Adaptive Traffic Signal Control Using Multi-Agent RL

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Problem Formulation

- Environment = Whole traffic Network
- Every junction is an Agent, working in a common environment.
- Every agent can experience a part(local data) of environment.

Agent Description

- State:
  Congestion at each incoming lane
  Congestion at immediate Neighbors incoming lanes
  Current Phase
- Action : Green signal duration {20,25,30,….65,70}
- Reward : Change in congestion at its lanes and neighbors lanes after performing action
- Objective : Maximize discounted sum of rewards

Data For Training:

- PTV Vissim Simulation for modelling Traffic behaviour
- Queue Counters for getting congestion in a lane at particular time
- Self Designed Network

Algorithm Used

- PPO, actor critic style
- Entropy Loss included as well
- Buffer of 100 latest samples

$$\mathrm{r}_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}$$

$$\mathrm{L}^{CLIP}(\theta) = E_t\left[min(r_t(\theta)\hat{A}_t, clip(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t)\right]$$

$$\mathrm{H}(\theta) = \sum_a -\pi_\theta(a_t|s_t)log(\pi_\theta(a_t|s_t))$$

$$\max\ [\mathrm{L}^{CLIP}(\theta) + \alpha H(\theta)]$$

Algorithm

For every Agent

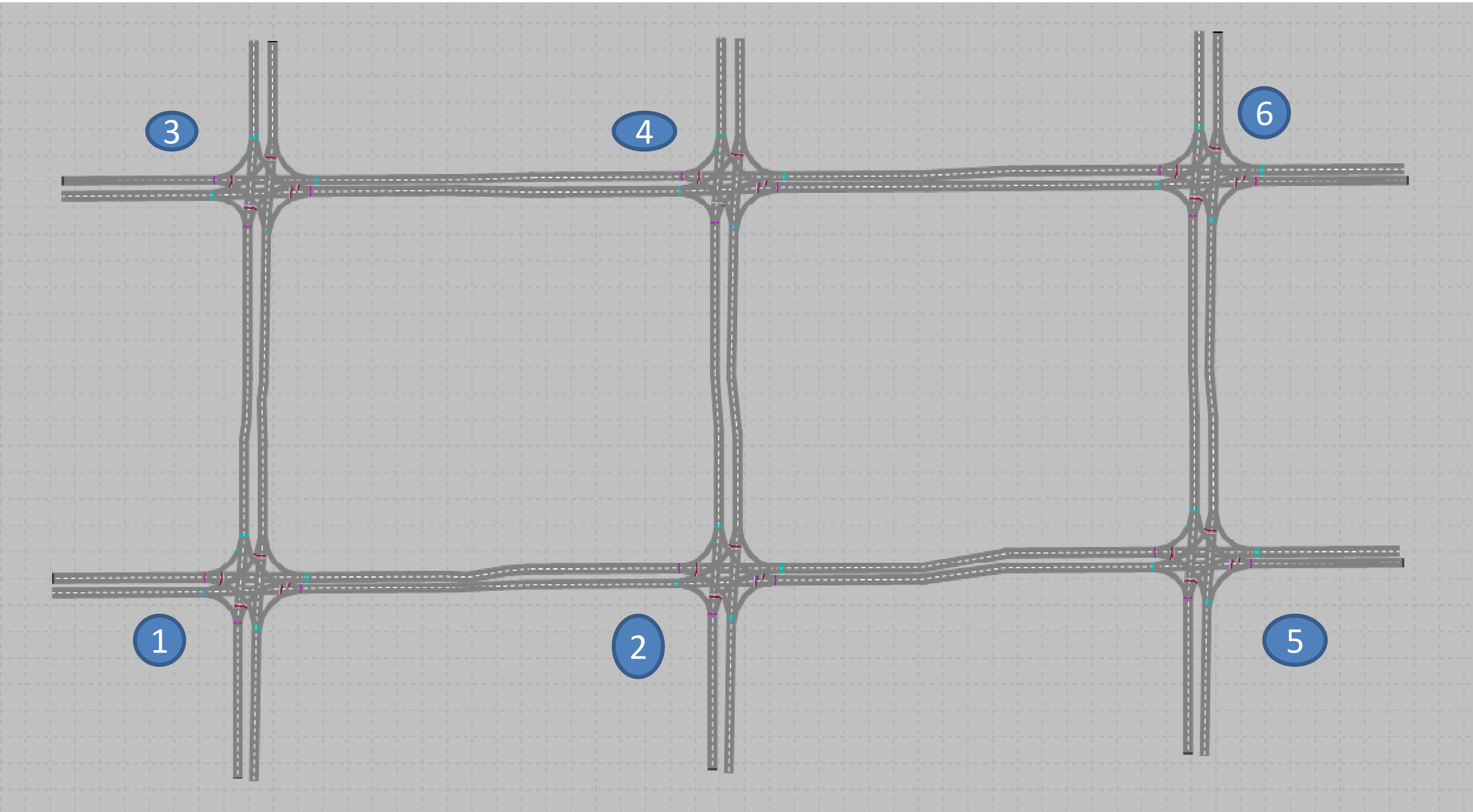
1. Get s,a,r,s’. put into buffer
2. Copy current policy parameter
3. Sample minibatch(32) from buffer
4. Train Actor, Critic(Mean square loss function)
5. Update pi_old with step 2 parameters

Actor Critic Network Details

- Both are simple Dense Network, 2 Hidden layers (64 nodes each)
- PPO loss epsilon = 0.2
- Entropy loss coefficient = 0.01
- Two actor networks(old, new), 1 critic network for every agent

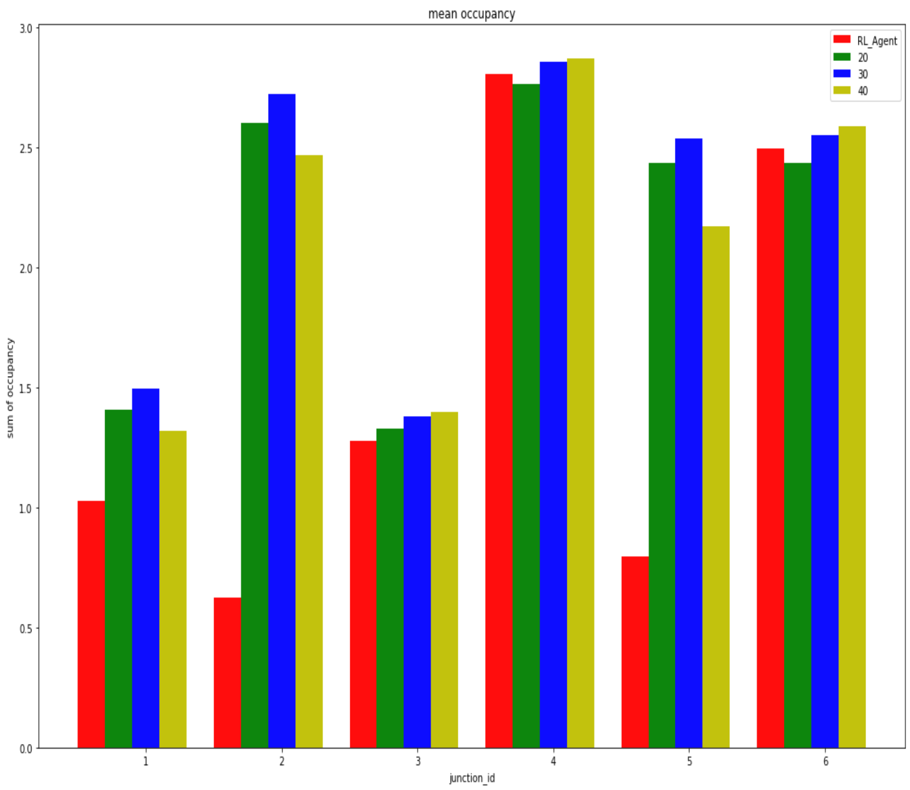
Traffic Network for experimentation

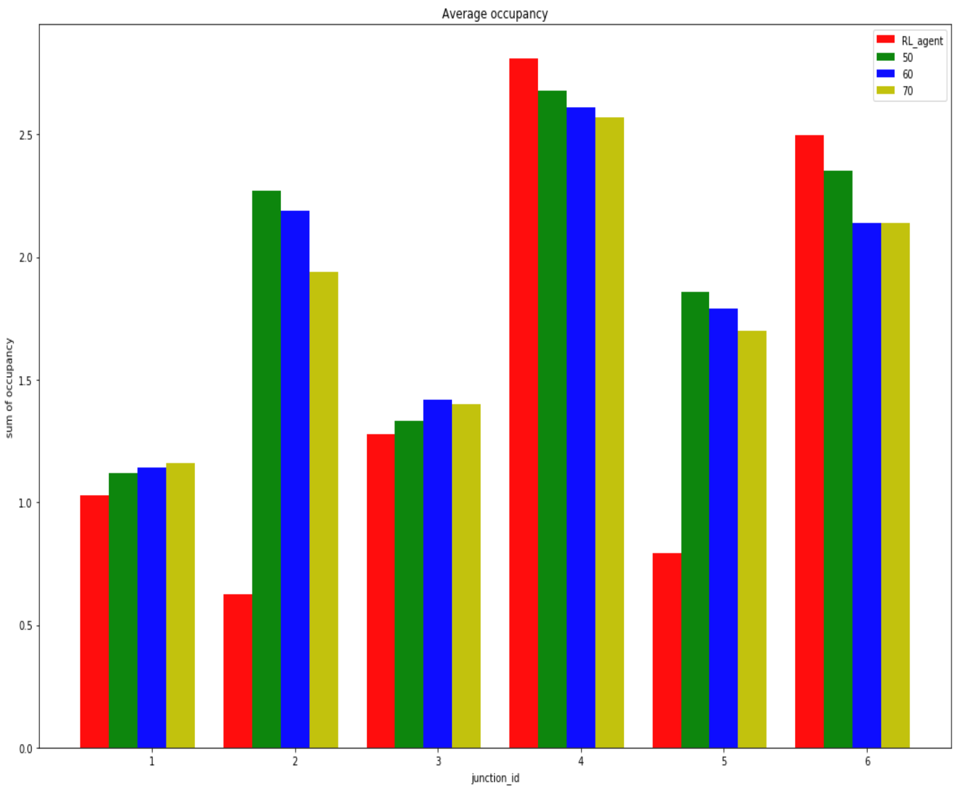
- 6 junctions, 8 signals(que_counters) per junction
- 10 Vehicle Input points
- Left, Straight, Right = 0.25, 0.50, 0.25



Experimentation and Results

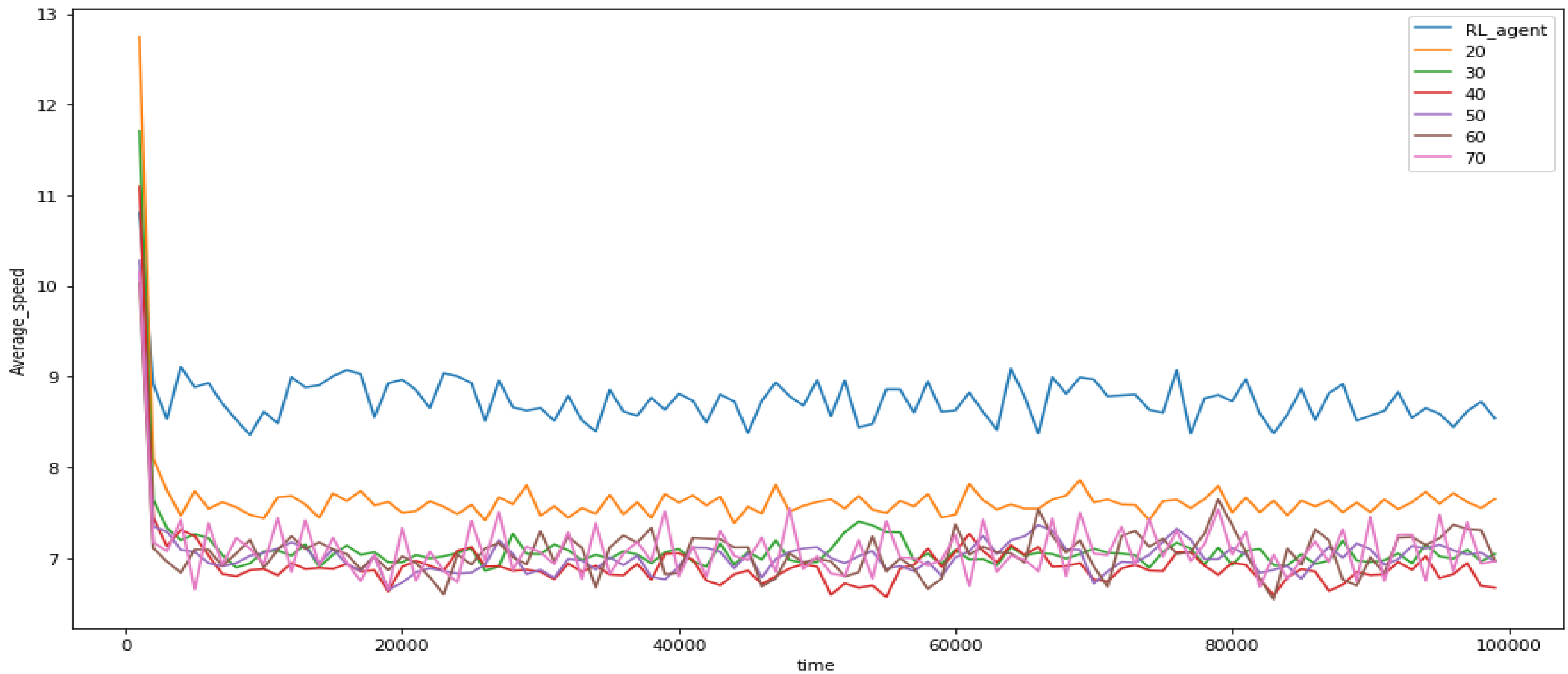
- 1k vehicles per hour at every incoming lane
- Avg Occupancy Comparison with fixed time algorithms





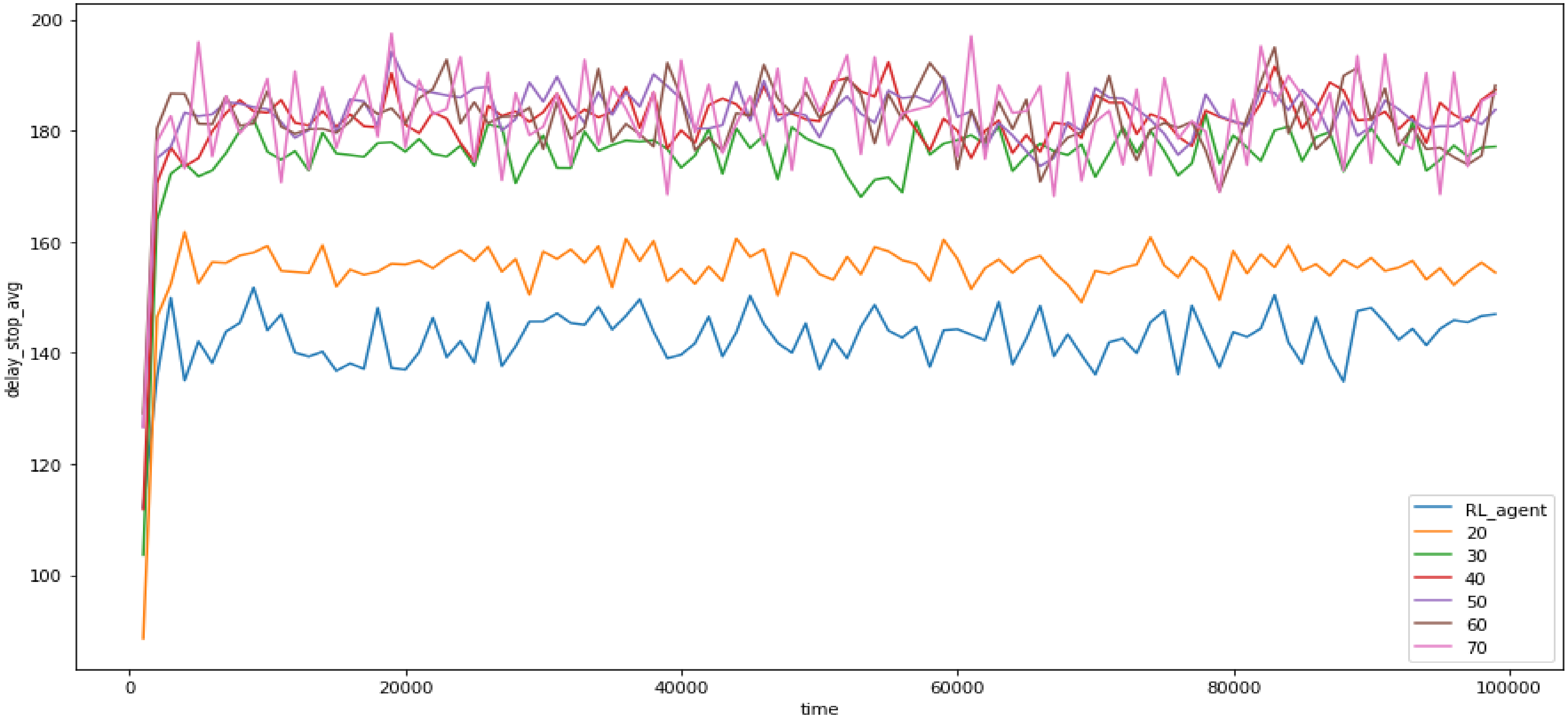
Experimentation and Results

- 1k vehicles per hour at every incoming lane,
- Avg Speed Comparison, calculated in 1000secs interval



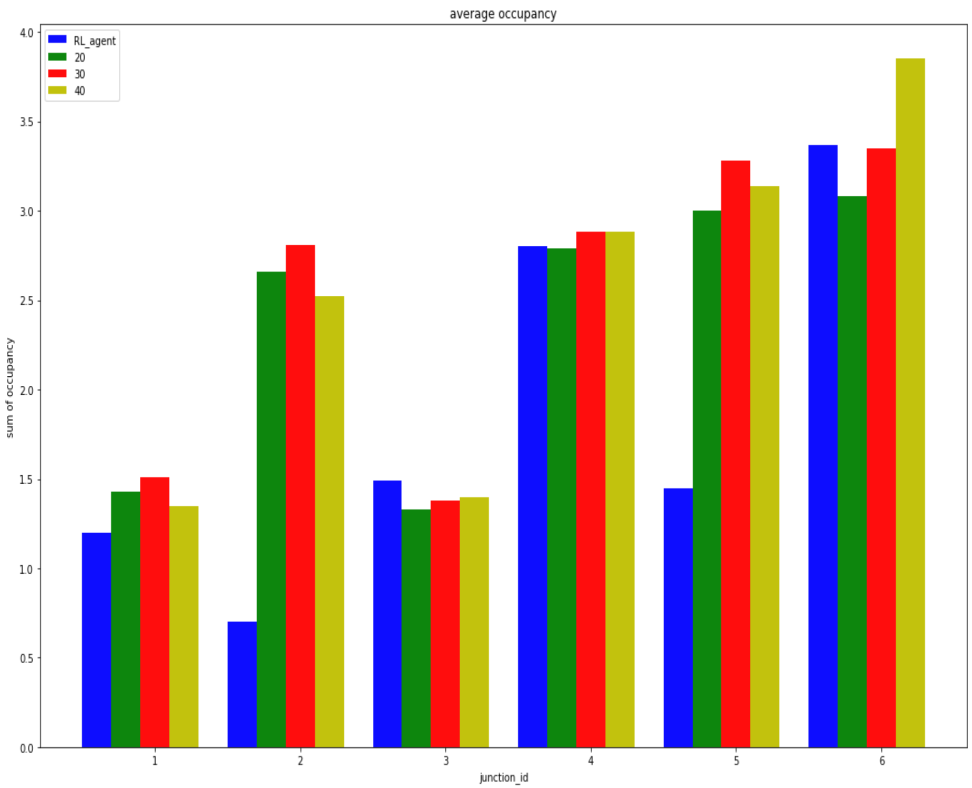
Experimentation and Results

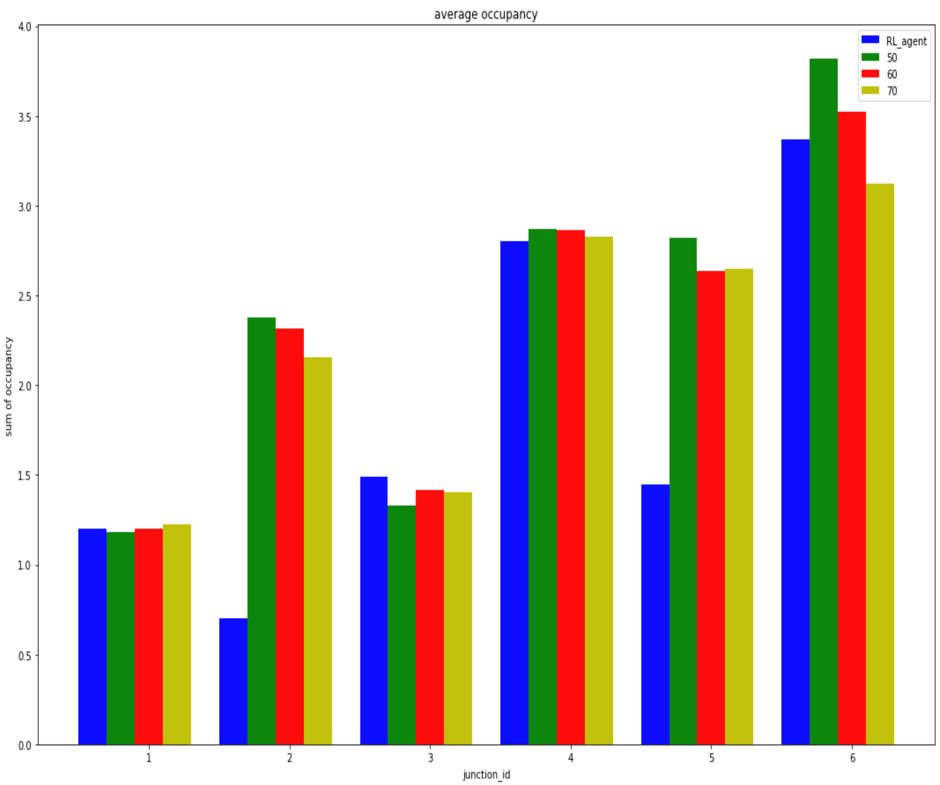
- 1k vehicles per hour at every incoming lane,
- Delay Stop Avg, calculated in 1000secs interval



Experimentation and Results

- 2k vehicles per hour at every incoming lane
- Avg Occupancy Comparison with fixed time algorithms





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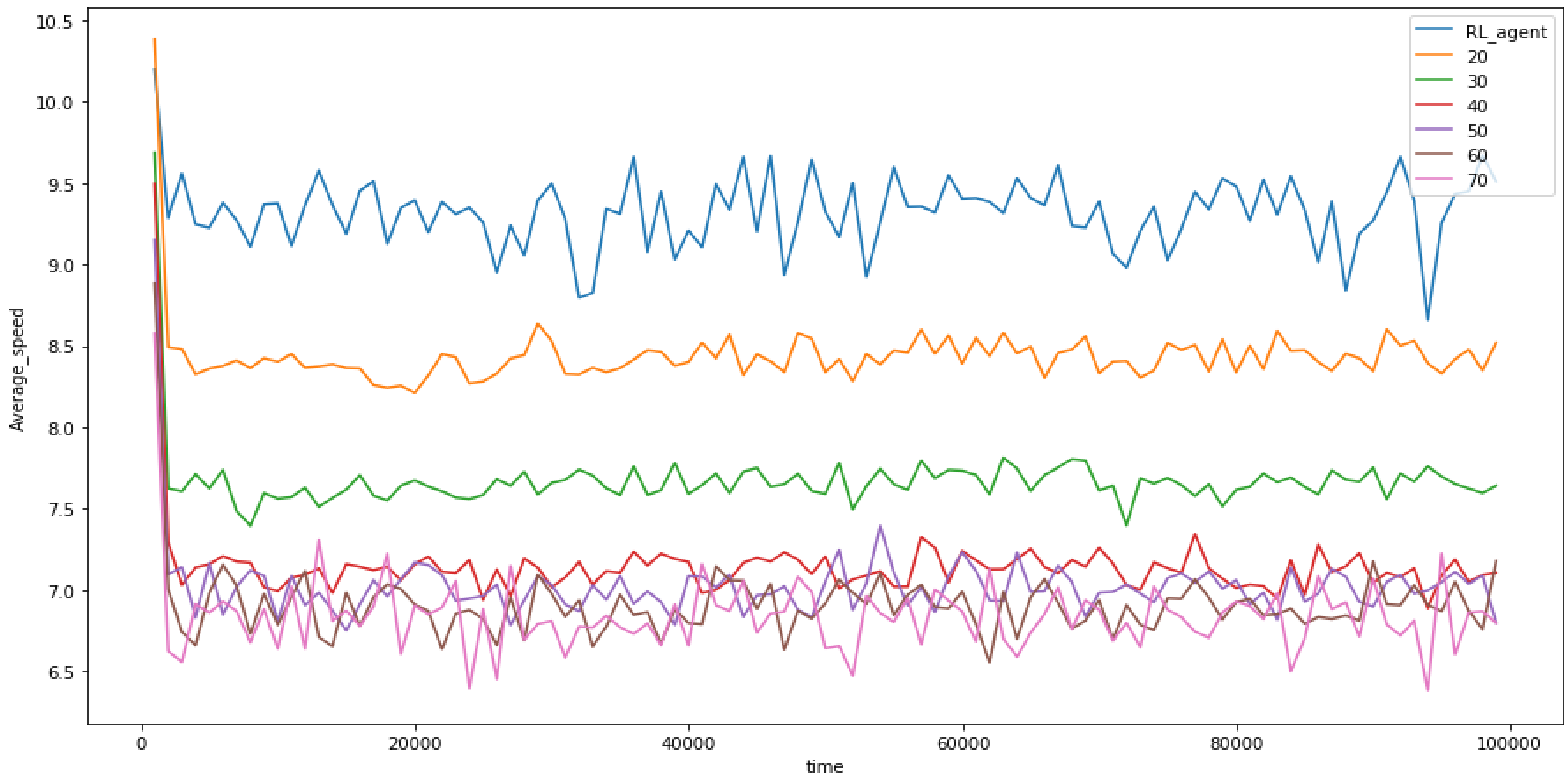

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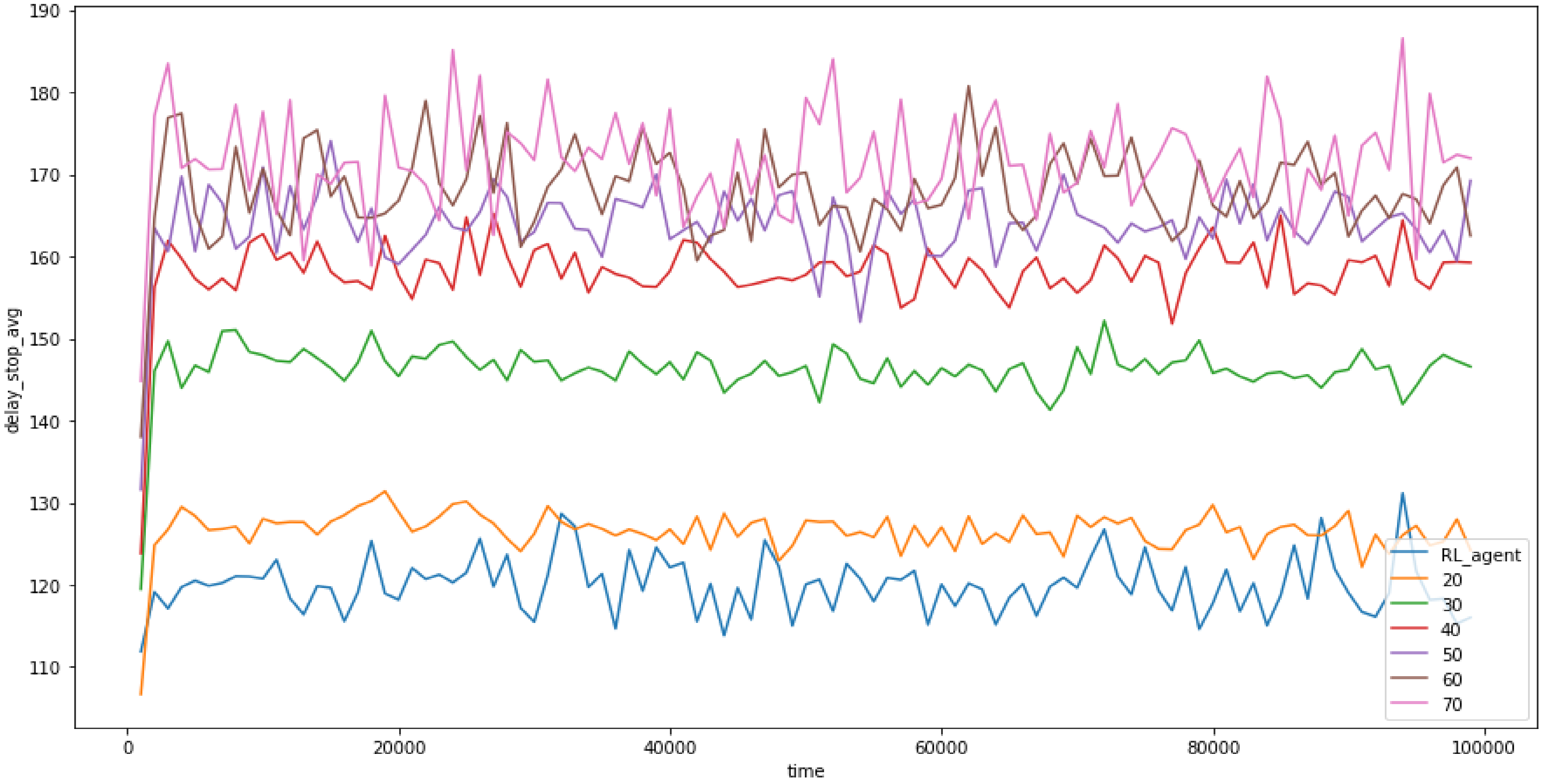
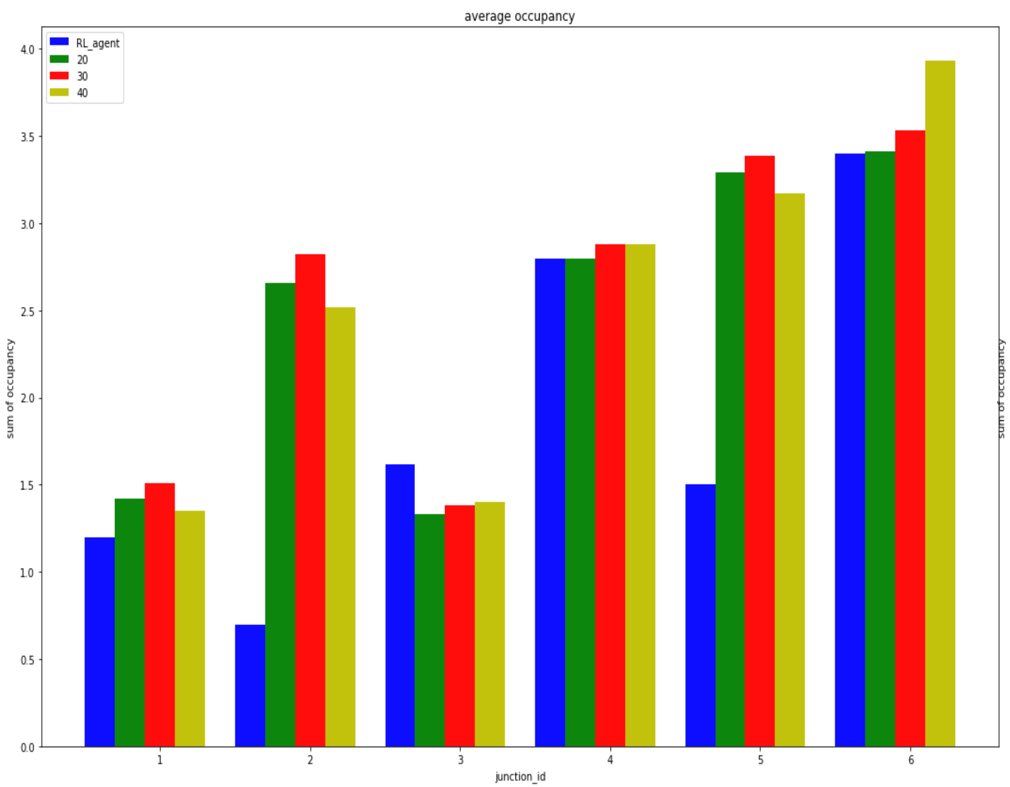
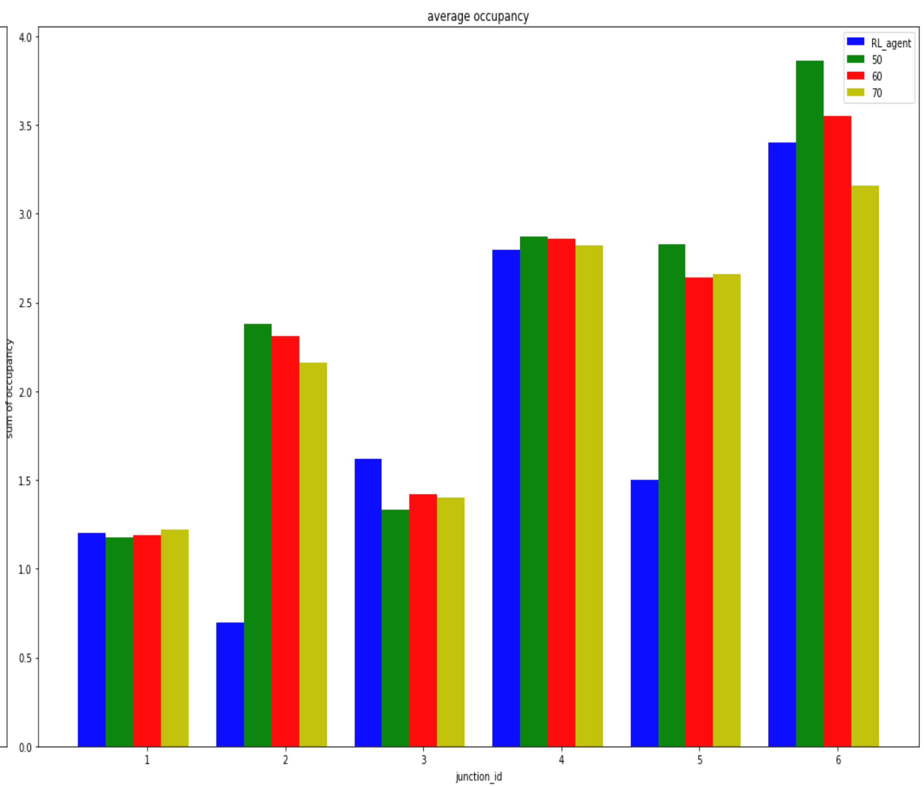


Experimentation and Results

- 3k vehicles per hour at every incoming lane
- Avg Occupancy Comparison with fixed time algorithms





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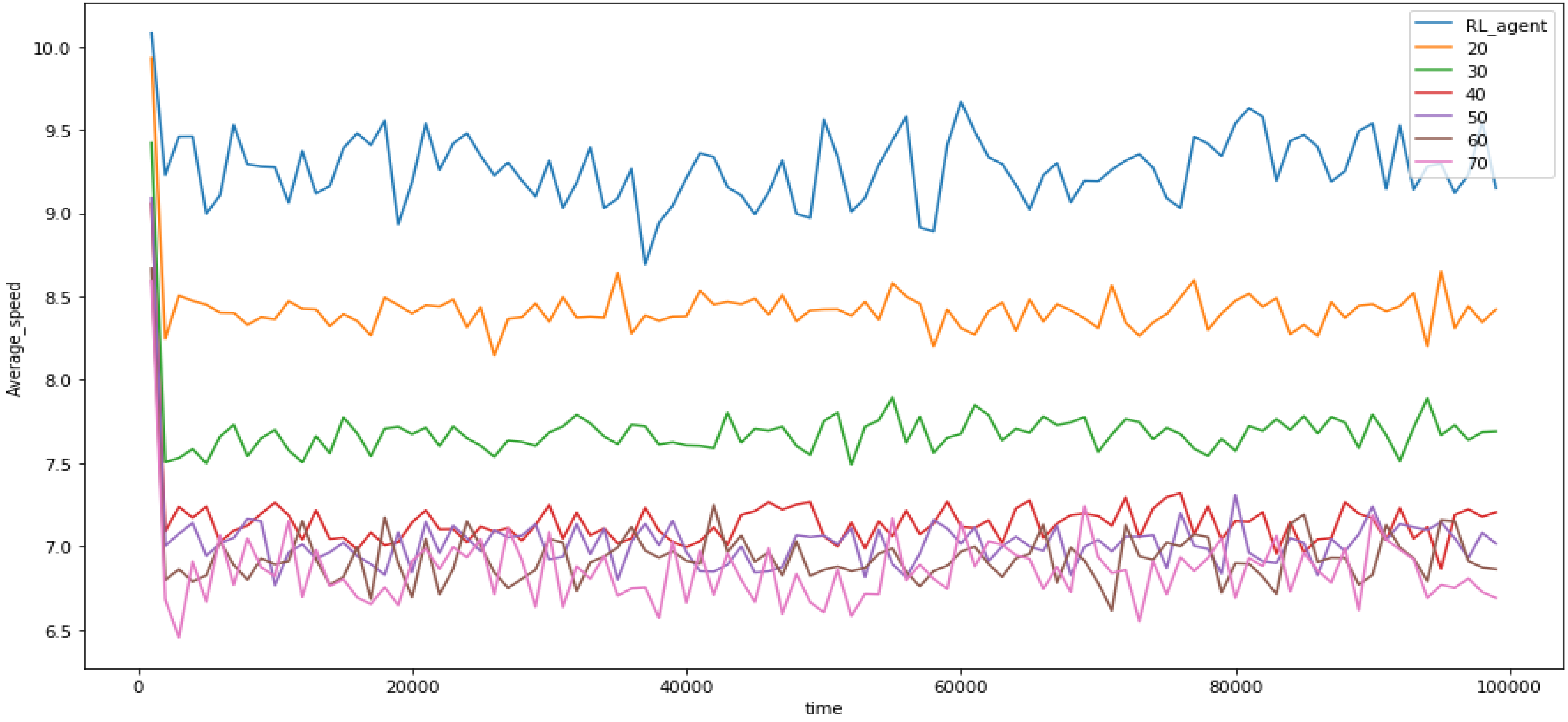

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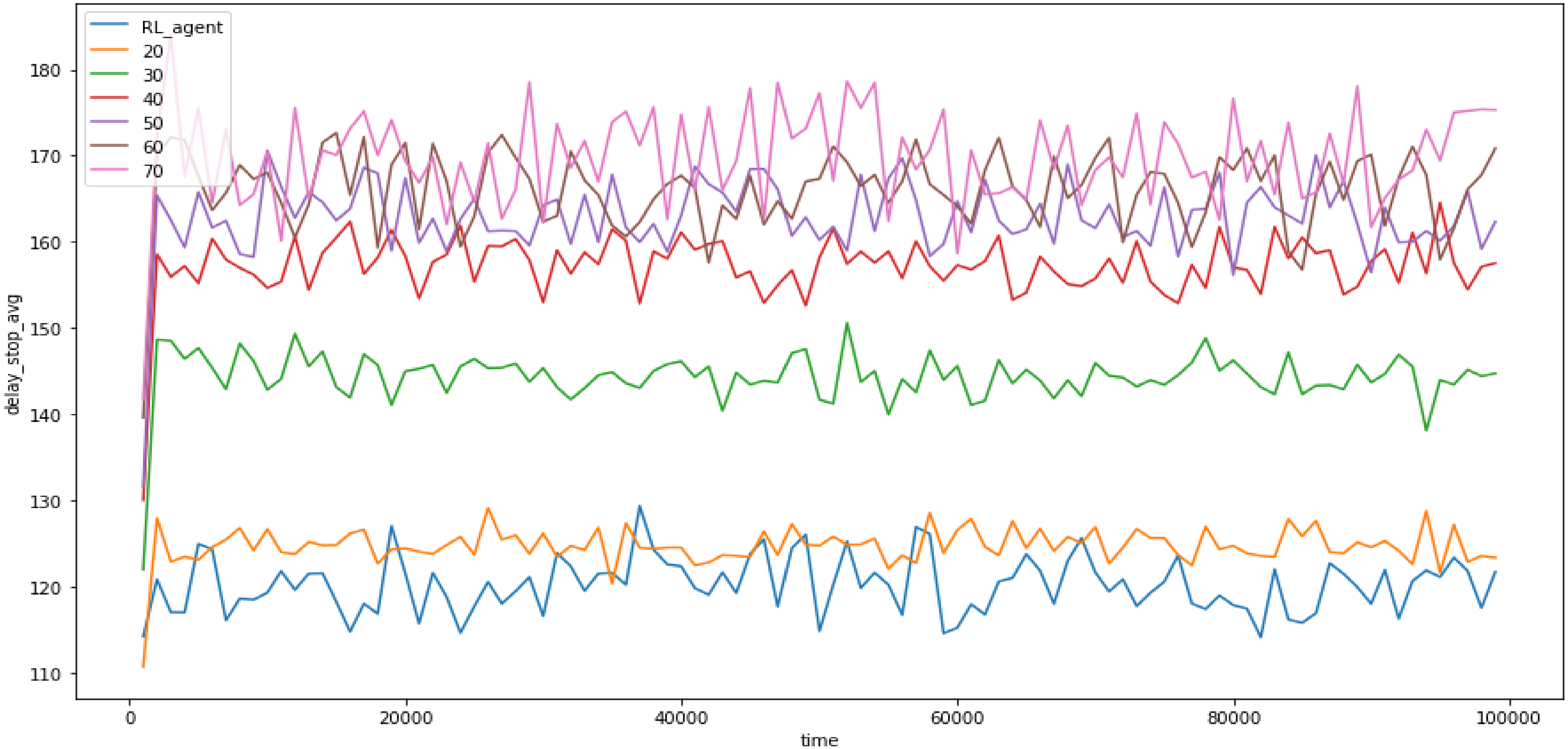
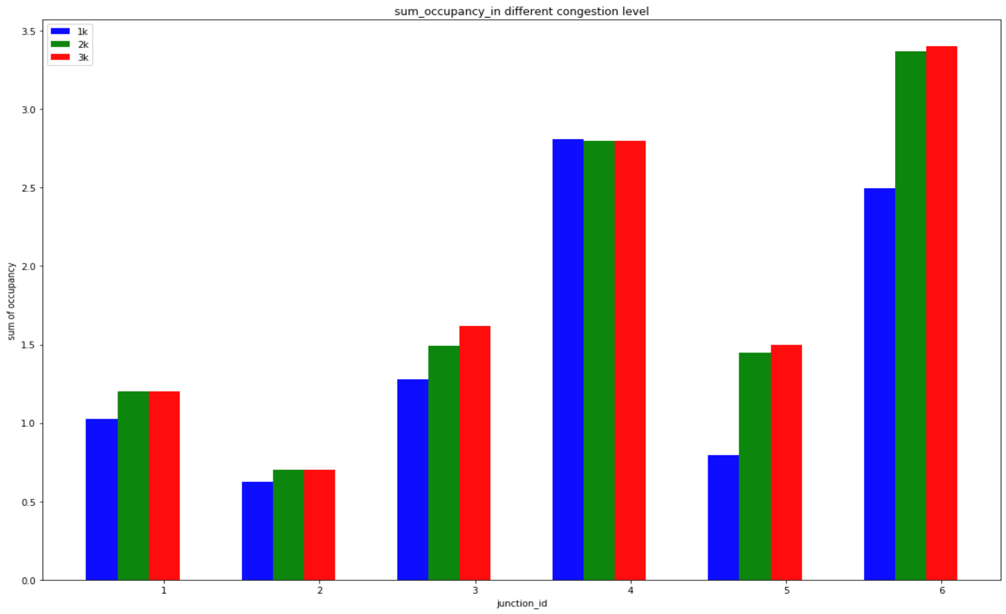
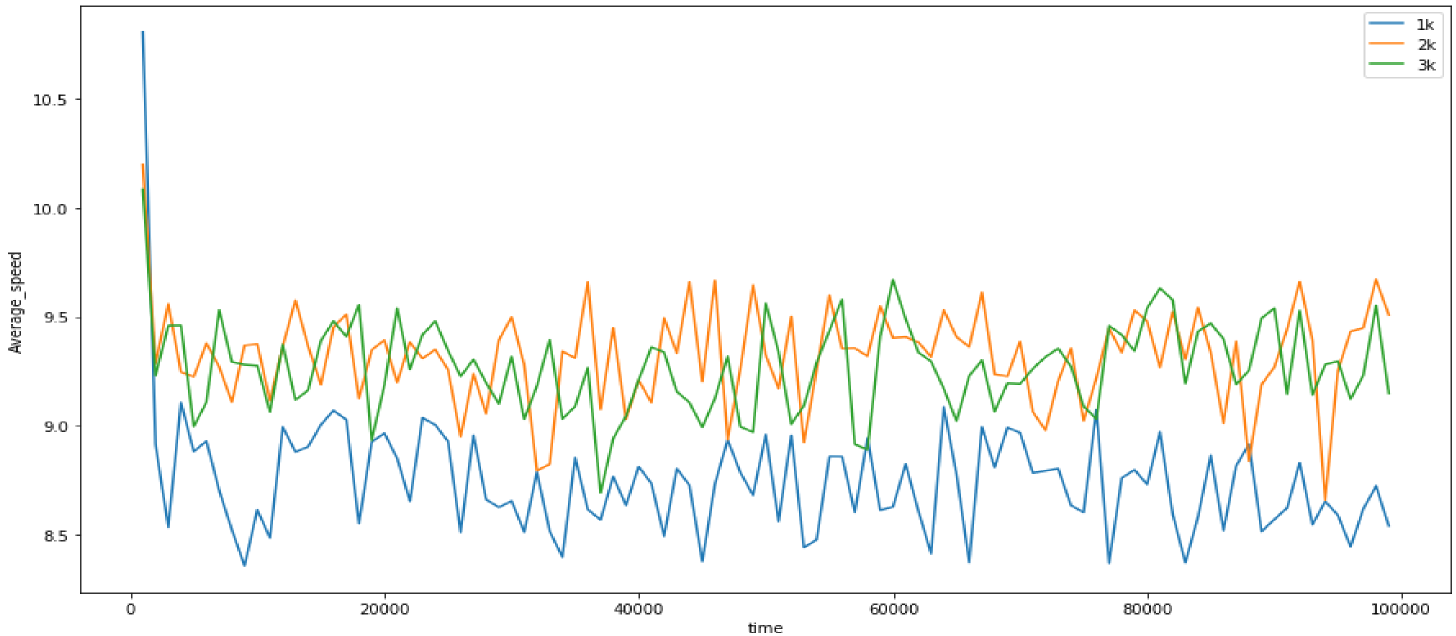


RL Agent Performance Comparison at different vehicle incoming density

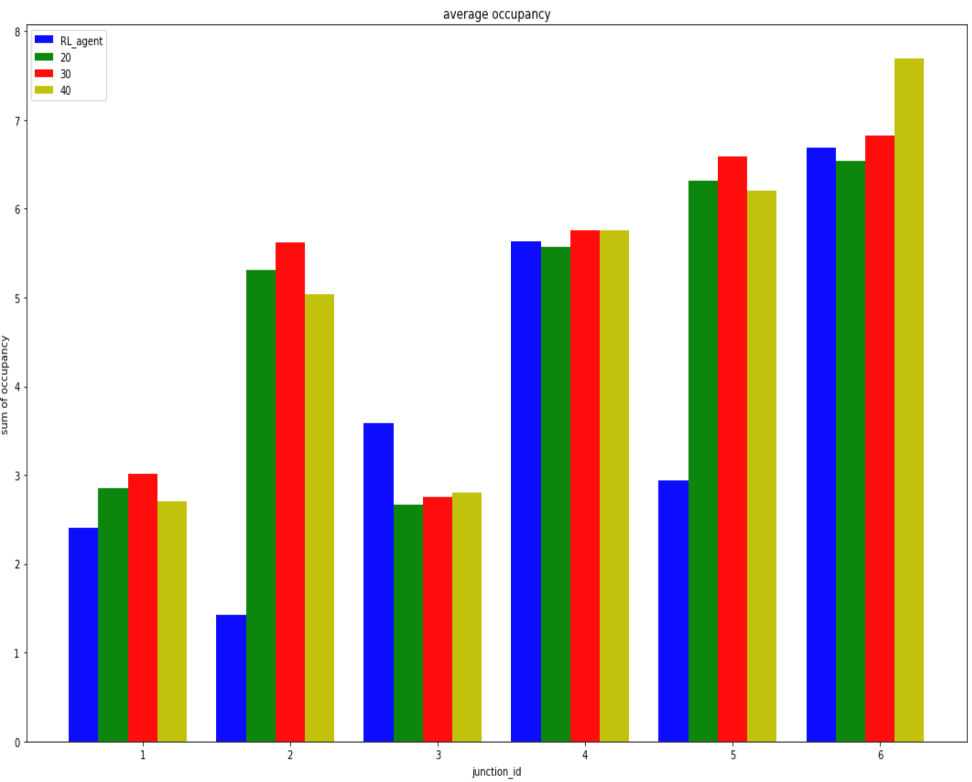


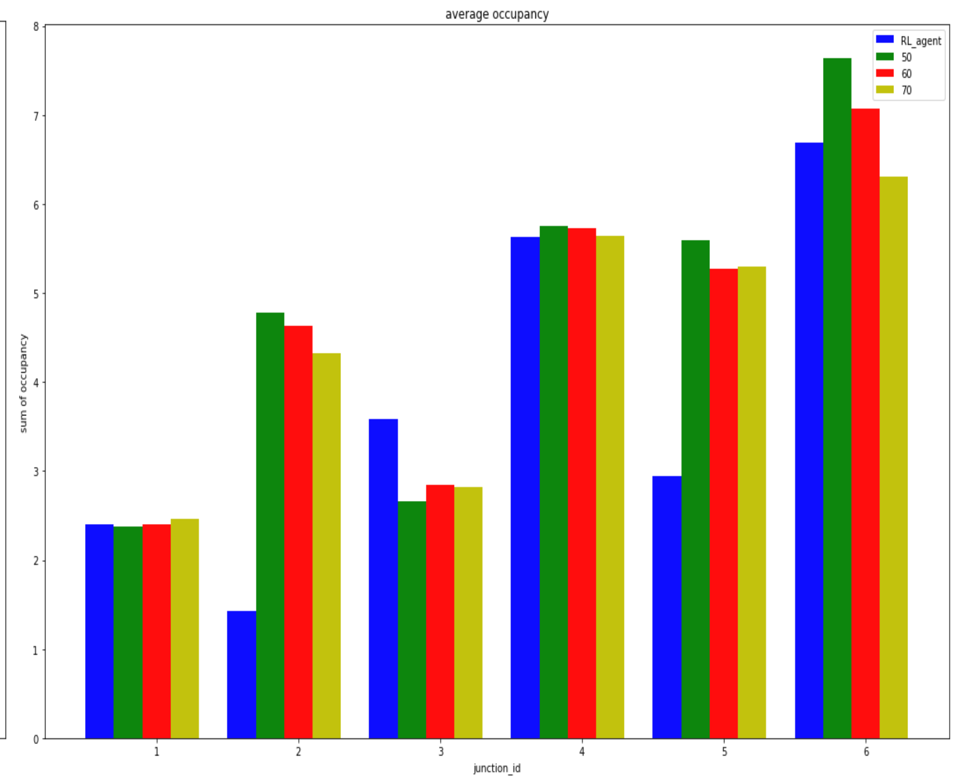


RL Agent Performance Comparison at different vehicle incoming density

Experimentation and Results

- Random vehicle input density:
  Changing after every 50 minutes
  Selected in range {500,1000,………,3000,3500} vehicles per hour
  Asymmetric vehicle incoming density at every junction
- Avg Occupancy Comparison with fixed time algorithms





- ➢ Agent was never trained in this kind of changing environment.
- ➢ Still it has generalized reasonably well.

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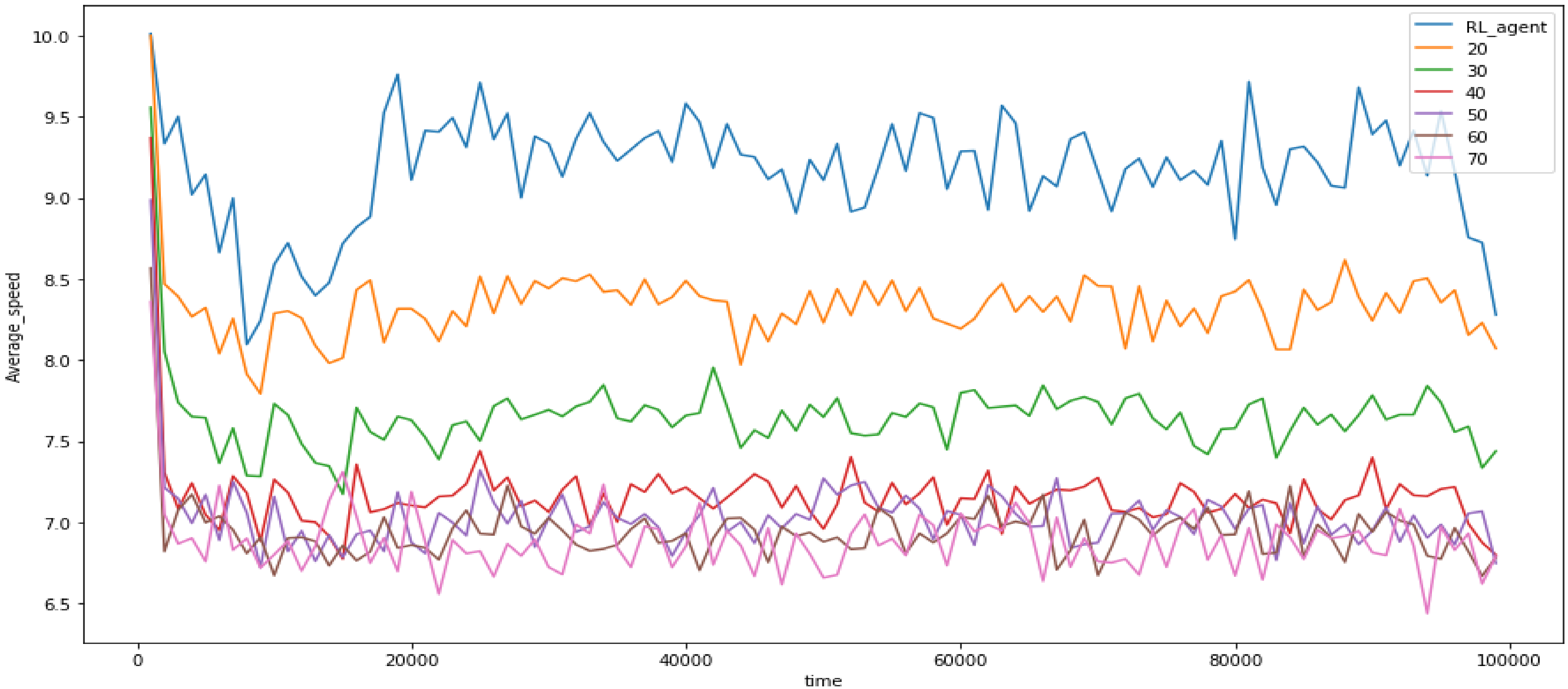

➢ Agent was never trained in this kind of changing environment.
➢ Still it has outperformed all fixed time algorithms.

Experimentation and Results

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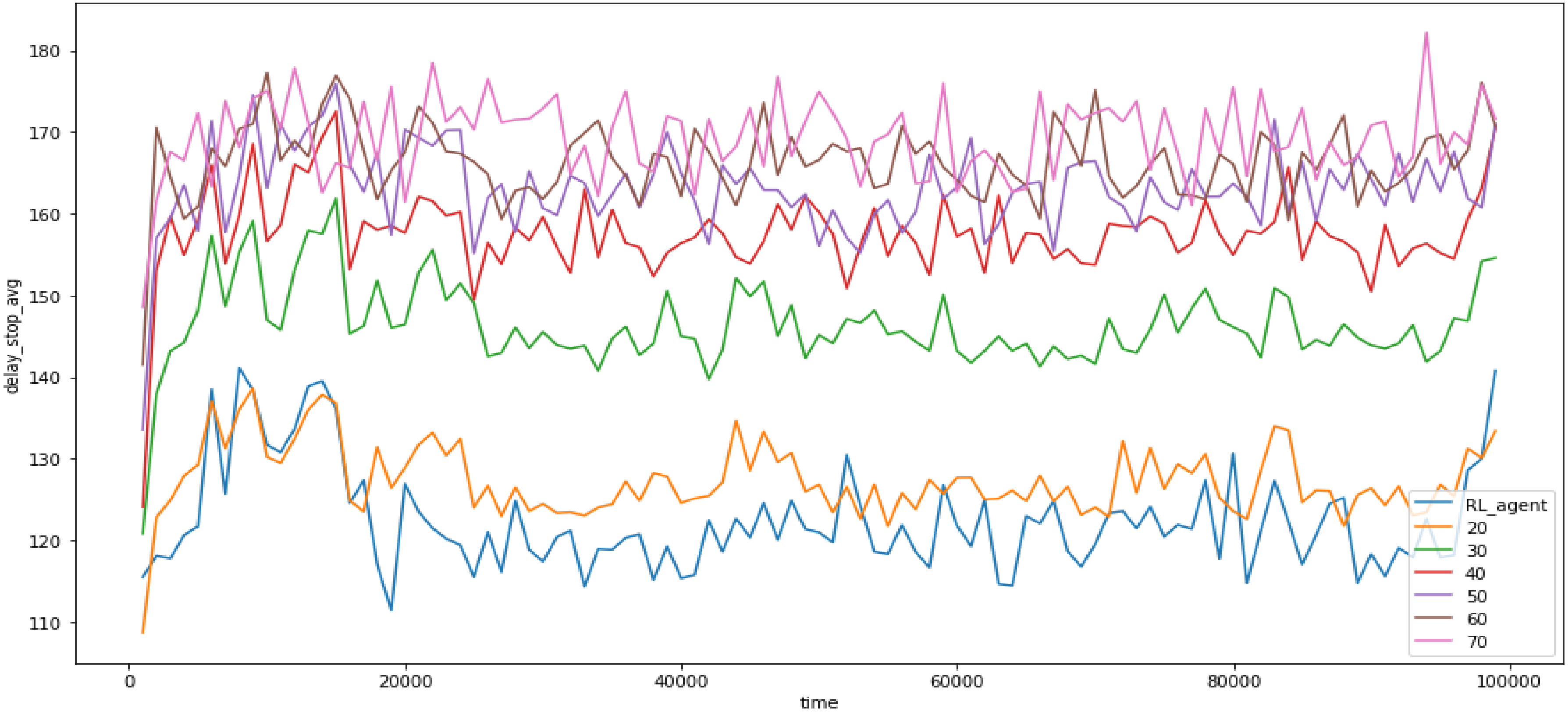
  Asymmetric vehicle incoming density at every junction
- Avg Delay Stop time Comparison with fixed time algorithms



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Phasing Analysis

- For Asymmetric Network simple phasing performs better.

References

- **Proximal Policy Optimization Algorithms (**John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, Oleg Klimov)

- **Multi-agent reinforcement learning for traffic signal control**, Prabuchandran K.J. , Hemanth Kumar A.N , Shalabh Bhatnagar