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Reinforcement learning for electric vehicle applications in power systems: A critical review

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Robust federated deep reinforcement learning for optimal control in multiple virtual power plants with electric vehicles

김상훈

shkim@ds.seoultech.ac.kr

서울과학기술대학교 데이터사이언스학과

Key concepts of V2G

Advances in Applied Energy 11 (2023) 100147

Contents lists available at ScienceDirect

Advances in Applied Energy

journal homepage: www.elsevier.com/locate/adapen

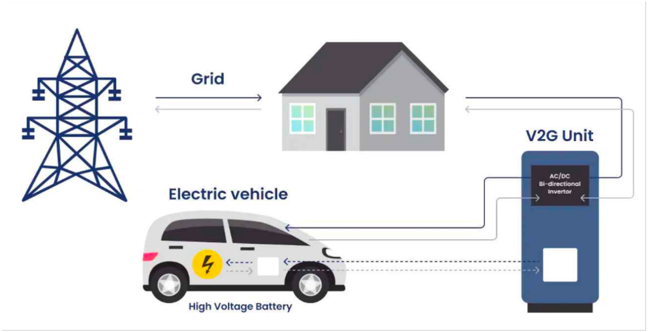
A Systematic Review on power systems planning and operations management with grid integration of transportation electrification at scale

Qianzhi Zhang[a], Jinyue Yan[b,c,*], H. Oliver Gao[a,d,*], Fengqi You[a,e,*]

[a] System Engineering, Cornell University, 220 Hollister Hall, Ithaca, NY 14853, USA
[b] Department of Building Environment and Energy Engineering, The Hong Kong Polytechnic University, Hong Kong
[c] Future Energy Center, Mälardalen University, 120 Olin Hall, Västerås 72123, Sweden
[d] Department of Civil and Environmental Engineering, Cornell University, 220 Hollister Hall, Ithaca, NY 14853, USA
[e] Robert Frederick Smith School of Chemical and Biomolecular Engineering, Cornell University, 120 Olin Hall, Ithaca, NY 14853, USA

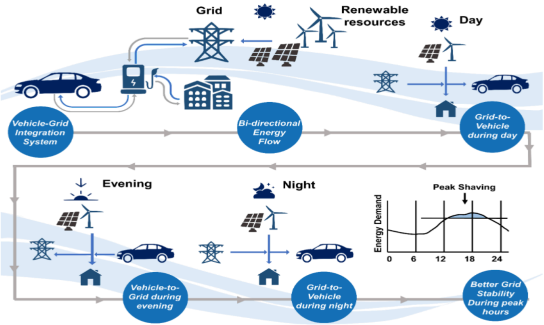
- The first paper provides an overview of V2G

What is V2G?



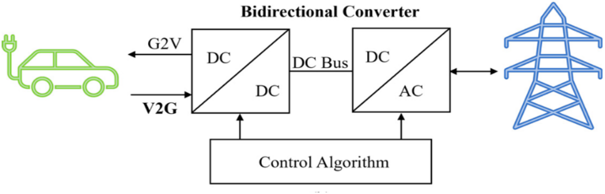
- Vehicle-to-Grid (V2G) technology allows electric vehicles (EVs) to return electricity to the power grid
- **uses EVs as mobile ESS**, helping to manage grid demand and supply

Advantages of V2G



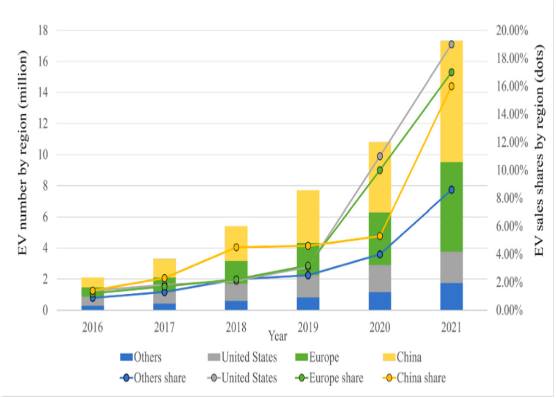
- **Peak shaving**
  - discharge power during peak times to reduce the maximum power demand on the grid

Advantages of V2G



- **Voltage support**
  - stabilize voltage levels in the power grid
- **frequency regulation**
  - stabilize grid frequency through frequency regulation
- **compensates for the intermittency of renewable energy**
  - promote the use of sustainable energy sources like solar and wind energy

Neccesities of V2G



- As the demand for EV increases, **the power load for EV charging also rises**
- To address this, V2G are essential

Institutionalization of V2G

굿모닝경제
http://www.goodkyung.com › news › articleView

'전기차를 ESS로' 2025년 V2G 의무화법 추진…세계시장 ...

2023. 6. 16. — 전기차에 양방향 충전기술을 탑재해 에너지저장장치(ESS)처럼 활용하는 **V2G**(Vehicle-to-Grid, 자동차전력망 연동기술) 의무화 법이 추진된다.

ev-volta.kr
https://ev-volta.kr › ...

'전기차를 ESS로' 2025년 V2G 의무화법 추진…세계시장 선점 ...

2023. 11. 2. — 전기차에 양방향 충전기술을 탑재해 에너지저장장치(ESS)처럼 활용하는 **V2G**(Vehicle-to-Grid, 자동차전력망 연동기술) 의무화 법이 추진된다. **V2G**가 ...

전기에너지뉴스
https://www.elec-inews.co.kr › news › articleView

전기차를 ESS로…2025년 양방향 V2G 충전시설 의무화

2023. 6. 16. — 2025년부터 전기차 및 완속 충전시설에 **V2G**(Vehicle-to-Grid, 자동차전력망 연동기술)를 위한 양방향 충전기술 탑재를 의무화하는 법 개정이 추진된다 ...

전기신문
https://www.electimes.com › news › articleView

V2G, 이제는 기술보다 제도·서비스 실증에 나서야

2024. 3. 13. — **V2G**의 국내 도입을 위해 다양한 요금제 제공과 VPP 사업자 역할 ... 의무 계약을 통해 무료 전기차 충전 서비스를 제공하고 있다. [출처=한국 ...

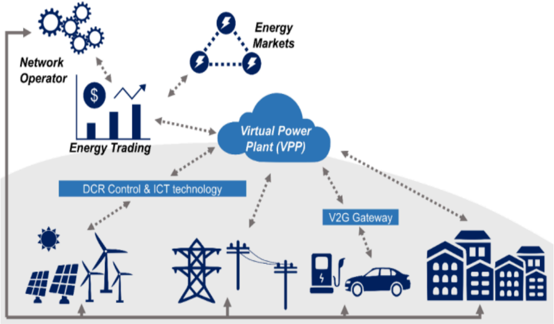
디지털투데이
https://www.digitaltoday.co.kr › news › articleView

美 캘리포니아주, 전기차 V2G 의무화 제안

2023. 5. 10. — [디지털투데이 AI리포터] 미국 캘리포니아주가 주 내에서 판매되는 전기차에 **V2G** 기능을 내장해야 한다는 법안을 제출했다. **V2G**(Vehicle to Grid)는 ...

- The process of legally institutionalizing V2G is underway.

current research trends in V2G



1. Approach viewing each EV as an agent
2. Approach assuming a Virtual Power Plant (VPP)

A review on RL for V2G

Renewable and Sustainable Energy Reviews 173 (2023) 113052

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Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

ELSEVIER

Check for updates

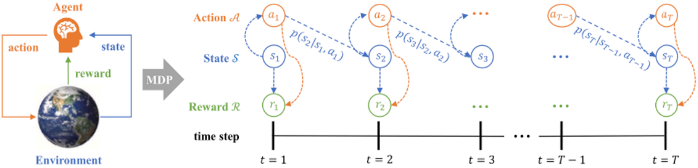
Reinforcement learning for electric vehicle applications in power systems: A critical review

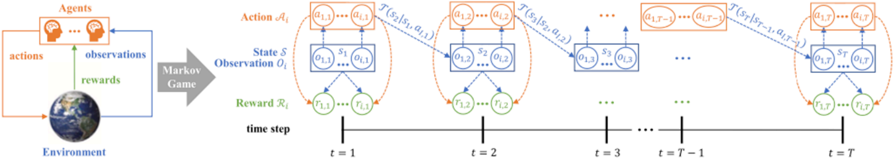
Dawei Qiu [a], Yi Wang [a,*], Weiqi Hua [b], Goran Strbac [a]

[a] Department of Electrical and Electronic Engineering, Imperial College London, London SW7 2AZ, UK
[b] Department of Engineering Science, University of Oxford, OX1 3QG, UK

- The second paper reviews studies that use RL to derive optimal operations for V2G, examining how state, action, and reward are defined.
    - In particular, approach viewing each EV as an agent

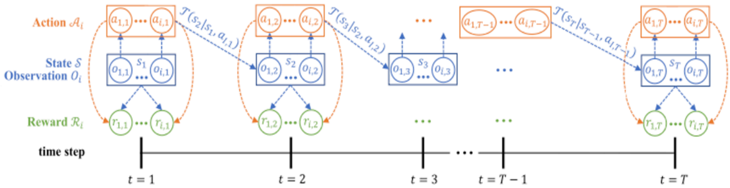
MDP vs Markov Game





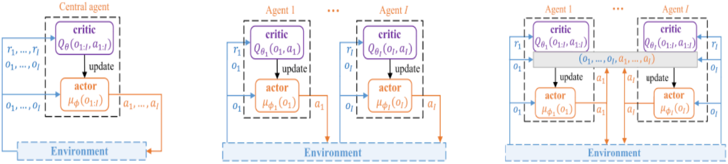
- When viewing **EV as an individual agent**, the use of **Multi-agent RL** is necessary, extending the MDP to a **Markov Game**.

Markov Game



- Markov game, represented as a tuple $\langle I, \mathcal{S}, \mathcal{O}_i, \mathcal{A}_i, \mathcal{R}_i, \mathcal{T}, \gamma \rangle$
  - I is the set of agents.
  - $\mathcal{O}_i$ denotes the set of local observations for each agent i.
  - $\mathcal{S}$ represents the collection of global states.
  - $\mathcal{T}$ is the state transition function, $\mathcal{T}(s_{t+1}|s_t, a_{I,t})$
- The global state s_t is defined as the tuple of local observations, expressed as $s_t = (o_{1,t}, \dots, o_{I,t})$.
- The trajectory for each agent i, denoted by τ_i, represented as $\tau_i = (o_{i,1}, a_{i,1}, r_{i,1}, o_{i,2}, \dots, r_{i,T})$.

Multi-agent RL



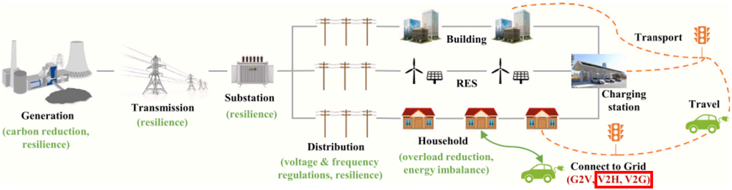
(a) CTCE (b) DTDE (c) CTDE

(a) **Centralized training with centralized execution (CTCE)**: Collecting the observation of all agents, train a single central network, assigns actions to each agent

(b) **Decentralized training with decentralized execution (DTDE)**: Each agent independently learns and executes its own policy

(c) **Centralized training with decentralized execution (CTDE)**: Collecting the observation of all agents, train the policy, each agent individually executes the policy based on its own local observations

V2H and V2G



- **V2H (Vehicle-to-Home)** focuses on **power demand management, flattening load profiles, and reducing their variability**.
- V2G focuses on enhancing overall system stability and efficiency, providing frequency regulation, voltage support, and reducing carbon intensity

MDP settings (V2H)

state

The local observations $o_{i,t}$ for each EV agent i at time step t is defined as follows:

$$o_{i,t} = [t, \Delta_{i,t}, S_{i,t}, \lambda_g^t, G_{i,t}^{res}, D_{i,t}^p, D_{i,t}^{ev}], \quad \forall i \in \mathcal{I}, \forall t \in \mathcal{T}$$

- $\Delta_{i,t}$: Charging interval for EV agent i.
- $S_{i,t}$: SoC of EV agent i at time t.
- λ_g^t: Grid electricity price at time t.
- $G_{i,t}^{res}$: Renewable generation at time t.
- $D_{i,t}^p$: Power demand at time t.
- $D_{i,t}^{ev}$: EV-specific charging demand at time t.

MDP settings (V2H)

action

The action $a_{i,t}$ for each EV agent i at time step t is defined as follows:

$$a_{i,t} = a_{i,t}^{\text{pow}}, \quad \forall i \in \mathcal{I}, \forall t \in \mathcal{T}$$

- $a_{i,t}^{\text{pow}}$: magnitude of charging or discharging power rates of EV agent i.

MDP settings (V2H)

reward function

The reward $r_{i,t}^{v2h}$ for each EV agent i at time step t is defined as follows:

$$r_{i,t}^{v2h} = r_{i,t}^{g2v} + r_{i,t}^{lf}, \quad \forall i \in \mathcal{I}, \forall t \in \mathcal{T}$$

- $r_{i,t}^{g2v}$: The reward received by EV agent i at time step t for grid-to-vehicle (G2V) power supply.
- $r_{i,t}^{lf}$: The reward received by EV agent i at time step t for load flattening.

reward function allows EV agents to **balance the immediate benefit of charging** their batteries with the **long-term benefits of reducing power demand fluctuations**.

A paper utilizing VPP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Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

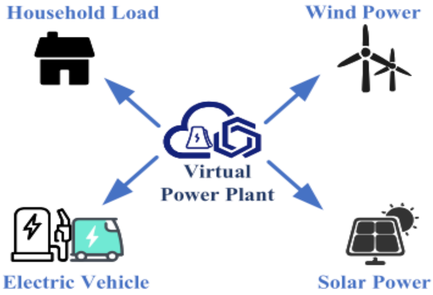
Robust federated deep reinforcement learning for optimal control in multiple virtual power plants with electric vehicles

Bin Feng [a], Zhuping Liu [a], Gang Huang [a,*], Chuangxin Guo [a,*]

[a] College of Electrical Engineering, Zhejiang University, Hangzhou, 310027, China

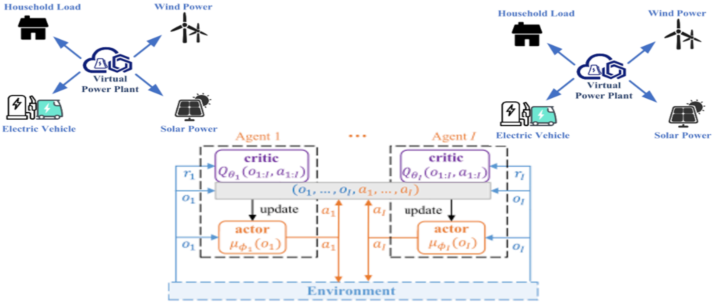
- The last paper explores **Federated Deep Reinforcement Learning (FDRL)** as a method for **optimizing energy management across multiple VPP**
  - In particular, approach viewing each VPP as an agent

Problems of Single VPP



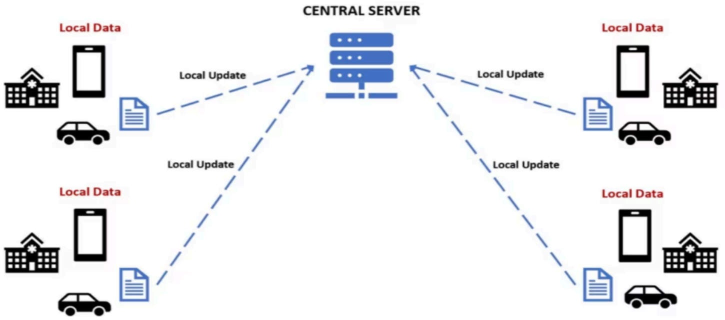
- Using data from a single VPP for training may result in low data collection efficiency and the creation of low-quality policies

Problems of Centralizing training



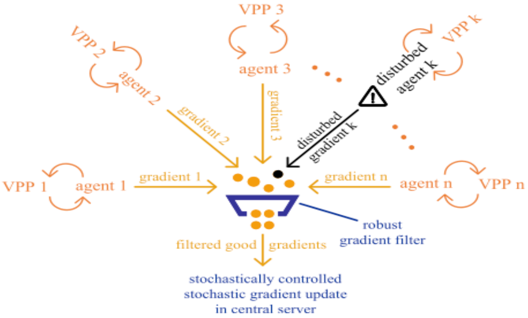
- Centralizing training data can cause privacy issues, as it may contain sensitive information
- also can lead to a high computational issues

Federated Learning



- **Instead of sharing data, agents send gradients to a central server**, which aggregates these updates to improve a global model.
- But, can be highly vulnerable to disturbances
- not all agents participating in federated learning can be considered reliable

Proposed method



- utilizes a robust gradient filter to effectively prevent disturbances
- integrating Stochastic Controlled Stochastic Gradient (SCSG) methods, improves sample efficiency and speeds up model convergence

MDP settings

The agent serves as the controller of the VPP

state

The state within each VPP is defined by three key variables:

- **EV Power**: total power that EV either consume or supply
- **total Load**: all demands or supplies of power, considering household loads, renewable energy outputs, and EV loads
- **Available Energy**: remaining energy of EV connected to the charging piles

action

The action space for each VPP includes three discrete actions, **charging the EV, discharging the EV, and idle**

MDP settings

reward function

The reward function is split in two parts : **Step rewards** and **Trajectory-ending rewards**

- **Step rewards** : optimize immediate operational decisions based on current state conditions
  - Total Load Value
  - SoC of the EVs when they leave the charging station
- **Trajectory-ending rewards** : evaluate the overall performance of the VPP over an extended period, incentivize long-term strategic decisions
  - Average SoC
  - Energy Acquired from the Grid
  - Excess Renewable Energy Output
  - Cost of Grid Electricity

Conclusion

- **Individual EV or VPP can be considered as agents**, which leads to differences in state, action, and reward
- **It is crucial to establish appropriate reward functions** in both perspectives
- Designing **robust policies** for various conditions is necessary, and **considering EV battery degradation** is also important

```
"Thank you for listening"
```