Reinforcement Learning Approach for Improving Platform Performance in Two-Sided Mobility Markets

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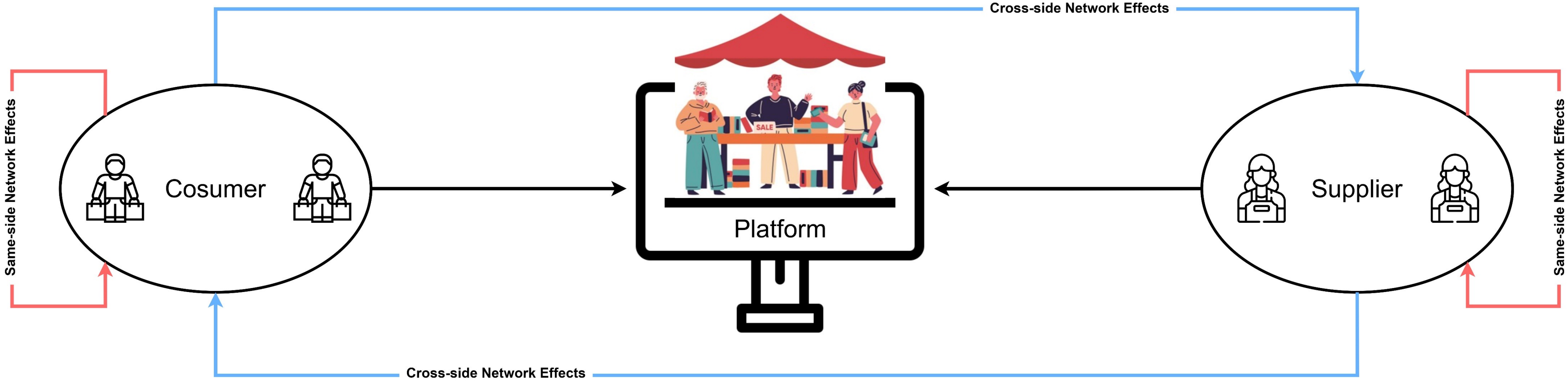
Highlights

- **MaaSSim** within-day microscopic simulator for two-sided platforms (on github)
- **MoMaS** (Two-sided Mobility Market Simulation) is a framework reproducing empirical growth patterns of platforms like Uber and Lyft.
- We reproduce variety of **platform growth trajectories** and reveal **complex non-nonlinear phenomena**
- Platforms control the market with fares, discounts, incentives, commissions – but what is the optimal strategy?
- We integrate **Reinforcement Learning** into MoMaS to optimize platform's performance by adaptive adjustment of commission rate.
- Our proposed **RL-based strategy** outperforms rule-based strategy of existing platforms in the market (Uber case study).

Two-sided Business Model



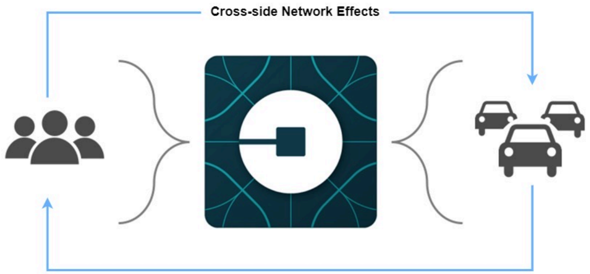
- Cross-side/Same-side NE: the value for one side of a network increases/decreases by adding users to the other/same side

- With positive NE utility and with negative NE disutility is produced

Two-sided Mobility Market

- Travellers make trip request
- Drivers supplies travelers' mobility need
- Platforms match demand to supply (private & pooled)

- Policymakers/Regulators
- General public



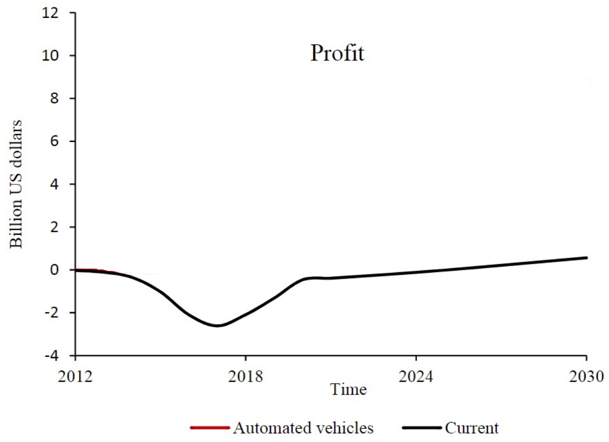
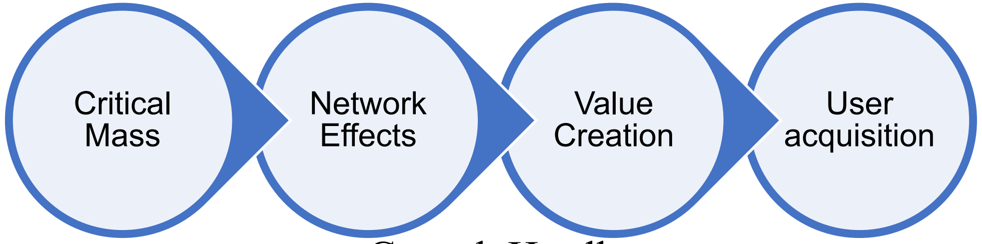


Fig 1. Uber profitability and the impact of AVs (Sun et al., (2022))

Two-sided mobility Market



Growth Hurdles:

1. Decentralized supply and demand
2. Conflicting interests of parties
3. Regulations

Understanding how platforms grow and what is their optimal growth pattern is of paramount importance not only to the platforms themselves, but also to other stakeholders (policy makers, general public), interested in predicting and controlling their potentially disruptive impact on the economy.

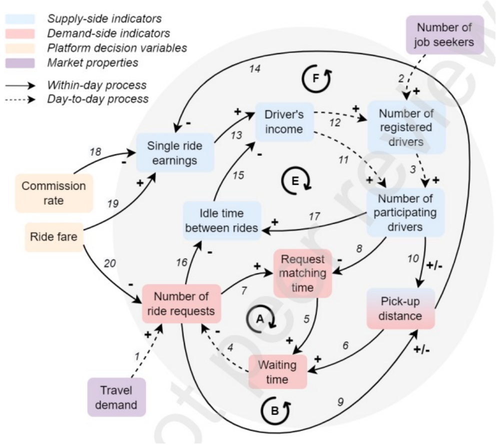


Fig 2. Conceptual representation of the ride-sourcing market (de Ruijter et al.,(2022))

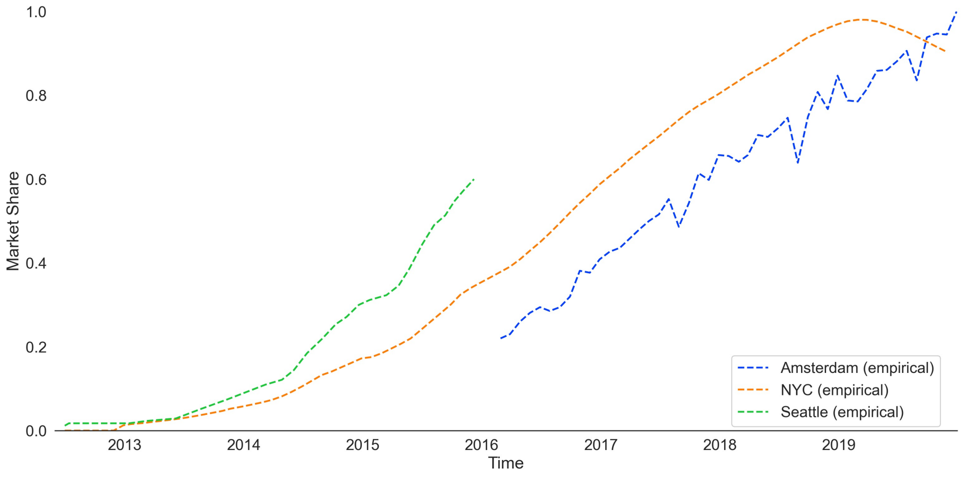


Fig 3. Empirical growth patterns for two-sided mobility platforms.

Methods: MoMaS Framework

MoMaS (Two-sided Mobility Market Simulation) is an adaptive, co-evolutionary framework built upon MaaSSim to capture the day-to-day dynamics of ride-sourcing system and reproduce the platform's growth mechanism.

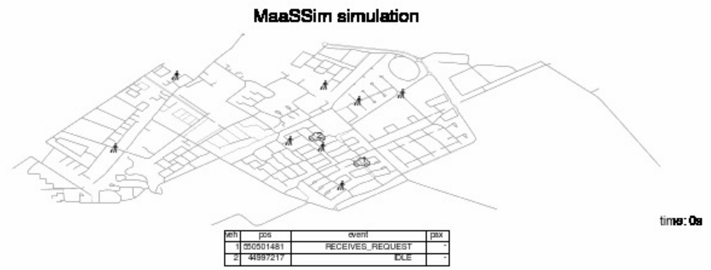


Fig 4. MaSSim simulator

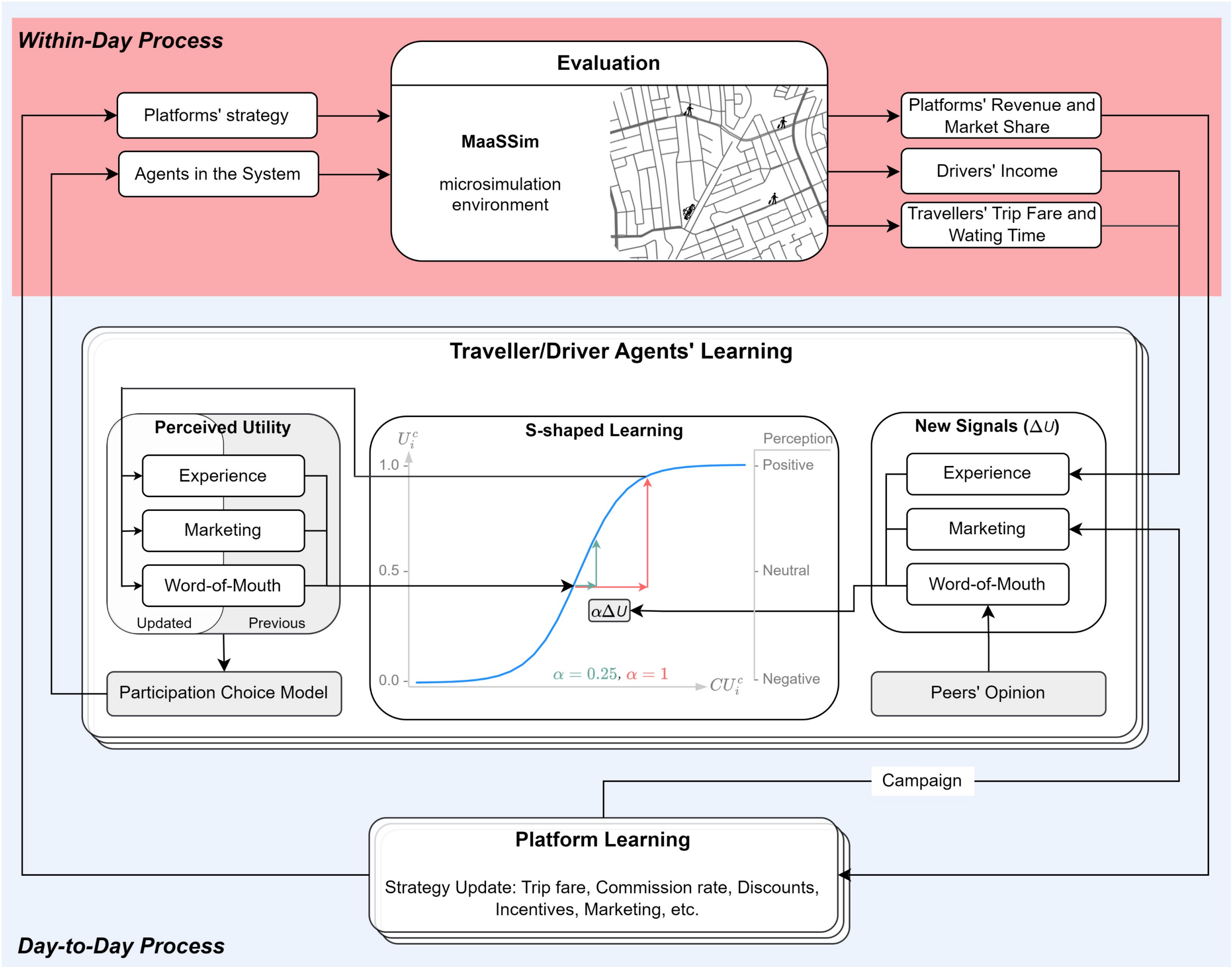


Fig 5. MoMaS at a glance.

Methods: RL-based Strategy

We model the platform as an RL agent employing the DQN algorithm with a delayed reward model to adjust the commission rate.

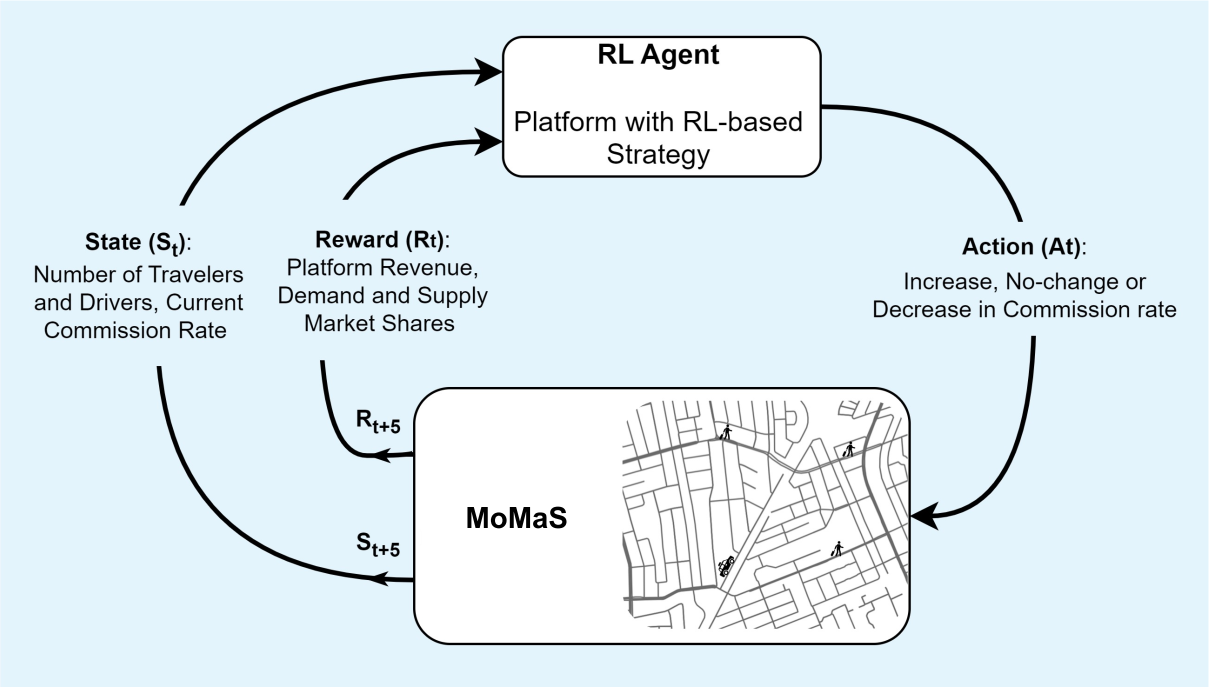
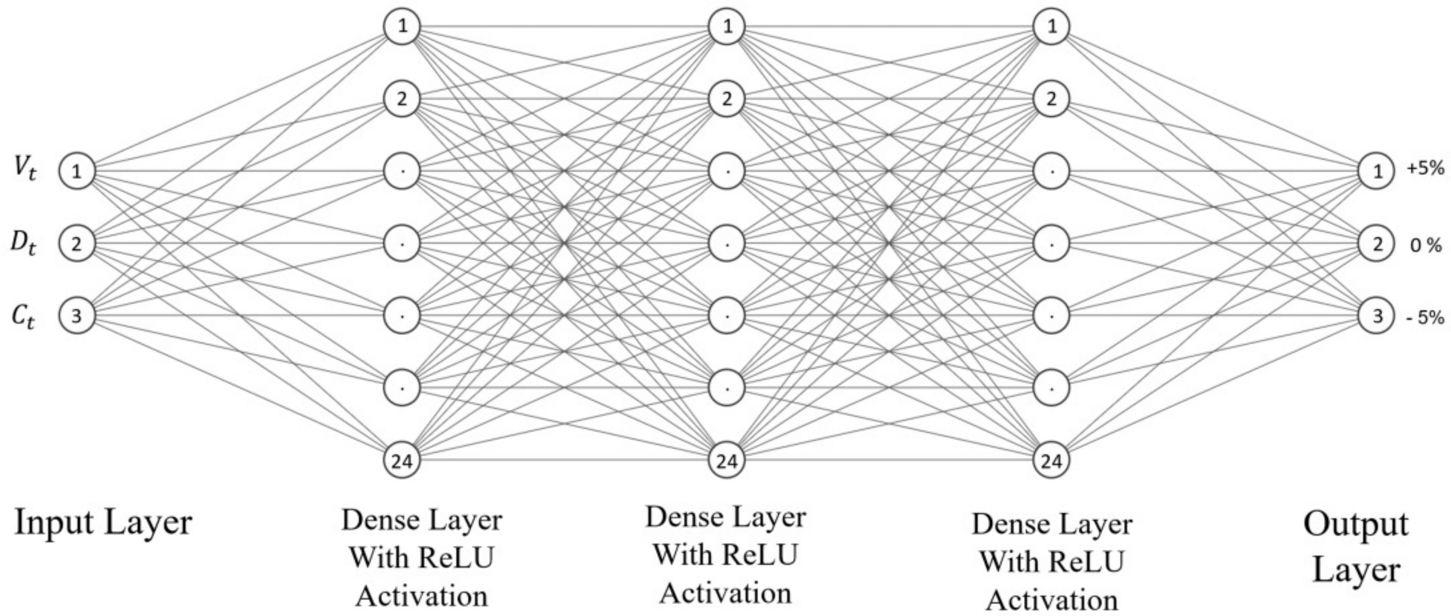


Fig 6. Proposed RL-based strategy model with the delayed reward for adjusting platform commission rate.

Methods: RL-architecture

3 input neurons for 3 state parameters,
3 dense hidden layers each of 24 neurons,
and a dense output layer with three neurons for three actions

We use Mean Squared Error (MSE) as the loss function, ReLU as the hidden layer activation function, and linear as the output layer activation function. We set the learning rate to 0.001 with epsilon decay of 0.995.



Methods: RL Model Formalization

State: The state S_t at time step t is represented with the number of travelers using the platform (V_t), the number of drivers working for the platform (D_t), and the current commission rate (C_t):

$$S_t = \{V_t, D_t, C_t\}$$

Actions: The action space of the platform includes *increase, no-change, or decrease* current commission rate, each associated with a step size of 0.05. Upon selecting an action a in time step t, the platform adjusts the commission rate and maintains it for the next 5 days period:

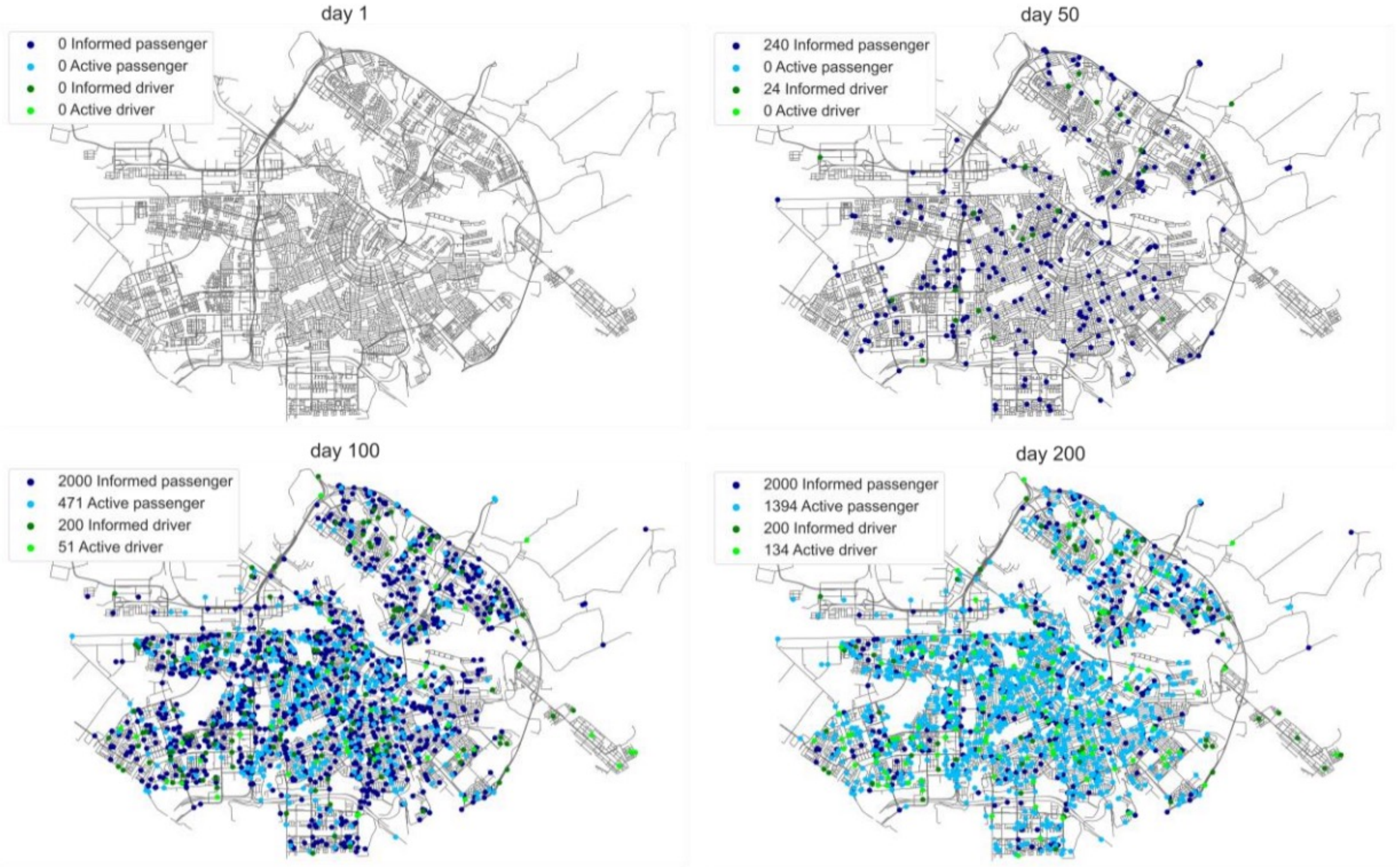
$$A_t = \{increase, \quad no - change, \quad decrease\}$$

Reward: The reward R_t is computed as the equally weighted sum of three factors: i) the platform revenue indicator, i.e., platform revenue divided by max recorded revenue (Fmax), ii) the demand market share, and iii) the supply market share. The reward is computed at the end of each time step:

$$R_t = \frac{F_t}{3F_{max}} + \frac{V_t}{3M_V} + \frac{D_t}{3M_D}$$

Results: Amsterdam Case Study with a Pool of 2000 Travelers and 200 Drivers

We simulate 2000 days of Amsterdam and let the platform grow



Results: Amsterdam Case Study with a Pool of 2000 Travelers and 200 Drivers

We compare the performance of the proposed **RL-based strategy** against the **rule-based strategy** over a period of 2000 days. RL-based strategy results in 12% improvement in platforms revenue.

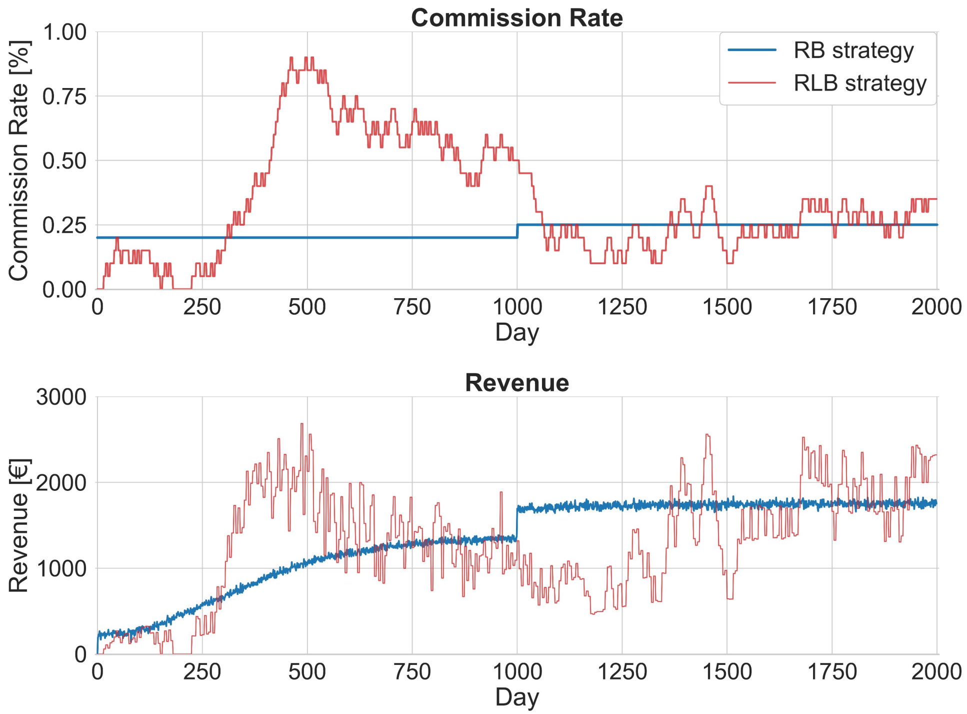


Fig 7. Commission rate and revenue of the platform under the rule-based (blue) and RL-based (red) strategies

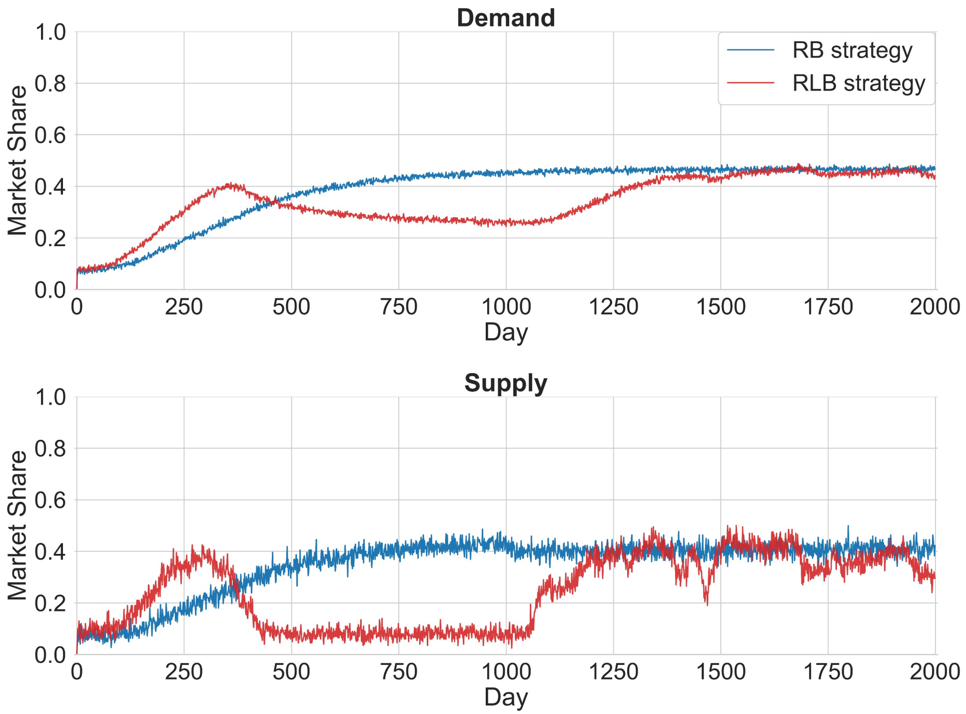


Fig 8. Platform market shares on both the demand and supply sides under the rule-based (blue) and RL-based (red) strategies

Results: Amsterdam Case Study with a Pool of 2000 Travelers and 200 Drivers

The **RL-based strategy** effectively generates and controls the market phenomena which is the reason underlying performance improvement.

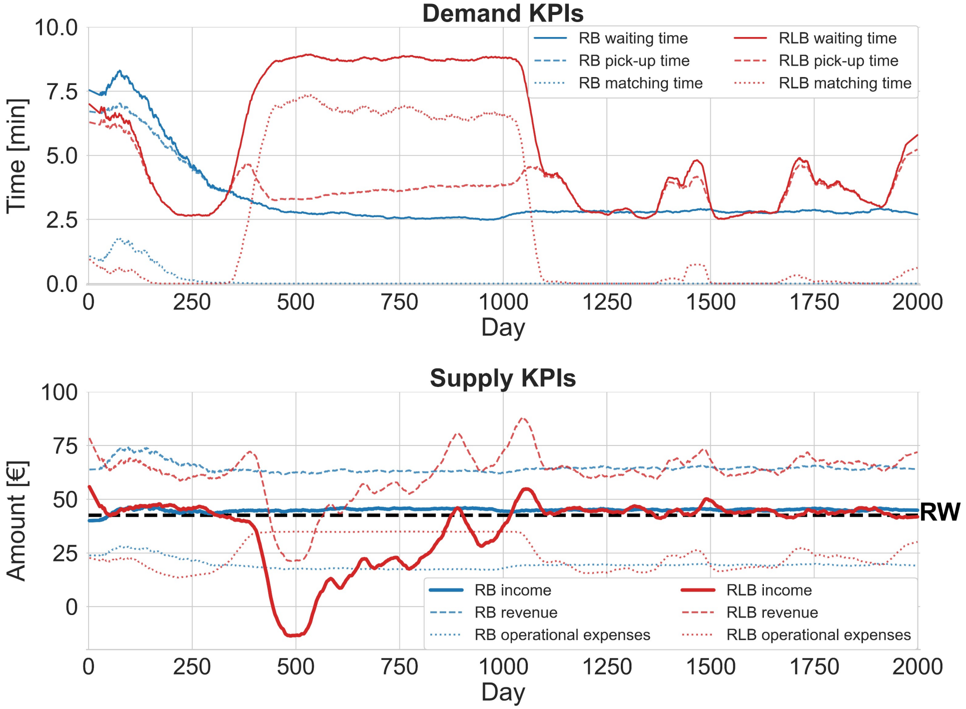


Fig 9. The evolution of the key performance indicators (KPIs) giving rise to cross-side network effects under the rule-based (blue) and RL-based (red) strategies in the market..

Takeaways

- We proposed a new RL strategy to optimize the performance of platforms like Uber through day-to-day adjustment of commission rate.

- We found that Reinforcement can improve the platform revenue without necessarily affecting the platform performance.

- RL-based strategies can effectively produce and better control the cross-side network effects in comparison to Rule-based strategies.

- Future studies may delve into more intricate strategies, incorporating additional tuning levers such as trip fares, discounts, and incentives within competitive multi-platform markets.

Thank you, questions?

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