EVS35
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A Data-Driven Approach for Online EV Charging Management Considering Travel Pattern Heterogeneity

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Presenter introduction

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Research Interests

- Transportation carbon neutrality
- Big data analysis of electric vehicle travel pattern
- Electric vehicle market and policy analysis

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■Tsinghua University, School of Vehicle and Mobility

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■Oak Ridge National Laboratory (U.S.) Transportation Energy Evolution Modeling

Joint Ph.D. student. 10/2018-10/2019

■ Participated in U.S.-China Clean Energy Research Center Project during Ph.D research,

■ Published over 9 peer-reviewed papers in related areas.

Contents

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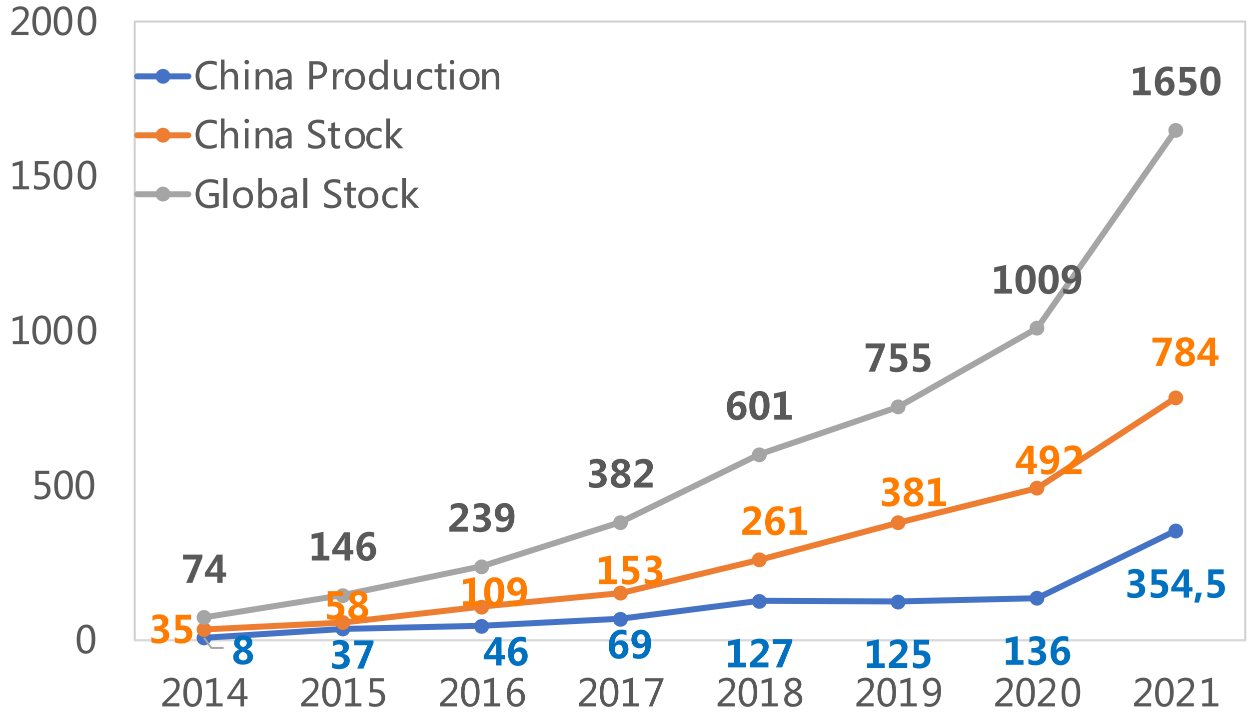
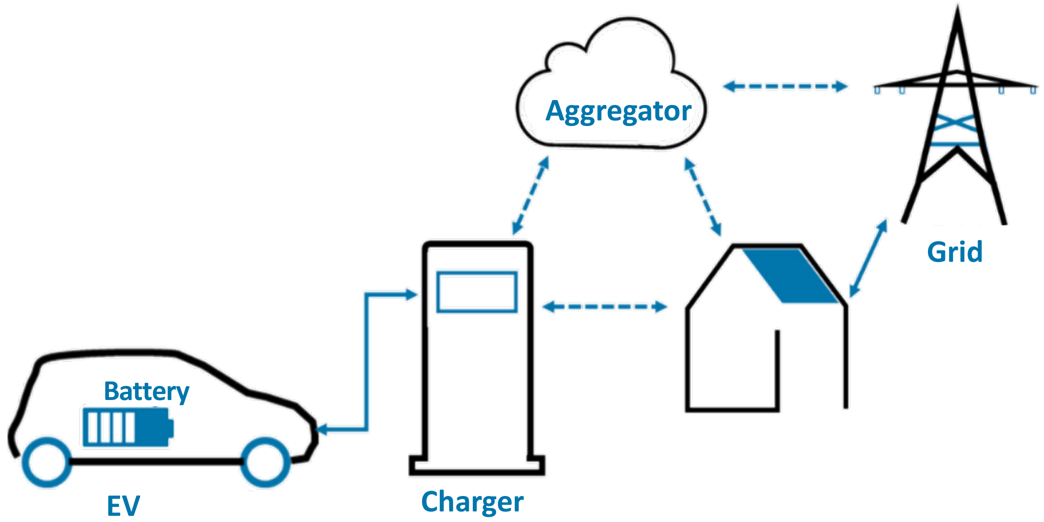
1. Introduction: Background

- Massive deployment of electric vehicles (EVs) combined with the integration of clean renewable sources has been regarded as an effective way to reduce carbon emission.
- **V2G** is considered as a solution to overcome the EV overburdening the power system.

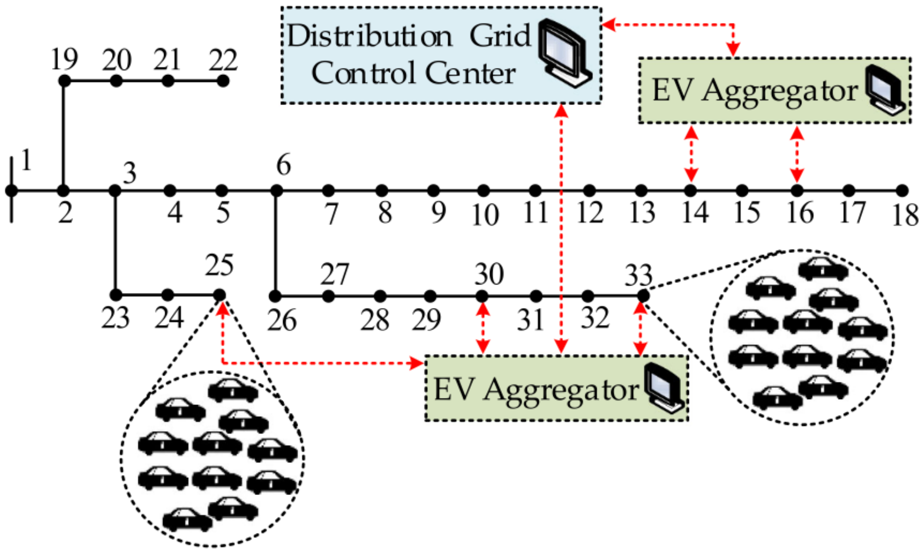
NEV production & stock (x10,000)





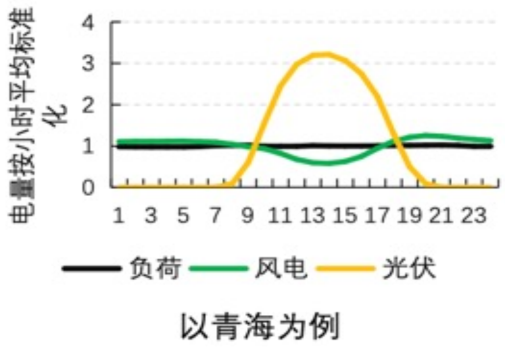
1. Introduction: Existed literature

- **Offline models:** Assume complete information of the future.
- **Online models:** Rely on an optimization model to generate the control strategy.

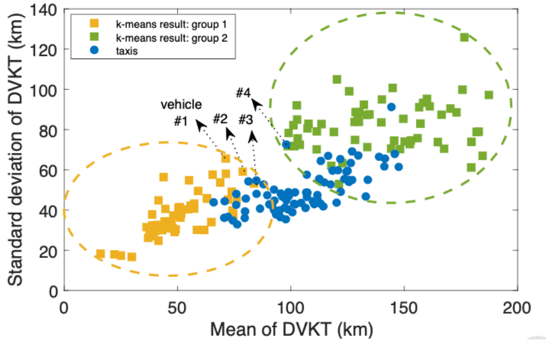


(Offline modelling example)

Unpredictable renewable generations



Unpredictable travel pattern



[1] Wang, J., Bharati, G.R., Paudyal, S., Ceylan, O., Bhattarai, B.P., Myers, K.S., 2019. Coordinated Electric Vehicle Charging With Reactive Power Support to Distribution Grids. IEEE Trans. Ind. Inf. 15, 54–63.

1. Introduction: Existed literature

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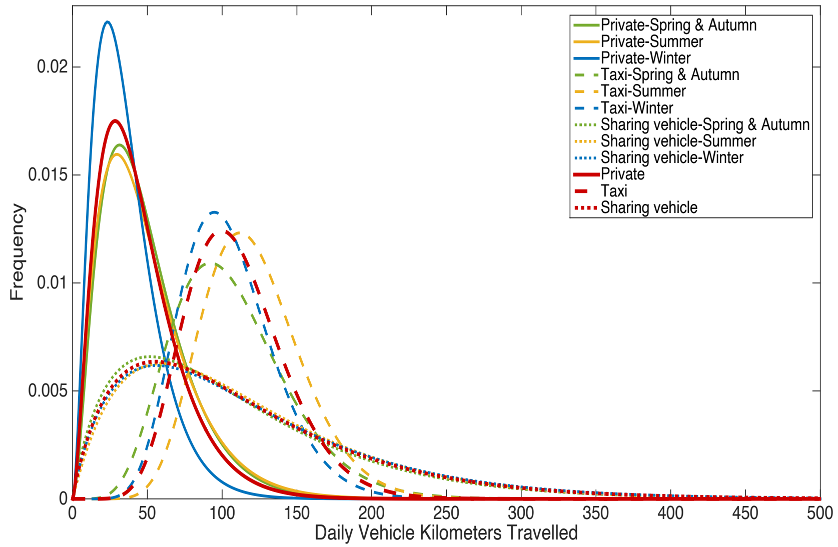
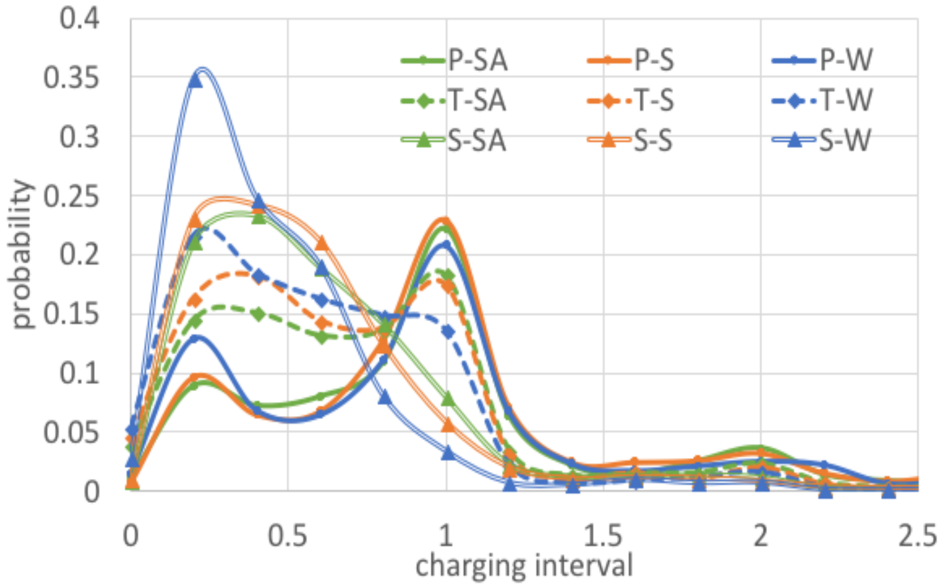
EV real-world travel pattern heterogeneity

- Travel distance distribution
- Charging time and charging preference difference





1. Introduction: Existed literature

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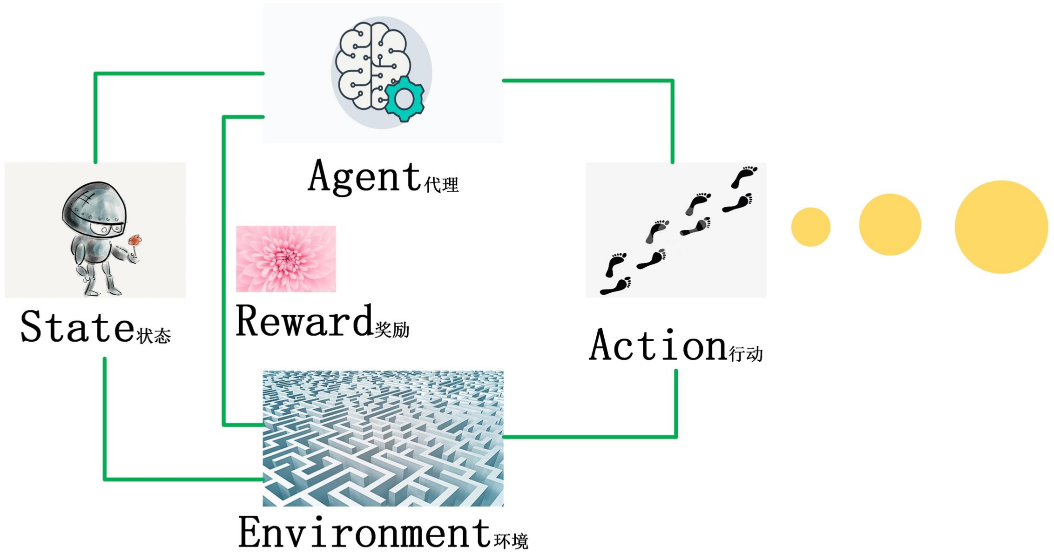
- **Model free online charging management**
  - To overcome this difficulty, reinforcement learning (RL), which is recently widely applied in automated vehicles.



However, the existing RL-based charging management works rarely take into account real-world travel pattern heterogeneity, especially that in China, the largest EV market.

This paper proposes a data-driven method for EV charging management based on deep Q-Network RL.

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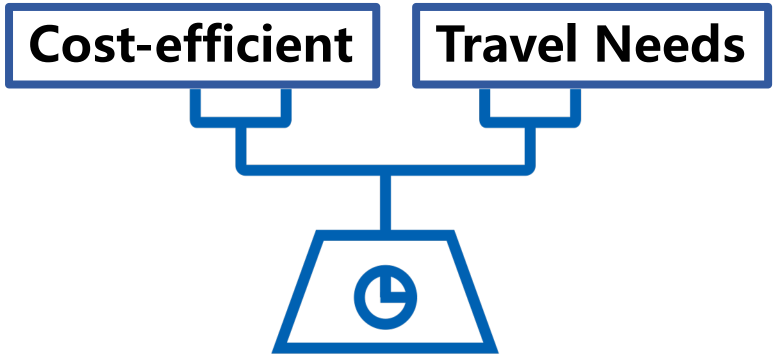
Problem Formulation

- The EV charging management is modeled as **a finite Markov Decision Process (MDP)** with discrete time step t = {1, 2, ..., T }.
- **Aim:**
- (1)To determine cost-efficient charging schedules with limited past electricity prices and vehicle energy information.
- (2) To meet travel demands.

State:
(1) Home or not
(2) The state of charge (SOC)
(3) The electricity prices for the former *N* hours



2. Problem Setup and Methodology: Methodology

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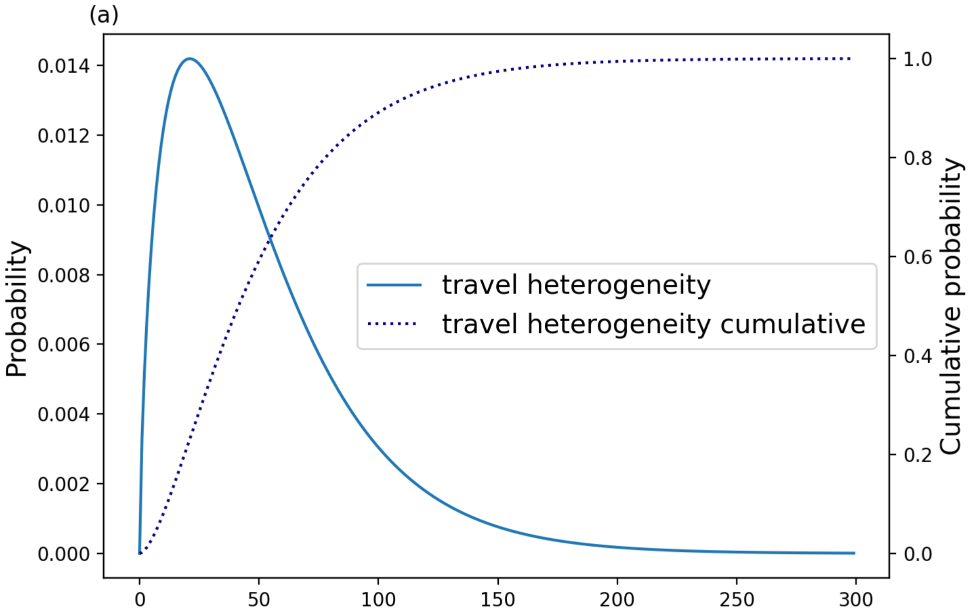
State：

Travel Pattern

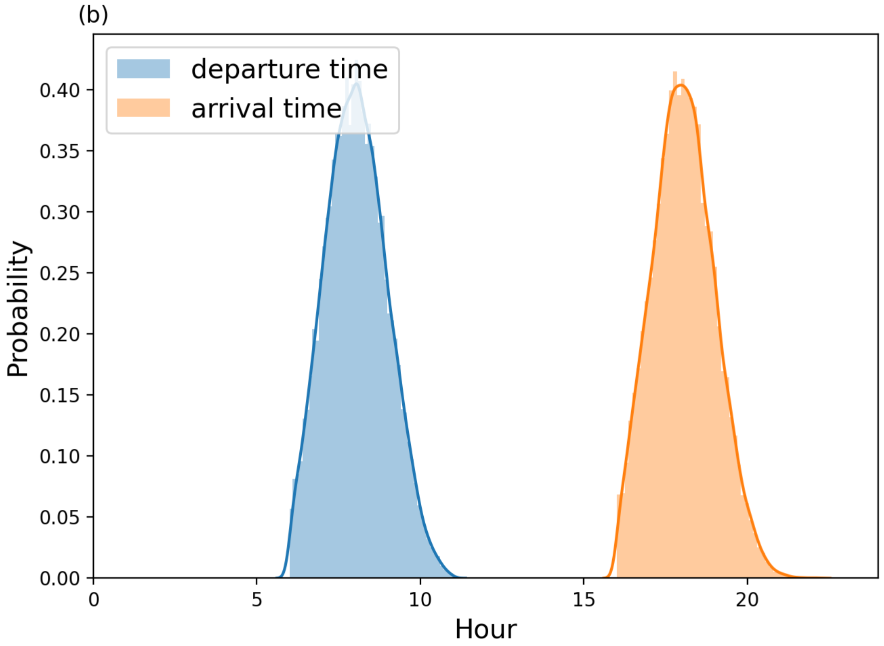
Data Source: National Monitoring and Management Centre for New Energy Vehicles (NMMC-NEV).

Daily vehicle kilometers travelled (DVKT) distribution: Gamma distribution

Distribution: Shanghai, 2018



$$y = f(x|\alpha,\beta) = \beta^{-\alpha} x^{\alpha-1} e^{-x/\beta} / \Gamma(\alpha)$$



$N(8, 1^2)$ $N(18, 1^2)$

bounded Normal distribution

2. Problem Setup and Methodology: Methodology

State：

Electricity price： hourly Experiment Uniform Shanghai Energy Price (EUSEP)

Derived from the Uniform Singapore Energy Price downloaded from the Energy Market Company

Time span: 1/1/2021 – 12/31/2021

Battery capacity: E_{max} = 49 kWh

Charging actions：

7kW(Charging)，-7kW (Discharging), 0

January		February		
Training	Test	Training	Test	…

Period	Average EUSEP (CNY/kWh)
Jan-21	0.248
Feb-21	0.296
Mar-21	0.329
Apr-21	0.312
May-21	0.320
Jun-21	0.321
Jul-21	0.532
Aug-21	0.435
Sep-21	0.496
Oct-21	1.565
Nov-21	1.099
Dec-21	1.514

Reward:

$$\hat{a}_t = \begin{cases} \min\{a_t, E_{max} - E_t\}, & \text{if } a_t \geq 0 \\ -\min\{-a_t, E_t\}, & \text{if } a_t < 0 \end{cases}$$

To ensure the battery capacity range.

$$r_t = \begin{cases} -P_t \cdot \hat{a}_t \cdot h_t \,, & t \neq t_\eta \\ -P_t \cdot \hat{a}_t \cdot h_t - \boxed{\tau \cdot (E_{max} - E_t)^2}\,, & t = t_\eta \end{cases}$$

A penalty if the EV departs when it is not fully charged.
τ – a comprehensive penalty factor.

Optimization of Action-Value Function

$$Q^*(s,a) = \max_\pi \mathbb{E}_\pi \left[\sum_{t'=t}^{T} \gamma^{t'-t} r_{t'} \middle| s_t = s, a_t = a, \pi \right]$$

Bellman equation

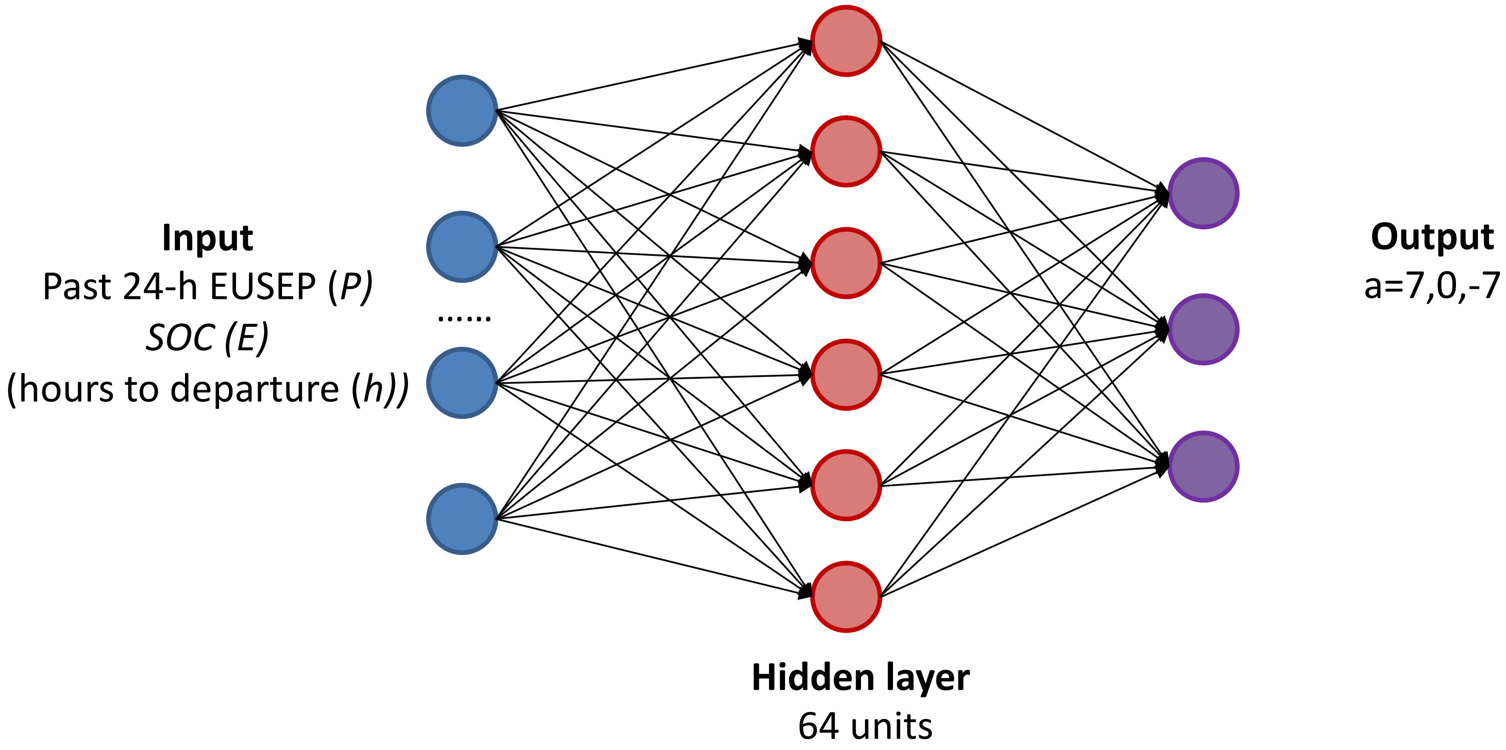
$$Q_{i+1}(s,a;\theta) = \mathbb{E}\left[r_t + \gamma \max_{a_{t+1}} Q_i(s_{t+1}, a_{t+1}; \theta) \middle| s_t = s, a_t = a \right]$$

$Q_i(s, a; \theta)$ will converge to $Q(s, a; \theta) \approx Q^*(s, a)$ finally.

2. Problem Setup and Methodology: Methodology

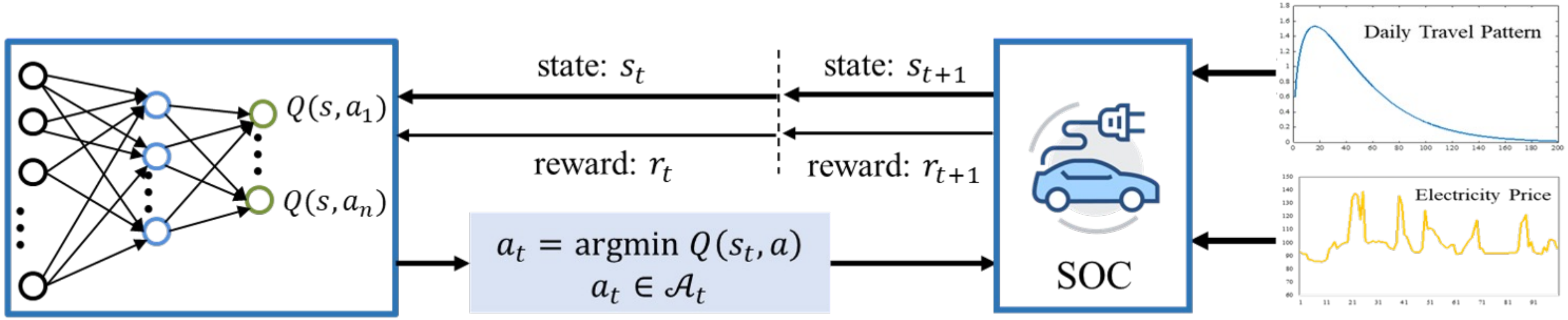
3-layer neural network

The input of the fully-connected neural network is the past 24-h electricity prices, the EV battery SOC calculated from the charging power and the daily vehicle kilometers travelled.



2. Problem Setup and Methodology: Methodology

Deep Q-network Method



Fully-Connected Neural Network

Algorithm 1 EV Charging/Discharging Managing

Input: Past 24-hour electricity prices and initial battery SOC.

Output: EV charging/discharging actions $a_{t_1:t_\eta}$.

for $t = t_1$ to t_η **do**

  Receive the electricity prices and initial battery SOC.

  Calculate action-value $Q(s_t, a; \theta)$ from the neural network.

  $a_t \leftarrow \text{argmax}_a Q(s_t, a; \theta)$.

  $s_{t+1} = f(s_t, a_t)$.

end for

2. Problem Setup and Methodology: Training process

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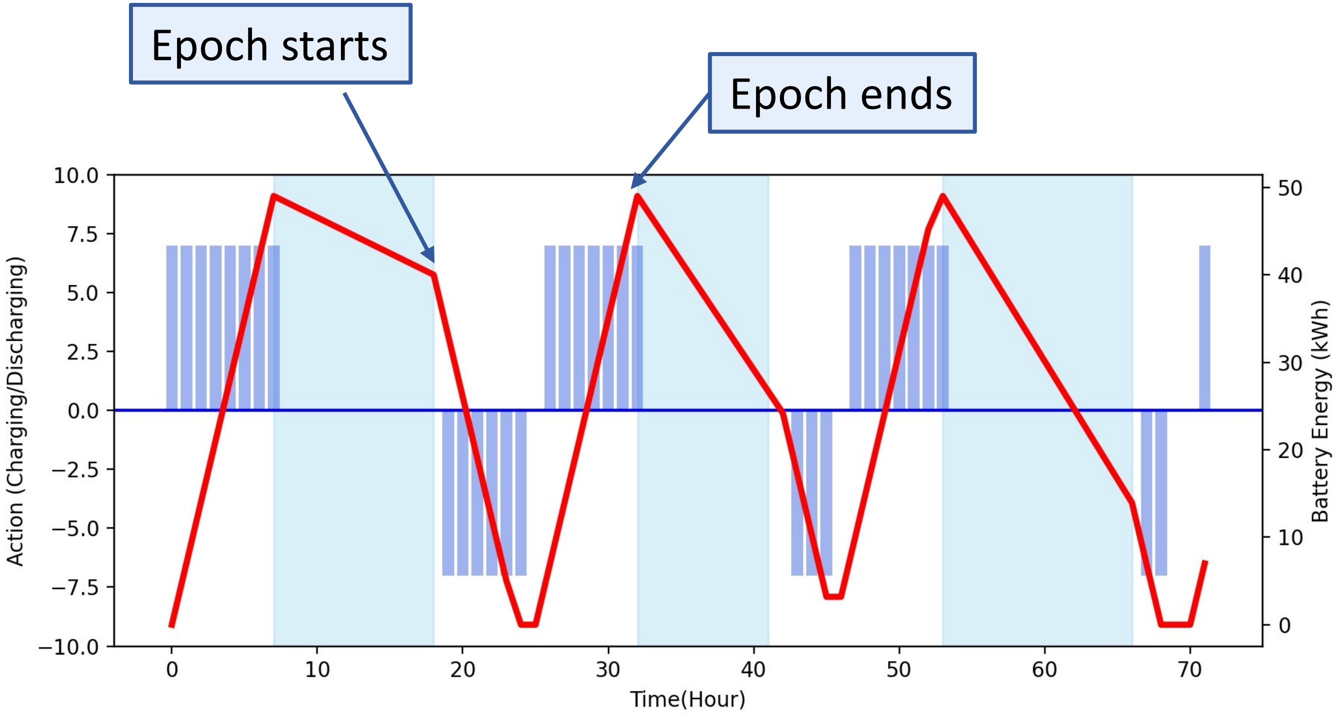


Assumptions:

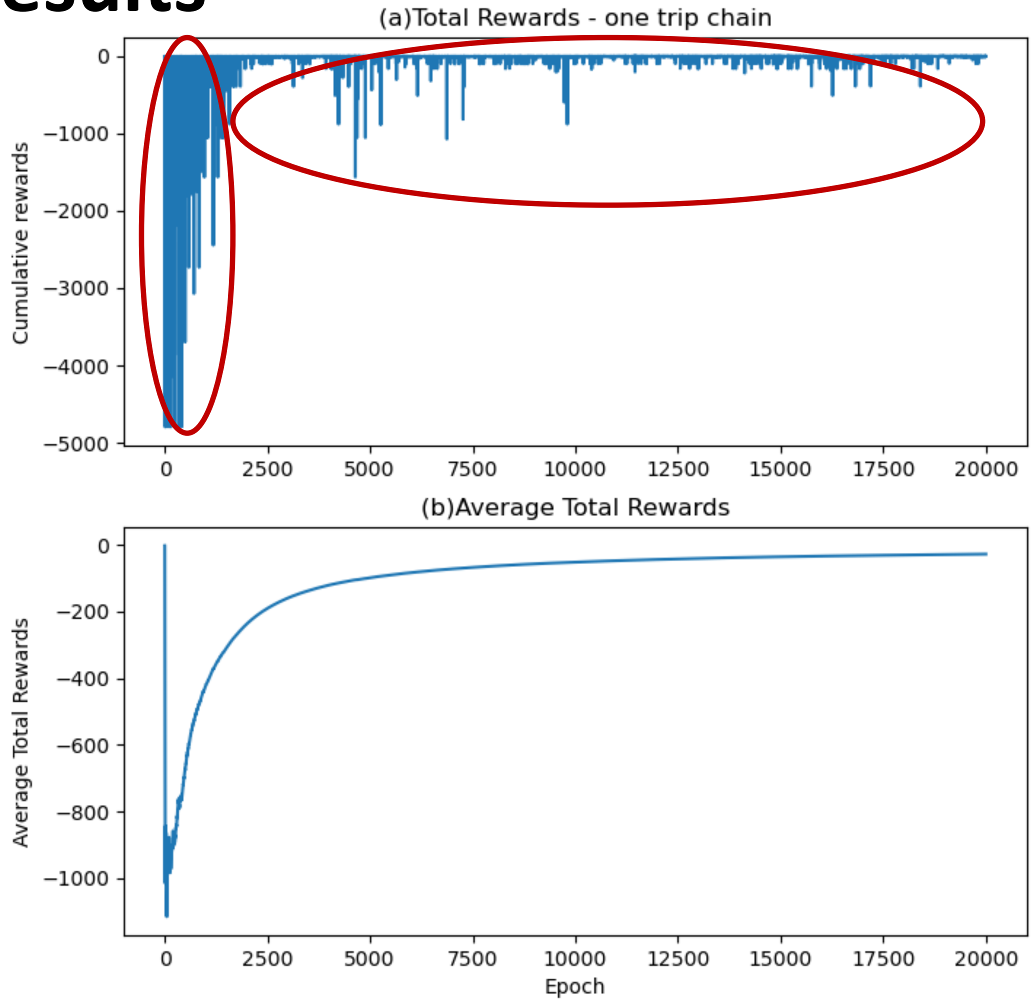
- Only charging at home
- Connect to the grid once at home

To guarantee the balance between exploration and exploitation, **ε-greedy policy** is adopted.

Loss function:

$$L(\theta) = \mathbb{E}[(r + \gamma \max_{a'} Q(s', a'; \theta) - Q(s, a; \theta))^2]$$

Results



- Training: 20000 epochs
- It shows that a good policy with a high cumulative reward can be learned by the proposed method.
- the charging/discharging actions are randomly chosen in the first 2,000 epochs
- and then the total rewards increase quickly and reach a relatively stable value with fluctuations.

3. Results and Discussion

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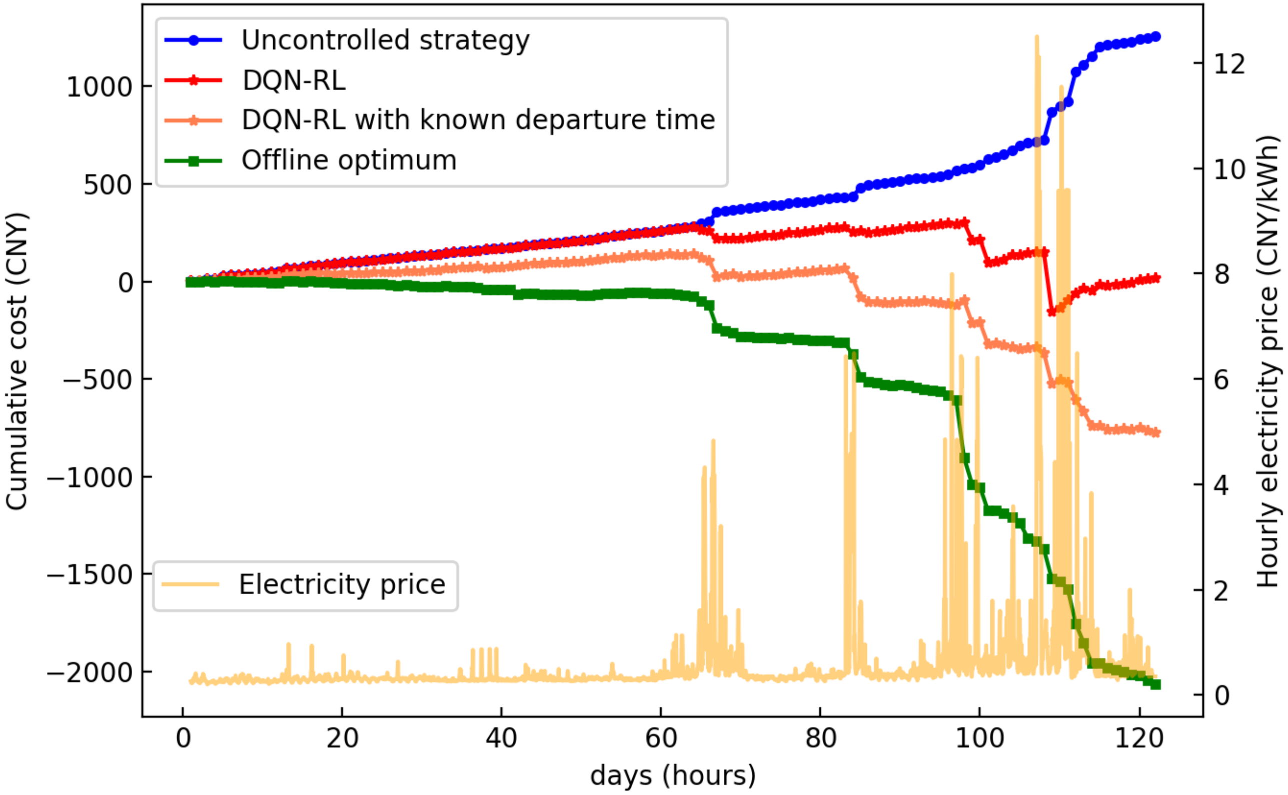
Test



- **Compared with the uncontrolled strategy, the proposed DQN-RL method can greatly reduce the cost.**
- The offline optimum can give the lowest cumulative cost and serve as a benchmark. However, the offline optimum is not practical due to the limited availability to the future information.

References:
Offline optimum: The offline optimum can give the lowest cumulative cost and serve as a benchmark. (NOT practical)
Uncontrolled strategy: the EV is charged at the maximum charging rate until reaching 49 kWh.

3. Results and Discussion

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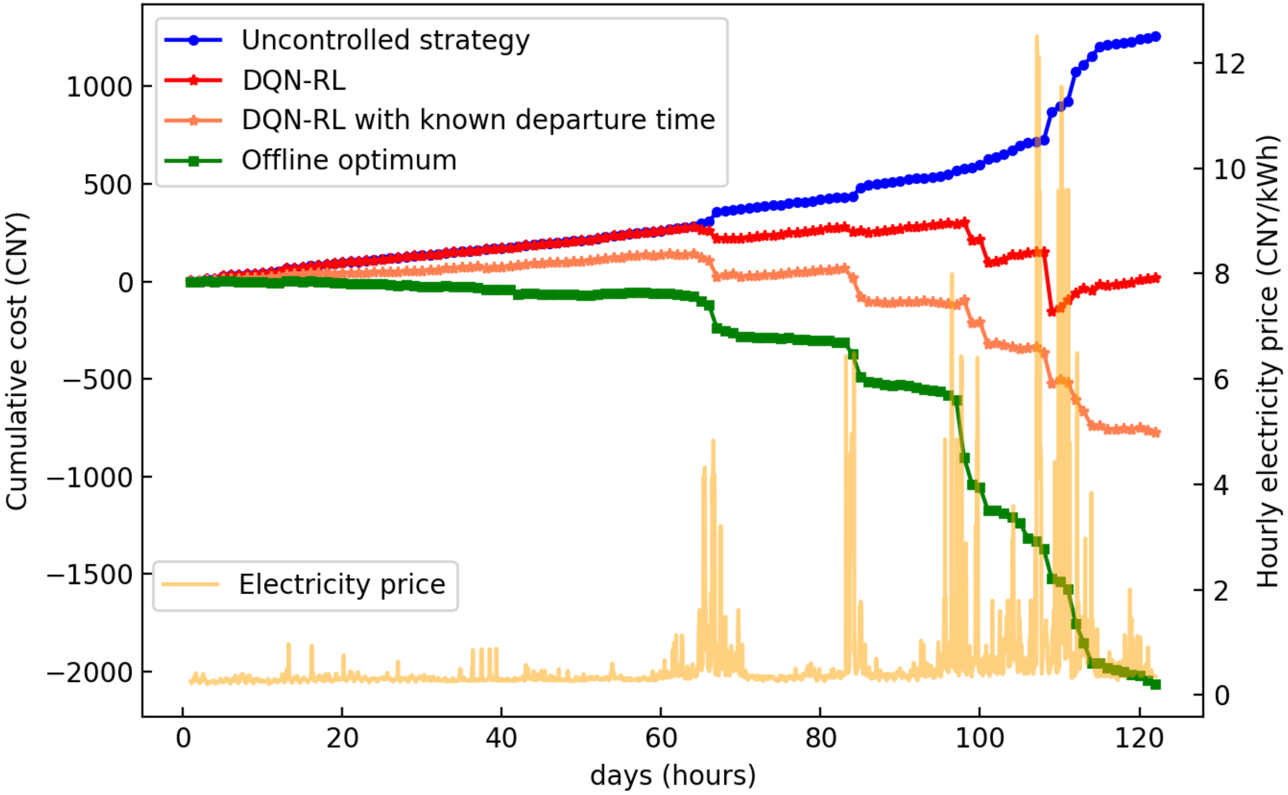
Test



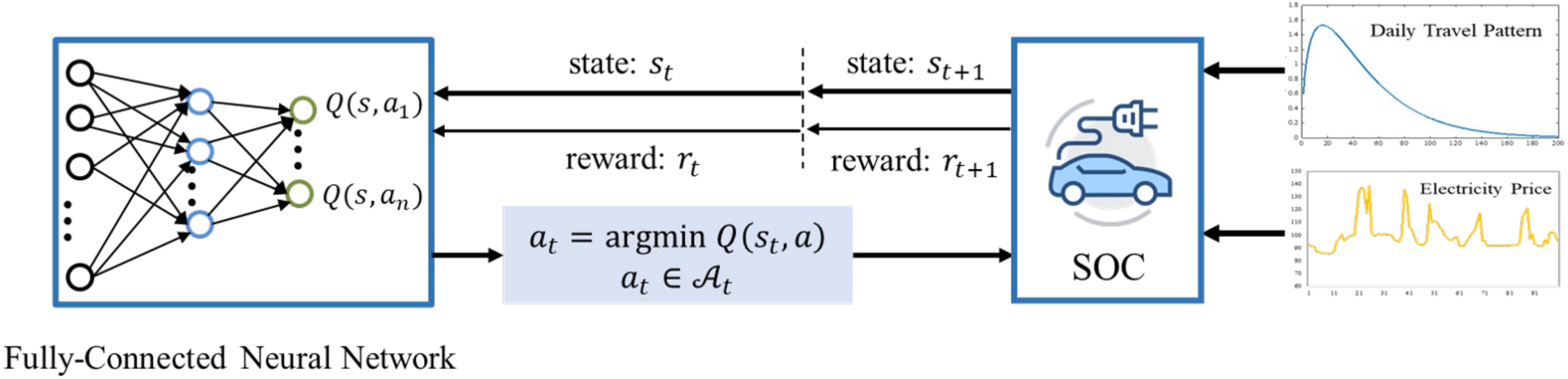
- **The improved DQN-RL:** the EV owners have a pre-decided departure time and the countdown hours is added to the expended state.
- The improved DQN-RL has much lower cost than the original DQN-RL.
- **Value of information (VOI) -**
  Value of pre-decided departure time

References:
Offline optimum: The offline optimum can give the lowest cumulative cost and serve as a benchmark. (NOT practical)
Uncontrolled strategy: the EV is charged at the maximum charging rate until reaching 49 kWh.

4. Conclusion and Future Research

Conclusion:

- In this paper, a Deep Q-Network based reinforcement learning method is proposed to solve the EV charging/discharging management problem in an online manner. The actual travel pattern heterogeneity in a typical city, Shanghai, is taken as an empirical example. The DQN-RL method is further improved by adding the known departure time to the states. The results reveal a significant advantage of the improved DQN-RL method over the uncontrolled charging method.



4. Conclusion and Future Research

Limitations

- We have to admit that this paper still has a few limitations, such as the lack of actual electricity prices in China. The actual real-time electricity prices in China will be very helpful for us to accurately evaluate the economical effects of V2G in China.
- The extra battery degradation is not taken into consideration in this paper, but in practice, high battery-swapping costs for the EV owners can occur if the V2G decreases the battery pack life.

Future research

- the action space can be changed from discrete space to continuous action space to reflect the variation of charging and discharging power.
- Moreover, this approach is the foundation to precisely evaluate the environmental and economical benefits of V2G.

Thank you for your attention！

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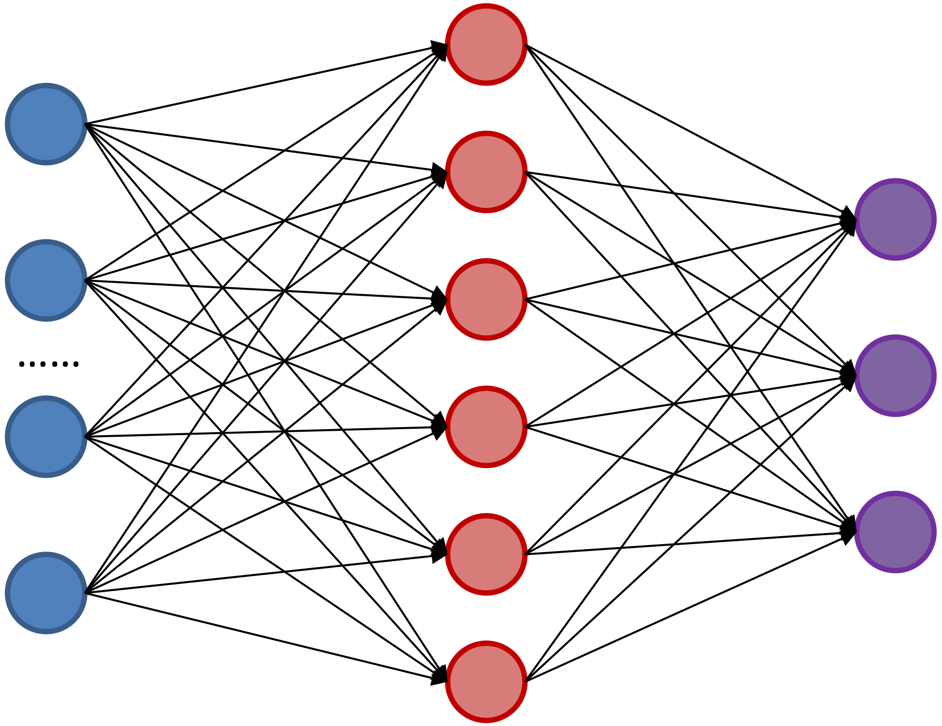
Input
Past 24-h EUSEP (*P*)
SOC (E)
(hours to departure (*h*))



Hidden layer
64 units

Output
a=7,0,-7