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A Three-stage Incentive Scheme for Integrated Energy-Traffic Systems Using Deep Q-Network

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Background & Motivation

Integrated Energy-Traffic Systems (IETS)

As can be predicted in the near future, urban areas will be incorporating higher penetration of EVs and e-hailing vehicles. In such a scenario, urban traffic system and electric power system will be closely interconnected, which could lead to the concept of integrated energy-traffic systems (IETS).

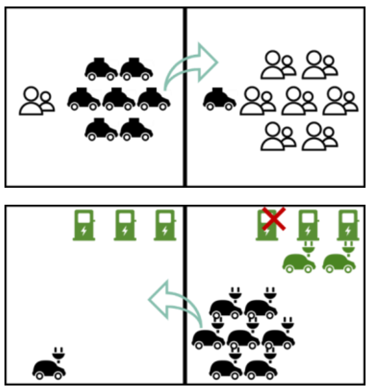
Optimization and Incentivization of IETS

Real-time price incentives of both charging services and ride-hailing services are used to improve the system's performance of revenue and security. The system operator solves the optimization problem to obtain a pricing strategy (i.e., prices for each area) with the aim of maximizing the total utility, which includes ride-hailing service revenues, charging station revenues, and penalties for violated constraints or unmet demands of ride-hailing and charging.

A Three-stage Incentive Scheme

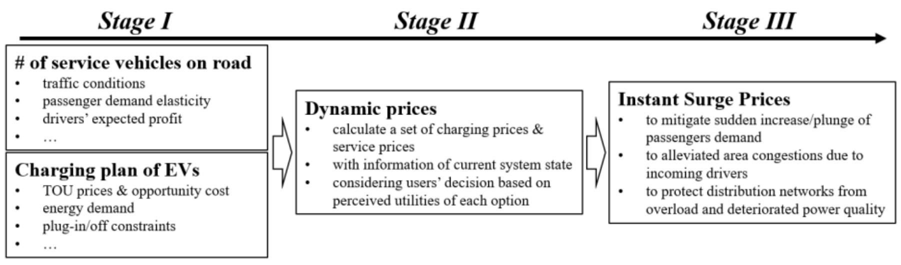
The pricing strategy is implemented in three stages, namely day-ahead equilibrium references, hour-level dynamic prices, and instant surge prices. These three stages work together to calculate an optimal price series for each area, which could help to mitigate unbalanced traffic load, unmet service demand and overload in electric power system.

Use price incentives to balance:

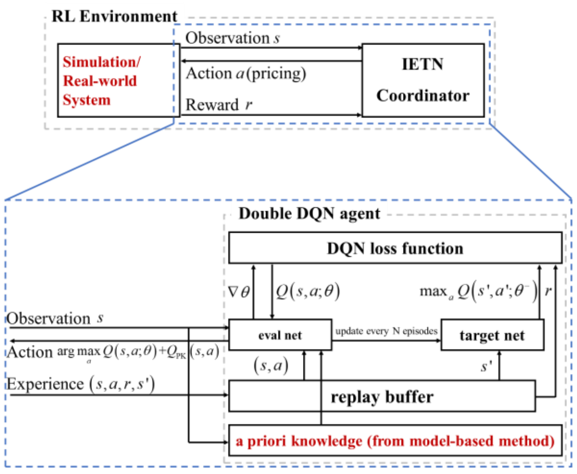


demand & supply of ride-hailing service

demand & supply of EV charging



Methodology



Double-DQN Method

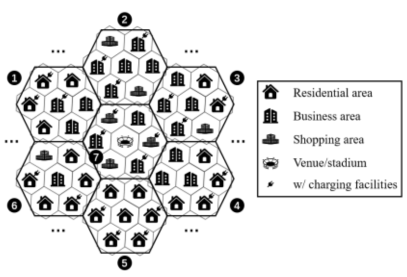
Reinforcement learning (RL) method is used to find the incentive strategy for the IETS with uncertainties. Double deep Q-network (Double-DQN), which is a model-free, online, off-policy RL method, is a proper method to get a better incentive strategy with discrete action space

Action Space

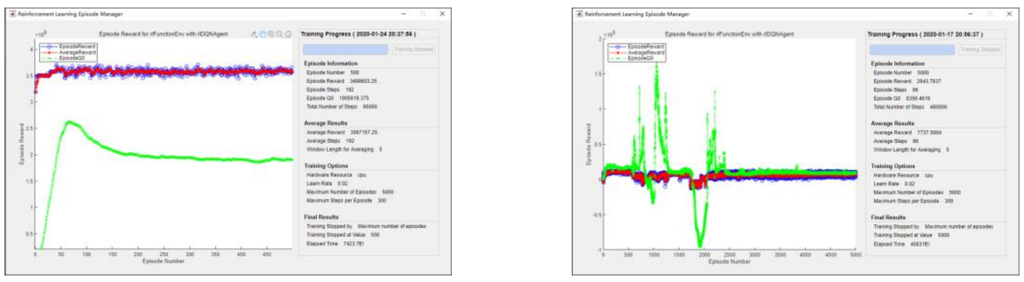
Action a is the changes on the base of PEV charging prices (calculated by model-based methods) and ride-hailing service prices, namely incentives. The incentive is set to be conducted on only one area at a time and is discretized into normal (0), low incentive ($\pm$10%) and high incentive ($\pm$30%). Reward r is the operational revenue from PEV charging and ride-hailing services minus the penalty related to traffic congestion and overload in electric power system.

Case Studies

Area Function and Charging Facilities of 7-area IETS



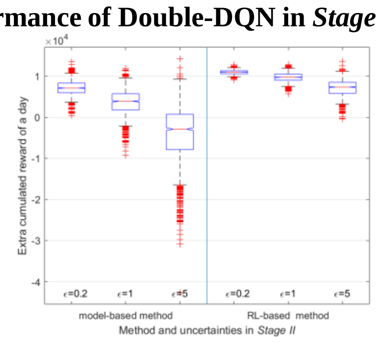
Training Process of Double-DQN in *Stage II*



a) without a priori knowledge

b) with a priori knowledge

Performance of Double-DQN in *Stage II*



Key findings

- RL-based method is proved to be more robust than model-based method when considering system uncertainties as it can have adaptive price incentives in different situations.
- Despite the long training time, RL-based method could meet the need of hour-level operational decisions as it has an extremely short time of application compared with model-based method.
- A priori knowledge can accelerate the training process of double-DQN by setting up a reference solution and removing unnecessary attempts.

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