Toward Understanding the Impact of User Participation in Dynamic Ridesharing

Wen Shen

12/12/2017

Traffic and Turkey

A Thanksgiving dinner

Traffic on the 405 Freeway in Los Angeles on Tuesday, 11/21/2017

Photo credit: NYT, KABC-TV

Las Vegas McCarran International Airport

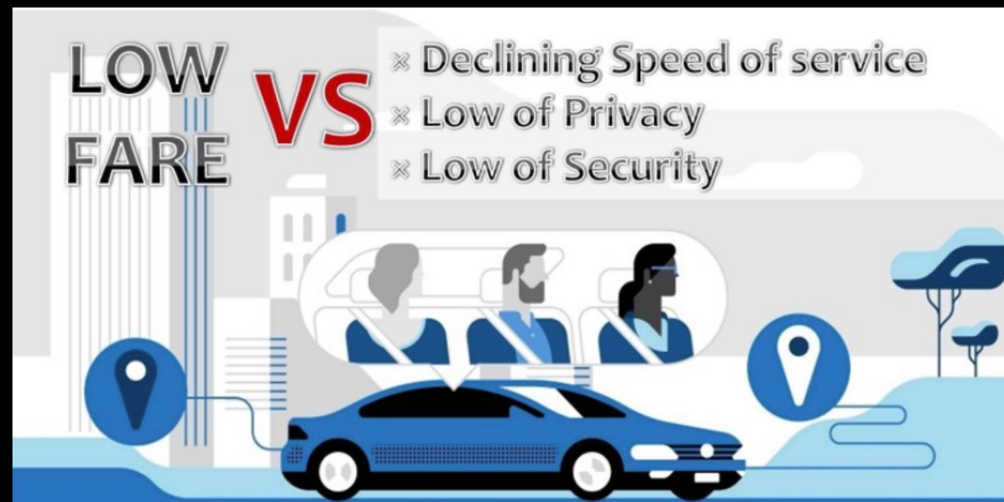
Photo credit: Las Vegas Review -Journal

Benefits of Ridesharing

Challenge: human factor

- User participation: tradeoffs

  -Privacy (Aivodji et al. 2016)
  -Quality of service (Shen and Lopes, 2015)
  -Reputation and trust (Furuhata 2013)



- Selfish behavior vs public good

  -Price of anarchy can be quite high (Shen et al. 2017; Youn et al. 2008)

Cost when passengers' behavior follow worst user equilibria

$$PoA = \frac{\max_{s \in Equil} Cost(s)}{\min_{s \in S} Cost(s)}$$

Cost when system achieves optimal efficiency

Photo credit: NYT, KABC-TV

Toward Understanding the Impact of User Participation in Dynamic Ridesharing

Photo credit: Business Insider

Outline

- Dynamic Ridesharing
- Method: Simulation Framework
- Data and Experimental Design
- Results
- Conclusion and future work

Dynamic Ridesharing

- Trip-Vehicle Assignment

- Modeling User Participation

Trip-Vehicle Assignment

- Heuristic algorithms do not scale
    - Branch-and-cut: up to 32 users (Cordeau 2006)
    - Annealing meta-heuristic algorithm: 100 users (Braekers et al. 2014)
    - Dynamic programming and large neighborhood search: up to 144 users (Ritzinger et al. 2016)

Trip-Vehicle Assignment

- Graph-theoretic approaches:
  - Shareability Networks: static, up to three passengers per vehicle (Santi et al. 2014)
  - An anytime algorithm: dynamic, high capacity, up to ten passengers per vehicle (Alonso-Mora et al. 2017)

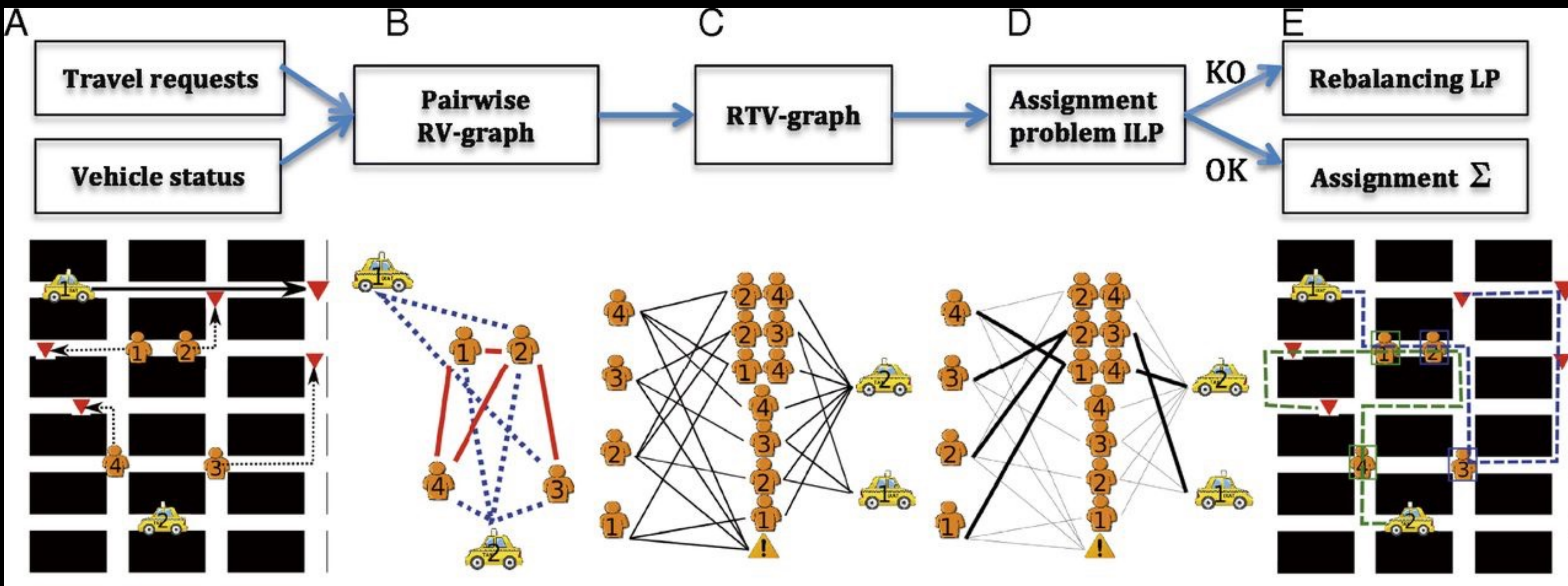


Photo credit; Alonso-Mora et al. 2017

Modeling User Participation

- Traditional approaches

  -Well defined games with complete information, e.g., selfish routing (Roughgarden 2005), finite congestion game (Christodoulou and Koutsoupias, 2005)

  -Assume that agents' utilities are determined by a unified function or drawn from a known probability distribution (Shen,Lopes and Crandall, 2016; Zhao et al. 2014)

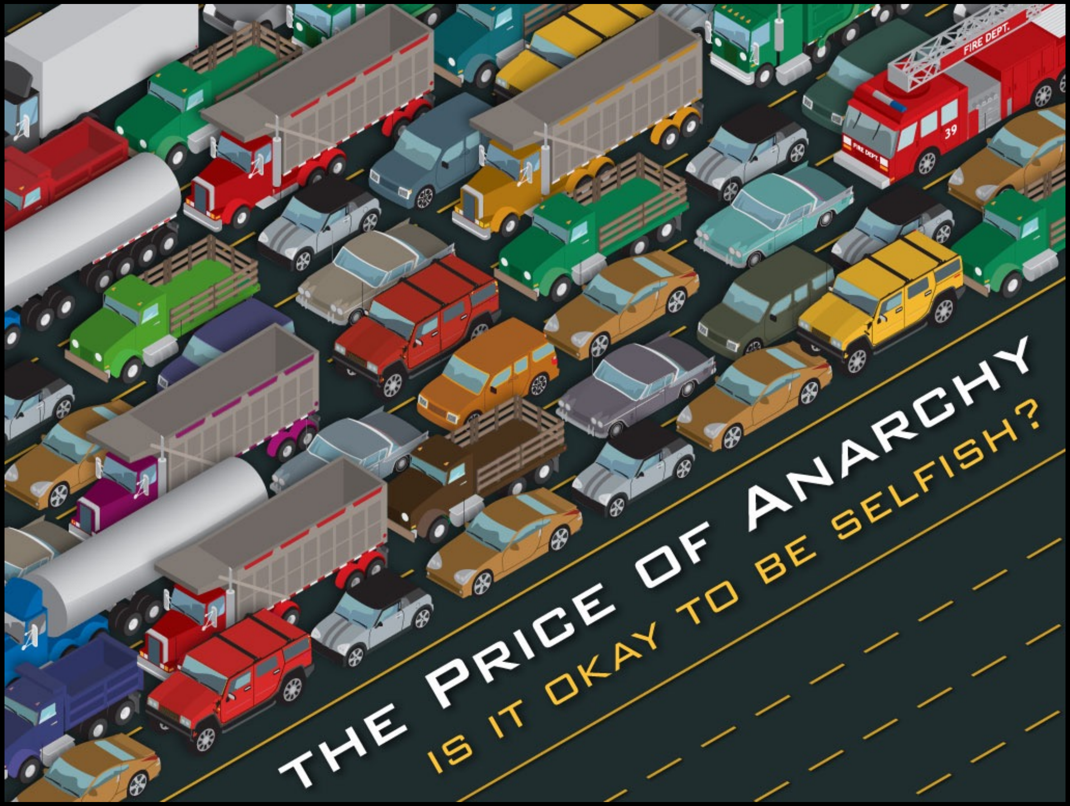
- Our approach

  - Different (varying) levels of user participation

  - Detailed simulation based on real-world data

Research Questions

- How do the levels of user participation influence the performance of dynamic ridesharing?
- To what extent passengers' uncoordinated behavior on ridesharing participation diminishes the efficiency of dynamic ridesharing systems?

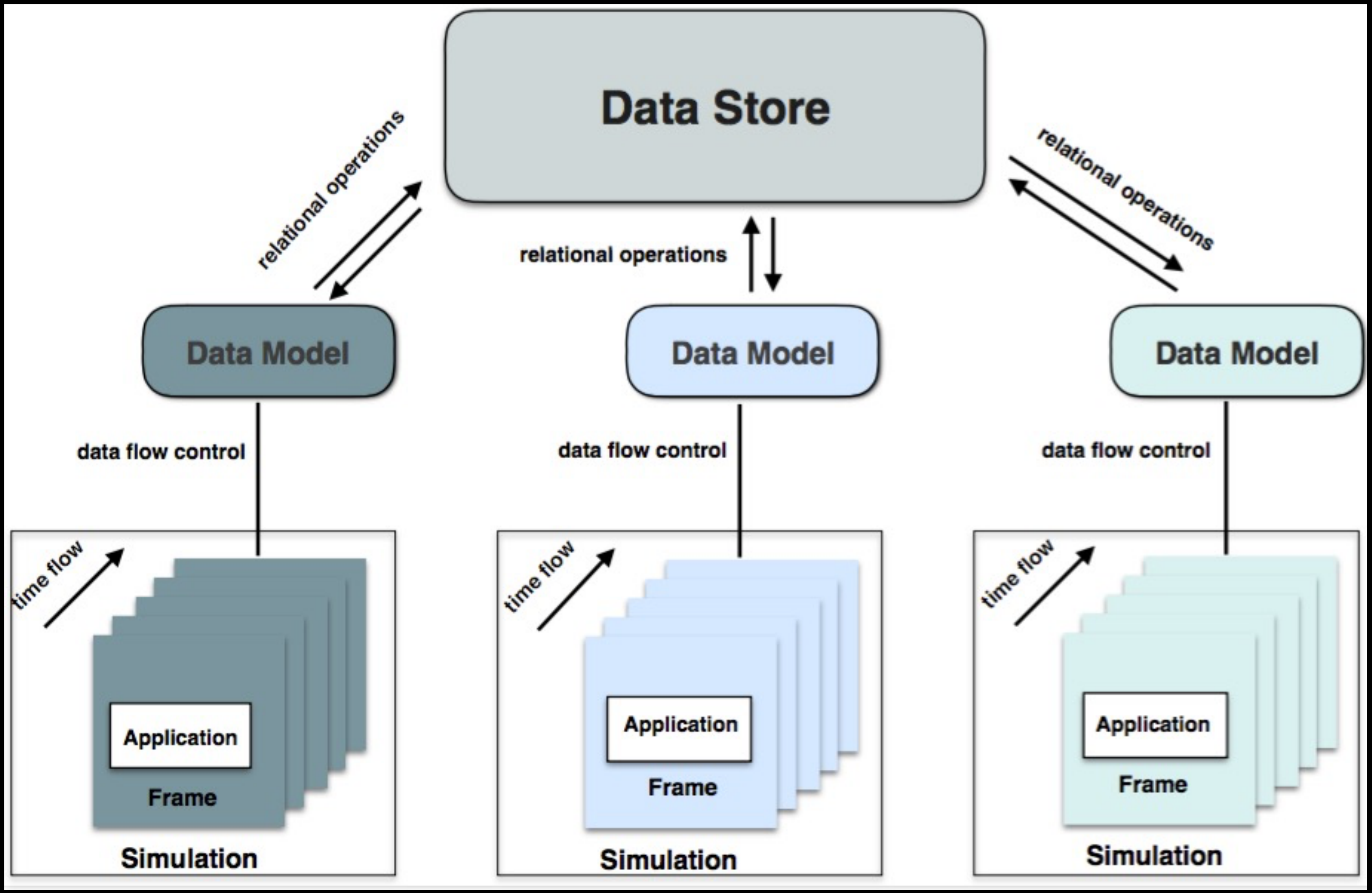


Outline

- Dynamic Ridesharing
- Method: Simulation Framework
- Data and Experimental Design
- Results
- Conclusion and future work

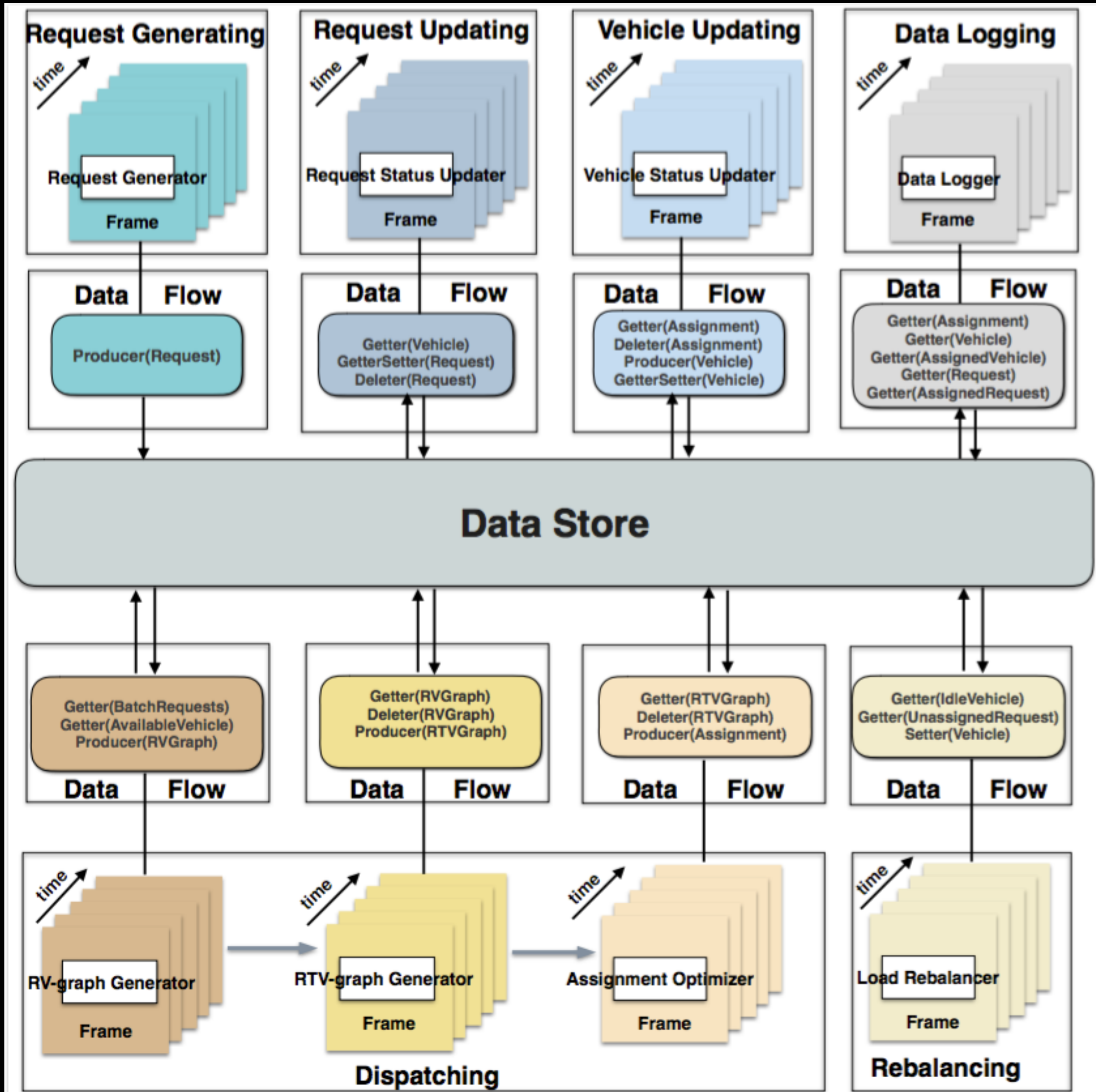
Reducing Simulation Complexity

- Spacetime (Lopes et al. 2017)



SpaceTime for Dynamic Ridesharing (STDR)

- Anytime algorithm for trip-vehicle assignment
- Spacetime for a modular design
- A data-driven approach for simulating city-scale ridesharing systems



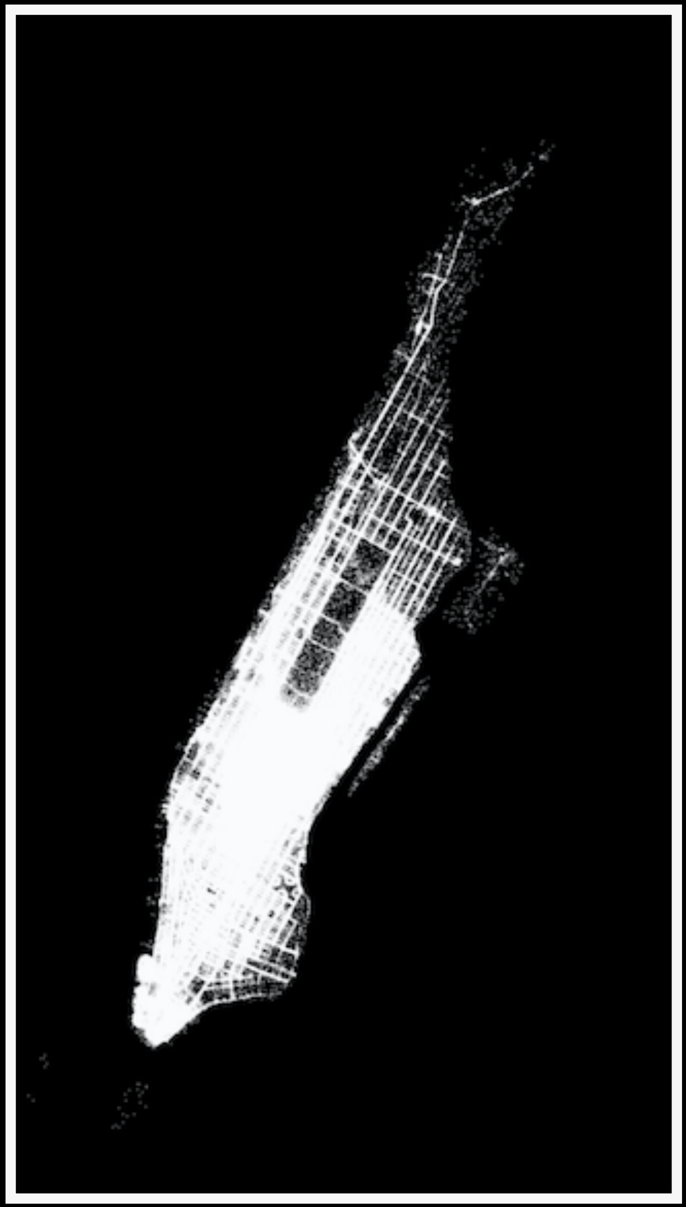
Request Generating
time
Request Generator
Frame
Data Flow
Producer(Request)
Request Updating
time
Request Status Updater
Frame
Data Flow
Getter(Vehicle)
GetterSetter(Request)
Deleter(Request)
Vehicle Updating
time
Vehicle Status Updater
Frame
Data Flow
Getter(Assignment)
Deleter(Assignment)
Producer(Vehicle)
GetterSetter(Vehicle)
Data Logging
time
Data Logger
Frame
Data Flow
Getter(Assignment)
Getter(Vehicle)
Getter(AssignedVehicle)
Getter(Request)
Getter(AssignedRequest)
Data Store
Getter(BatchRequests)
Getter(AvailableVehicle)
Producer(RVGraph)
Data Flow
Getter(RVGraph)
Deleter(RVGraph)
Producer(RTVGraph)
Data Flow
Getter(RTVGraph)
Deleter(RTVGraph)
Producer(Assignment)
Data Flow
Getter(IdleVehicle)
Getter(UnassignedRequest)
Setter(Vehicle)
Data Flow
time
RV-graph Generator
Frame
time
RTV-graph Generator
Frame
time
Assignment Optimizer
Frame
Dispatching
time
Load Rebalancer
Frame
Rebalancing

Outline

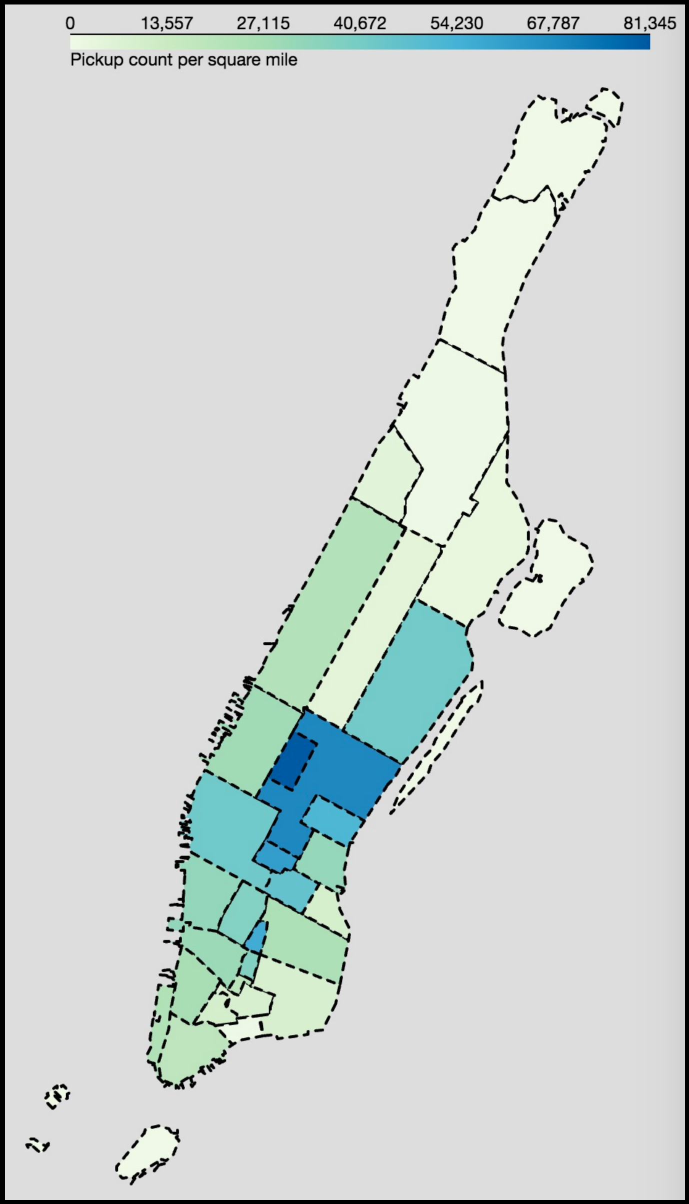
- Dynamic Ridesharing
- Method: Simulation Framework
- Data and Experimental Design
- Results
- Conclusion and future work

Data

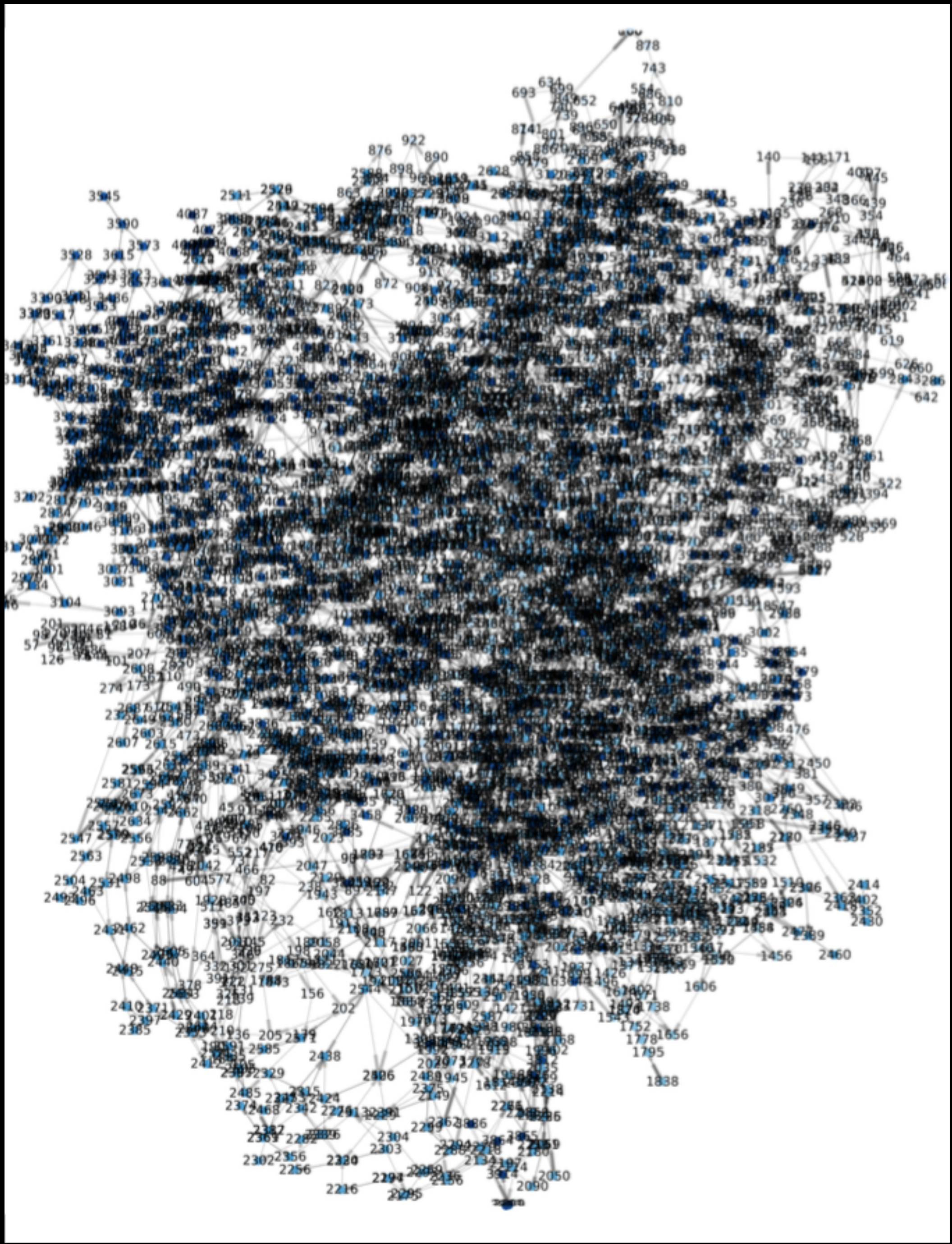
- New York City Taxi dataset: A typical week (June 6th - June 12th, 2011) in Manhattan
- 3,014,628 trips ranging from 391,246 (Sat.) to 465,331(Mon.) per day, serviced by a fleet of 13,586 taxis
- Each trip: pickup datetime, drop-off datetime, passenger count, pickup longitude, pickup latitude, drop-off longitude, and drop-off latitude
- Road network: Manhattan (extracted from OpenStreetMap)



Request distribution of Manhattan (06/08/2011)



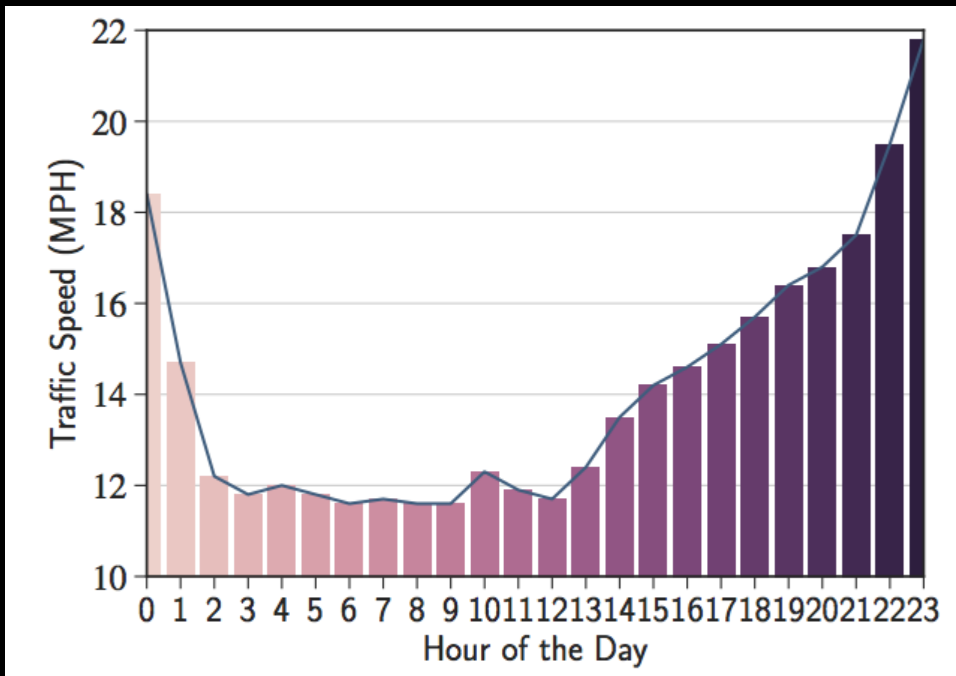
Request density by neighborhood of Manhattan (06/08/2011)



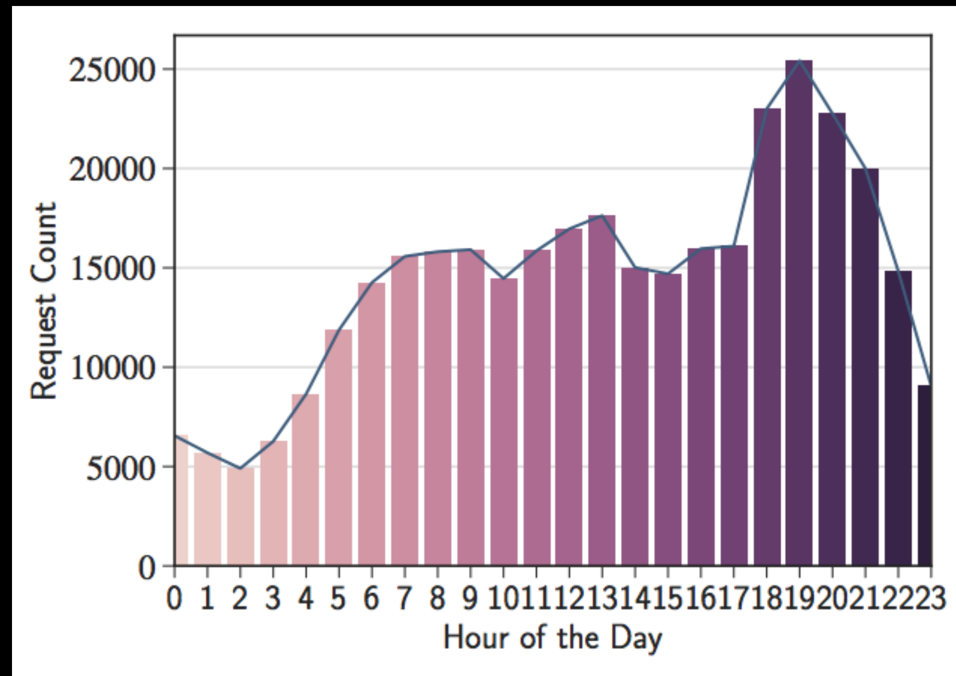
Road graph of Manhattan (4,092 nodes, 9,453 edges)

Independent Variables

- Varying the levels (0%, 10%, …, 100%) of user participation for different systems
    - Size of vehicle fleet: 1000, 2000, 3000, 4000
    - Vehicle capacity: 1, 2, 4, 6, 8, 10
    - Maximum waiting time (min): 2, 4, 6, 8
- Varying request density and traffic conditions (fleet = 3000, capacity = 4, max. waiting = 6)
    - Density: half of the demand, normal demand, double of the demand
    - travel time estimate: 12:00 (lowest speed), 19:00 (highest speed), mean daily travel time estimate (average speed)



Average traffic speed (MPH) per hour on Wednesday, 06/08, 2011



Count of requests per hour on Wednesday, 06/08, 2011

Dependent Variables

- Total cost

$$C(p) = \sum_{r \in R_o} \delta_r + \sum_{r \in R_d} c_d$$

travel delay for all serviced requests

cost for all the denied requests

- Price of anarchy

$$PoA = \frac{\max_{p \in P_{sue}} C(p)}{\min_{p \in P} C(p)}$$

the total cost when passengers' decisions on participation are under the worst user equilibria

the total cost when the system achieves optimal efficiency

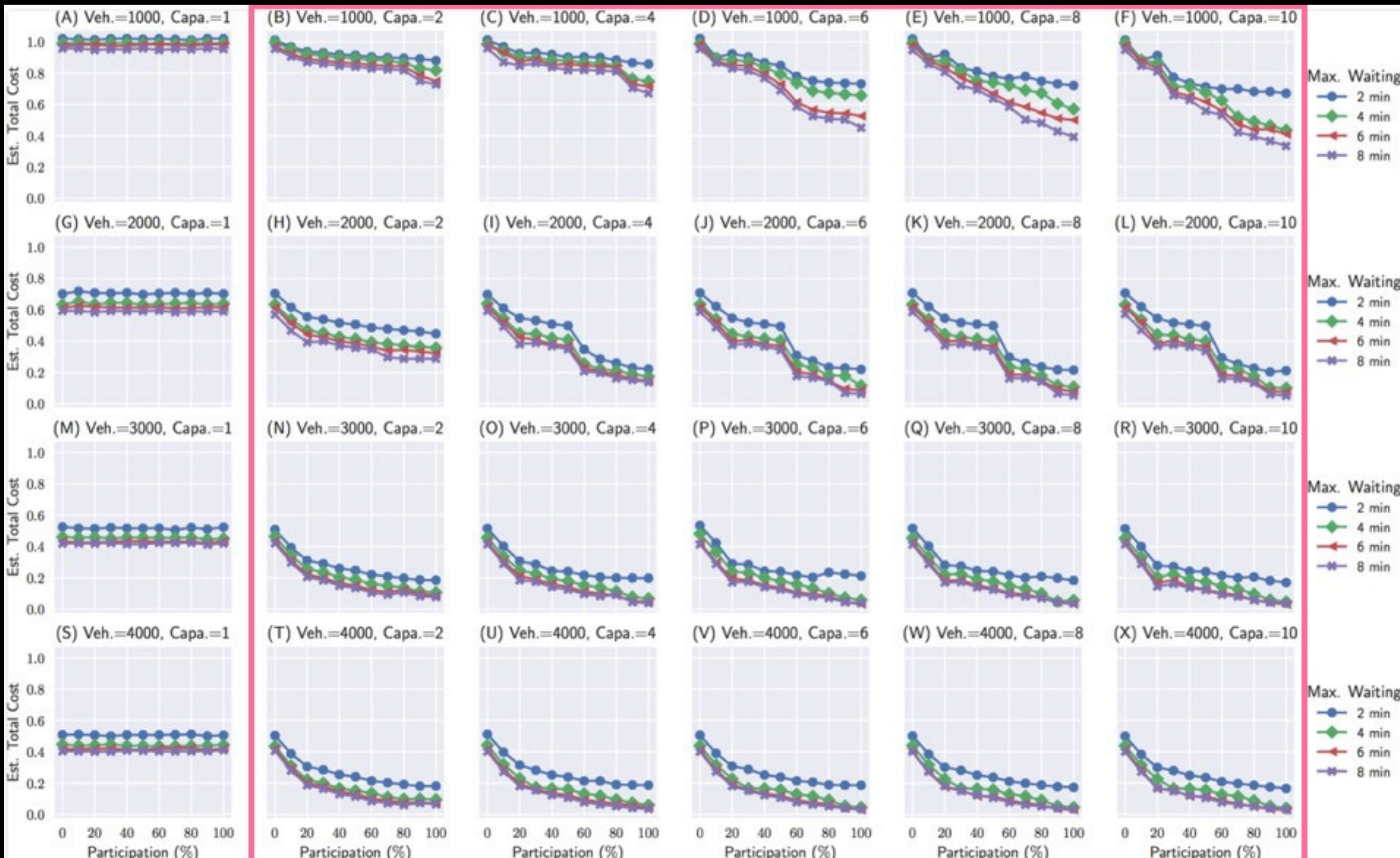
Simulation setup

- Hardware
  - 24-core 3.0 GHz
  - 128GB RAM
- Solver
  - Gurobi academic version 7.0.2
- Accelerating simulation: 0.1 (discounting factor)
- Number of simulations: 1,122
- Five weeks

Outline

- Dynamic Ridesharing
- Method: Simulation Framework
- Data and Experimental Design
- Results
- Conclusion and future work

Total Cost

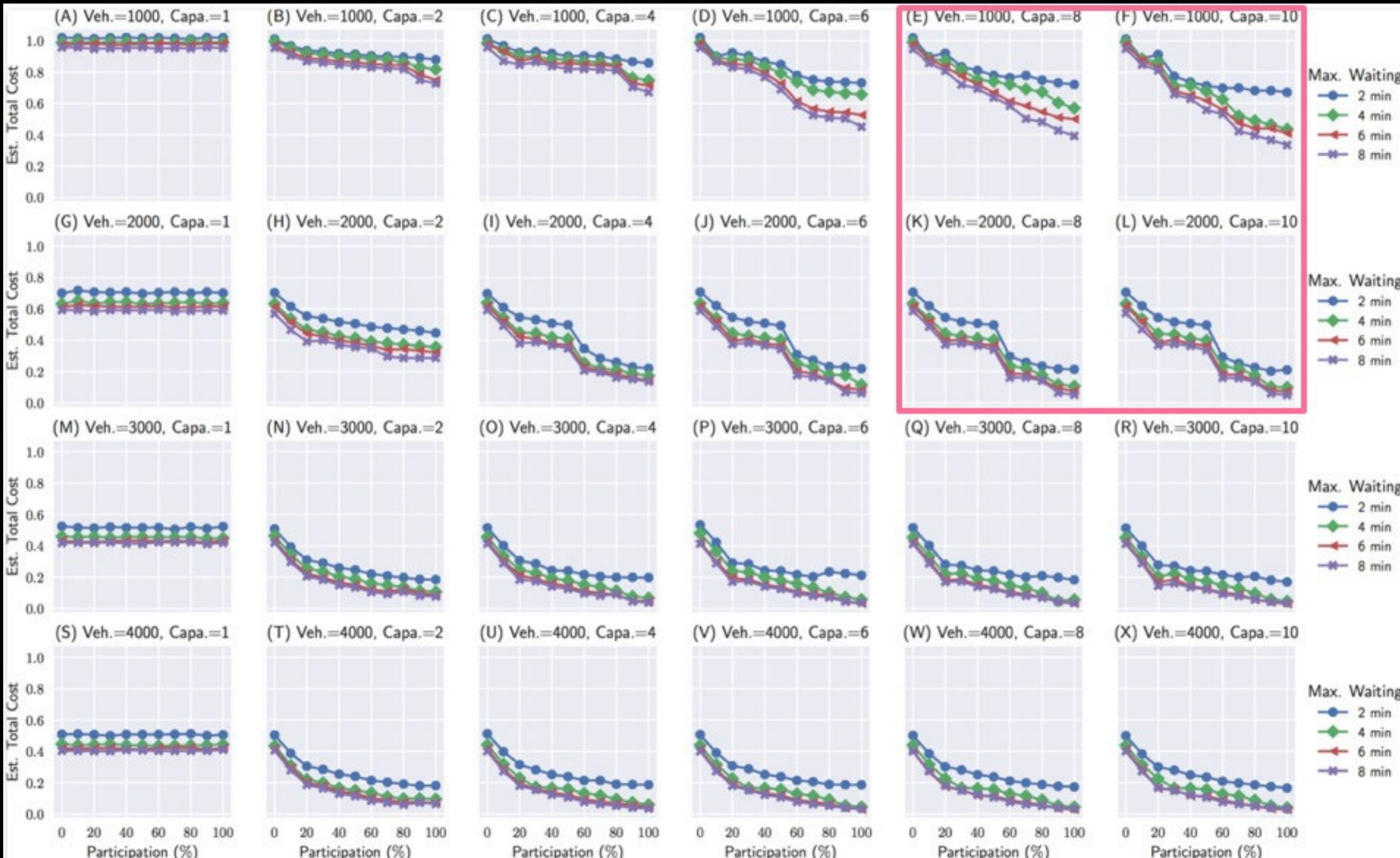


(A) Veh.=1000, Capa.=1
(B) Veh.=1000, Capa.=2
(C) Veh.=1000, Capa.=4
(D) Veh.=1000, Capa.=6
(E) Veh.=1000, Capa.=8
(F) Veh.=1000, Capa.=10
(G) Veh.=2000, Capa.=1
(H) Veh.=2000, Capa.=2
(I) Veh.=2000, Capa.=4
(J) Veh.=2000, Capa.=6
(K) Veh.=2000, Capa.=8
(L) Veh.=2000, Capa.=10
(M) Veh.=3000, Capa.=1
(N) Veh.=3000, Capa.=2
(O) Veh.=3000, Capa.=4
(P) Veh.=3000, Capa.=6
(Q) Veh.=3000, Capa.=8
(R) Veh.=3000, Capa.=10
(S) Veh.=4000, Capa.=1
(T) Veh.=4000, Capa.=2
(U) Veh.=4000, Capa.=4
(V) Veh.=4000, Capa.=6
(W) Veh.=4000, Capa.=8
(X) Veh.=4000, Capa.=10
Est. Total Cost
0.0
0.2
0.4
0.6
0.8
1.0
Participation (%)
0
20
40
60
80
100
Max. Waiting
2 min
4 min
6 min
8 min

Performance improves as participation increases

- Observation 1: User participation typically improves the performance of dynamic ridesharing systems, but the degree of improvement generally slows down as user participation increases to a high level.

Total Cost

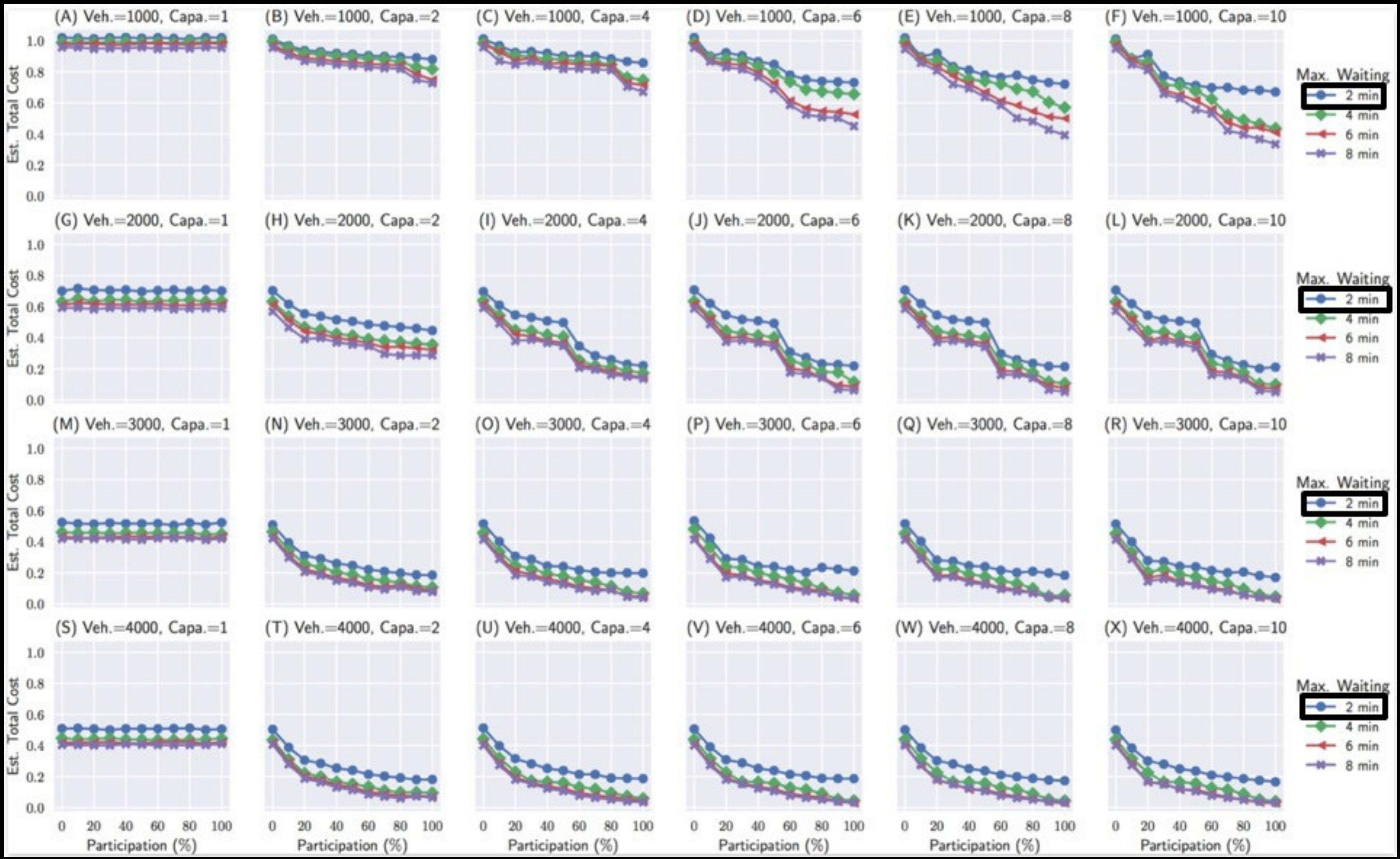


(A) Veh.=1000, Capa.=1
(B) Veh.=1000, Capa.=2
(C) Veh.=1000, Capa.=4
(D) Veh.=1000, Capa.=6
(E) Veh.=1000, Capa.=8
(F) Veh.=1000, Capa.=10
(G) Veh.=2000, Capa.=1
(H) Veh.=2000, Capa.=2
(I) Veh.=2000, Capa.=4
(J) Veh.=2000, Capa.=6
(K) Veh.=2000, Capa.=8
(L) Veh.=2000, Capa.=10
(M) Veh.=3000, Capa.=1
(N) Veh.=3000, Capa.=2
(O) Veh.=3000, Capa.=4
(P) Veh.=3000, Capa.=6
(Q) Veh.=3000, Capa.=8
(R) Veh.=3000, Capa.=10
(S) Veh.=4000, Capa.=1
(T) Veh.=4000, Capa.=2
(U) Veh.=4000, Capa.=4
(V) Veh.=4000, Capa.=6
(W) Veh.=4000, Capa.=8
(X) Veh.=4000, Capa.=10
Est. Total Cost
Participation (%)
Max. Waiting
2 min
4 min
6 min
8 min

Greater impact when equipped with small fleets of high-capacity vehicles

- Observation 2: User participation typically has a greater impact on the performance of dynamic ridesharing systems with small fleets of high-capacity vehicles.

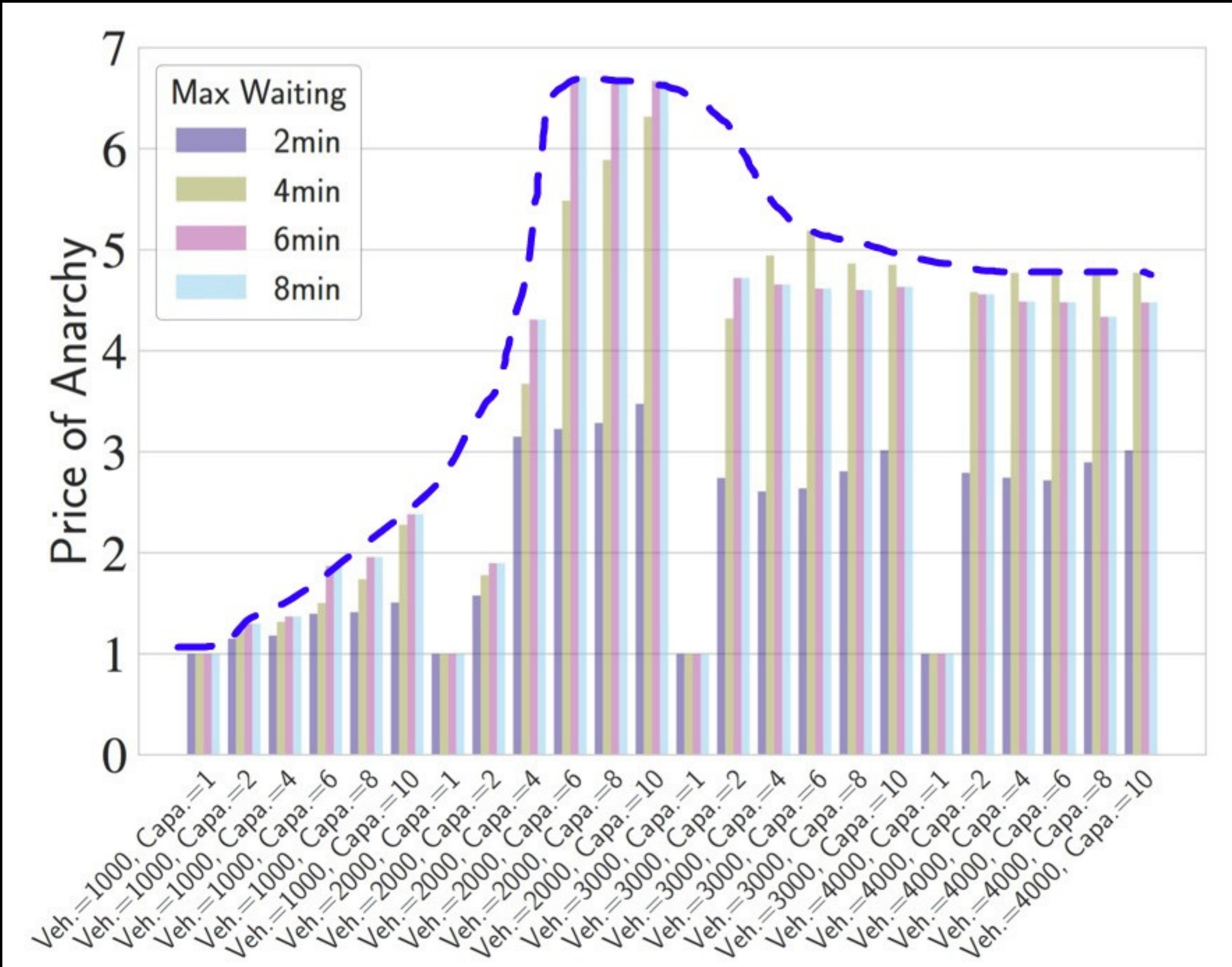
Total Cost



(A) Veh.=1000, Capa.=1
(B) Veh.=1000, Capa.=2
(C) Veh.=1000, Capa.=4
(D) Veh.=1000, Capa.=6
(E) Veh.=1000, Capa.=8
(F) Veh.=1000, Capa.=10
(G) Veh.=2000, Capa.=1
(H) Veh.=2000, Capa.=2
(I) Veh.=2000, Capa.=4
(J) Veh.=2000, Capa.=6
(K) Veh.=2000, Capa.=8
(L) Veh.=2000, Capa.=10
(M) Veh.=3000, Capa.=1
(N) Veh.=3000, Capa.=2
(O) Veh.=3000, Capa.=4
(P) Veh.=3000, Capa.=6
(Q) Veh.=3000, Capa.=8
(R) Veh.=3000, Capa.=10
(S) Veh.=4000, Capa.=1
(T) Veh.=4000, Capa.=2
(U) Veh.=4000, Capa.=4
(V) Veh.=4000, Capa.=6
(W) Veh.=4000, Capa.=8
(X) Veh.=4000, Capa.=10
Est. Total Cost
Participation (%)
Max. Waiting
2 min
4 min
6 min
8 min

Smaller impact for systems with a short maximum waiting time

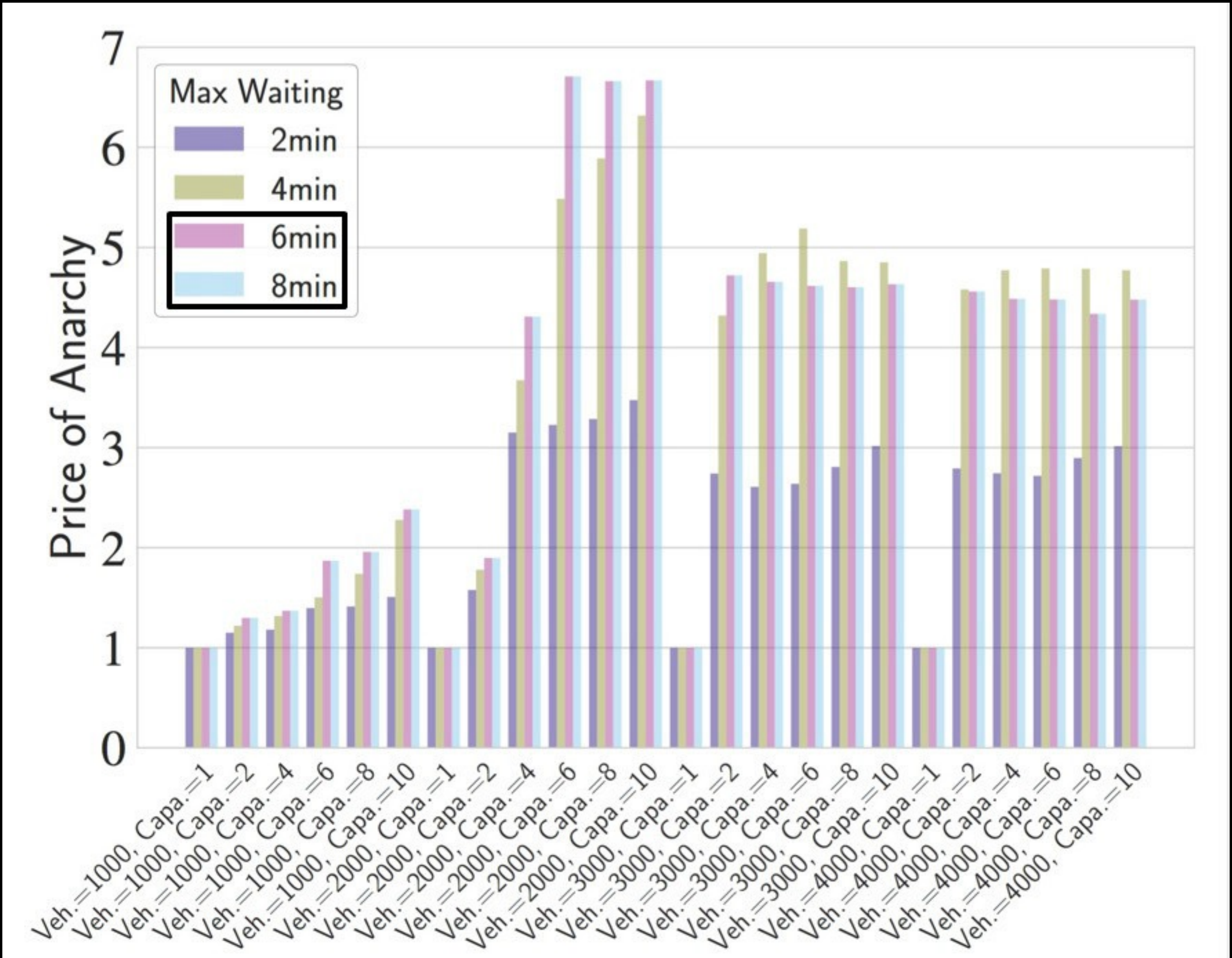
- Observation 3: User participation typically has a smaller impact on the performance of dynamic ridesharing systems with a short period of maximum waiting time allowed.



Max Waiting
2min
4min
6min
8min
Price of Anarchy
0
1
2
3
4
5
6
7
Veh.=1000, Capa.=1
Veh.=1000, Capa.=2
Veh.=1000, Capa.=4
Veh.=1000, Capa.=6
Veh.=1000, Capa.=8
Veh.=1000, Capa.=10
Veh.=2000, Capa.=1
Veh.=2000, Capa.=2
Veh.=2000, Capa.=4
Veh.=2000, Capa.=6
Veh.=2000, Capa.=8
Veh.=2000, Capa.=10
Veh.=3000, Capa.=1
Veh.=3000, Capa.=2
Veh.=3000, Capa.=4
Veh.=3000, Capa.=6
Veh.=3000, Capa.=8
Veh.=3000, Capa.=10
Veh.=4000, Capa.=1
Veh.=4000, Capa.=2
Veh.=4000, Capa.=4
Veh.=4000, Capa.=6
Veh.=4000, Capa.=8
Veh.=4000, Capa.=10

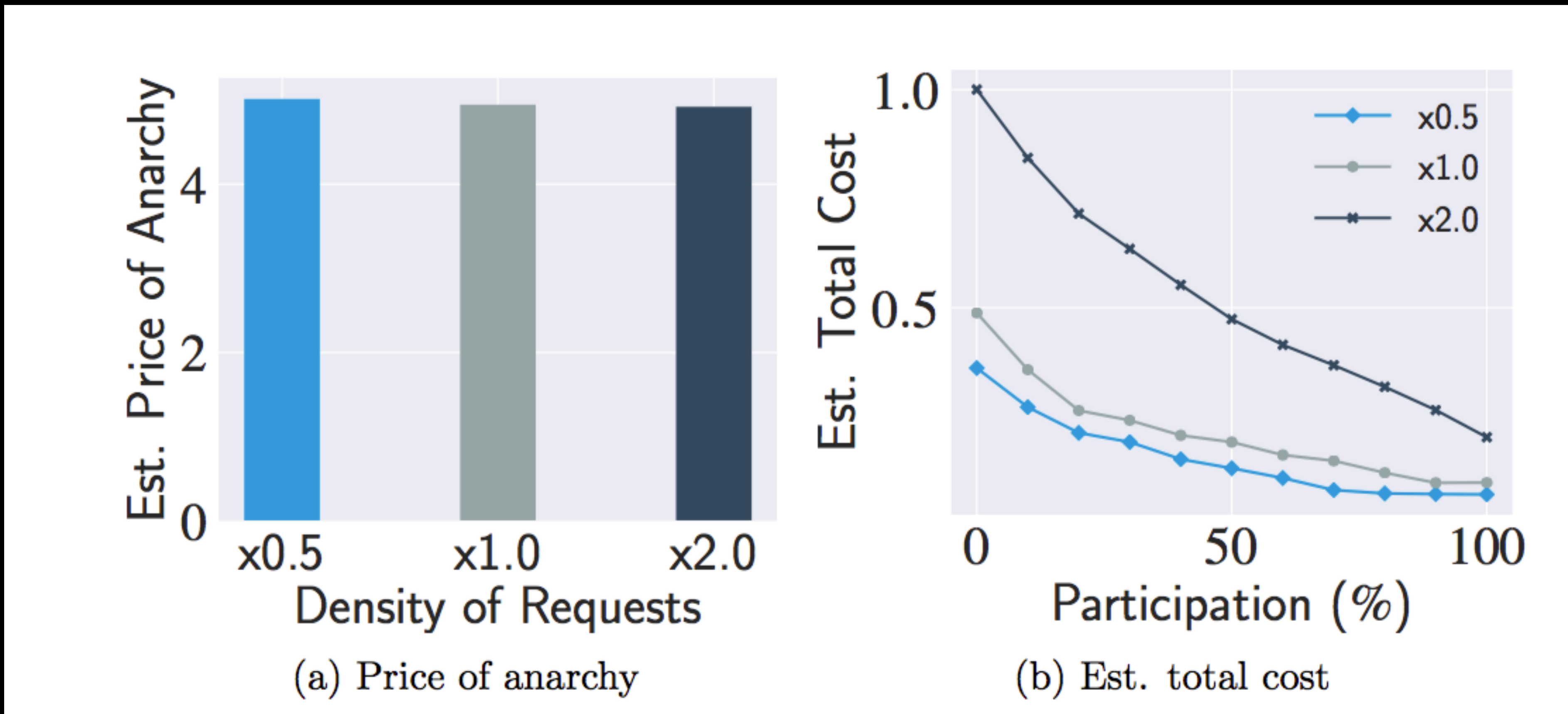
Price of anarchy increases and then decreases as fleet size increases

- Observation 4: As the fleet size increases, the price of anarchy due to users' uncoordinated choices on participation typically first increases and then decreases.

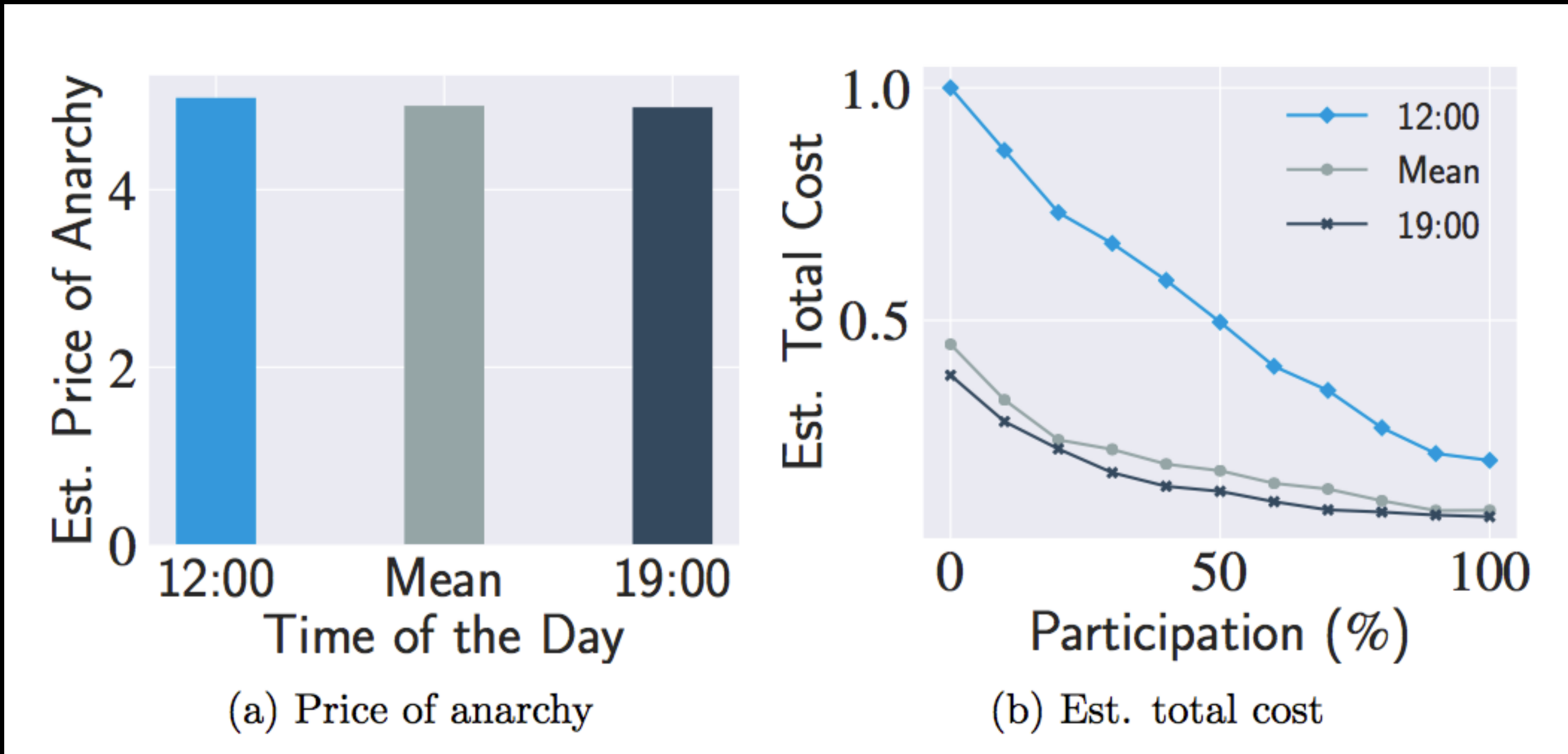

Max Waiting
2min
4min
6min
8min
Price of Anarchy
0
1
2
3
4
5
6
7
Veh.=1000, Capa.=1
Veh.=1000, Capa.=2
Veh.=1000, Capa.=4
Veh.=1000, Capa.=6
Veh.=1000, Capa.=8
Veh.=1000, Capa.=10
Veh.=2000, Capa.=1
Veh.=2000, Capa.=2
Veh.=2000, Capa.=4
Veh.=2000, Capa.=6
Veh.=2000, Capa.=8
Veh.=2000, Capa.=10
Veh.=3000, Capa.=1
Veh.=3000, Capa.=2
Veh.=3000, Capa.=4
Veh.=3000, Capa.=6
Veh.=3000, Capa.=8
Veh.=3000, Capa.=10
Veh.=4000, Capa.=1
Veh.=4000, Capa.=2
Veh.=4000, Capa.=4
Veh.=4000, Capa.=6
Veh.=4000, Capa.=8
Veh.=4000, Capa.=10

Price of anarchy keeps steady for systems with long maximum waiting time

- Observation 5: The price of anarchy due to users' uncoordinated choices on participation typically keeps steady when the maximum waiting time is sufficiently long.



A comparison of the price of anarchy and efficiency on a ridesharing system (fleet size = 3000, capacity = 4, and maximum waiting time = 6 mins) by varying request density



A comparison of the price of anarchy and efficiency on a ridesharing system (fleet size = 3000, capacity = 4, and maximum waiting time = 6 mins) by varying the time of the day used for travel time estimate.

Request density or traffic condition has litter impact on price of anarchy

- Observation 6: Request density or traffic condition typically has little impact on the price of anarchy, although the system efficiency generally increases when the request density reduces or the traffic condition improves.

Discussion

- What are the implications?
  - sweet spots exist
  - tradeoffs are needed
- Will the observations generalize?
  - not known yet

Outline

- Dynamic Ridesharing
- Method: Simulation Framework
- Data and Experimental Design
- Results
- Conclusion and future work

Conclusion

- Research question:
  - How and to what extent user participation influences the efficiency of dynamic ridesharing systems?
- Contributions:
  - Spacetime for Dynamic Ridesharing
  - An extensive empirical study
- Take-aways:
  - Specific configurations of ridesharing systems can be identified to counter the effect of passengers' uncoordinated behavior regarding participation on the system efficiency
  - To achieve desired outcomes, stakeholders should make tradeoffs between system efficiency and price of anarchy based on realistic simulations with real-world data.

Future work

- Can we generalize the findings in other road networks?
- How to incentivize user participation?
- What if some parts of the ridesharing networks fail?

Autonomous Mobility on Demand Systems

Photo credit: Vox