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AnthroPOLIS
HUMAN CENTERED MOBILITY

Anthropolis Chair and Future Cities Lab

Joint Seminar Series 2021-2022

September 29th, 2021

Anthropolis Chair and Future Cities Lab Joint Seminar Series 2021-2022

- 14 seminars during this 2nd edition
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04/10/2021

Session 1: Anthropolis Chair and Future Cities Lab Joint Seminar

Implementing and Using Reinforcement Learning for Empty Empty Shared Vehicle Rebalancing in Multi-Agent Transport Simulation MATSim

Presented by

Tarek CHOUAKI
PhD Student
tarek.chouaki@irt-systemx.fr

Jakob Puchinger
Supervisor

Sebastian Horl
Co-Supervisor

Please welcome AMoD

- The advent of autonomous vehicles offer a whole range of new opportunities
- Autonomous Mobility on-Demand promises to improve transportation quality for users and fleet usage efficiency for operators

But we should not forget that:

- Autonomous on-demand vehicles are not arriving in an empty space
- They have to efficiently collaborate with other services to achieve an attractive overall transportation offer
- The manner in which an autonomous on-demand vehicles fleet is operated strongly impacts its performance

Challenges to tackle for AMoD

- Adaptiveness
  - The mobility context is highly dynamic and constantly evolving
  - The offer of mobility can drastically change in a short period of time (before and after the Covid-19 crisis for example)
- Proactivity
  - An AMoD system can rely on past experience to predict future demand and act beforehand in order to better satisfy transportation queries
- Integration
  - An AmoD system interacts, directly or indirectly, with other mobility systems. A good integration of these different services together is crucial for overall performance

Potential of using Reinforcement Learning for operating AMoD

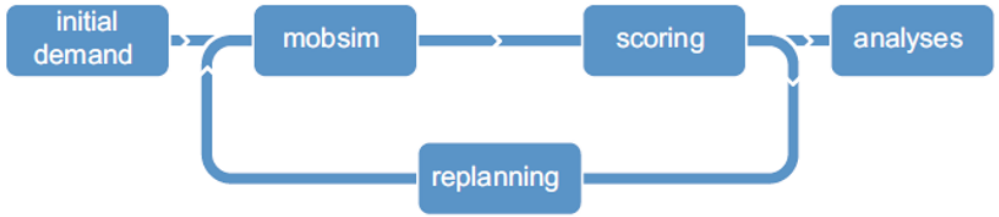
- A system that continuously learns from the consequences of its decisions can adapt to changes in a situation and act in a proactive way. And if these actions are evaluated regarding the overall mobility performance, a good integration of AMoD in its environment can be achieved.
- Hence our PhD topic : **Reinforcement Learning and Stochastic Optimization for the design of on-demand mobility services by simulation**

About the PhD subject

- Scientific Goals
  - Design on-demand mobility services and simulate them in combination with classical public transports using MATSim
  - Use techniques of decision under uncertainty to operate such a service in an efficient manner
  - Take into account the infrastructure supporting the service; i.e the charging stations and the parking areas
- Our Practical Objective
  - Arrive to a simulation of the future Paris-Saclay area (horizon 2030) mixing existing and future public transports alongside AMoD services with the infrastructure supporting it
  - Be able to forecast the impact of the upcoming Grand Paris Express
- Also involves :
  - Develop the required MATSim modules to simulate such a service
  - Implement scenarios on various other regions.
  - Maintain the reproducibility of the simulations

Agent-Based simulation of mobility using MATSim

- MATSim is an open-source activity based, multi-agent simulation framework implemented in JAVA
- It simulates each agent individually, i.e microscopic
- It uses a queue based model for travelling through links of the network
- MATSim performs iterations of the simulation applying the co-evolutionary principle : each agent tries to optimize its schedule while competing with other agents
- The agents changing their plans to maximize individual scores allows us to assess service impacts on modal shares

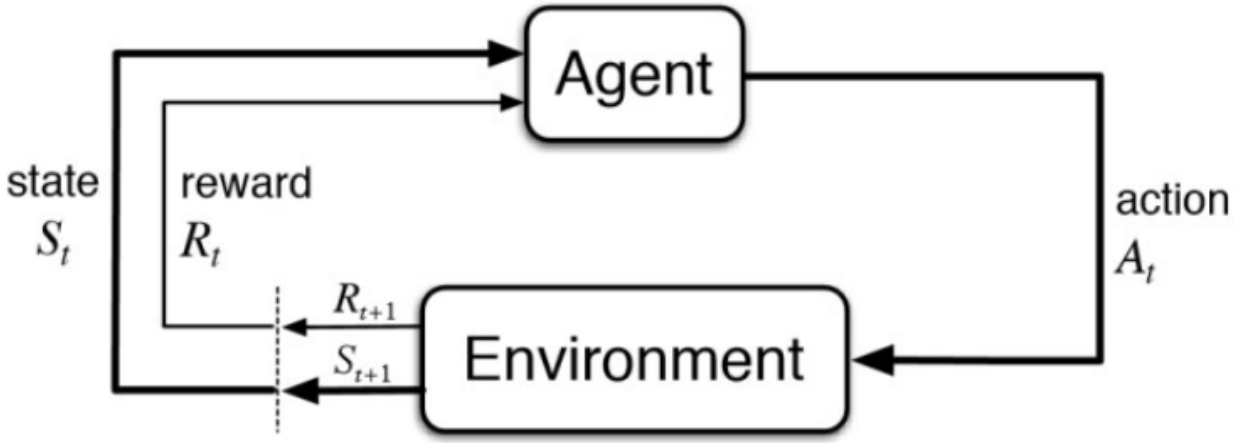


State of the art

- MATSim provides various rebalancing algorithms
- One tries to estimate the next demand [1]
  - Modelling the rebalancing problem as a transportation problem
  - Estimating the number of requests during the next time slot from the same time slot of previous iterations
- Existing studies use RL for rebalancing & dispatch in simulation
  - The tools used for the simulation often do not allow to assess the impact on travelers' choices and modal shares (**[2][3]**)
  - Some of the studies are performed on built-in simulators and are hardly **reproducible** (**[3]**)
  - **[4]** Uses a centralized RL approach for empty vehicle rebalancing
  - Electric vehicles and **recharging** decisions are not considered
- Our study
  - Introduces a **first decentralized RL** algorithm for empty vehicle rebalancing in **MATSim**
  - Is fully **reproducible**
  - Serves as a foundation for next studies

Reinforcement learning

- The considered agent(s)
  - The agent has a set A of possible actions
  - A value function V indicating the desirability of being in a given state
  - A policy P mapping environment's states to actions
  - A model of the reinforcement (how the agent learns)
- The environment in which the agent evolves
  - The environment has a set S of possible state
  - The environment can be fully or partially observable by the agent(s)
  - It can be static (changes only when agent performs an action) or dynamic
  - After each action, the agent receives a reward value by the environment



How to implement Reinforcement learning in MATSim

- First implement a rebalancing strategy that uses RL
- Rebalancing is usually performed periodically considering discrete zones of the network
- Exploring how rebalancing strategies are implemented in MATSim's DRT module
- An existing functionality estimates the next demand from the previous iteration
- Technical questions that arise:
    - How to position the reinforcement learning loop relatively to the simulation loop ?
        - Apply reinforcement after each MATSim iteration
        - Apply reinforcement after iterating in MATSim and then simulate again
    - Where to implement the RL algorithm ?
        - Directly inside the DRT module, in JAVA
        - As an external API that is called by the DRT module

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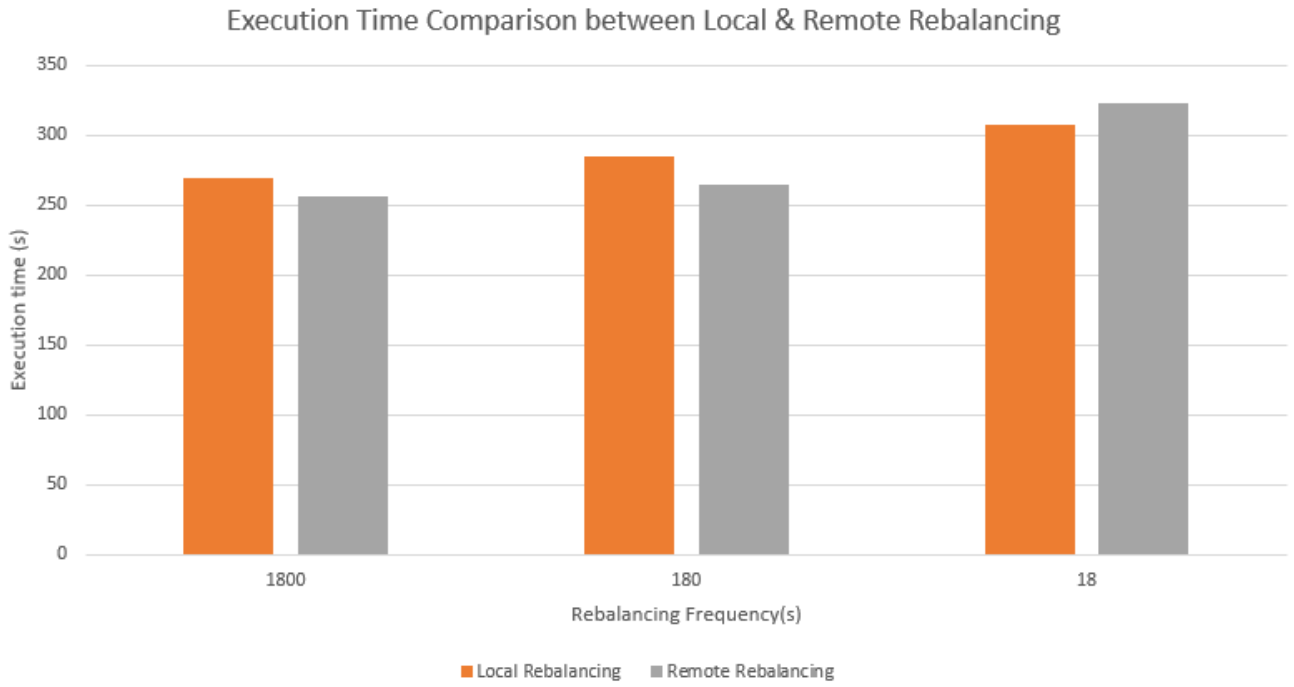
Remote Rebalancer

- An external API to be requested by MATSim's DRT module
  - A **Remote Rebalancer** tool written in Python
  - Communication with MATSim through TCP requests
    - Allows to have the rebalancing part running in another machine/server
    - Allows to test various algorithms without the need to touch MATSim's code
  - Is it reasonable to perform the rebalancing out of MATSim and have it wait for answers ?
    - The benchmarks say yes !



A first RL algorithm in MATSim:

- We implemented a Q-Learning rebalancing algorithm
  - Decentralized : Each vehicle learns on its own
  - An agent's state is comprised of:
    - Its discretized position on the road network (current zone)
    - The discretized current time
  - The action space corresponds to the zones that the network is discretized to
    - A vehicle chooses one zone to rebalance to and moves to its centroid
  - The reward received by a vehicle is the number of passengers since last rebalancing
  - After each action **a** from state **s** leading to state **s'**, the vehicle updates its Q-Table based on the reward **r**

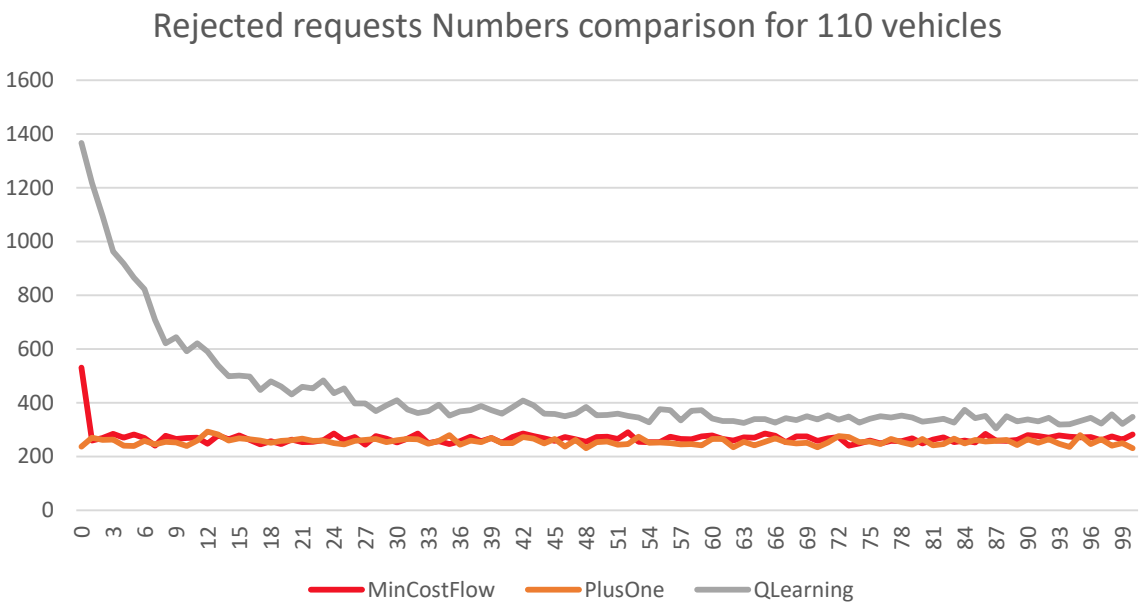
$$Q[s,a] \leftarrow (1-\alpha)Q[s,a] + \alpha(r + \gamma \max_{a'} Q[s',a'])$$

  - At each step, there a probability that the vehicle choses a random action (ε-greedy)
- The implementation was done as an external software MATSim calls through TCP requests

Our experiments:

- Tested on an open MATSim Scenario (Cottbus)
  - The replanning of the agents was disabled
- Alongside MATSim's default vehicle assignment
  - A request is rejected if the expected max wait time for the users is over a certain threshold
  - The objective is then twofold : reduce waiting times and the number of rejected requests
- First tests of the QLearning algorithm with 200 vehicles
- We tested the rebalancing algorithms already present (MinCostFlow and PlusOne) in MATSim with various fleet sizes until they showed rejected requests
- We then tested the QLearning algorithm with different values for the parameters (alpha, gamma and epsilon) and different fleet sizes and compared the best settings

Our results:


Rejected requests Numbers comparison for 110 vehicles
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MinCostFlow
PlusOne
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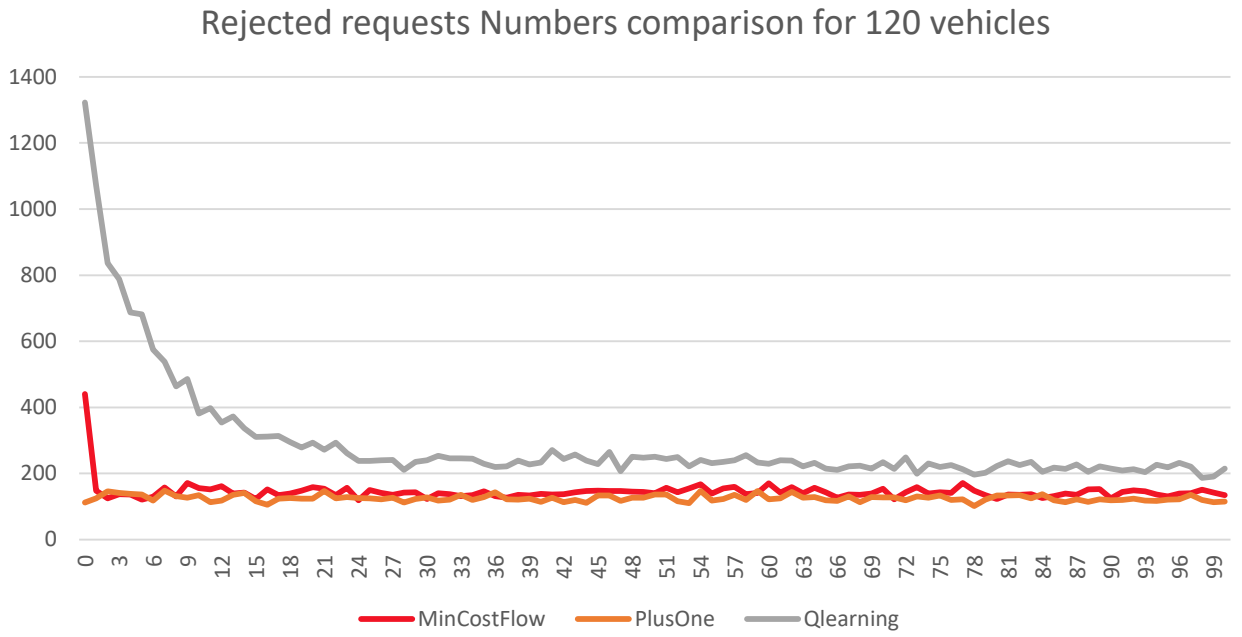
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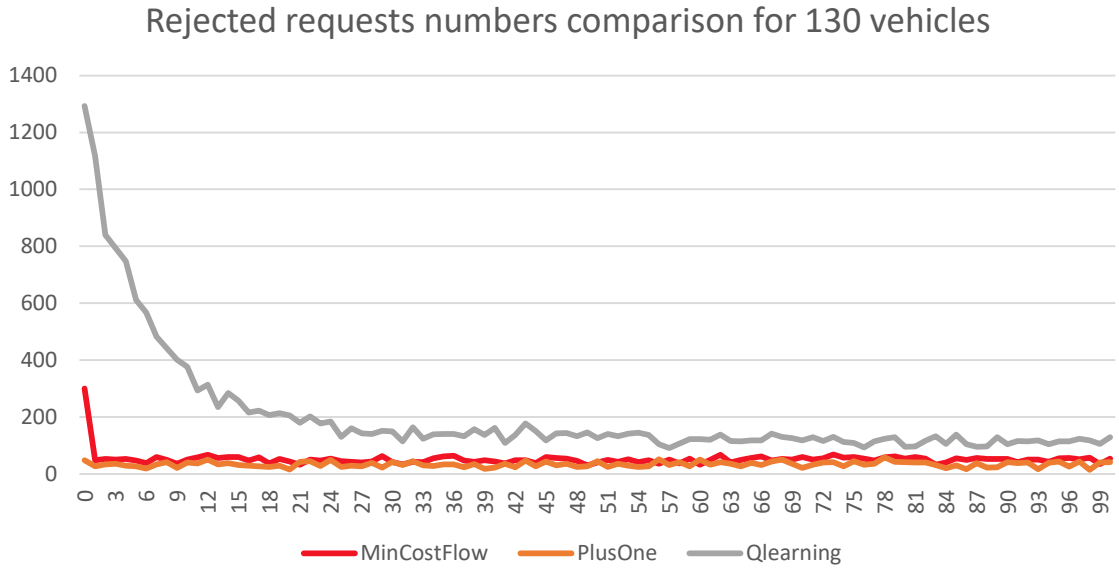
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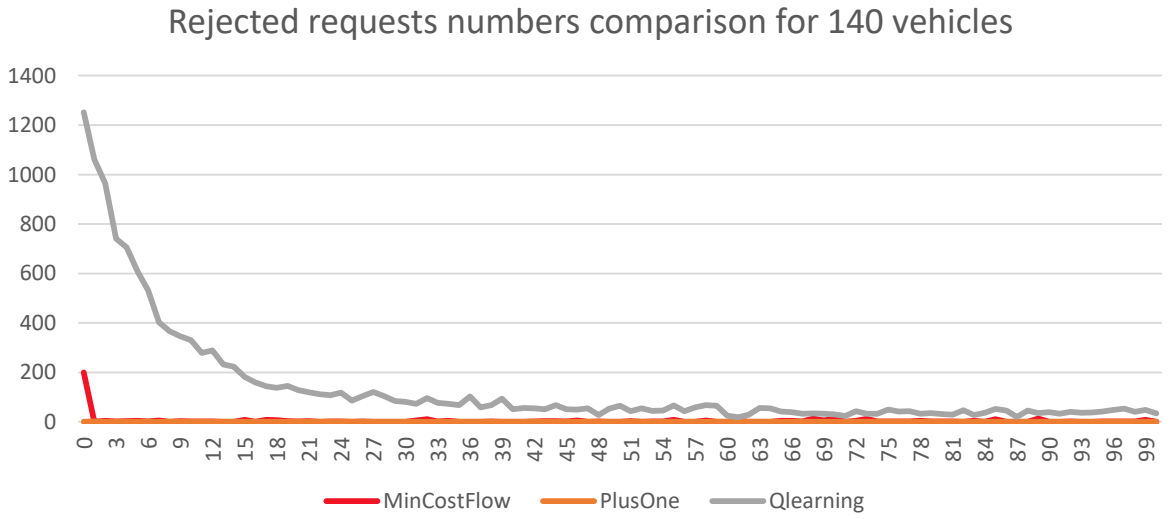
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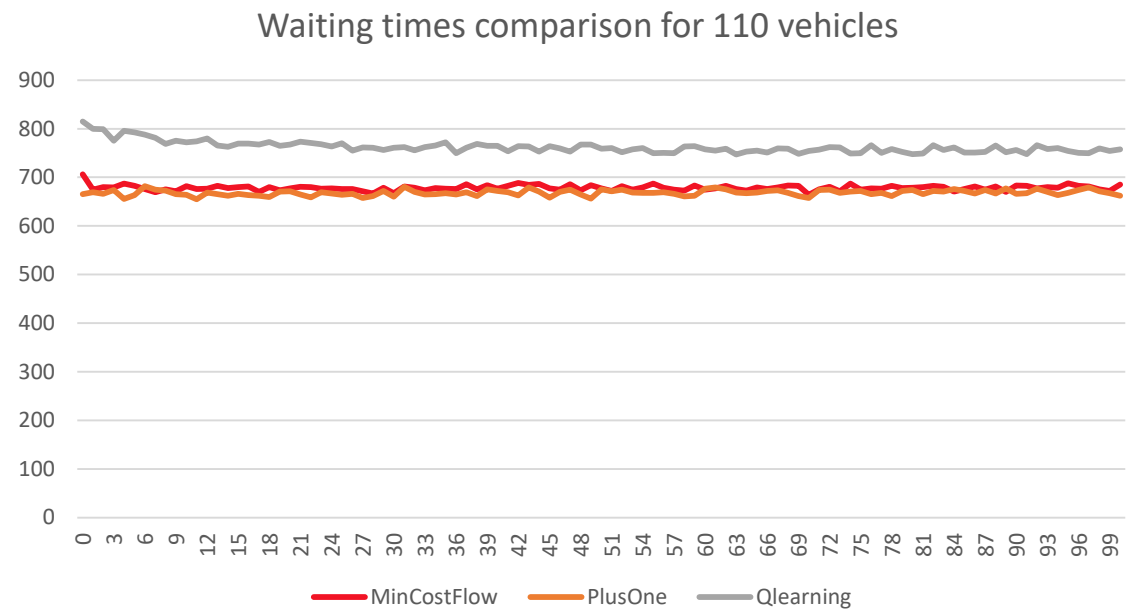
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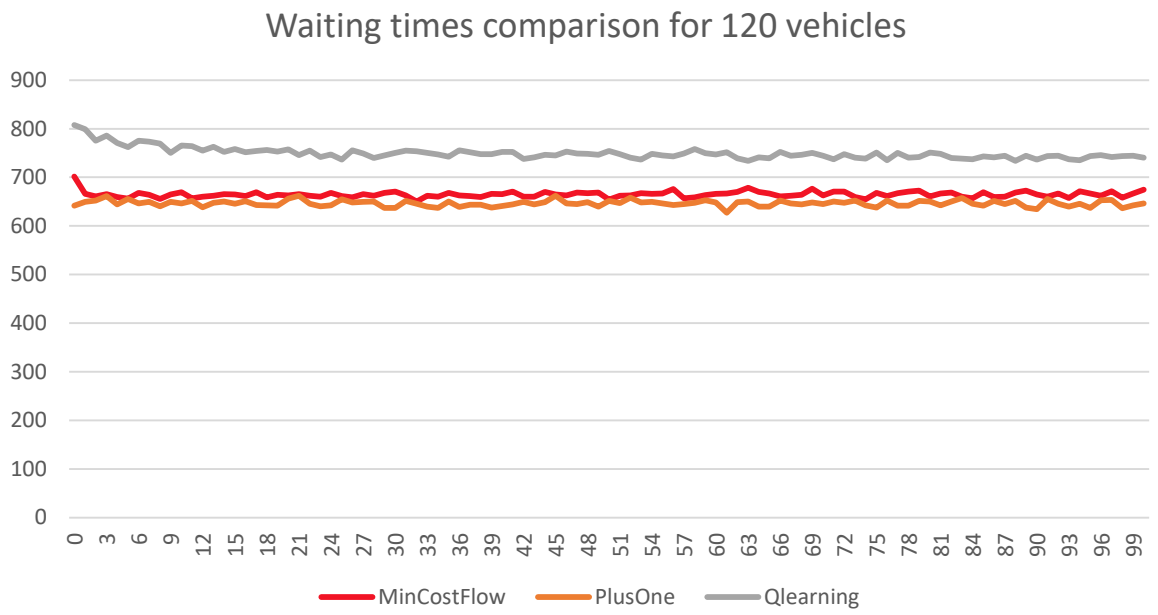
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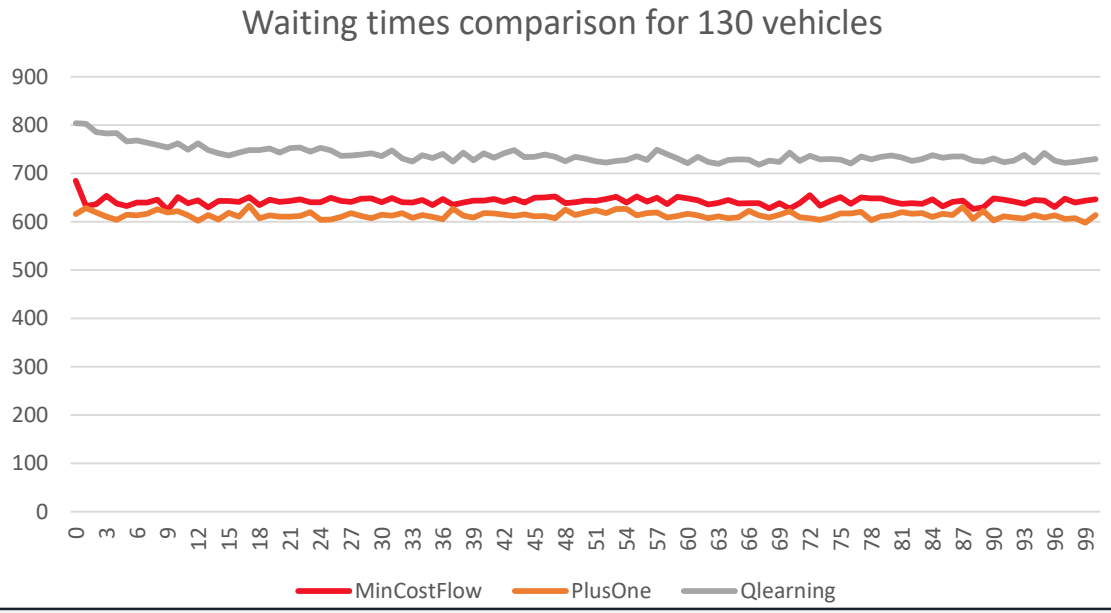
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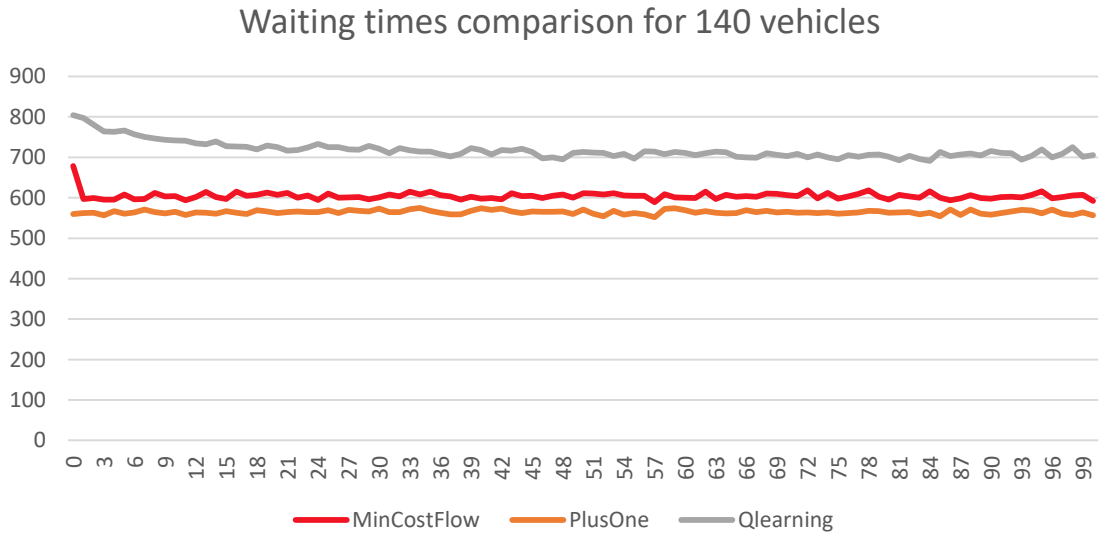
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Conclusions from out first results

- A decentralized QLearning rebalancing algorithm is able to show good results on a static demand
- A more dynamic testbed is needed to benchmark the algorithm

Other reward signals for the algorithm are being tested

- A reward reflecting the cost/revenue of the service
- A lexicographic reward with the number of passengers and waiting times
  - The first results show similar performance to the first QLearning algorithm

Research perspectives

- Take into account **electric vehicles** in the RL algorithm
  - Including the state of charge in the state and charging stations in the possible actions
  - Curse of dimensionality, need to use more compact representations
- Test on a scenario of the Paris-Saclay area
  - More realistic and more dynamic demand
  - **Alongside public transports** with a focus on **intermodality**
  - Then test on other scenarios
- Combine MATSim simulations with **Cost-Benefit Analysis**
  - In collaboration with another PhD student

Referefences

- [1] Regue, Robert, et Will Recker. « Proactive Vehicle Routing with Inferred Demand to Solve the Bikesharing Rebalancing Problem ». Transportation Research Part E: Logistics and Transportation Review 72 (décembre 2014): 192-209. https://doi.org/10.1016/j.tre.2014.10.005.
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Thank you for your attention

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Nest Seminar

DOES THE LABOR COMPETITION REALLY MATTER TO URBAN AGGLOMERATION DEVELOPMENT ?

Han WANG, PhD Candidate, Beihang University, Beijing

WEDNESDAY, OCTOBER 13th, 2021 | 10-11 AM CEST

Link to the seminar