Collaborative Sciences Center for ROAD SAFETY

www.roadsafety.unc.edu

Applying AI techniques to high-resolution crosslinked data sources for safe and efficient driver-pedestrian interactions at intersections

The University of Tennessee, Knoxville

THE UNIVERSITY OF TENNESSEE KNOXVILLE

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R43 - Project Team

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- University of North Carolina, Chapel Hill
- City of Chattanooga

THE UNIVERSITY OF TENNESSEE KNOXVILLE
DEPARTMENT OF MECHANICAL, AEROSPACE & BIOMEDICAL ENGINEERING

THE UNIVERSITY OF NORTH CAROLINA HIGHWAY SAFETY RESEARCH CENTER

OAK RIDGE National Laboratory

Overview: Research Objectives

Goal - Investigate a new framework for Signal Phase and Timing Control constrained by pedestrian safety with multi-agent Reinforcement Learning.

The key objectives are:

1. Explore and process traffic dataset from the Shallowford corridor in Chattanooga, collected with Gridsmart cameras.
2. Build a lightweight algorithm for queue estimation based on patrial information, suitable for AI application.
3. Develop a decentralized multi-agent learning algorithms that optimizes the signal phase and timing plan to reduce vehicular and pedestrian delays.
4. Build a simulation replica of the intersections on the Shallowford corridor to establish baseline with actuated controller and show improvement with RL controller.

Overview-Research Components

Data Elements

- **City of Chattanooga** – Real-time access to GridSmart cameras (working 38 +100 planned)
- **TDOT** - Radar Detector Sensors
- Probe Data – **WAZE**
- Incident Data - **TITAN, GEARS, DPS, WAZE**

Data linking – Data Fibers, DSRC, 5G/LTE

Analytics

Ped estimates

SPaT data
Road Geometry
Traffic volume

Queue lengths

Decentralized Multi-Agent-Learning algorithm

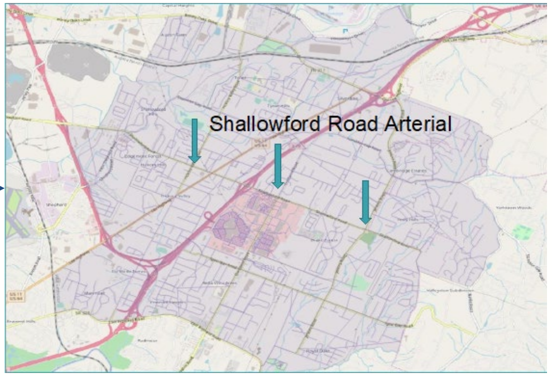
Optimized SPaT plan

Simulation/Validation

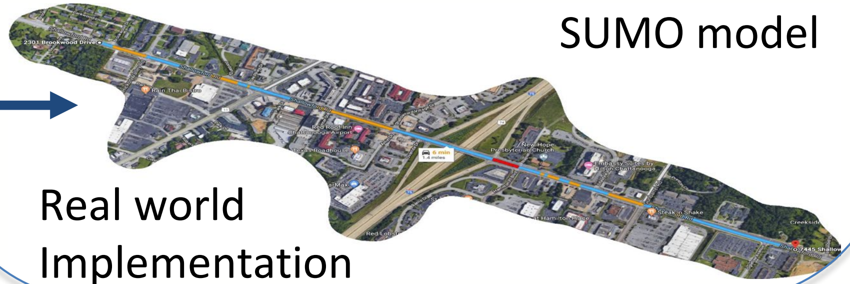
X2P communications

VR micro simulation with full visualization

Traci-for-Matlab



SUMO model



Real world Implementation

'Digital Twin' for Regional Mobility, Chattanooga, TN

Situational Awareness from real-time data feeds

+

Simulation, Modeling, and Machine Learning

+

Cyber-Physical control actions

Allows observability at a regional scale

Identifies and evaluates improvements
Demonstrates feasibility/ anticipated outcomes

Algorithmically actuates hardware

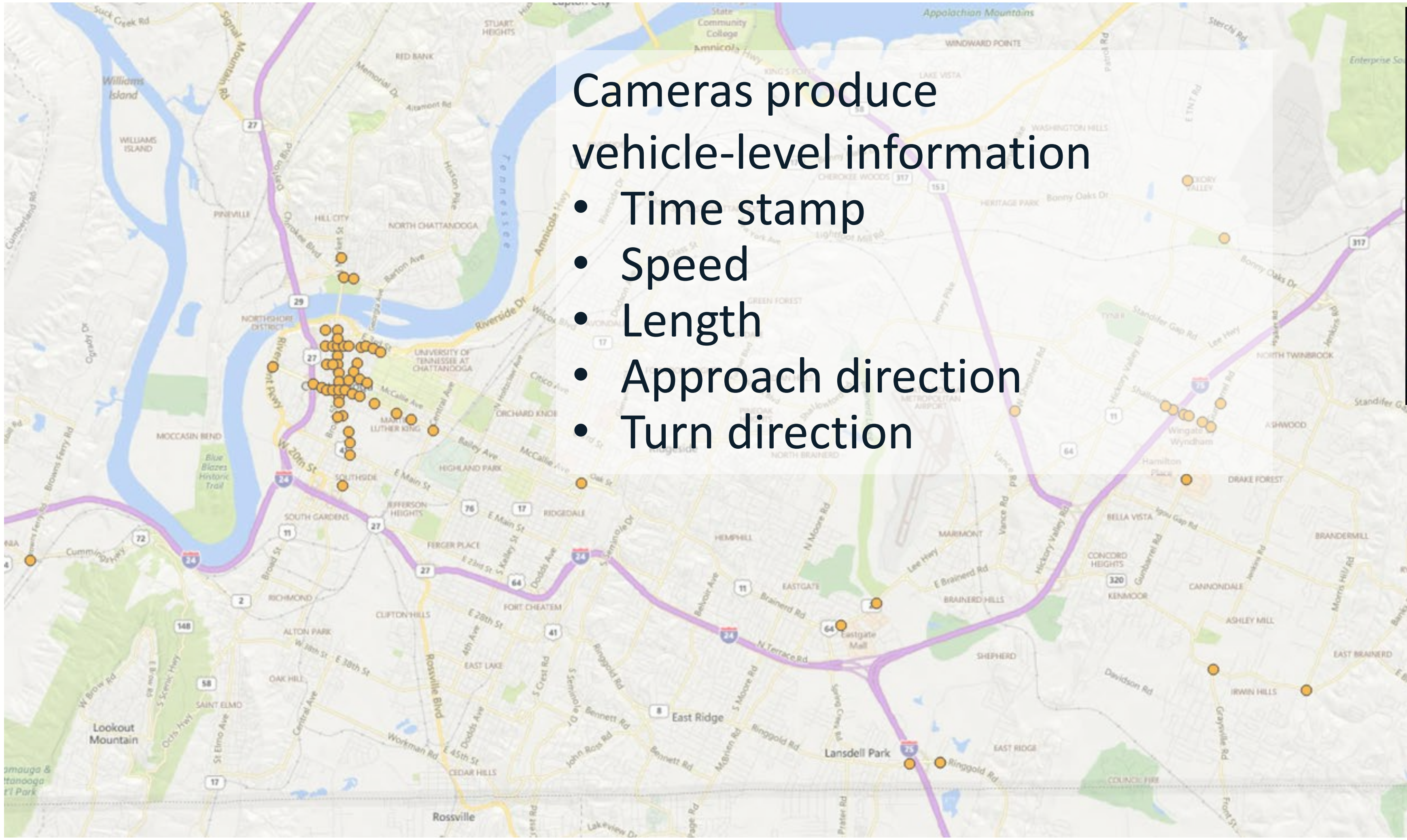
Problem Statement

- Improve Traffic Throughput
- Reduce "Green Idling"
- Produce a Real-time Adaptive Signal Controller via Reinforcement Learning and Continuous Negotiations between cooperative signals

Trained and tested on the CTwin real-time traffic data from the Shallowford Road corridor

Significant opportunity as a live testbed for connected fleets, CAVs, V2I, and active control

71 GridSmart Cameras



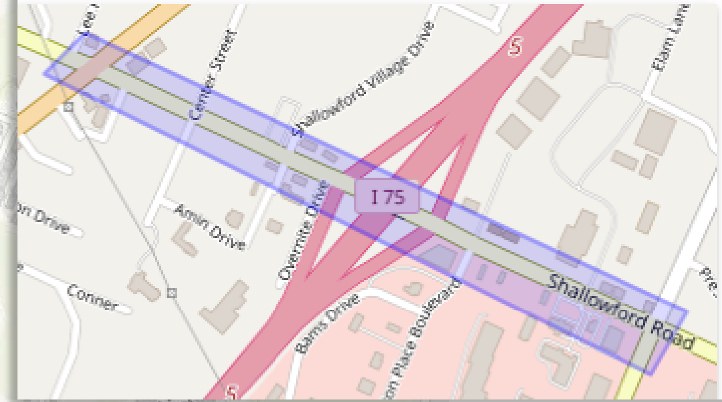
Cameras produce vehicle-level information

- Time stamp
- Speed
- Length
- Approach direction
- Turn direction

Used with permission from Berres, A. S., LaClair, T. J., Wang, C. (Ross), Xu, H., Ravulaparthy, S., Todd, A., Tennille, S. A., & Sanyal, J. (2021). Multiscale and Multivariate Transportation System Visualization for Shopping District Traffic and Regional Traffic. Transportation Research Record, 2675(6), 23–37. https://doi.org/10.1177/0361198120970526

Corridor-Level Visualization: Shallowford Road Corridor

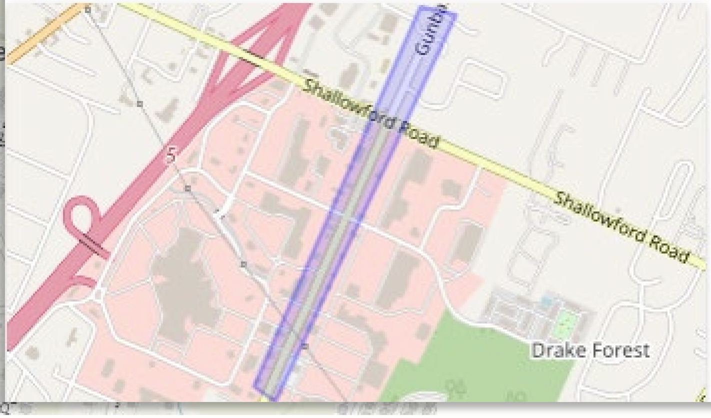
Shallowford Rd from Lee Hwy to Gunbarrel Rd



Summary

GridSmart Cameras: 6
Radar Detectors: 1
CCTV Cameras: 1
Traffic Signals: 7

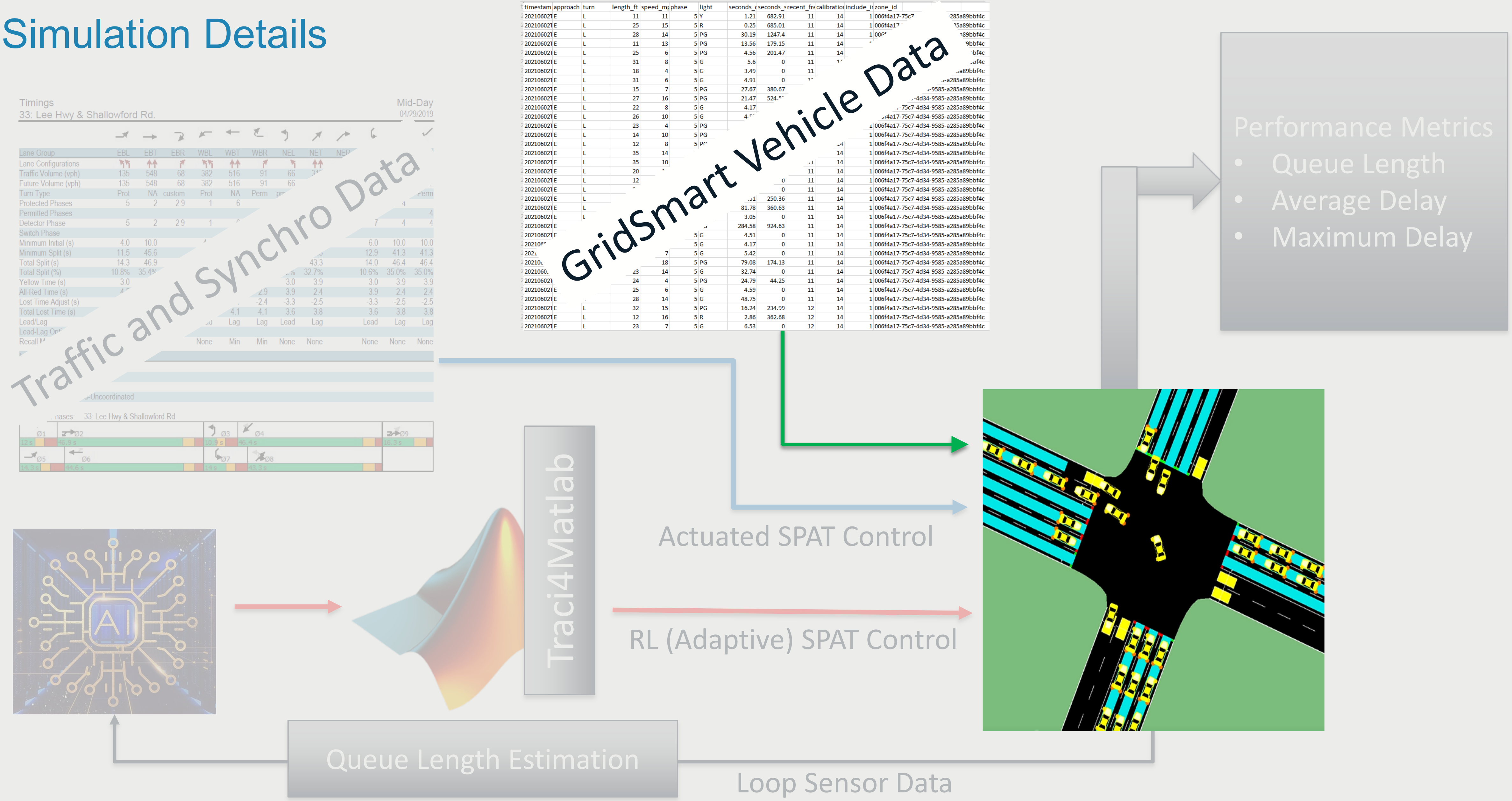
Gunbarrel Rd from Publix to Hamilton Plaza



Summary

GridSmart Cameras: 3
Radar Detectors: 0
CCTV Cameras: 0
Traffic Signals: 4

Simulation Details



Recorded GRIDSMART Data

- Signal Timing

time	code	signal
42.2	215	RYURUYUURRRUUUUU
44.8	215	RRURURUURRRUUUUU
47.1	215	RRUGURUURRRUUUUU
58	215	RRUYURUURRRUUUUU
100.1	215	RRURURUURRRUUUUU
102.7	215	GRURUGUURRRUUUUU
108.8	215	YRURUGUURRRUUUUU
110.7	215	RRURUGUURRRUUUUU
113.4	215	RGURUGUURRRUUUUU
225.9	215	RYURUYUURRRUUUUU
228.5	215	RRURURUURRRUUUUU
230.8	215	RRUGURUURRRUUUUU
241.8	215	RRUYURUURRRUUUUU
243.8	215	RRURURUURRRUUUUU
246.5	215	RGURUGUURRRUUUUU
409.9	215	RYURUYUURRRUUUUU
412.5	215	RRURURUURRRUUUUU
414.8	215	RRUGURUURRRUUUUU
425.7	215	RRUYURUURRRUUUUU
427.8	215	RRURURUURRRUUUUU
430.4	215	RGURUGUURRRUUUUU
455.1	215	RYURUYUURRRUUUUU
457.7	215	RRURURUURRRUUUUU
500	215	RRUGURUURRRUUUUU
511	215	RRUYURUURRRUUUUU
513	215	RRURURUURRRUUUUU
515.7	215	RGURUGUURRRUUUUU
526.7	215	RYURUYUURRRUUUUU
529.3	215	RRURURUURRRUUUUU
531.6	215	RRUGURUURRRUUUUU
542.6	215	RRUYURUURRRUUUUU
544.6	215	RRURURUURRRUUUUU
547.3	215	RGURUGUURRRUUUUU
742.4	215	RYURUGUURRRUUUUU
745	215	RRURUGUURRRUUUUU

- Vehicle Data

timestam	approach	turn	length_ft	speed_mp	phase	light	seconds_c	seconds_s	recent_fre	calibratio	include_ir	zone_id
20210602T	E	L	11	11	5	Y	1.21	682.91	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	25	15	5	R	0.25	685.01	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	28	14	5	PG	30.19	1247.4	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	11	13	5	PG	13.56	179.15	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	25	6	5	PG	4.56	201.47	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	31	8	5	G	5.6	0	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	18	4	5	G	3.49	0	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	31	6	5	G	4.91	0	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	15	7	5	PG	27.67	380.67	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	27	16	5	PG	21.47	524.59	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
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20210602T	E	L	14	10	5	PG	35.42	318.87	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	12	8	5	PG	9.64	343.73	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	35	14	5	PG	25.98	360.08	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	35	10	5	PG	9.87	1299.52	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	20	16	5	PG	72.48	232.12	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	12	8	5	G	3.75	0	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	26	4	5	G	2.72	0	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	25	11	5	PG	13.31	250.36	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	12	17	5	PG	81.78	360.63	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	26	5	5	G	3.05	0	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	14	14	5	PG	284.58	924.63	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	15	10	5	G	4.51	0	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	14	8	5	G	4.17	0	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	27	7	5	G	5.42	0	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	28	18	5	PG	79.08	174.13	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	23	14	5	G	32.74	0	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	24	4	5	PG	24.79	44.25	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	25	6	5	G	4.59	0	11	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
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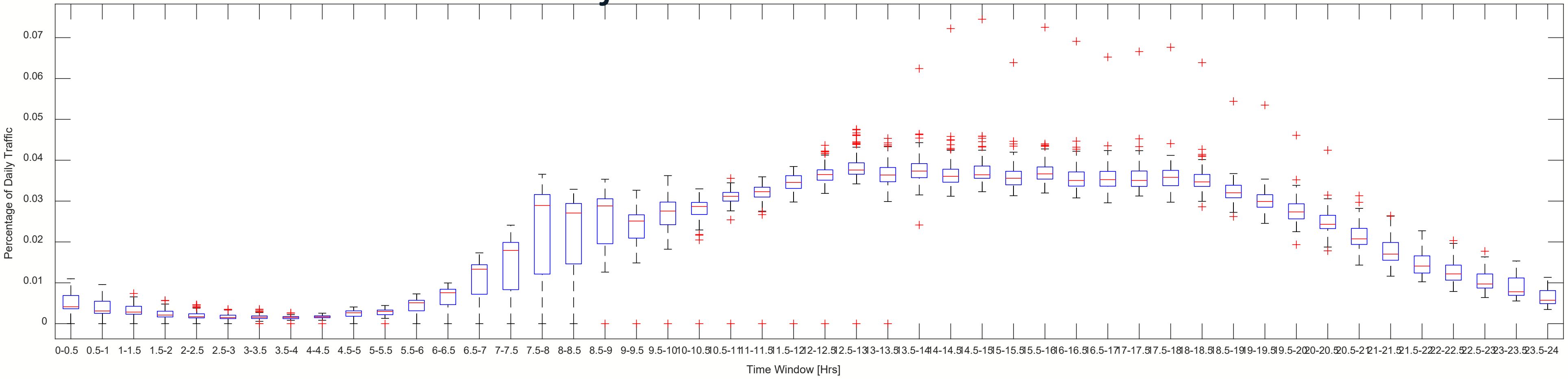
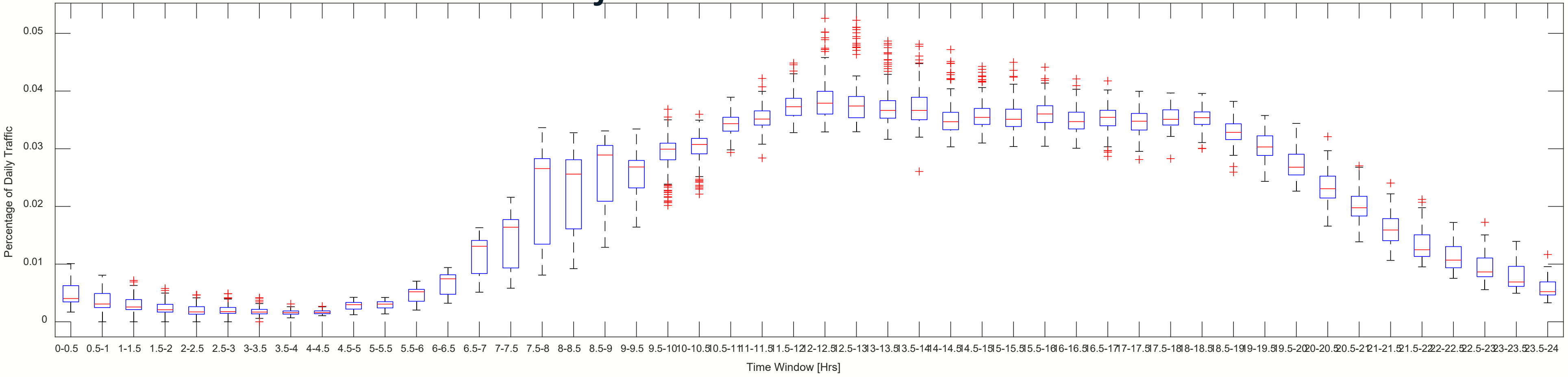
20210602T	E	L	32	15	5	PG	16.24	234.99	12	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	12	16	5	R	2.86	362.68	12	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c
20210602T	E	L	23	7	5	G	6.53	0	12	14	1	006f4a17-75c7-4d34-9585-a285a89bbf4c

Daily Traffic Intensity

I-75S junction with Shallowford road

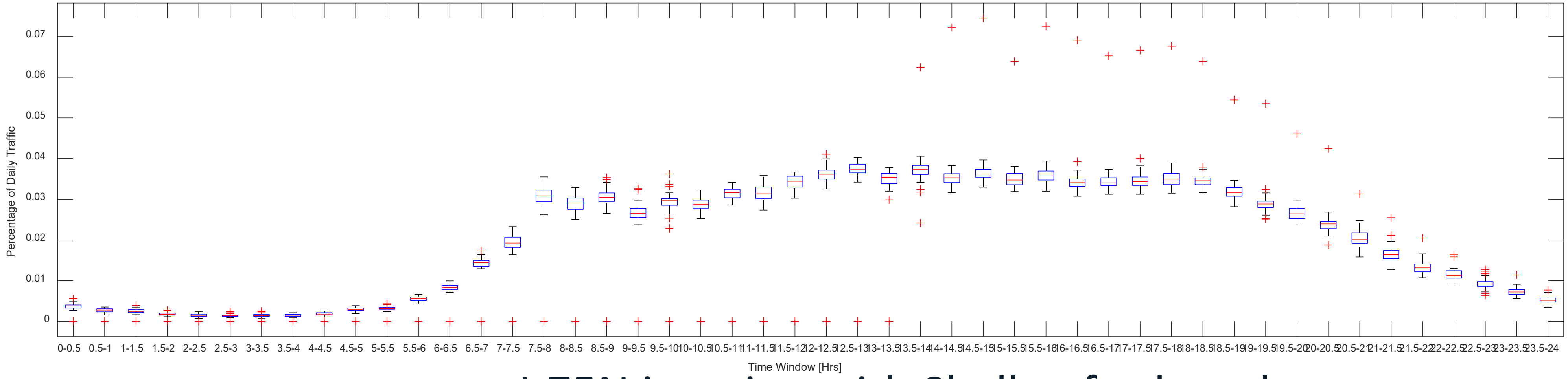


I-75N junction with Shallowford road

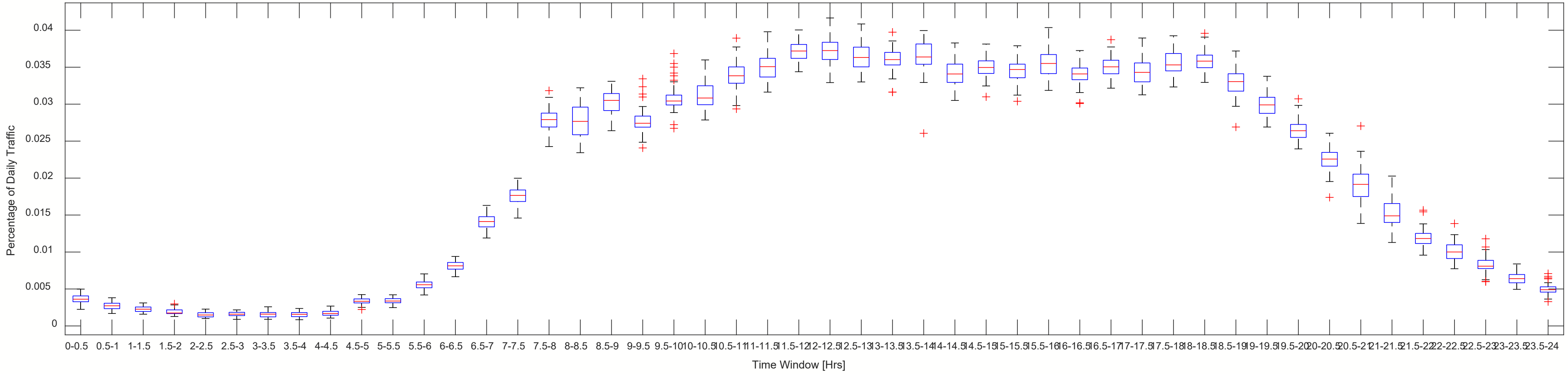


Tues-Thurs Data [50 Samples]

I-75S junction with Shallowford road

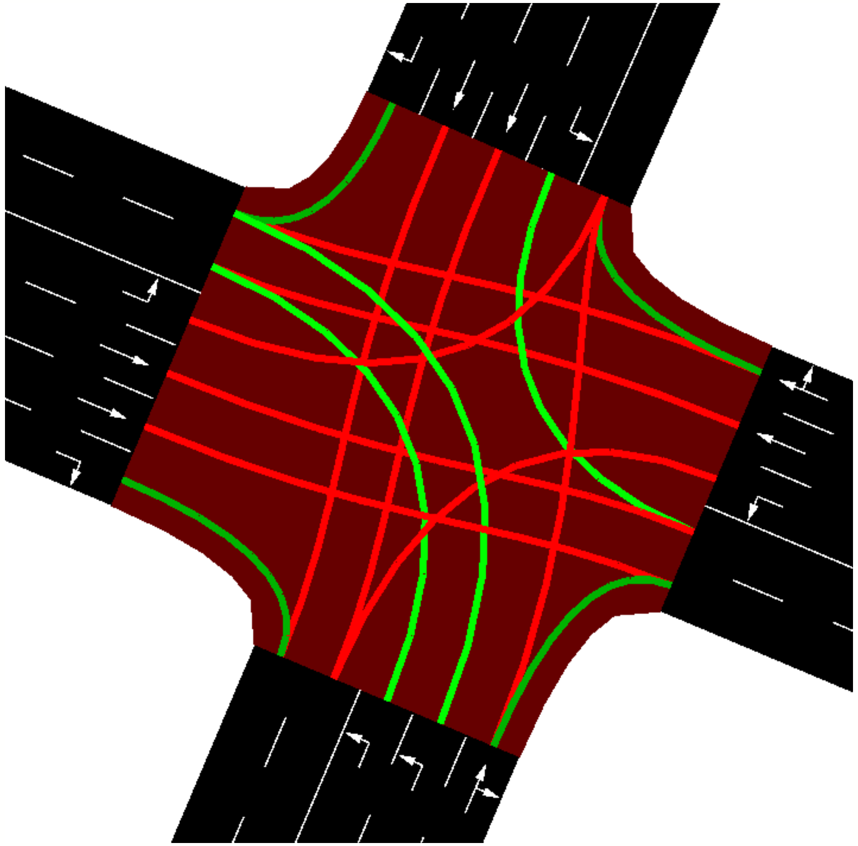


I-75N junction with Shallowford road

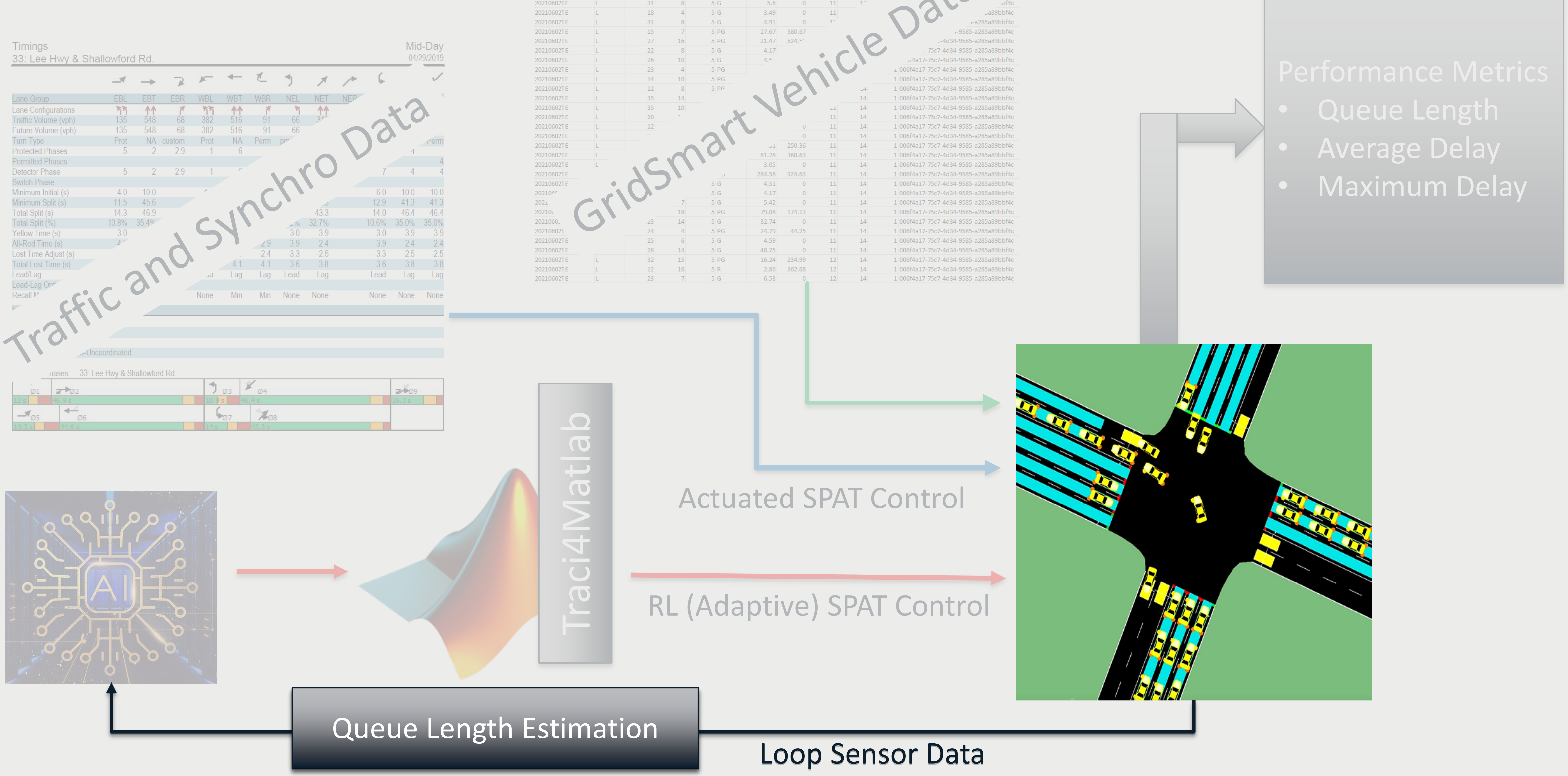


Testing Environment

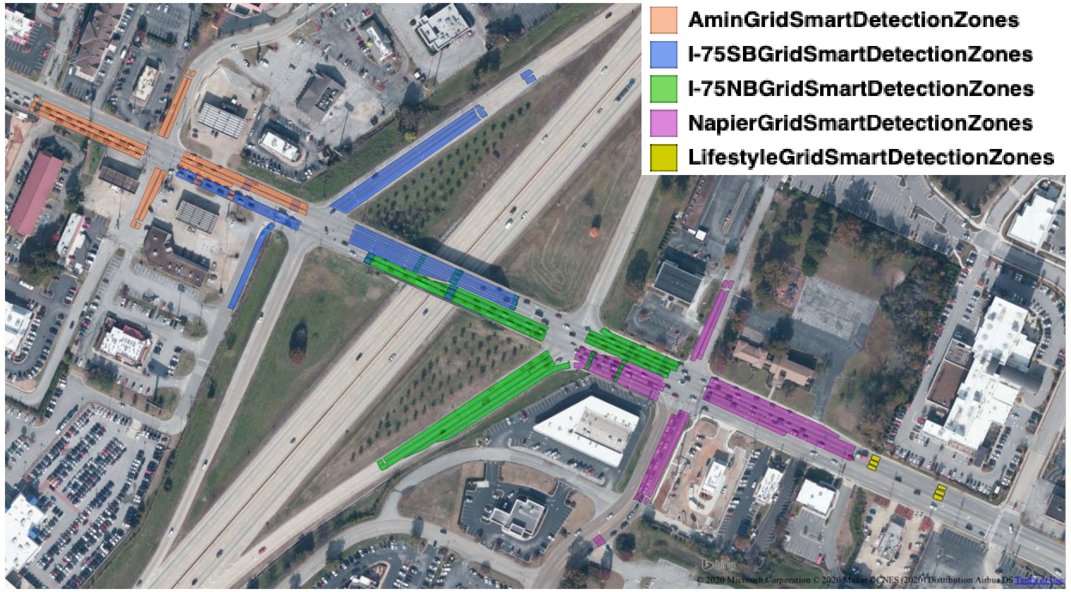
- Convert GRIDSMART Data into SUMO coding
  - Vehicle Routes
  - Signal Timing
- Automatically generate necessary SUMO programming



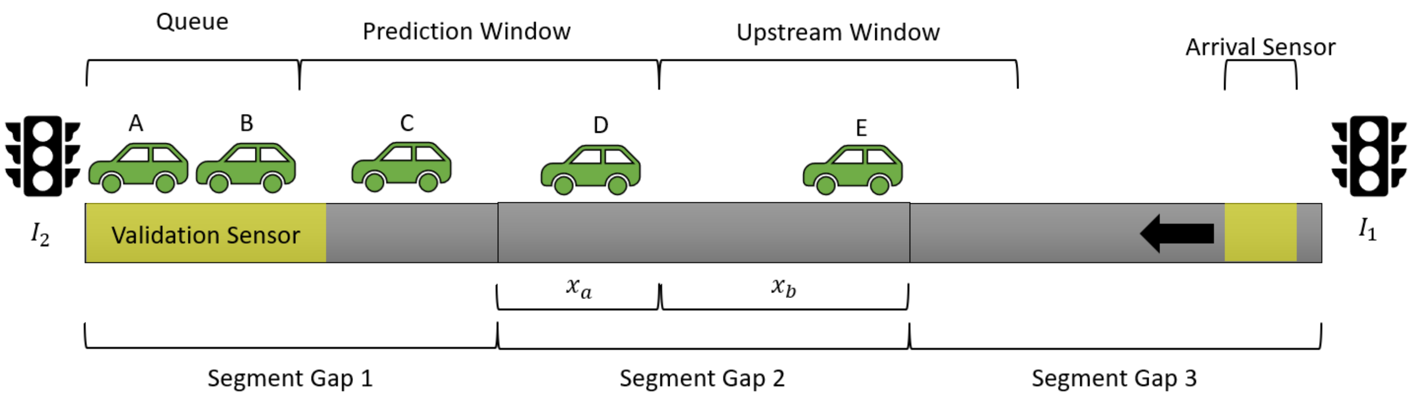
Simulation Details



Queue estimation from Gridsmart data

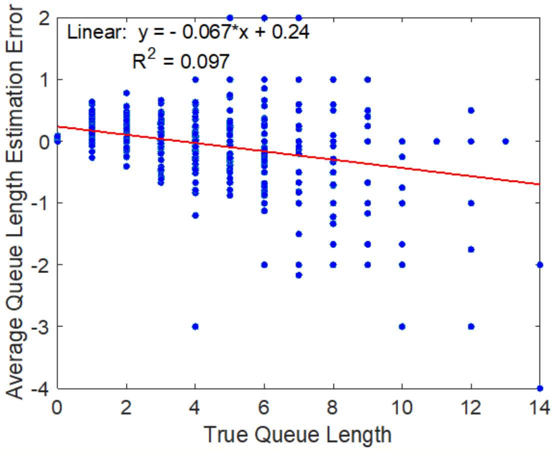


- Sensors are fisheye lens cameras
- Most traffic data is collected using computer vision.
- Signal status is collected from controller
- Detection happens based on defined *detection zones*.

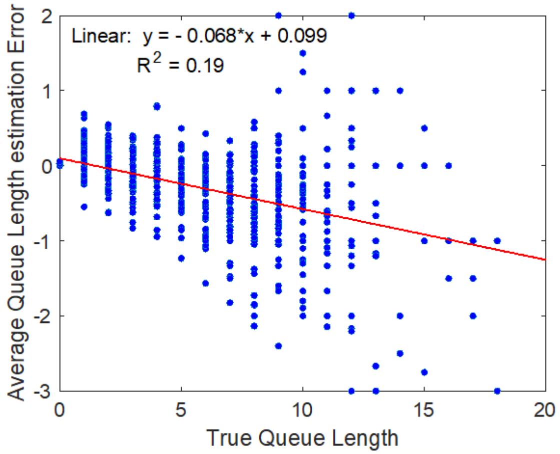


Queue Estimation Results

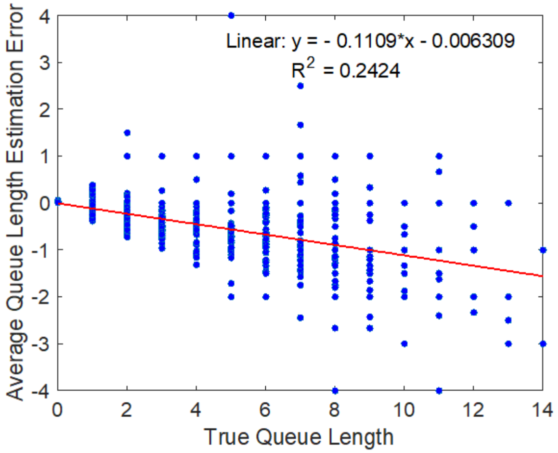
Queue Length	Average Queue Value	Standard Deviation
0	0.0440	0.0213
1	0.0933	0.2459
2	-0.0124	0.3399
3	-0.1532	0.3725
4	-0.2372	0.4877
5	-0.3038	0.6287
6	-0.3832	0.6698
7	-0.4621	0.8691
8	-0.5900	0.8482
9	-0.6118	0.8864
10	-0.8108	0.8309
11	-0.6312	0.9327
12	-0.8355	1.0464
13	-0.9455	1.0248
14	-0.7813	1.6018
15	-0.5833	0.9843
16	-0.9286	0.4499
17	-1.5000	0.5000
18	-2.0000	1.4142



(a) Morning Queues



(b) Midday Queues

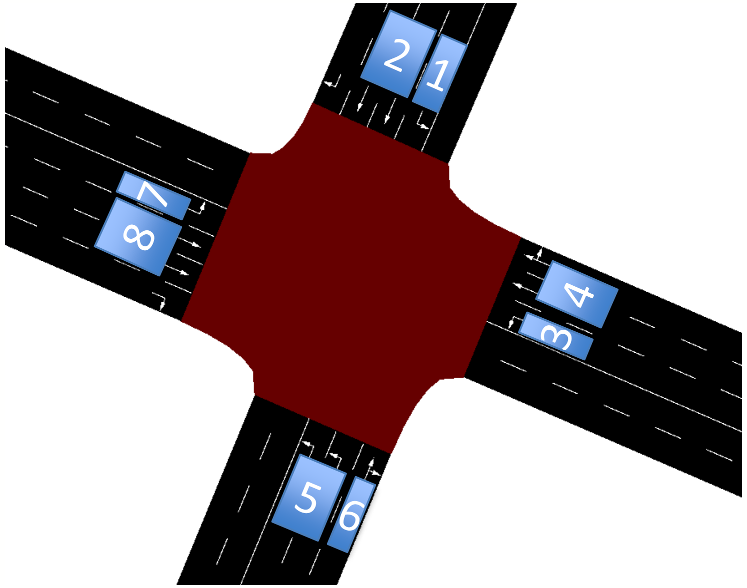


(c) Evening Queues

Simulation Details

RL Strategy

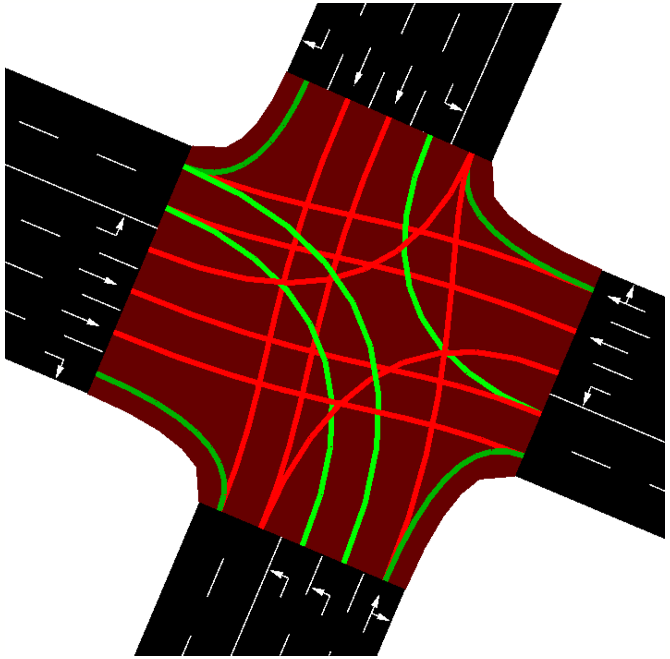
State: Queue lengths waiting at intersections

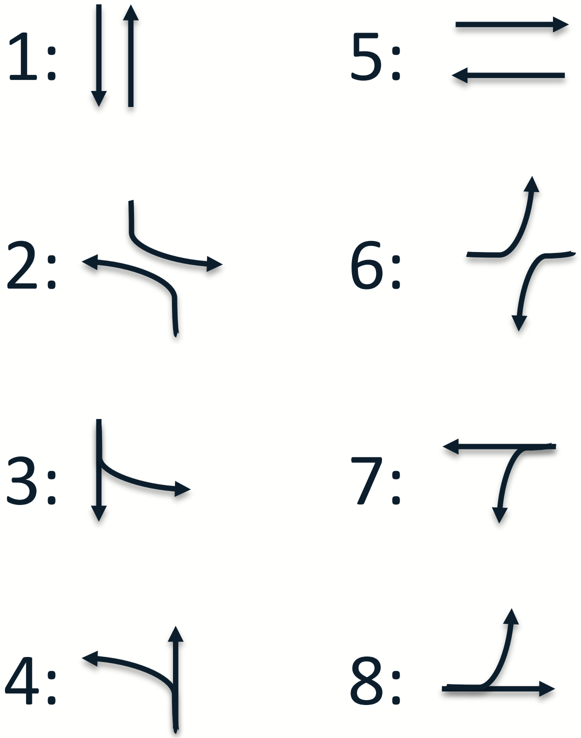


- 1: Southbound Left
- 2: Southbound Through
- 3: Westbound Left
- 4: Westbound Through
- 5: Northbound Left
- 6: Northbound Through
- 7: Eastbound Left
- 8: Eastbound Through

RL Strategy

Action: Choosing the next traffic phase



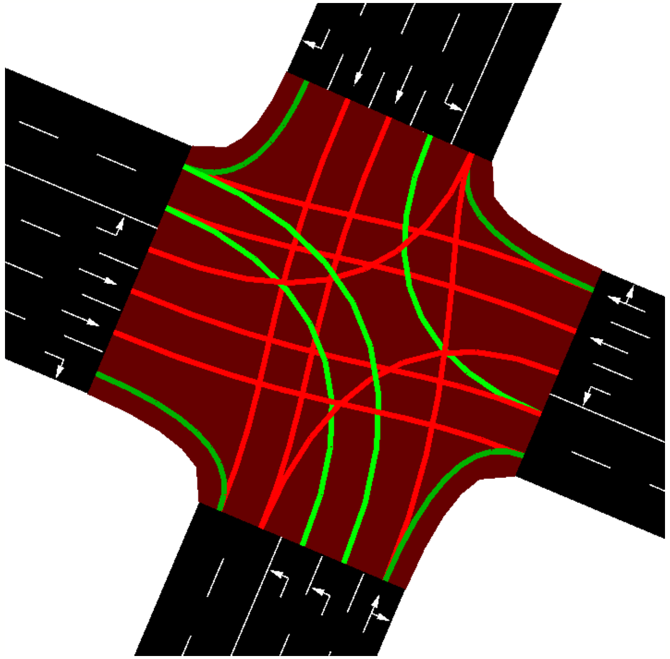


RL Strategy

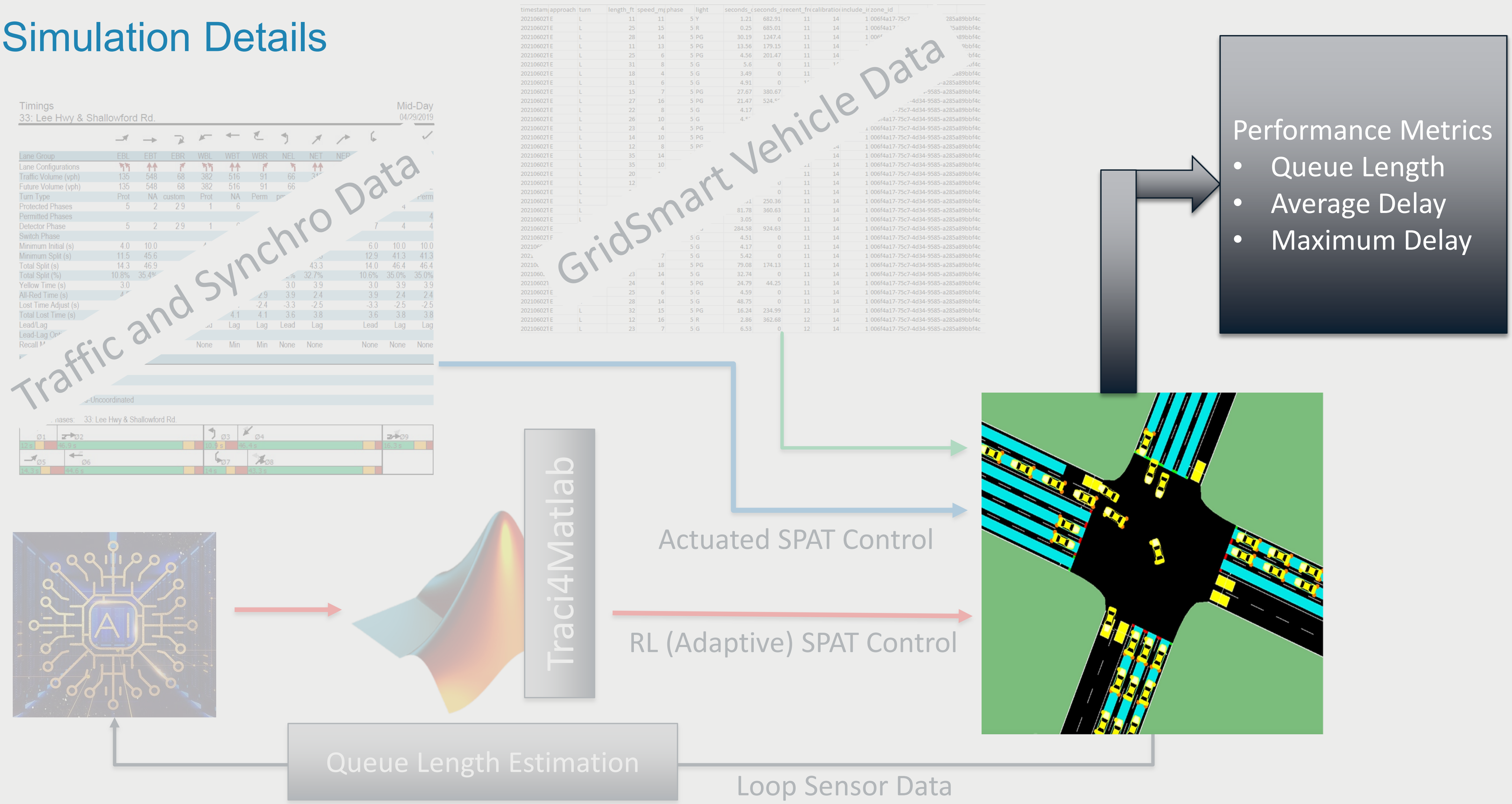
Reward: Values given to agents for taking a specific action at a specific state
Q-Value: Value assigned to state-action pairs based on prior experiences

$$Q(S,A) = Q(S,A) + \alpha[R + \gamma \max_{A} Q(S',A) - Q(S,A)]$$

- $Record\ State, s_t^i$
- $Update\ Optimal\ rewards/states\ based\ on\ T(s,a,s')$
- $Select\ Optimal\ action, a_t^i$
- $Calculate\ Reward\ r_{t+1}^i(s_{t+1}^i)$
- $Update\ Q - Values\ Q_{t+1}(s_t^i, a_t^i)$



Simulation Details



Traffic flow parameters – 3 levels of traffic volume

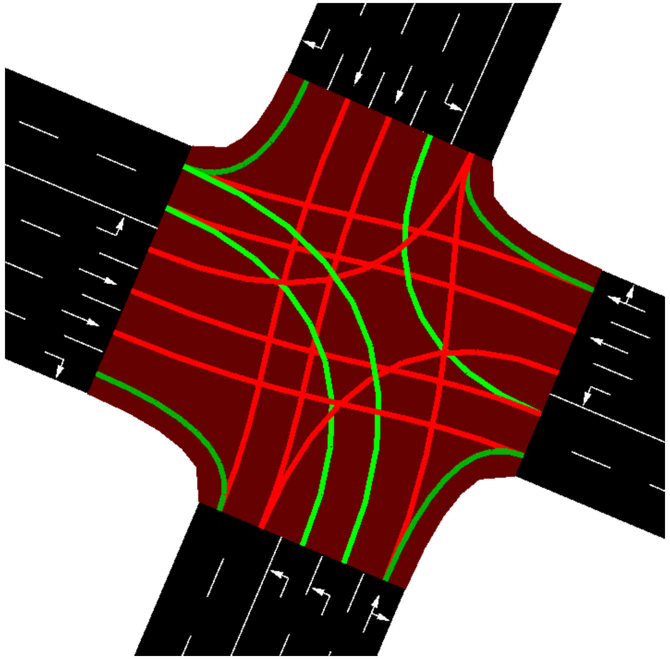
Low traffic

High traffic volume

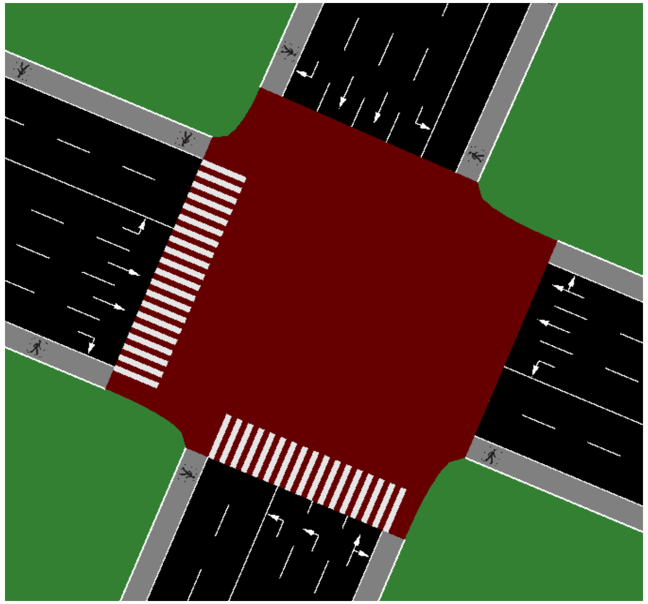
Unusual traffic pattern

Direction	AM	PM	Modified PM
Eastbound Left	57	104	106
Eastbound Through	133	583	586
Northbound Left	133	621	976
Northbound Through	86	311	378
Westbound Left	17	140	144
Westbound Through	388	452	1113
Southbound Left	19	99	99
Southbound Through	72	255	419

Table 1: Directional Vph for Each Traffic Scenario



Pedestrian study parameters - 2 levels of pedestrian volume



- Shallowford Road and Gunbarrel Road
- Major Arterial Lane
- RL programmed to prioritize Density
- Delay Applied to Maintain Fairness

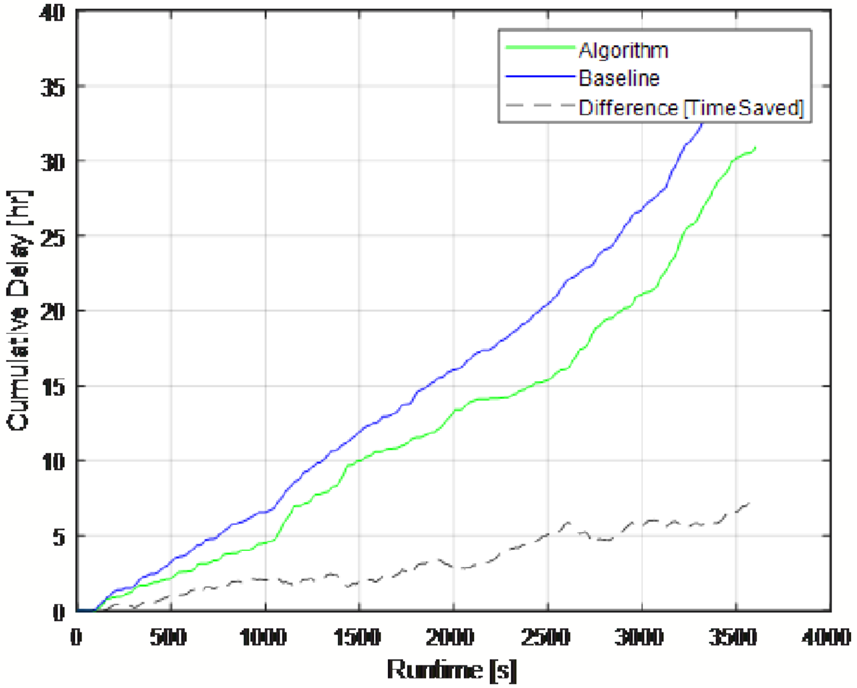
- Pedestrian data is generated through a binomial distribution and a census for pedestrian flows at an intersection to help represent the concentration of low and moderate levels of pedestrian traffic.
- Value of these flows were based on the Level of Service(LoS) metric for measuring pedestrian congestion along walkways and the assumption that the sidewalks present in the current simulations are approximately 4 feet wide.
- The result is that the pedestrian flows for simulated low and moderate levels result in 10 and 550 pedestrians per hour, respectively.

Low (morning) vehicular traffic + no pedestrian traffic

Reasonable performance from both RL and actuated controllers – still **RL performs at ~19% lower delay**

Direction	Average RL Delay	RL Std	Average Actuated Average	Actuated Std
Eastbound Left	2.57	7.91	1.46	4.91
Eastbound Through	4.52	10.23	4.88	9.05
Northbound Left	4.78	10.65	5.6	11.07
Northbound Through	4.16	10.73	8.62	12.84
Westbound Left	0.29	2.01	0.29	1.87
Westbound Through	8.60	13.51	10.69	12.16
Southbound Left	0.76	5.00	1.48	6.03
Southbound Through	4.92	13.62	5.37	11.74

Table 2: Delay of Traffic in AM Scenario with No Pedestrian Traffic



Net Delay Di□erence for AM Traffic with No Pedestrian Traffic

Low (morning) vehicular traffic + low pedestrian traffic

Direction	Average RL Delay	RL Std	Average Actuated Average	Actuated Std
Eastbound Left	1.87	5.98	2.08	5.98
Eastbound Through	6.80	12.66	5.46	9.67
Northbound Left	3.35	8.77	11.48	16.47
Northbound Through	3.59	8.77	11.48	16.47
Westbound Left	0.12	1.38	0.59	3.31
Westbound Through	6.67	11.42	12.43	13.36
Southbound Left	0.51	2.86	1.79	6.91
Southbound Through	7.13	16.46	4.57	10.37

Table 3: Delay of Traffic in AM Scenario with No Pedestrian Traffic

Direction	Average RL Delay	RL Std	Average Actuated Average	Actuated Std
Northbound	0.08	0.78	0.15	1.46
Eastbound	0.03	0.59	0.09	1.24
Southbound	0.04	0.57	0.50	4.03
Westbound	0.05	0.66	0.16	1.39

Table 4: Delay of Pedestrians in AM Scenario with Low Pedestrian Traffic

Low (morning) vehicular traffic + low pedestrian traffic

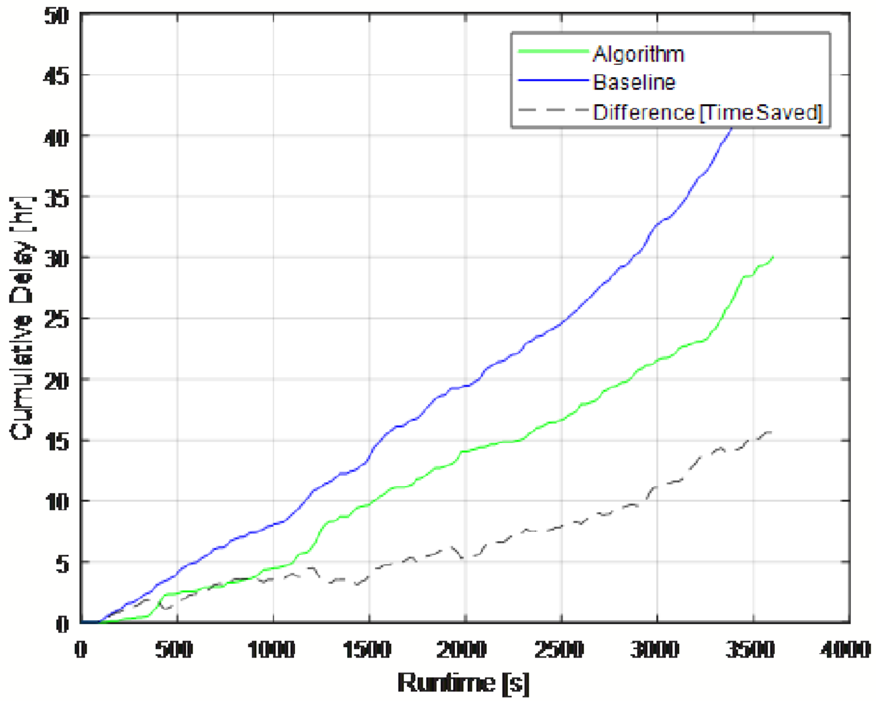


Figure 5: Net Delay Di□erence for AM Traffic with Low Pedestrian Traffic

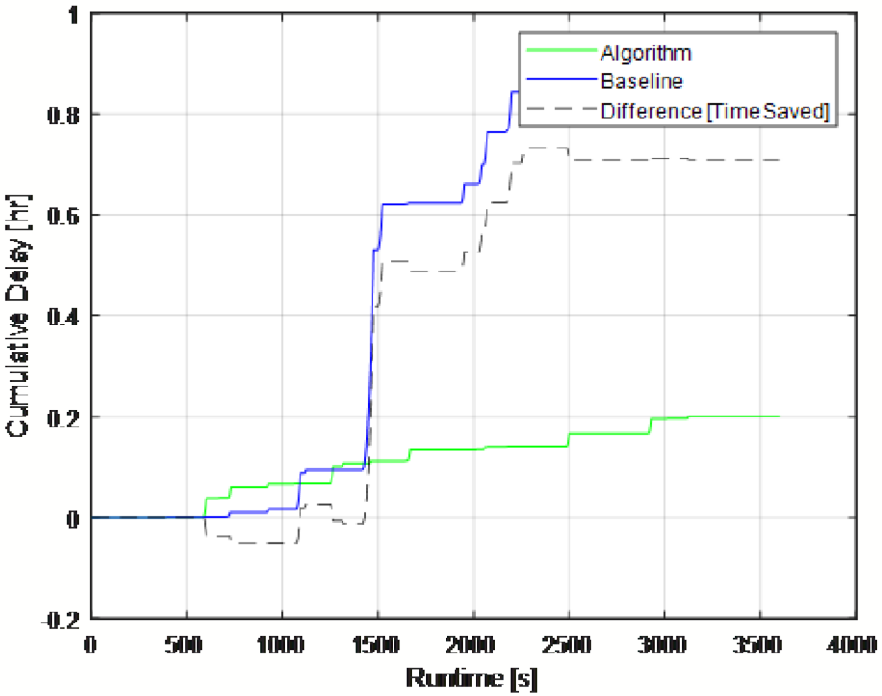


Figure 6: Net Delay Di□erence for AM Pedestrians with Low Pedestrian Traffic

Low (morning) vehicular traffic + moderate pedestrian traffic

Direction	Average RL Delay	RL Std	Average Actuated Average	Actuated Std
Eastbound Left	2.85	9.44	2.12	6.68
Eastbound Through	2.35	6.36	6.88	11.56
Northbound Left	2.74	6.81	11.11	17.11
Northbound Through	2.34	6.30	12.14	17.45
Westbound Left	0.30	2.06	0.49	3.27
Westbound Through	8.79	12.69	13.61	15.78
Southbound Left	0.25	1.87	2.21	8.13
Southbound Through	1.04	3.83	5.17	11.99

Table 5: Delay of Vehicles in AM Scenario with Moderate Pedestrian Traffic

Direction	Average RL Delay	RL Std	Average Actuated Average	Actuated Std
Northbound	2.34	5.05	10.20	13.54
Eastbound	1.13	3.41	12.29	18.12
Southbound	2.56	6.24	8.36	13.62
Westbound	2.70	5.56	7.67	11.34

Table 6: Delay of Pedestrians in AM Scenario with Moderate Pedestrian Traffic

Low (morning) vehicular traffic + low pedestrian traffic

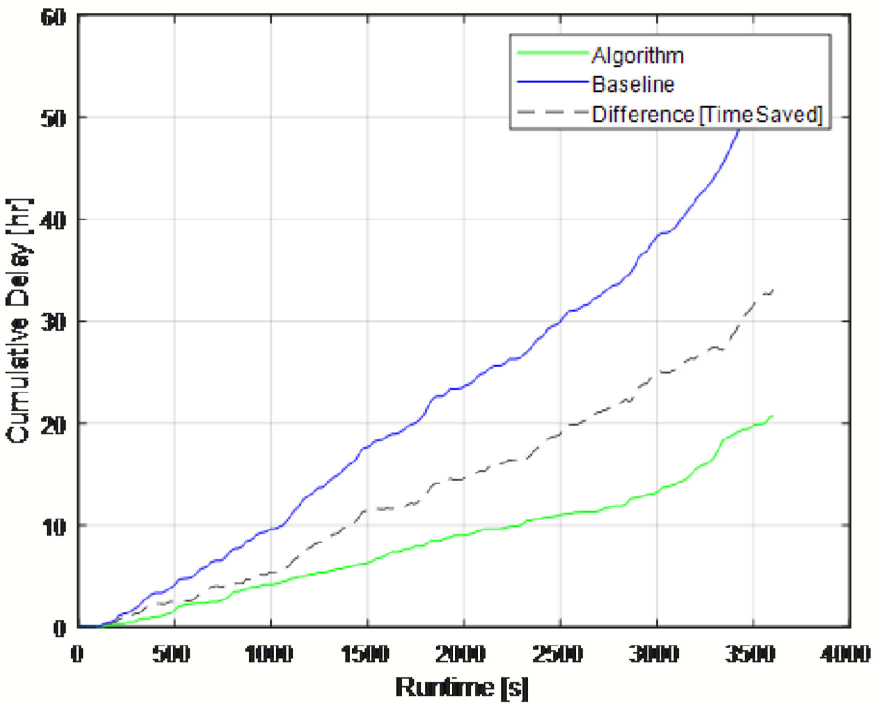


Figure 7: Net Delay Di□erence for AM Traffic with Moderate Pedestrian Traffic

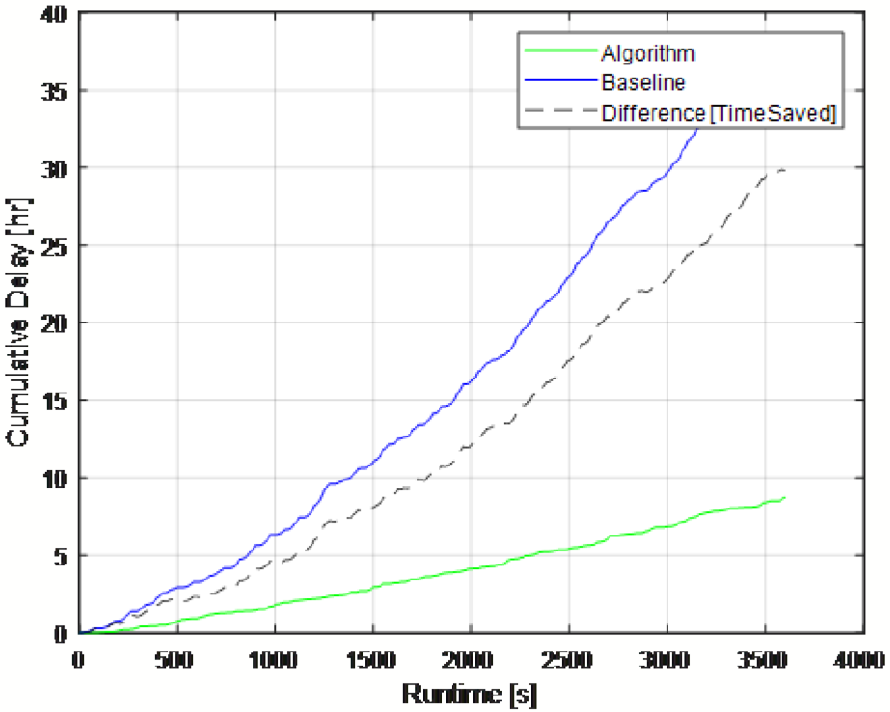
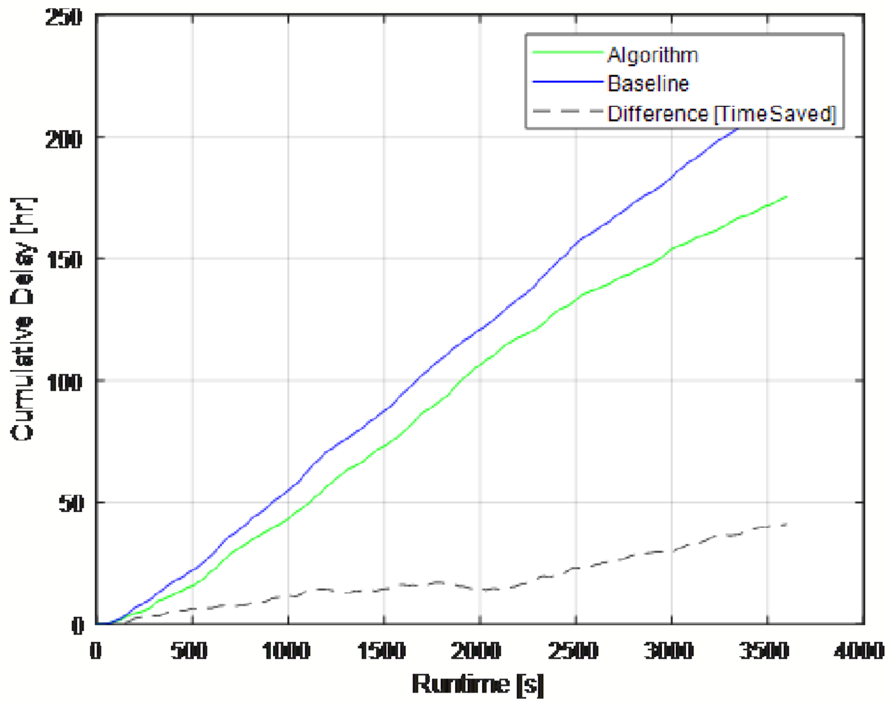


Figure 8: Net Delay Di□erence for AM Pedestrians with Moderate Pedestrian Traffic

High (evening) vehicular traffic + no pedestrian traffic

Direction	Average RL Delay	RL Std	Average Actuated Average	Actuated Std
Eastbound Left	7.11	13.82	6.02	11.69
Eastbound Through	21.15	21.80	24.52	20.39
Northbound Left	9.76	13.49	16.00	17.52
Northbound Through	12.86	17.81	23.11	20.60
Westbound Left	17.67	22.08	12.56	17.40
Westbound Through	78.81	19.45	89.47	24.12
Southbound Left	7.92	13.18	17.99	22.30
Southbound Through	20.14	22.44	26.77	24.97

Table 7: Delay of Traffic in PM Scenario with No Pedestrian Traffic



Net Delay Di□erence for PM Traffic with No Pedestrian Traffic

High (evening) vehicular traffic + low pedestrian traffic

Direction	Average RL Delay	RL Std	Average Actuated Average	Actuated Std
Eastbound Left	6.81	12.62	9.97	16.04
Eastbound Through	21.24	21.53	27.76	23.04
Northbound Left	7.72	10.63	18.77	19.09
Northbound Through	13.12	18.01	23.50	21.71
Westbound Left	19.49	23.21	10.03	15.88
Westbound Through	77.98	18.8	91.26	26.36
Southbound Left	8.81	14.55	19.06	23.92
Southbound Through	19.81	22.57	27.86	24.53

Table 8: Delay of Traffic in PM Scenario with Low Pedestrian Traffic

Direction	Average RL Delay	RL Std	Average Actuated Average	Actuated Std
Northbound	1.09	6.59	0.74	4.77
Eastbound	0.04	0.70	0.87	6.64
Southbound	0.64	4.76	0.54	3.78
Westbound	0.28	2.35	1.03	6.01

Table 9: Delay of Pedestrians in PM Scenario with Low Pedestrian Traffic

High (evening) vehicular traffic + low pedestrian traffic

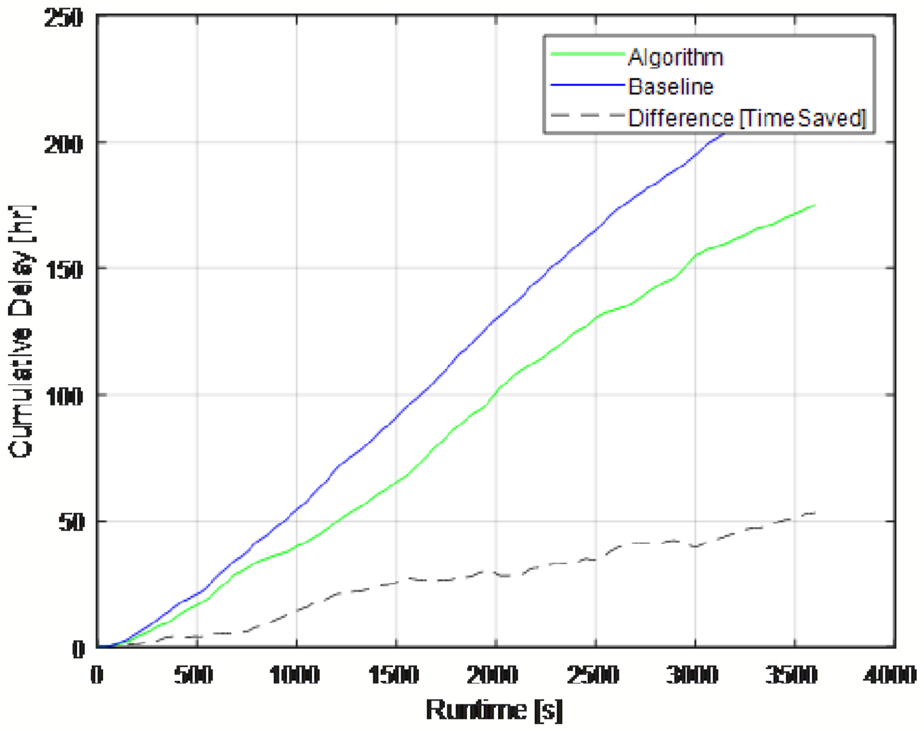


Figure 10: Net Delay Di□erence for PM Traffic with Low Pedestrian Traffic

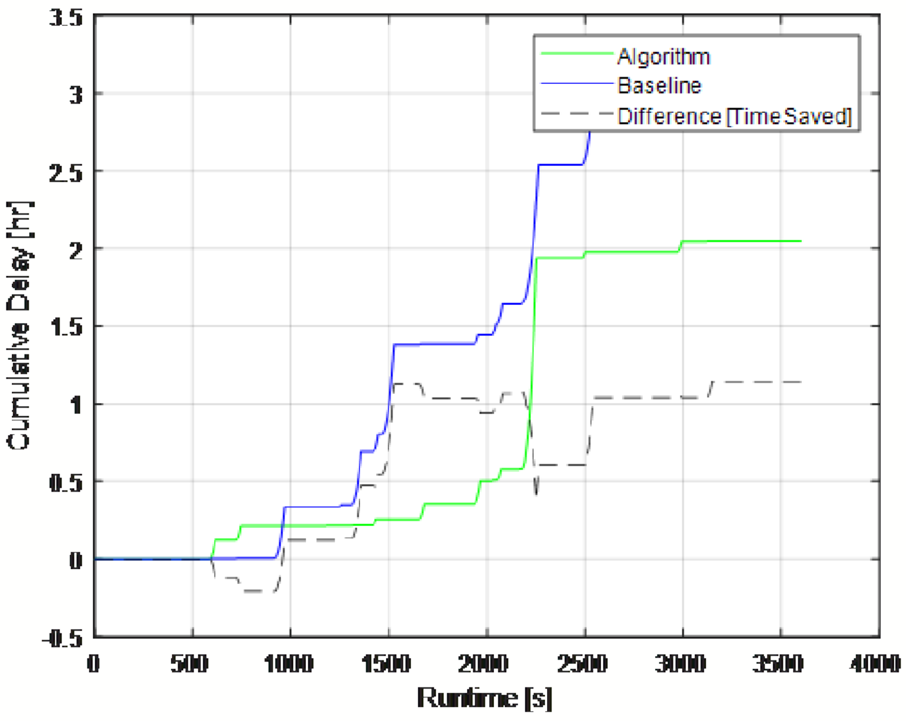


Figure 11: Net Delay Di□erence for PM Pedestrians with Low Pedestrian Traffic

High (evening) vehicular traffic + moderate pedestrian traffic

Direction	Average RL Delay	RL Std	Average Actuated Average	Actuated Std
Eastbound Left	3.64	8.11	10.43	16.93
Eastbound Through	22.30	25.57	31.90	24.88
Northbound Left	37.10	33.14	25.35	23.07
Northbound Through	12.91	16.75	31.36	24.38
Westbound Left	33.63	32.24	15.72	21.43
Westbound Through	83.31	26.36	96.84	27.68
Southbound Left	5.84	12.98	19.17	23.31
Southbound Through	12.59	18.89	28.35	25.61

Table 10: Delay of Traffic in PM Scenario with Moderate Pedestrian Traffic

Direction	Average RL Delay	RL Std	Average Actuated Average	Actuated Std
Northbound	8.72	15.19	19.57	21.55
Eastbound	3.19	8.05	19.48	25.59
Southbound	6.13	11.89	13.43	20.16
Westbound	4.29	8.34	16.64	19.67

Table 11: Delay of Pedestrians in PM Scenario with Moderate Pedestrian Traffic

High (evening) vehicular traffic + moderate pedestrian traffic

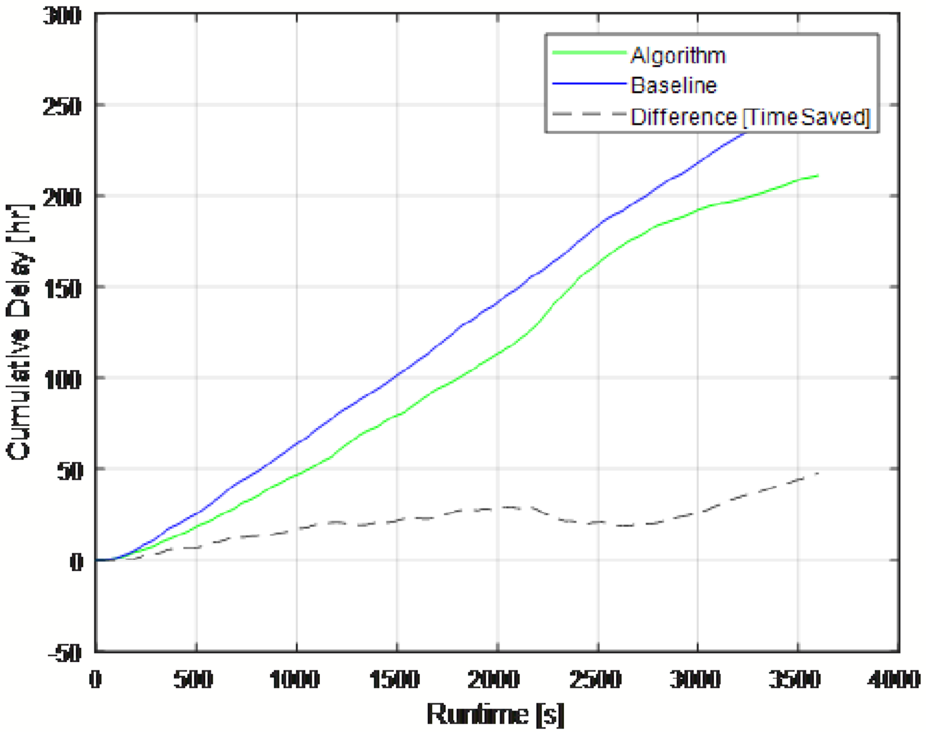


Figure 12: Net Delay Di□erence for PM Traffic with Moderate Pedestrian Traffic

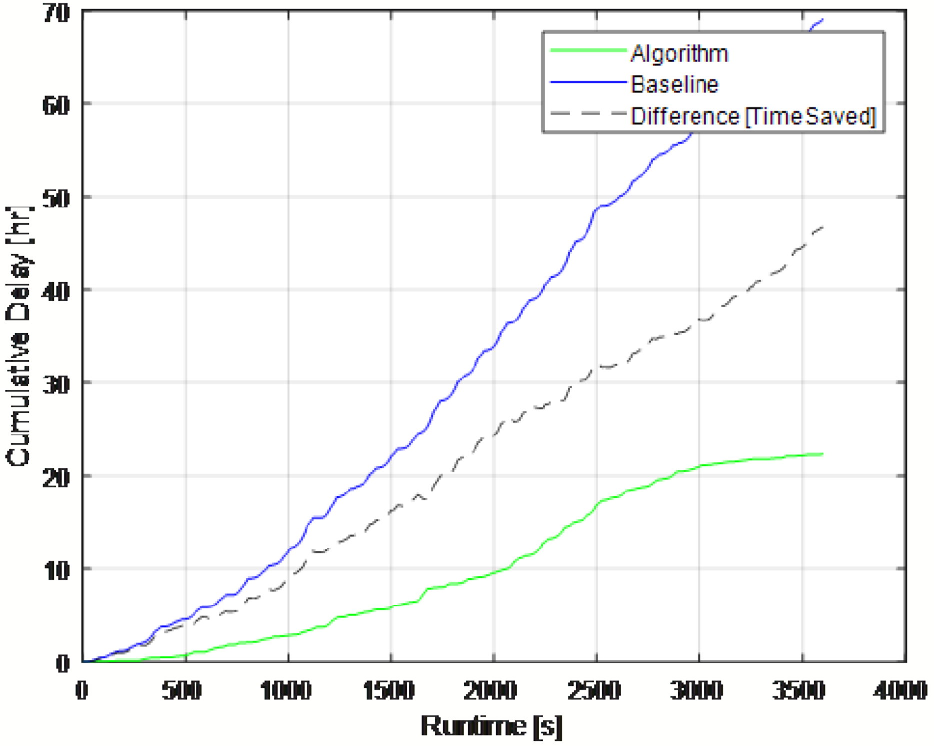
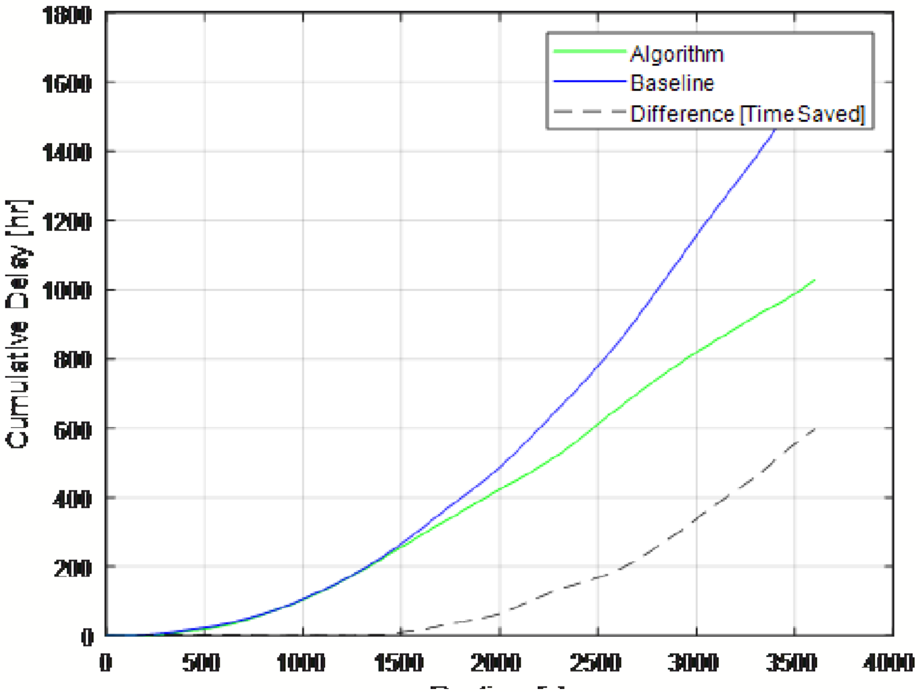


Figure 13: Net Delay Di□erence for PM Pedestrians with Moderate Pedestrian Traffic

Unusually high (modified) vehicular traffic + no pedestrian traffic

Direction	Average RL Delay	RL Std	Average Actuated Average	Actuated Std
Eastbound Left	28.96	41.06	9.70	15.58
Eastbound Through	119.74	90.99	30.05	23.24
Northbound Left	246.02	134.56	96.28	64.36
Northbound Through	307.01	160.21	324.72	196.84
Westbound Left	33.98	37.63	338.68	226.68
Westbound Through	183.32	86.9	772.36	483.25
Southbound Left	5.82	12.63	18.17	24.52
Southbound Through	102.56	85.85	33.33	25.10

Table 12: Delay of Traffic in unusually high traffic scenario with no Pedestrian traffic



Net delay difference for unusually high traffic scenario with no Pedestrian traffic

Unusually high (modified) vehicular traffic + low pedestrian traffic

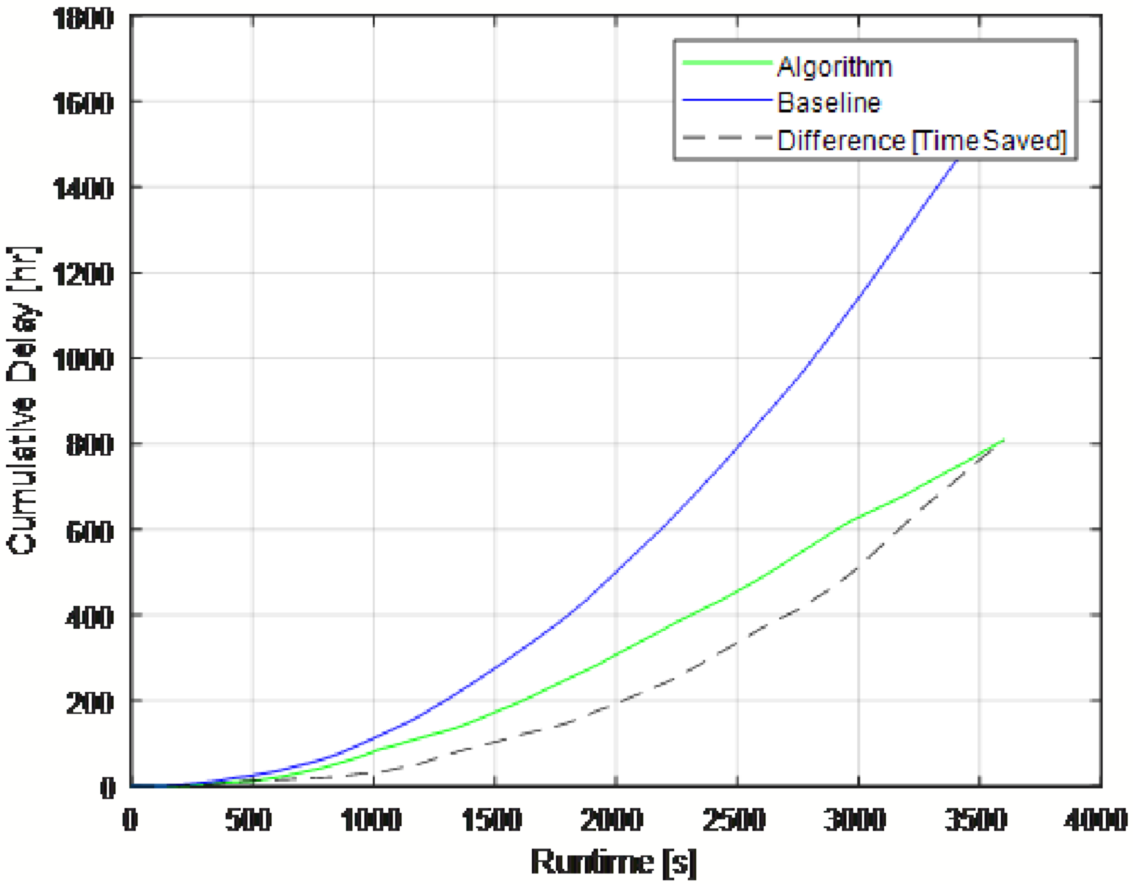
Direction	Average RL Delay	RL Std	Average Actuated Average	Actuated Std
Eastbound Left	43.36	48.98	12.23	19.17
Eastbound Through	145.79	96.85	37.25	28.66
Northbound Left	195.26	130.77	50.53	40.48
Northbound Through	103.91	89.19	159.83	98.39
Westbound Left	21.33	33.72	434.23	306.4
Westbound Through	177.92	94.03	864.36	548.52
Southbound Left	8.26	15.34	20.98	25.69
Southbound Through	113.63	106.19	30.01	28.32

Table 12: Delay of Traffic in unusually high traffic scenario with low Pedestrian traffic

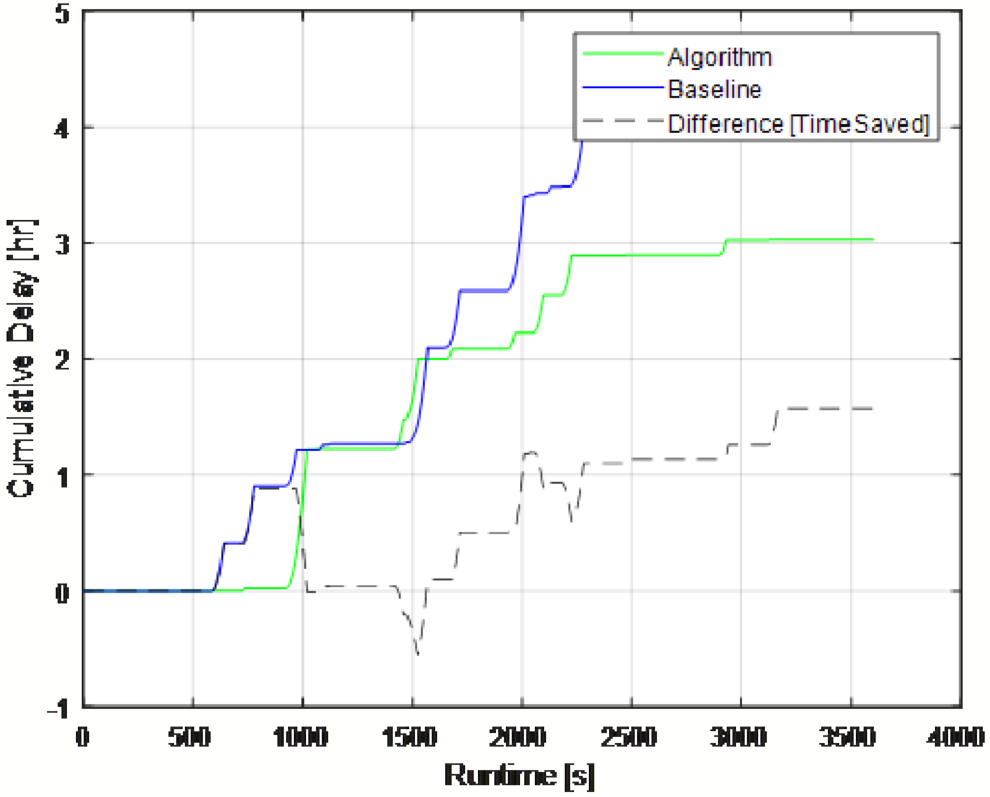
Direction	Average RL Delay	RL Std	Average Actuated Average	Actuated Std
Northbound	0.78	4.77	1.36	6.90
Eastbound	0.01	0.03	0.82	6.19
Southbound	0.39	3.10	0.81	5.24
Westbound	1.86	9.71	1.61	8.00

Table 12: Delay of Pedestrians in unusually high traffic scenario with low Pedestrian traffic

Unusually high (modified) vehicular traffic + low pedestrian traffic



Net delay difference for vehicular traffic in unusually high traffic scenario with low Pedestrian traffic



Net delay difference for pedestrians in unusually high traffic scenario with low Pedestrian traffic

Unusually high (modified) vehicular traffic + moderate pedestrian traffic

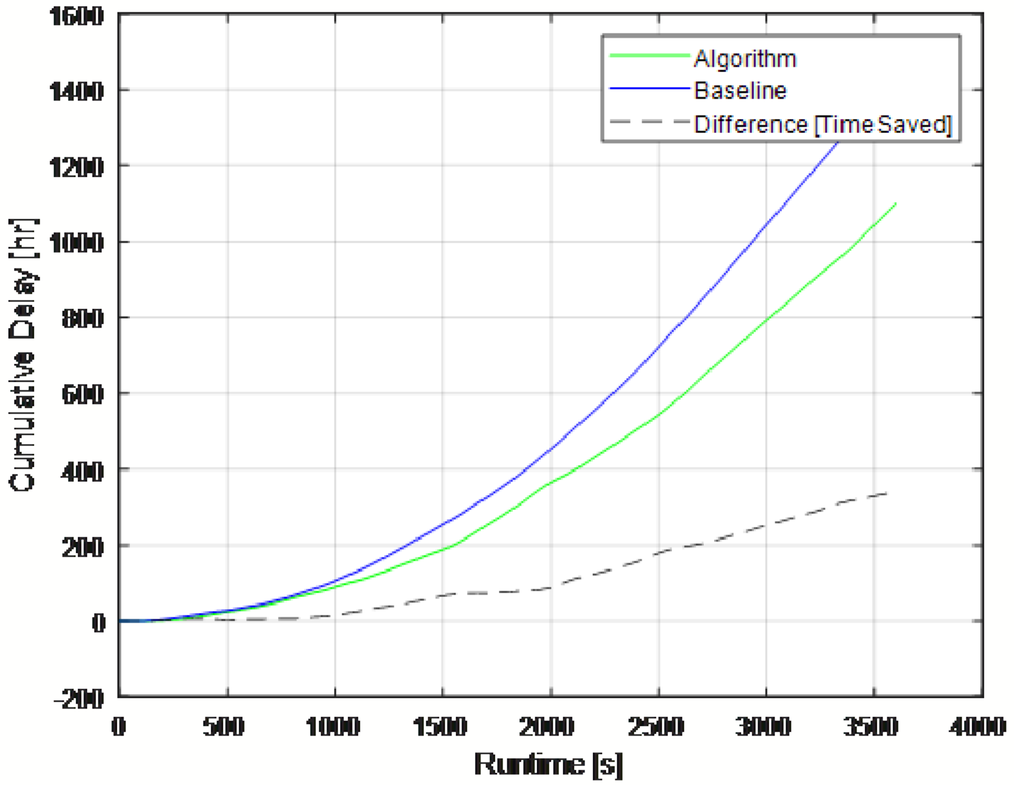
Direction	Average RL Delay	RL Std	Average Actuated Average	Actuated Std
Eastbound Left	46.54	55.29	13.87	20.07
Eastbound Through	78.43	85.86	38.32	29.87
Northbound Left	229.26	74.23	131.66	125.04
Northbound Through	131.66	125.04	220.29	125.96
Westbound Left	87.62	99.18	311.86	207.75
Westbound Through	229.52	160.51	720.13	444.38
Southbound Left	17.57	30.00	23.56	27.41
Southbound Through	278.98	314.73	38.44	30.06

Table 12: Delay of Traffic in unusually high traffic scenario with moderate Pedestrian traffic

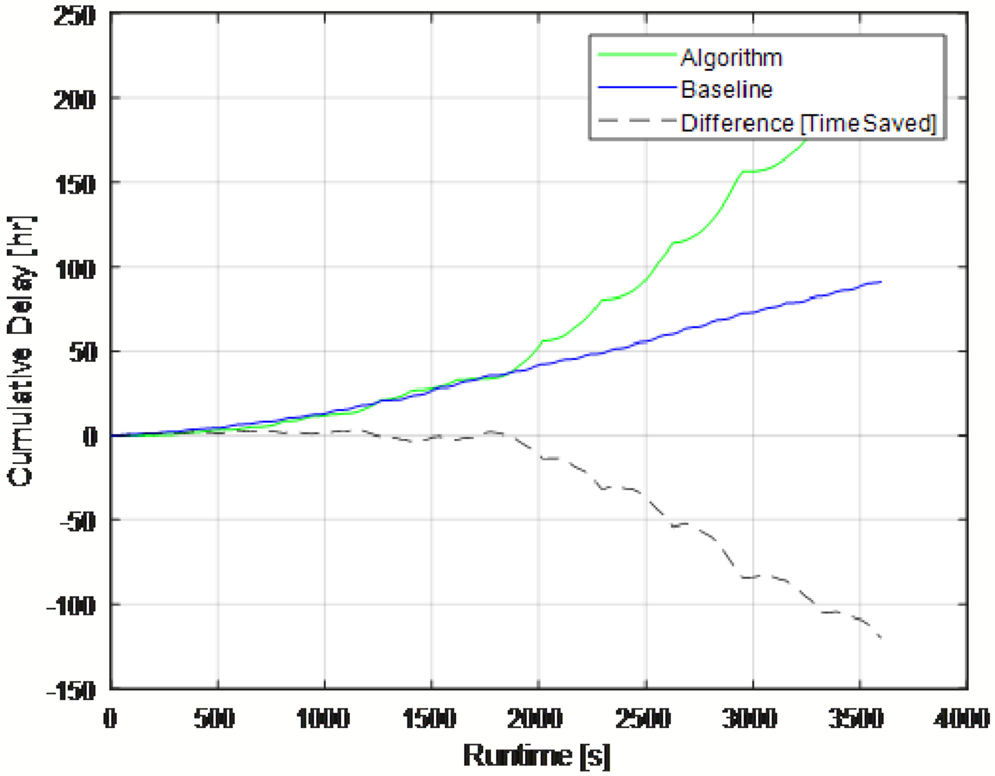
Direction	Average RL Delay	RL Std	Average Actuated Average	Actuated Std
Northbound	80.32	90.17	24.91	25.54
Eastbound	17.65	43.88	25.24	30.33
Southbound	71.78	90.40	18.01	24.62
Westbound	41.06	65.39	22.84	24.44

Table 12: Delay of Pedestrians in unusually high traffic scenario with moderate Pedestrian traffic

Unusually high (modified) vehicular traffic + moderate pedestrian traffic



Net delay difference for vehicular traffic in unusually high traffic scenario with moderate Pedestrian traffic



Net delay difference for pedestrians in unusually high traffic scenario with moderate Pedestrian traffic

Exploring decentralization

Linear Network

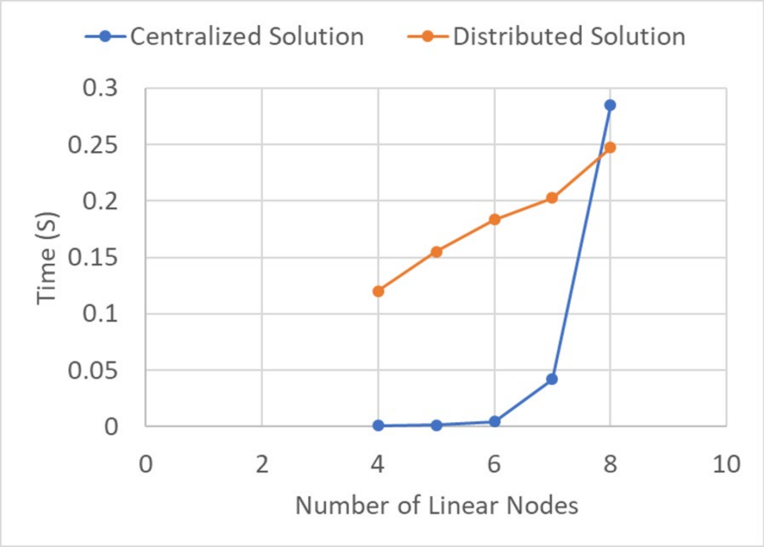
		Time To Calculate Cross Streets (s)			
# crosses	# nodes	Centralized	Format	Decentralized	Format
1	5	0.00235	in-line		
2	8	10.962	in-line	0.911	in-line
2	9	457.535	in-line	0.709	in-line
4	12			0.887	grid
4	16			0.515	grid
36	121			20.577	grid

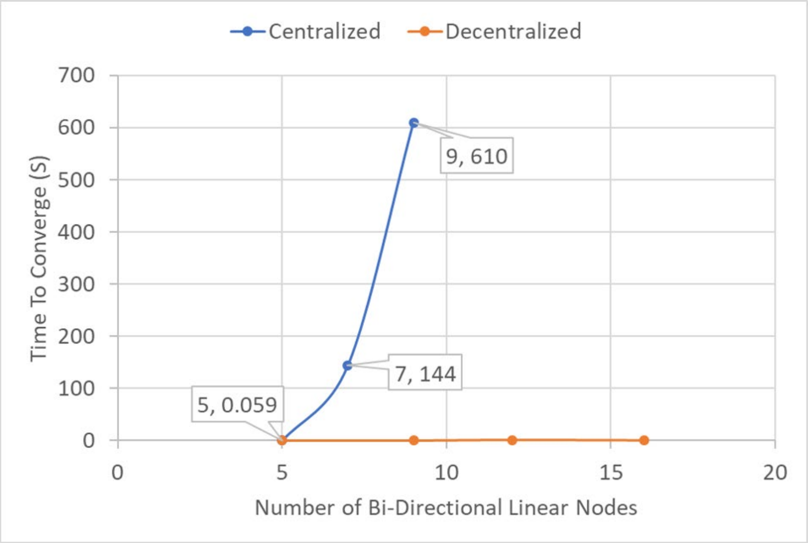
Key Issues

- Solving for optimal timing given a set of phases and arrival rates takes a relatively large amount of time or compute power.
- This problem does not scale well as the number of intersections in an area increases.

Strategy

- Subdivide as much as possible to distribute computational load
- Explicitly include upstream "U" and downstream "D" agents in problem definition for each agent.
- Broadcast and rebroadcast information between agents to achieve a "system collaborative" solution.

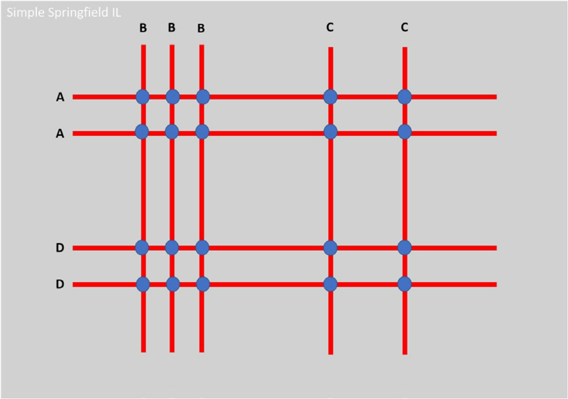


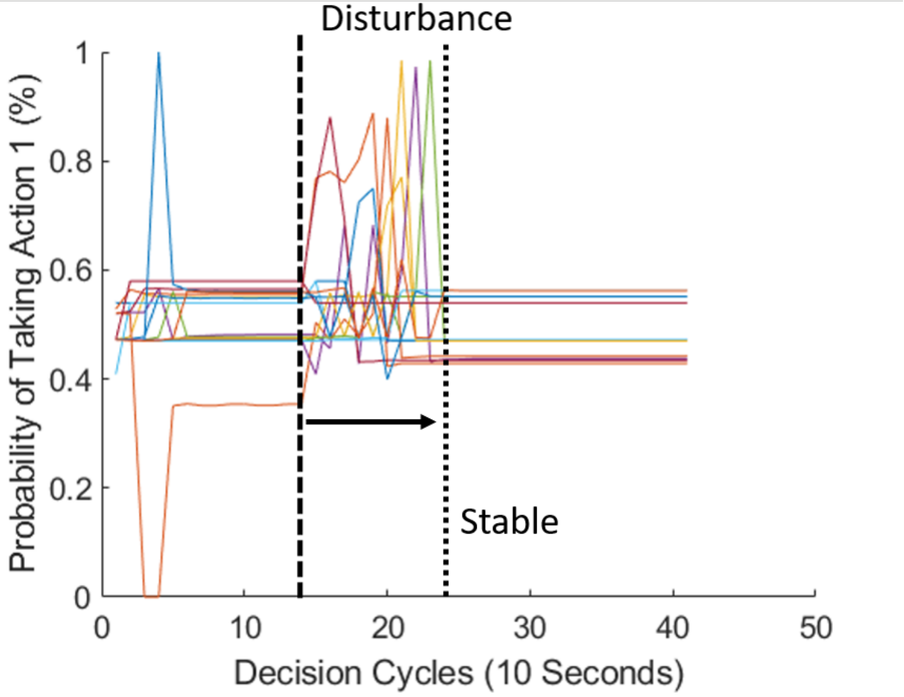


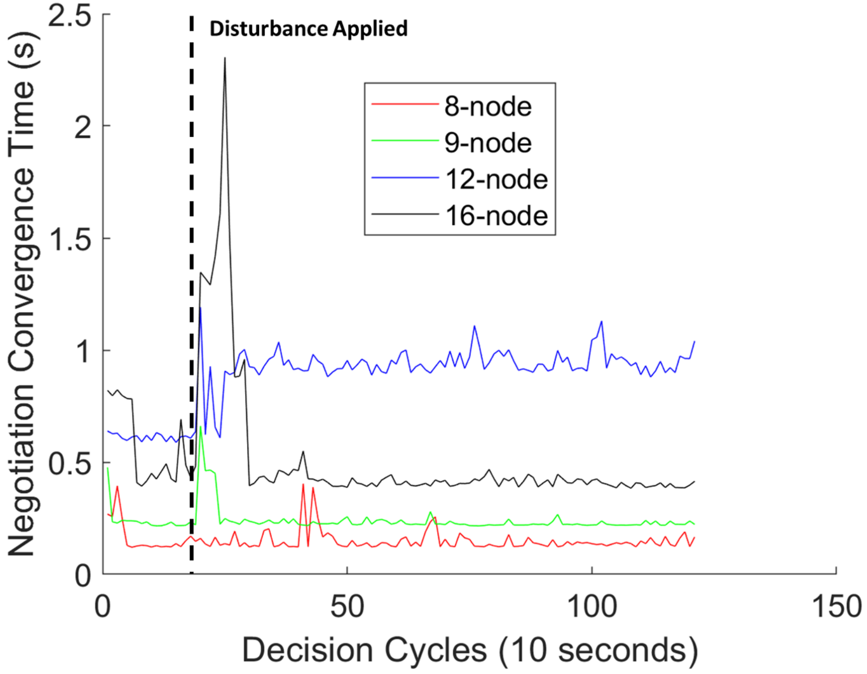
Exploring decentralization

Grid Network:

1. Based on traffic signal network in Illinois (Springfield)
2. No turning considered EW and NS only
3. Traffic arrives randomly according to Poisson process and arrival rates shift midway through test
4. Compared with Q-learning on same setup (no negotiations)







Synthetic Pedestrian Dataset

- 300 low resolution images
- 3 traffic camera positions
- 10 character models
- Random variations in location and number of pedestrians

YOLO Detection Model

- Ultralytics YOLOv5 model was trained on the synthetic data.

- Provides the number of pedestrians at intersection, as well as the bounding boxes and confidence values for each detected person.

Application on real data

- The current model is capable of limited cross-domain applicability on real data.

YOLOv5
Synthetic data
model

Conclusion

1. When presented with traffic scenarios recreated through historical data, the **RL algorithm outperforms actuated controller** by attempting to predict the incoming flow of traffic, balance the needs of vehicular drivers with that of pedestrians crossing, and making adjustments in an effort to optimize the service rate of vehicular drivers.
2. In isolated cases, pedestrian crossings may be more delayed, such as when the vehicle volume is excessively large, resulting in the penalties of vehicle delays outweighing the delay of pedestrians. But such relative weighting is a designer choice, and **the performance is tunable by adjusting the model parameters**
3. The model is **extremely flexible requires minimal maintenance.** It is able to perform with accuracy for each period of time presented, with strongly differing traffic patterns.
4. **Pedestrian safety is implicitly programmed** into the RL algorithm, which along with real-time video-based pedestrian detection techniques will enable the deployment of intelligent, safe, reactive signal controllers with significantly improved performance.

Future work

1. Considering deployment challenges are the next big step - hardware interfaces and standard protocols need to be studied for taking the step towards implementation.