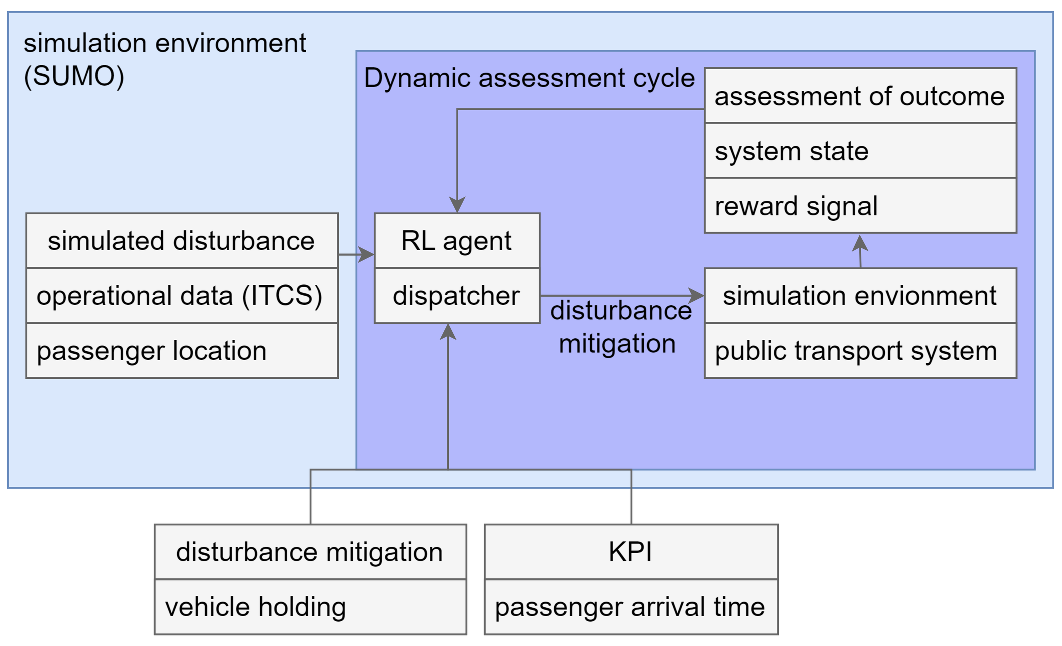
A digital twin for passenger centred intermodal disturbance management in public transport

Minimal Reinforcement Learning example for transfer coordination.
The optimal departure time of the connecting vehicle can be learned successfully.

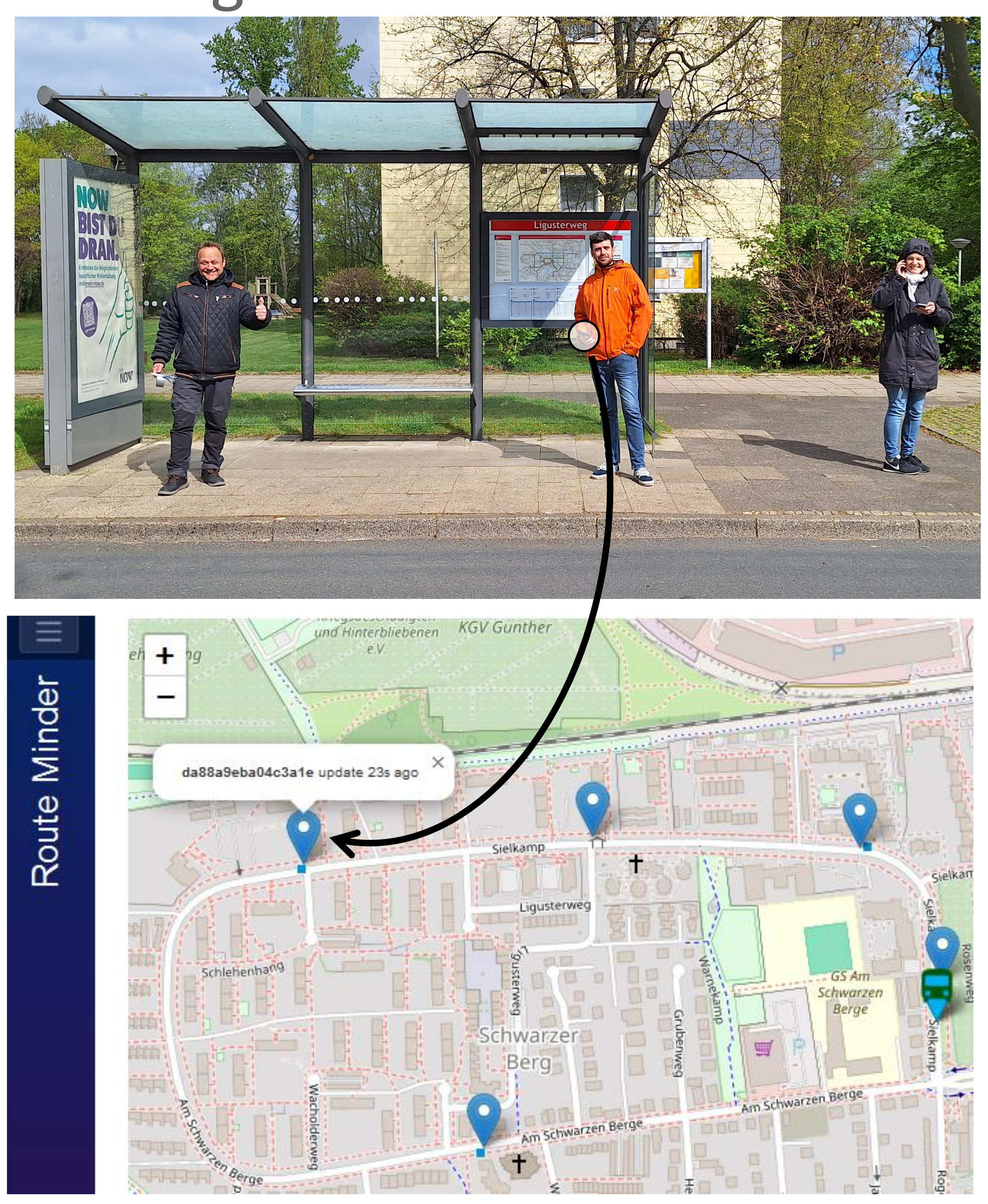
Passenger-centred disturbance management



Interaction between the SUMO based Reinforcement Learning (RL) environment and the dispatcher agent.

Current disturbance management in public transport (PT) focusses on minimising operational impacts. We propose passenger-centric inter-modal disturbance management system (PC-IDMS) to consider passengers' concerns during small disturbances.

Passenger localization



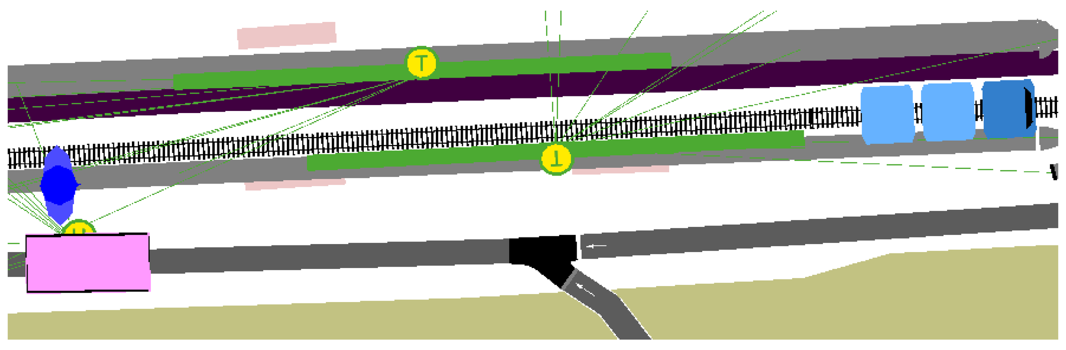
A BLE based smartphone application registers the passenger's location. These data are key for PC-IDMS. Within this minimal example we rely on simulated data.

Summary

- passenger-centred disturbance management (PC-IDMS) mitigates risk of connection loss at interchanges
- Reinforcement Learning can effectively apply transfer connection under uncertainty
- The minimal example yields promising results; other operational means will be integrated

SUMO minimal example

We simulate a small disturbance situation (missed connection) in a minimal example (2 vehicles, 1 passenger). Random traffic light phases influence the delayed arrival



Broken transfer: Feeding vehicle (pink) arrived, connecting vehicle (light blue) left without passenger

time of the feeding vehicle (pink bus). Furthermore, the passenger walking speed is random.

Reinforcement Learning for transfer coordination

State space

- Simulation time (continuous)
- Interchange time (continuous)
- Passenger waiting time (continuous)
- Passenger trip stage (discrete)
- Connecting vehicle trip stage (discrete)

Action space

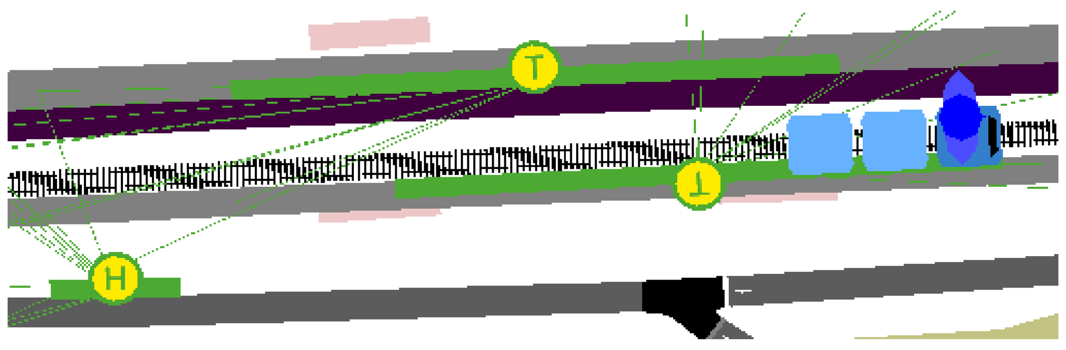
- Hold connecting vehicle for 60 s
- Make connecting vehicle leave stop

Reward function

$$r = \begin{cases} 200 + t_r & \textit{if arrived} \\ -100 & \textit{if not arrived} \\ t_{n,i} - t_{n,w} + d_{n,i} & \textit{else} \end{cases}$$

With remaining sim time t_r, normalized interchange time $t_{n,i}$, normalized waiting time $t_{n,w}$ and normalized distance between passenger and connecting vehicle at interchange $d_{n,i}$.

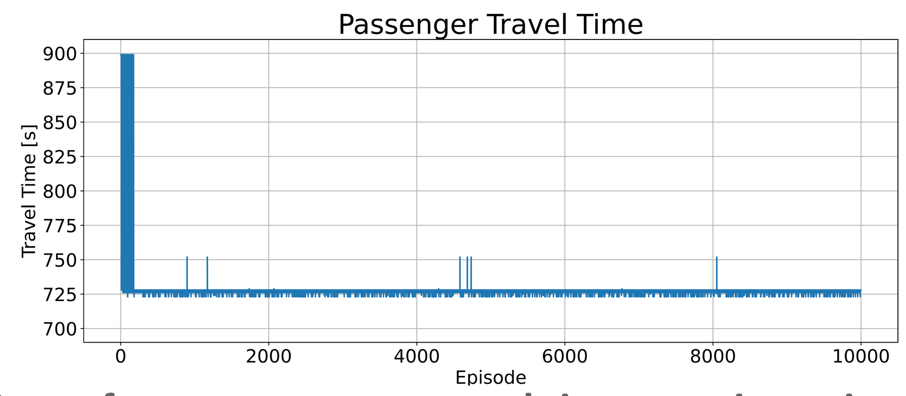
The RL agent can dispatch the departure time of the connecting vehicle to ensure the planned interchange. An episode ends after 900 s or if the passenger reaches the destination before.



Succeeded transfer: Passenger reached connecting vehicle and continues journey to destination

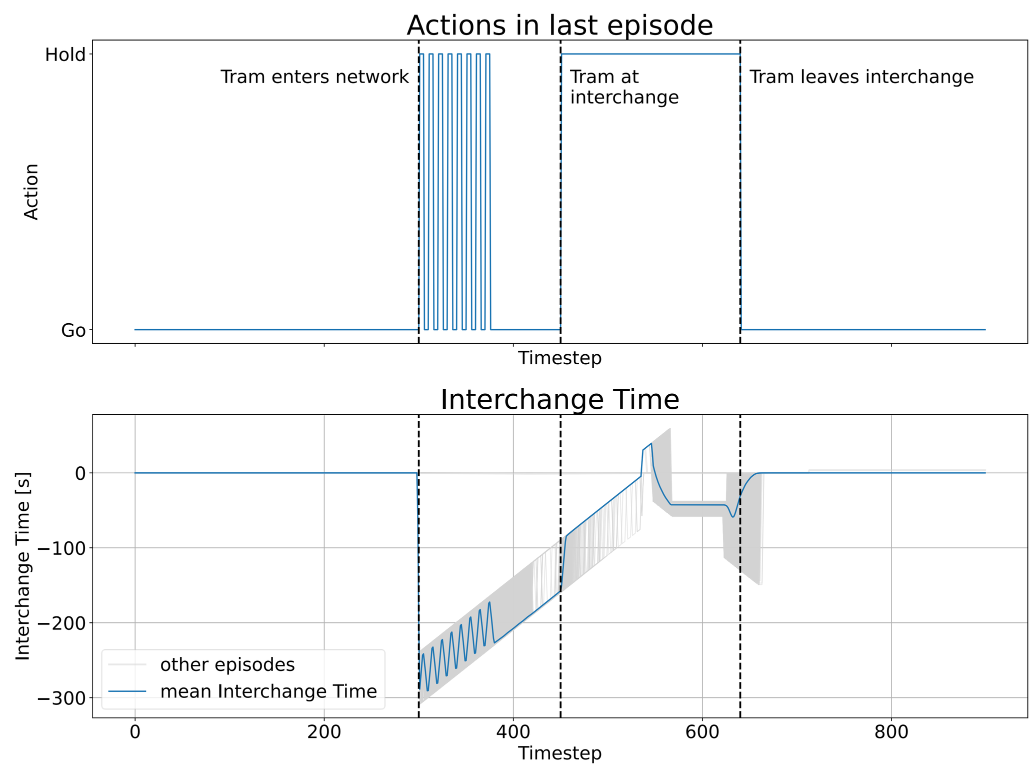
Results

After learning to hold the tram at the interchange stop, additional episodes are required for departure time optimization.

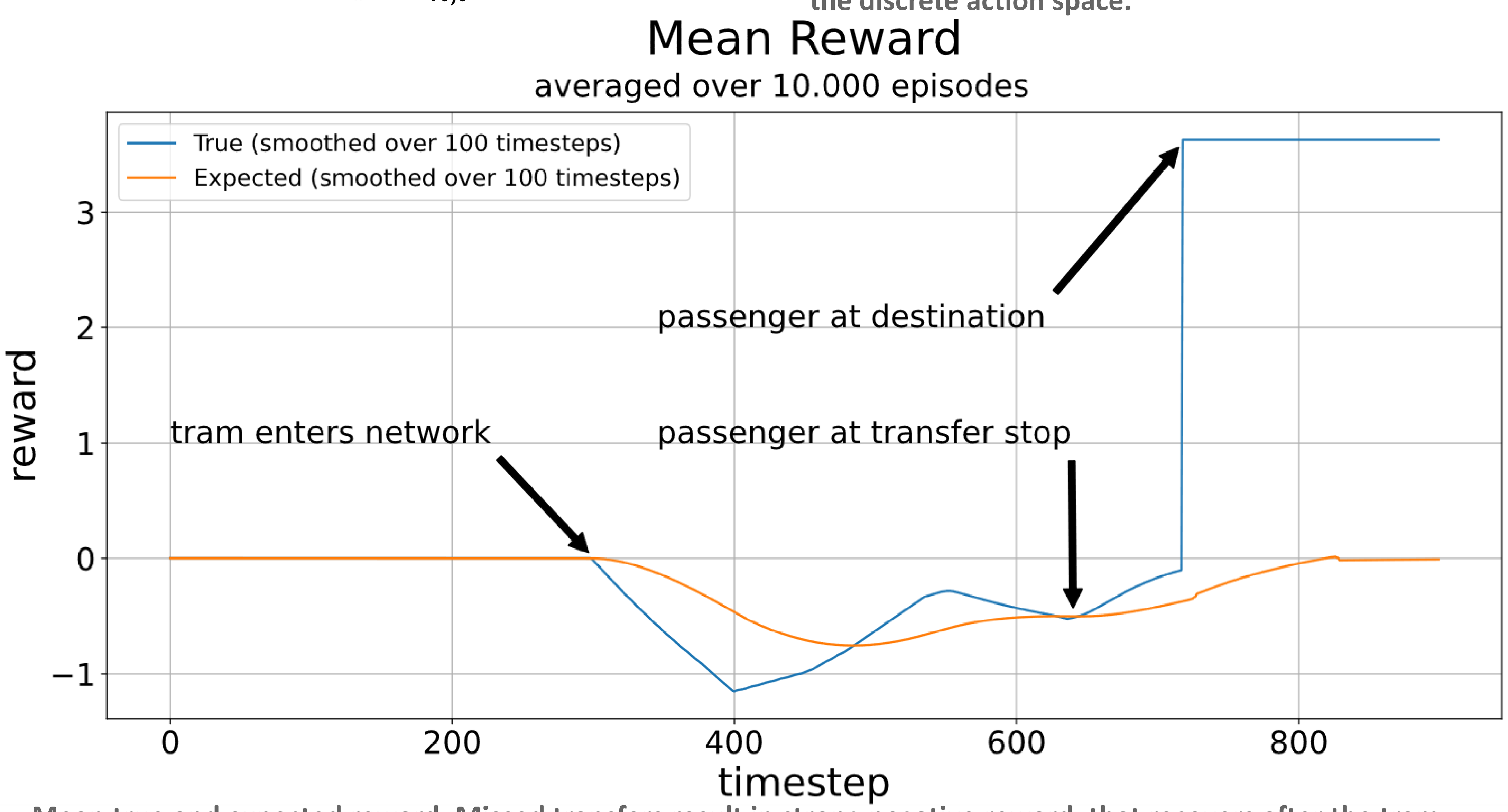


Even after convergence, travel time remains noisy due to random person walking speed and travel time of the feeding vehicle.

Vehicle holding can be applied only if the tram is inside the network with the interchange upstream.



We limit action updates to a 5 s interval to reduce noise. Mitigating negative interchange time takes time due to the discrete action space.



Mean true and expected reward. Missed transfers result in strong negative reward, that recovers after the tram left the simulation.

Funded by the European Union NextGenerationEU

Supported by: Federal Ministry for Economic Affairs and Climate Action on the basis of a decision by the German Bundestag

This work results from the joint research project STADT:up (grant number 19A22006x).

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