

# Mixed-Traffic Intersection Management Utilizing Connected and Autonomous Vehicles as Traffic Regulators

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# Outline

- ❑ **Introduction**
- ❑ Motivating Example
- ❑ System Model
- ❑ Our Approaches
- ❑ Experimental Results
- ❑ Conclusion

# Connected and Autonomous Vehicles (CAV)

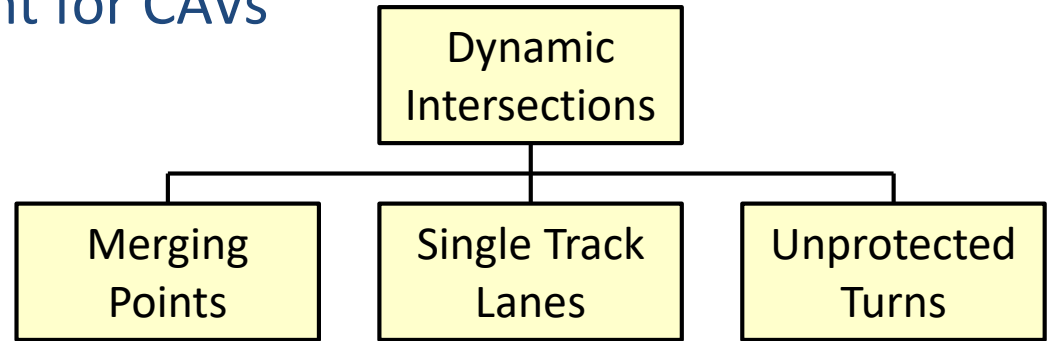
## □ Great potentials to improve safety and traffic performance

- Precise control compared to human-driving vehicles (HV)
- Vehicle-to-everything communication

# Intersection Management

## ❑ Intersection management for CAVs

- Modeling
- Protocol design
- Scheduling
- Analysis
- One of the highly-researched areas



## ❑ Various similar traffic scenarios

- Provide extensibility to intersection management

# Motivations

- ❑ Current studies mostly assume that traffic consists of pure CAVs, without any HV
- ❑ CAVs in mixed-traffic intersection protocols suffer performance loss due to the presence of HV
- ❑ It is challenging to fully utilize CAV's potentials in mixed-traffic
  - HVs do not change their behaviors to accommodate the presence of CAVs

# Goal

- ❑ Lessen the performance loss caused by HV in mixed-traffic intersection
  - Being able to schedule CAVs and HVs within mixed-traffic
  - Extendable to dynamic intersections
  - Effective even without a high CAV penetration rate

# Contributions

## □ Schedule CAVs to control the subsequent HVs

- An optimal dynamic programming approach to a single conflict zone model
- An optimal mixed integer linear programming (MILP) formulation for a trajectory-based model
- An efficient MILP-based approach keeping good solution quality

## □ Experimental results and SUMO simulation indicate that

- Controlling CAVs by our approaches is effective to regulate mixed-traffic even if the CAV penetration rate is low
- This brings incentive to early adoption of CAVs

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# Scheduling in Mixed Traffic

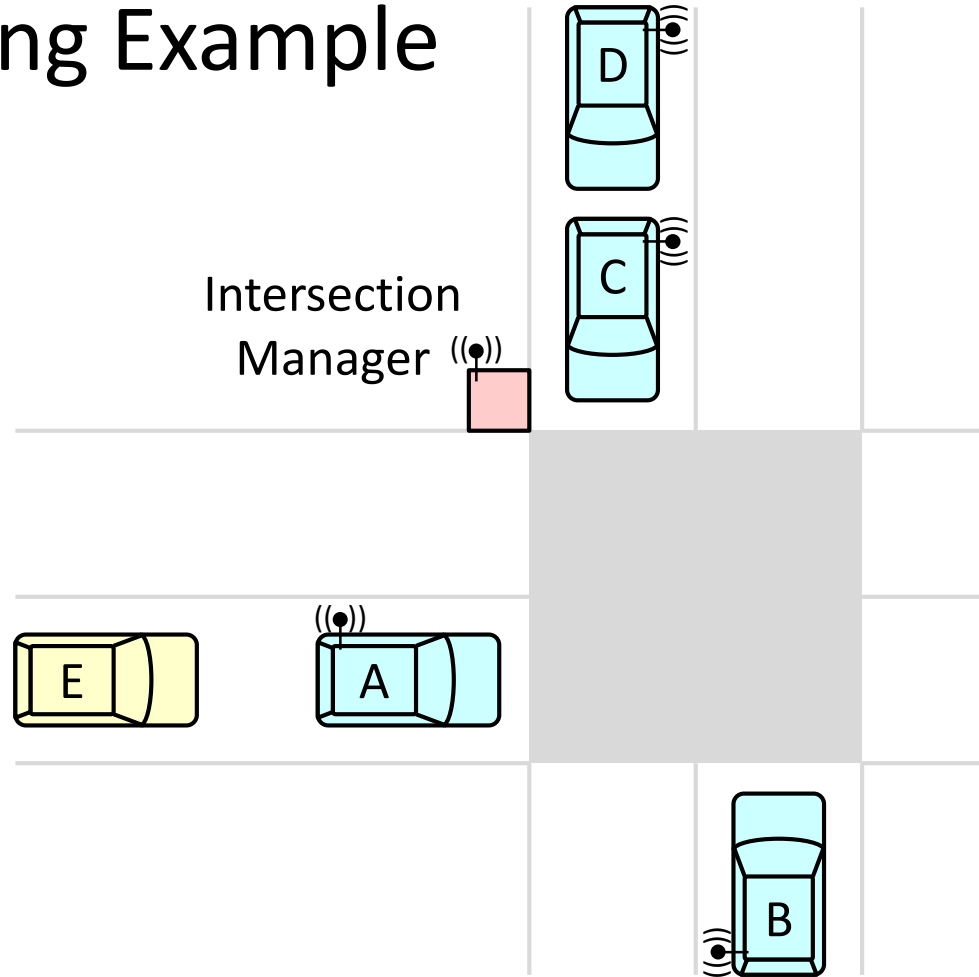
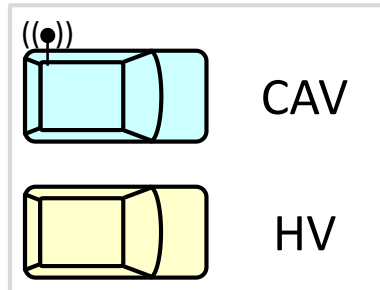
- Inspired by "Dissipation of Stop-And-Go Waves via Control of Autonomous Vehicles: Field Experiments" [Stern 2018]
  - Even if only part of the traffic is controllable within a non-overtaking scenario preceding vehicles can regulate the following vehicles

# Motivating Example

□ There are 4 CAVs and 1 HV

➤ CAVs: A, B, C, and D

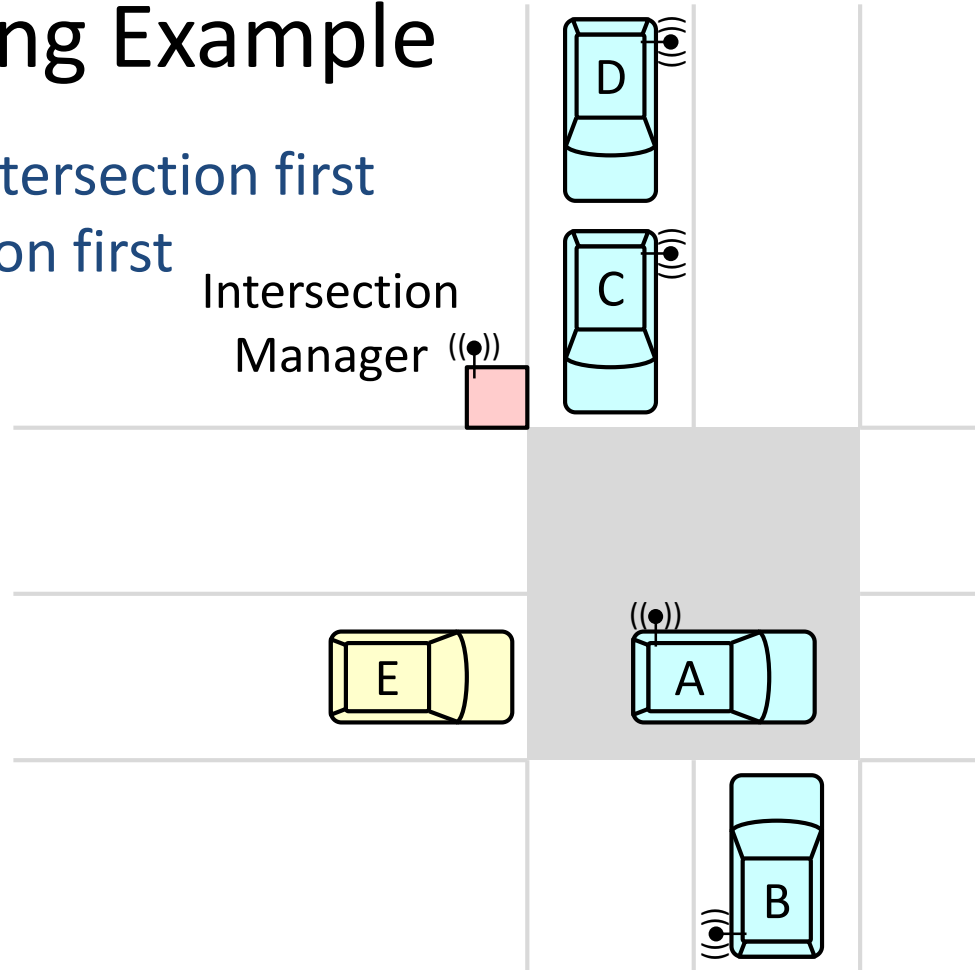
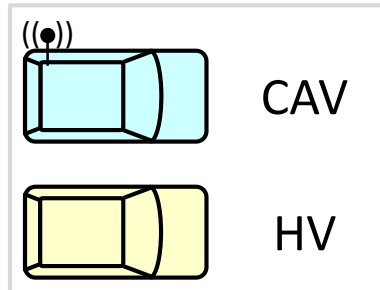
➤ HV: E



# Motivating Example

□ CAV A passes through the intersection first as it arrives at the intersection first

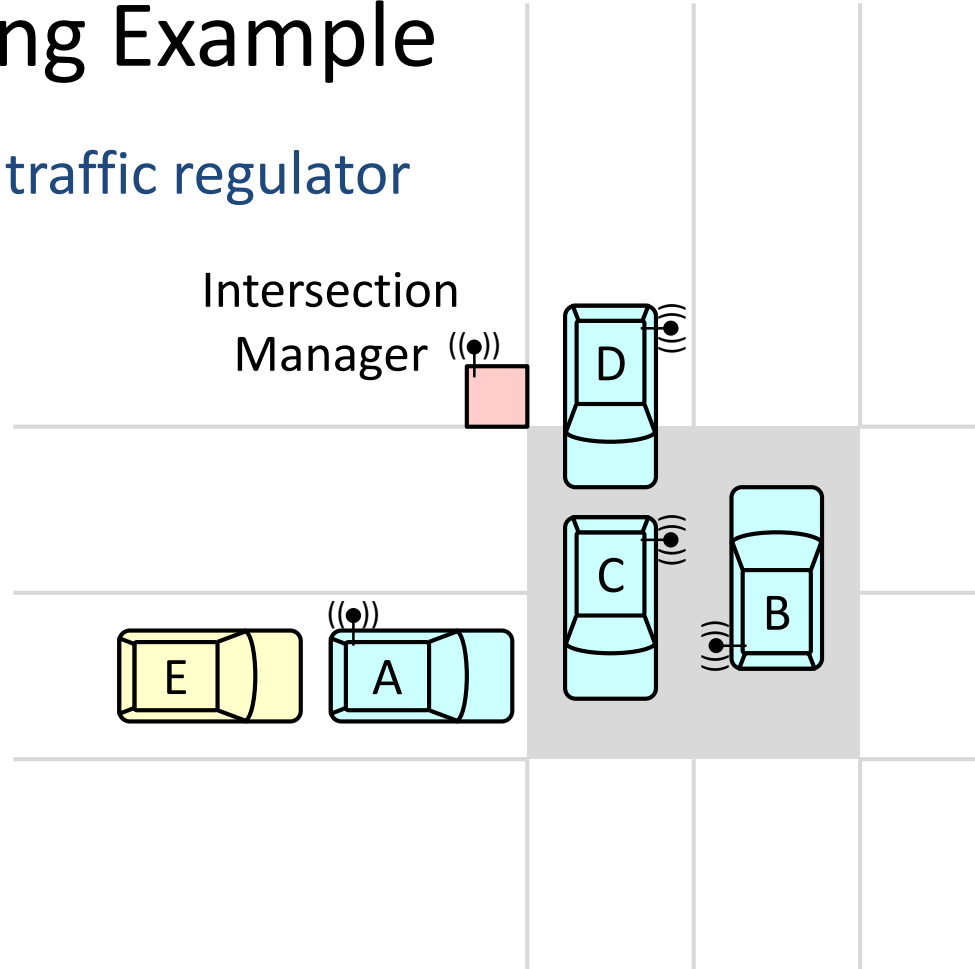
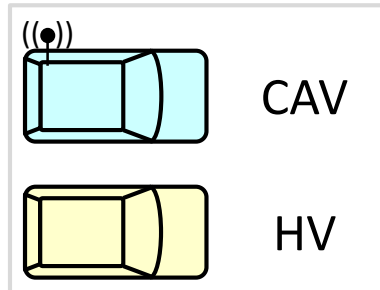
- Leave CAVs B, C, and D to pass through the intersection with the presence of HV E
- Result in performance loss



# Motivating Example

## □ CAV A can play the role as a traffic regulator

- CAV A blocks HV E
- CAVs B, C, and D can pass through the intersection first without the presence of HV E
- The overall performance can be improved



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# Behaviors of CAVs and HVs

- ❑ An overtaking-prohibited mixed-traffic intersection
- ❑ CAVs behave depending on whether there exists an HV at the head (as the first vehicle) of any lane
  - If yes, CAVs go slower due to the uncertain behaviors of HVs
  - Otherwise, CAVs may use a more efficient CAV protocol and go faster
- ❑ CAVs follow the intersection manager's order to decide when they pass through the intersection
- ❑ HVs pass through the intersection as soon as possible

# Intersection Models

- ❑ Based on how the vehicles are allowed to enter the conflict zone, we have two intersection models
- ❑ Single conflict zone model
  - Only a vehicle can enter the intersection (conflict zone) at a time
- ❑ Trajectory-based model
  - As long as all the trajectories of the vehicles in the conflict zone do not conflict with each other, vehicles can enter the conflict zone

# Problem Formulation (1/2)

## □ Problem input parameters

- $V_{l,i}$ : the  $i$ -th vehicle on lane  $l$
- $L$ : the number of lanes
- $N_l$ : the number of vehicles on lane  $l$
- $H_{l,i}$ : 1 / 0 if  $V_{l,i}$  is an HV / CAV
- $A_{l,i}$ : the estimated arrival time of  $V_{l,i}$
- $G$ : the time gap for the next passing vehicle if there is no HV at the head on each lane
- $G^+$ : the time gap for the next passing vehicle if there exists an HV at the head on a lane



# Problem Formulation (2/2)

□ Given the input parameters, the problem is to decide the time when each vehicle enters the intersection

➤  $t_{l,i}$ : the entering time of  $V_{l,i}$

□ The objective is to minimize the entering time of the last passing vehicle

➤  $\min \max_{1 \leq l \leq L, 1 \leq i \leq N_l} t_{l,i}$

- It also represents the performance of the intersection processing all vehicles

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- ❑ **Our Approaches**
  - Dynamic Programming Approach
  - MILP Formulation
  - MILP-Based Approach
- ❑ Experiments
- ❑ Conclusion

# Our Approaches

- ❑ Dynamic programming approach

- Optimal to the single conflict zone model

- ❑ MILP formulation

- Optimal to the trajectory-based model

- ❑ MILP-based approach

- Efficient and real-time-applicable

# Dynamic Programming Approach (1/2)

- ❑ In the single conflict zone model, we can represent the system as the number of vehicles passed through each lane
  - State  $\Theta = (\theta_1, \theta_2, \dots, \theta_L)$
- ❑ Given a state  $\Theta$ , the previous state  $\Theta'$  must be the same as  $\Theta$  except for one lane having exact one less passed vehicle
  - $\theta'_l = \theta_l - 1$  for exact one  $l$ , and the objective only depends on the time gap for  $v_{l,\theta_l}$
  - Therefore, the optimality holds with the subproblems
- ❑ Given a state, the passing time of the next vehicle is also known since the head vehicle of each lane is known

# Dynamic Programming Approach (2/2)

- $OBJ(\Theta) = \min_i ( \max ( A_{i,\theta'_i}, OBJ(\Theta'_i) + TimeGap(\Theta'_i, l) ) )$ 
  - $\Theta'_i$  indicates that  $\Theta$  is the state derived from  $\Theta'$  where the vehicle from lane  $i$  pass through next
  - $TimeGap()$  is the passing time of the next vehicle depending on the state of the intersection
- Return an optimal solution to the single conflict zone model with a polynomial time complexity

# MILP Formulation

- ❑ Convert the trajectory-based model and the constraints into MILP formulation
  - Overtaking is prohibited
  - Time gap must be large enough (for safety)
  - HVs are non-schedulable
- ❑ Return an optimal solution to the trajectory-based model with an exponential time complexity

# MILP-Based Approach

## □ Divide and conquer

- Divide the problem
- Solve the subproblems with MILP
- Combine them for a solution

## □ Efficient and real-time-applicable

- Still keep good solution quality, though without guarantee of optimality

## □ With a given subproblem size, the computation time scales linearly with the problem size

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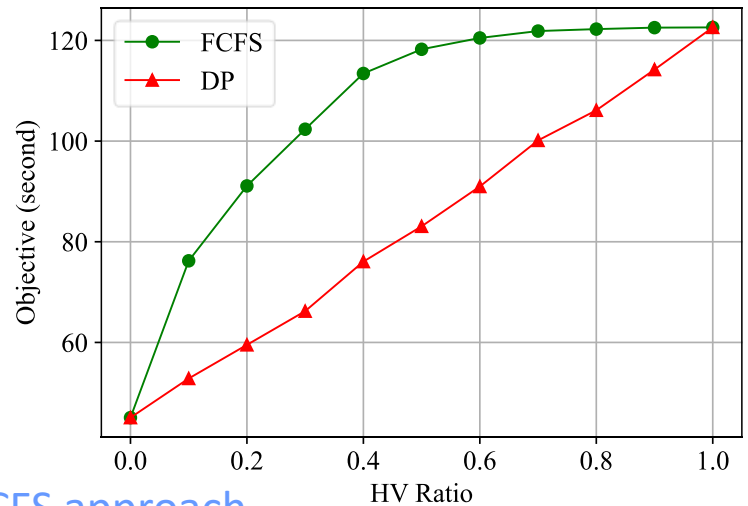
# Experimental Setting

- ❑ Set the experimental parameters
  - 4 lanes and 5 vehicles on each lane
  - $G = 1$  (second),  $G^+ = 3$  (second)
  - Poisson arrival with  $\lambda = 0.5$  vehicle per second
- ❑ Run experiments on a laptop with 1.8GHz Intel Core i7-8550U processor and 16GB memory
- ❑ Use Gurobi as the MILP solver
- ❑ Compare our approaches with the first-come-first-served (FCFS) approach

# Dynamic Programming Approach

## Comparison between the FCFS approach and the dynamic programming approach for the single conflict zone model

- When the CAV penetration rate is 0
  - Without controllable vehicles, the two approaches are the same
- When the CAV penetration rate is 1
  - With all controllable vehicles, the two approaches are the same
- Otherwise
  - The dynamic approach outperforms the FCFS approach



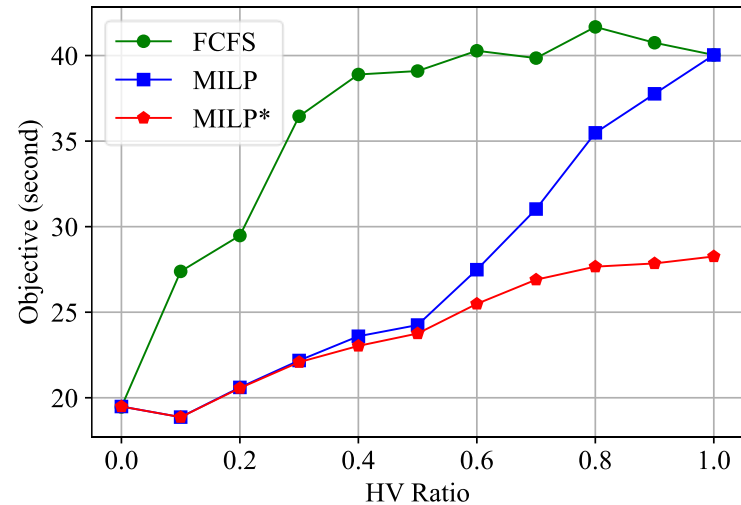
# MILP Formulation

## Comparison between the FCFS approach and the MILP formulation for our trajectory-based model

➤ MILP\* is the case where HVs are assumed to be connected and schedulable

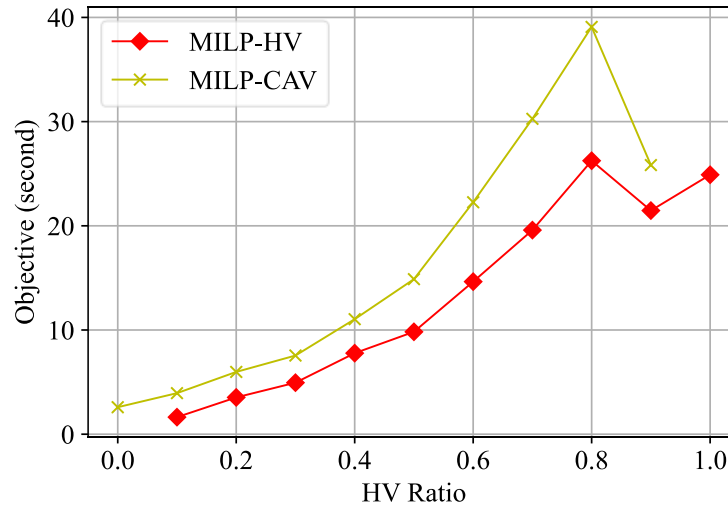
- Having half vehicles controllable is comparable to having all vehicles controllable

➤ Average runtime 0.42 second



# MILP Formulation: CAVs vs HVs

- The waiting time of CAVs is larger than that of HVs
  - Using CAVs to block HVs lets CAVs suffers extra waiting times but improve the overall traffic performance



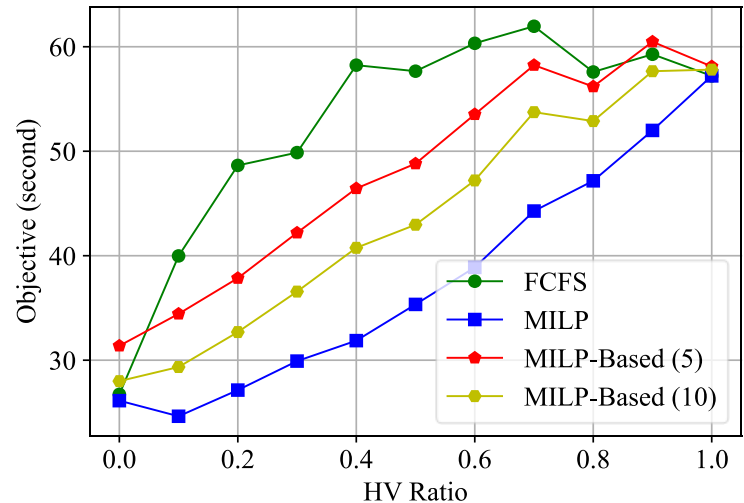
# MILP-Based Approach

## □ When the subproblem size increases

- The performance improves

## □ When the subproblem size is the number of vehicles

- It is equivalent to the MILP formulation which returns an optimal solution



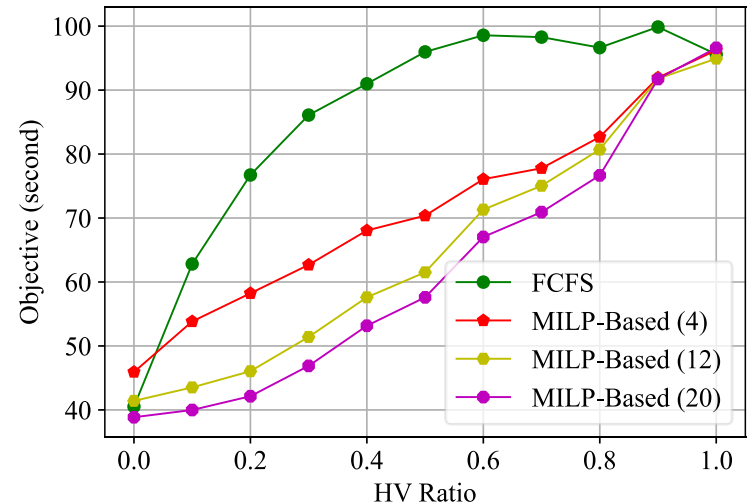
# MILP-Based Approach: Computation Time

## ❑ Larger subproblem size

- Fewer sub-cases
- Better objective value
- Longer computation time

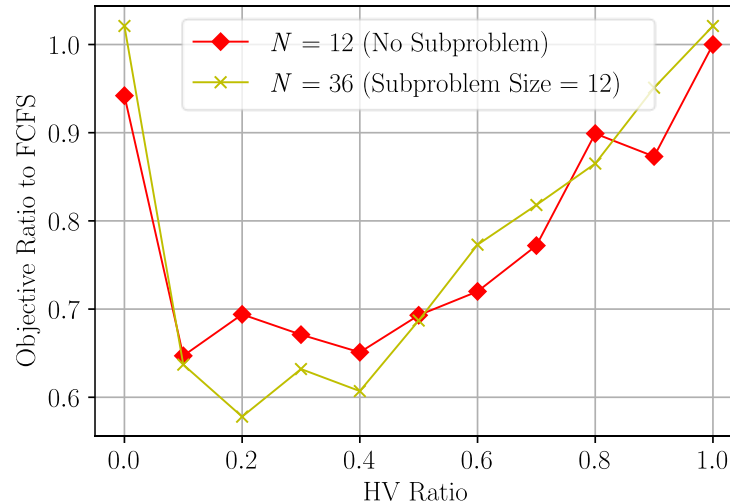
## ❑ Tradeoff between solution quality and computation time

- The MILP-based approach with subproblem sizes 4, 12, and 20 takes 0.01, 0.08, and 0.42 second, respectively
  - Real-time applicable



# MILP-Based Approach vs. MILP Formulation

- Splitting a problem into subproblems (solved by the MILP-based approach) with size 12 gives similar improvement as optimally solving a problem (MILP formulation) with size 12



# SUMO Simulation Setting

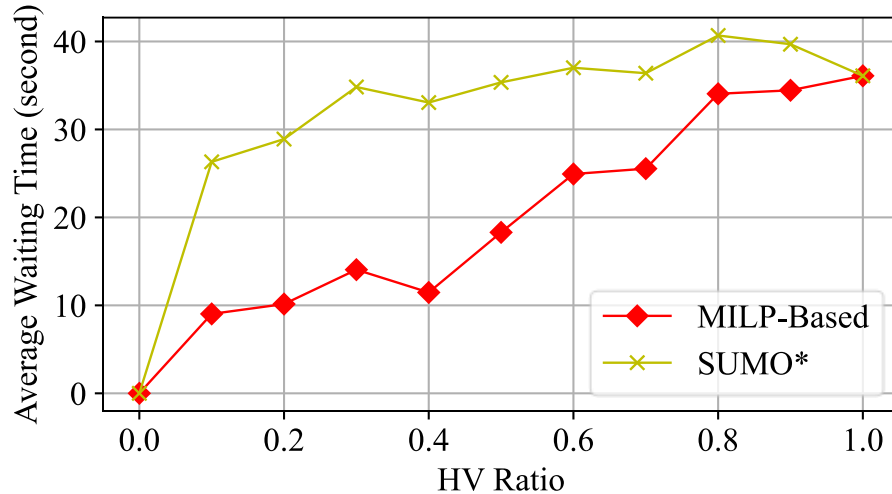
## □ Simulation of an unsignalized intersection

| Type                 | Parameter               | Value                      |
|----------------------|-------------------------|----------------------------|
| Simulation           | Simulation Step         | 0.1 (s)                    |
|                      | Road Length             | 500 (m)                    |
| Intersection Manager | Sensing Range           | 100 (m)                    |
|                      | Scheduling Period       | 1 (s)                      |
| Vehicle              | Max Speed               | 16 (m/s)                   |
|                      | Max Acc/Deceleration    | 3/-4.5 (m/s <sup>2</sup> ) |
|                      | Min Gap                 | 2.5 (m)                    |
|                      | Vehicle-Following Model | Krauss Model               |



# SUMO Simulation Results

- ❑ The MILP-based approach significantly outperforms the SUMO unsignalized intersection



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# Conclusion

- ❑ Target the problem of mixed-traffic intersection management by using CAVs as traffic regulators
  - Dynamic programming approach, MILP formulation, and MILP-based approach
- ❑ Controlling CAVs by our approaches is effective to regulate mixed-traffic even if the CAV penetration rate is low
  - This brings incentive to early adoption of CAVs
- ❑ Future directions
  - Management with specific lanes for CAVs and HVs
  - Management considering different dynamics of CAVs and HVs

# Q&A