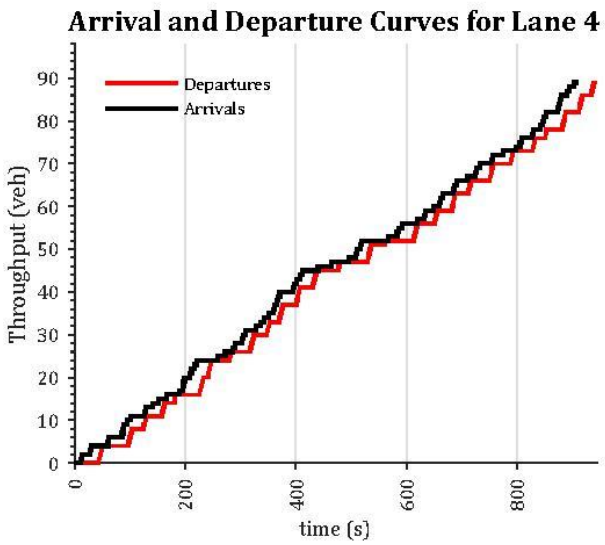


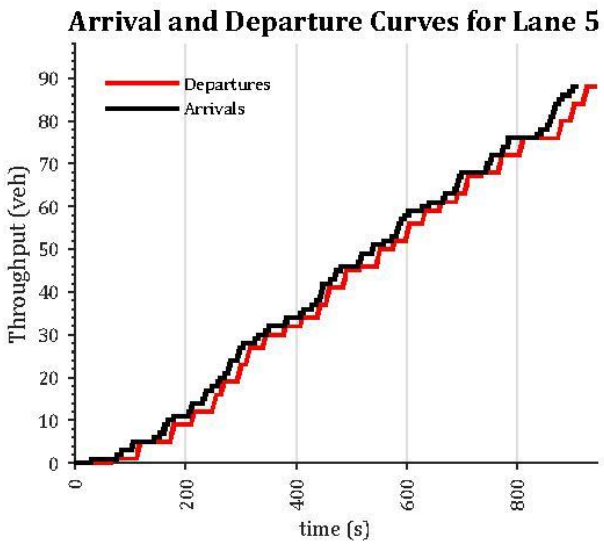
# 15-minute Simulation Result (per lane)

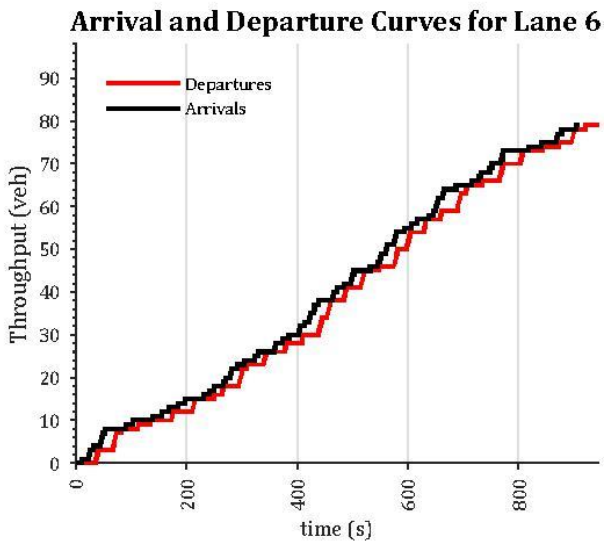


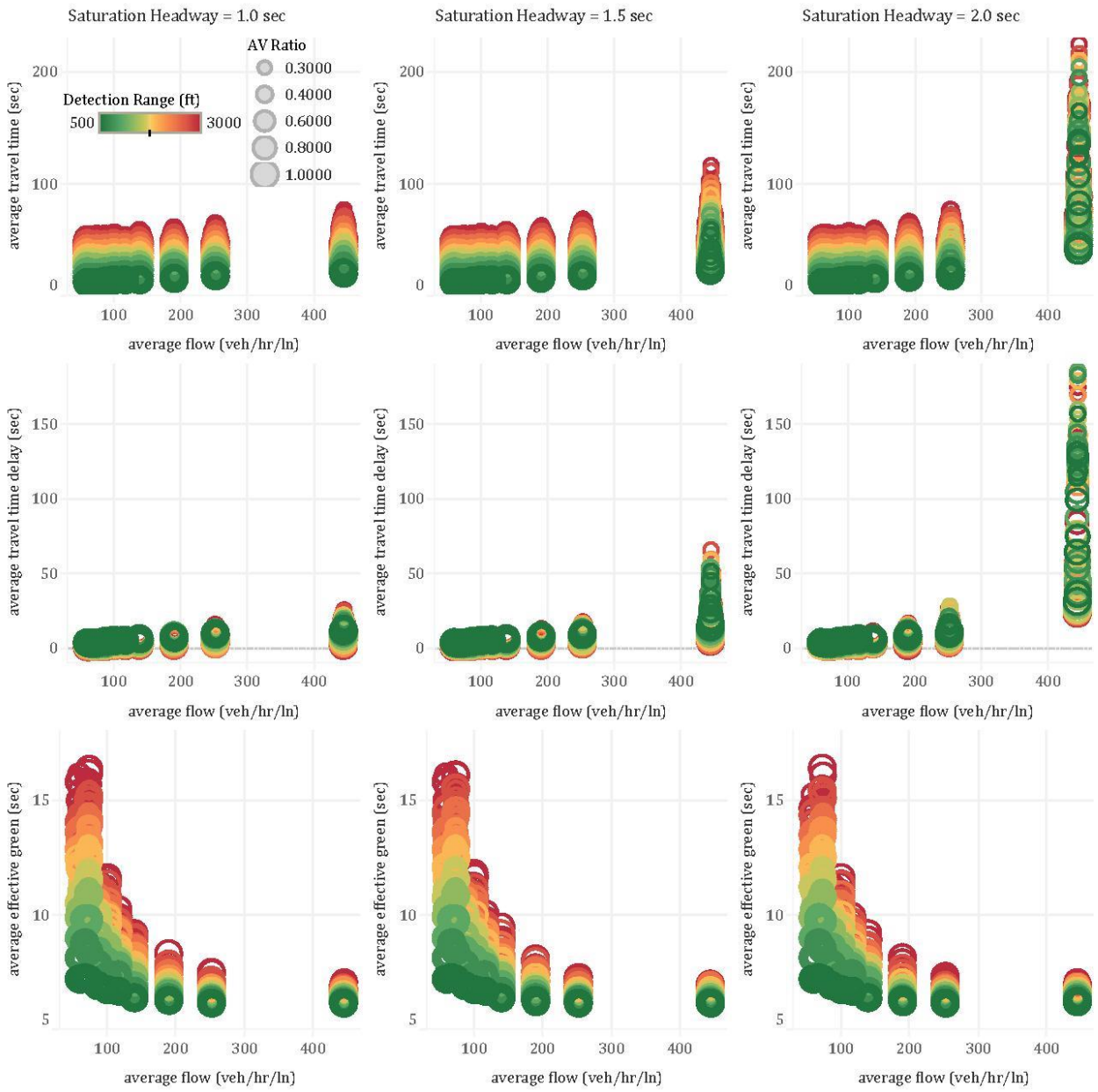



# Sensitivity Analysis Results




***Measures***: average travel time (vertical axis of first row), average travel time delay (vertical axis of the second row), average effective green (the vertical axis of the third row)

***Dimensions***: AV ratio (size), average flow (color), saturation headway at the stop bar (columns)

***Observations***:

Average travel time delay increases with flow

Average travel time delay decrease with detection distance

Shorter green intervals are assigned for higher flows (sensitive to flow fluctuation)

Flow threshold of 450 vehicles/hour/lane cause a surge in average travel time delay (indicating the congested situation)

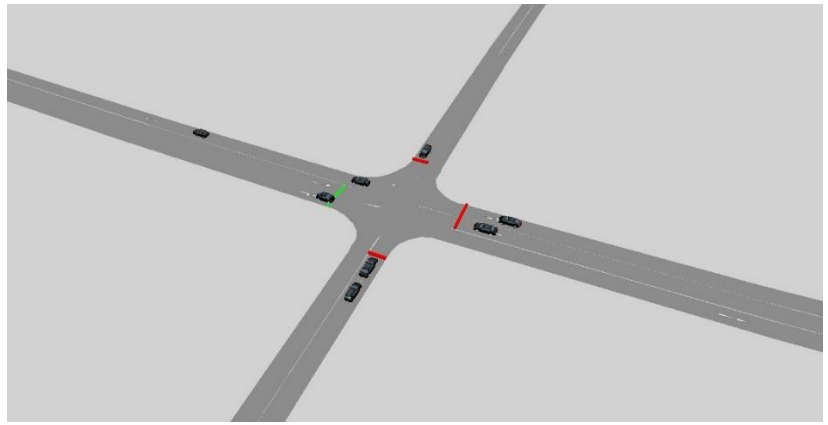
# VISSIM model for Actuated Signal Control

State of the art control for current isolate intersections is actuated control logic (Used as a baseline for comparison to IICS algorithm).

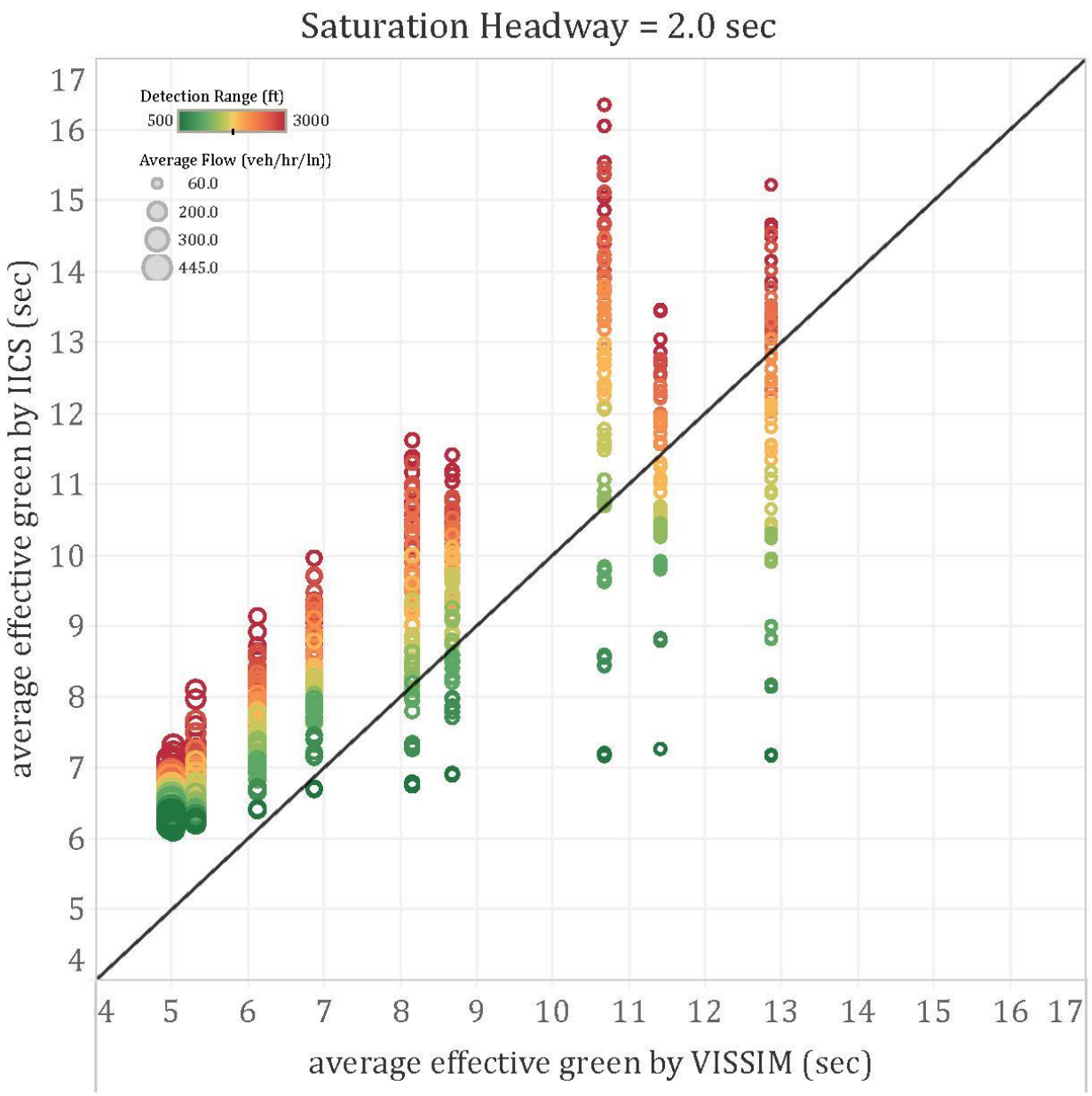
Loop detectors are placed in the pavement within a short distance from the stop bar. Every time a vehicle occupies the space inside the loop detector a call is sent to the signal controller to assign green. Two major cases may happen:

A phase being gap-out: a minimum green is assigned, however since no more vehicles showed up, the green is terminated and given to another phase.

A phase being maxed-out: vehicles keep coming in the ongoing phase, however to prevent excessive delay on other phases the a maximum green duration is set. In this case the green keeps being extended up to the threshold and then becomes maxed-out.)

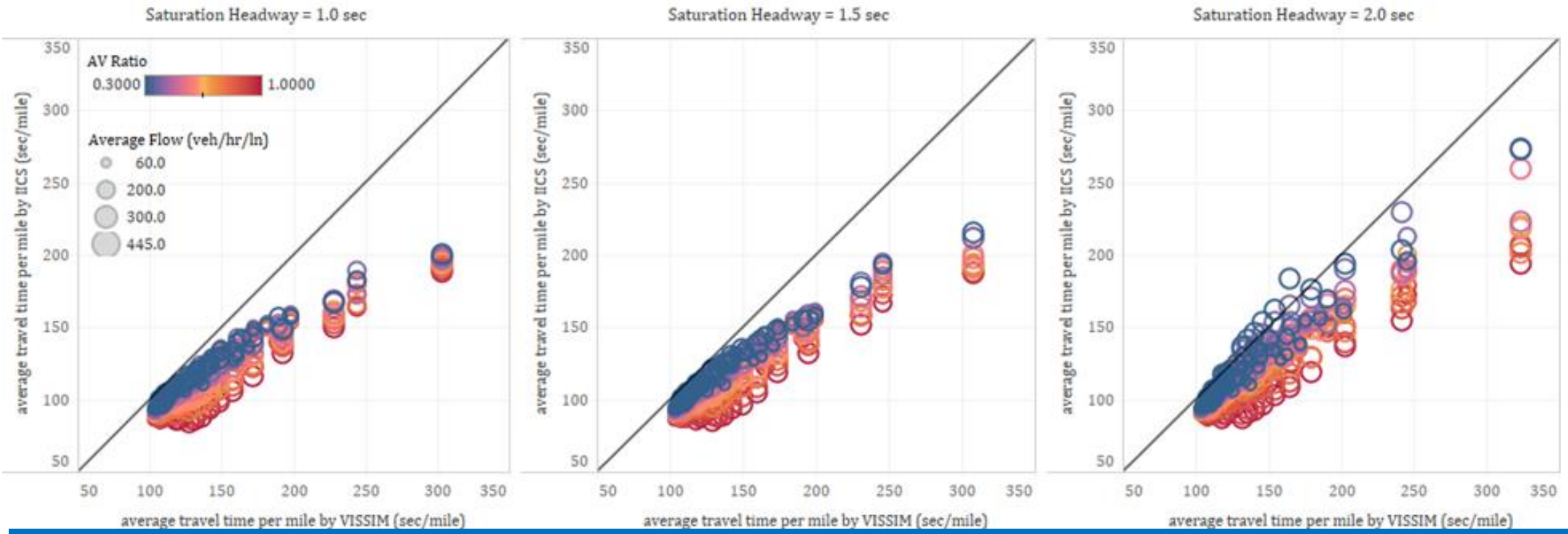


# Average Effective Green Comparison




Higher Flow leads to more frequent switches in the right-of-way

# Comparison with Actuated Control (Average travel time per mile)




IICS strategy leads to lower average travel times per mile compared to fully actuated control with all conventional vehicles

The rate of improvement increases as the saturation headway de- creases, AV penetration rate increases, or average ow increases,

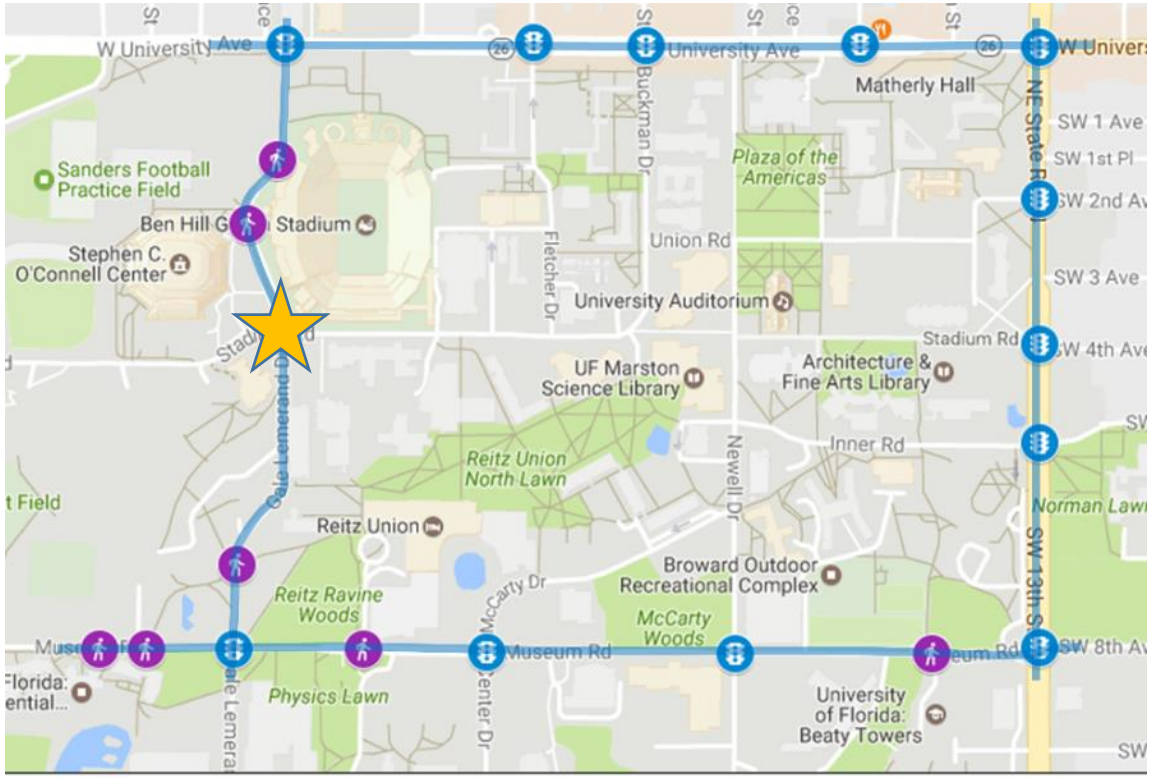
# Next Steps and Continued Research

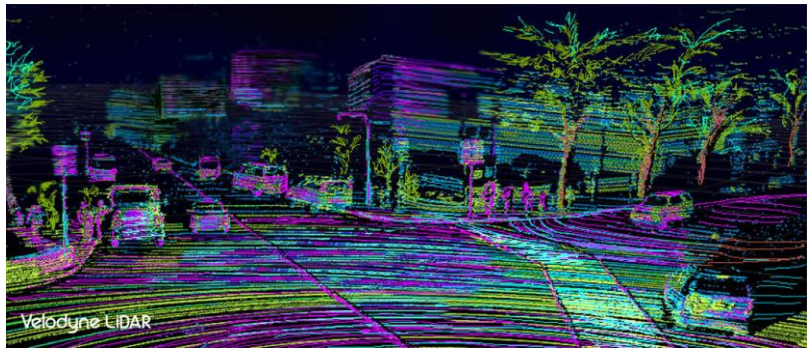
***Inclusion of Bicycles/Peds/Scooters:***

Expand the algorithm for multimodal traffic

***Additional Sensor Fusion***:
Fusion of different sensors may prove beneficial for different scenarios

***Field Deployment in Gainesville***:
Deploy the system at an isolated intersection on campus




https://www.engadget.com/2017/11/29/velodyne-lidar-helps-self-driving-cars-survive-the-highway/

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