Papers Review

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Sustainable Energy, Grids and Networks

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Intelligent charging and discharging of electric vehicles in a vehicle-to-grid system using a reinforcement learning-based approach

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Applied Energy

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Uncertainty analysis of the electric vehicle potential for a household to enhance robustness in decision on the EV/V2H technologies

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Abstract_First Paper

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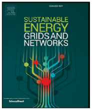

ELSEVIER

Intelligent charging and discharging of electric vehicles in a vehicle-to-grid system using a reinforcement learning-based approach

Julie Maeng [a], Daiki Min [b], Yuncheol Kang [b,*]

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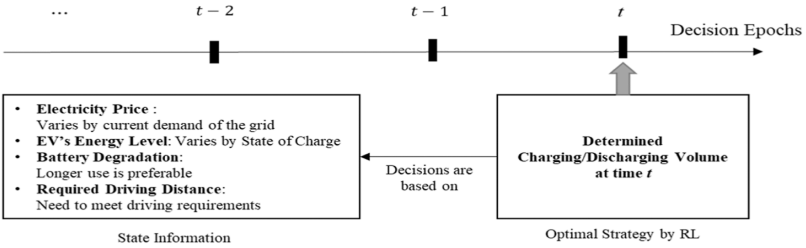
- individual EV charging/discharging is formulated as sequential decision-making problem
- DDPG is implemented and compared with other baseline models

Motivation

1. **Recent studies** that employed RL with V2G **tended to focus on multiple EV**, rather than individual EV V2G

2. **mathematical model** that optimizes V2G operation **may not adequately** describe a system owing to **the presence of random parameters**

Sequential decision-making frameowrk



- Sequential decisions must be made based on factors such as
  - electricity price
  - EV SoC
  - battery degradation
  - driving distance

MDP settings

State

The state at each time step t is defined as $S_t = \{p_t, e_t\}$

- p_t: The electricity price at time t
- e_t: SoC at time t.

Action

The action a_t at each time step t :

$$-A \leq a_t \leq A$$

where:

- A: The maximum capacity of charging or discharging

MDP settings

Reward

The reward function r_t at each time step t is defined as:

$$r_t = \begin{cases} -\frac{C}{T} & \text{if } s_t = \text{terminal} \\ -p_t \times a_t - \kappa_t & \text{otherwise} \end{cases}$$

where:

- C: The cost of the battery
- T: The total time steps

At the end of episode when the battery capacity reaches end-of-life (80%) a penalty of $-\frac{C}{T}$ is applied, indicating that longer episodes incur a smaller penalty

- agent tends to select actions that maximize battery usage

MDP settings

Reward

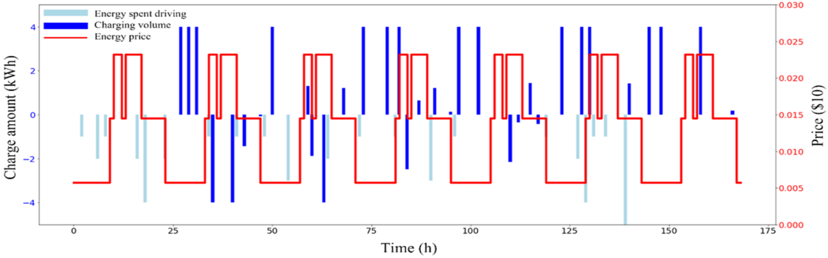
$$r_t = \begin{cases} -\frac{C}{T} & \text{if } s_t = \text{terminal} \\ -p_t \times a_t - \kappa_t & \text{otherwise} \end{cases}$$

- p_t: price of electricity at time t
- a_t: amount of energy charged or discharged at time t
- κ_t: penalty for when the EV cannot complete the required trip

The term $-p_t \times a_t$ calculates charging costs or discharging revenue at time t, while κ_t penalizes for untraveled distances

Results_DDPG

DDPG was implemented to solve problem



- red lines : hourly electricity prices
- light blue bar : amount of energy spent during driving
- dark blue bar : charged/discharged amount of energy by the RL agent

Baseline models

evaluate the performance of RL agent with two baselines : **(1) random operation** and **(2) heuristic-based selection**

(1) random operation

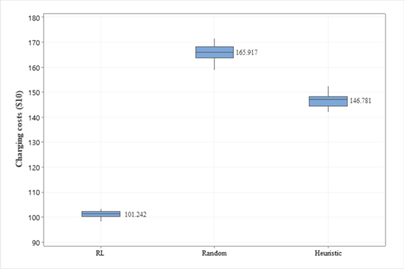
- does not consider factors such as the electricity price and reaminig SoC
- randomly selected from the range of $-A$ and A

(2) heuristic-based selection

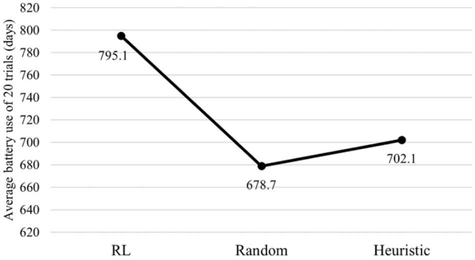
Classification	Time Period		Energy Charge (KRW/kWh)		
			Summer	Spring/Fall	Winter
Low-voltage ($\leq$380 V)	Off-peak	23:00–09:00	57.5	58.6	80.6
	Mid-peak	09:00–10:00 12:00–13:00 17:00–23:00	145.2	70.4	128.1
	On-peak	10:00–12:00 13:00–17:00	232.4	75.3	190.7
High-voltage ($\geq$3300 V)	Off-peak	23:00–09:00	52.4	53.4	69.8
	Mid-peak	09:00–10:00 12:00–13:00 17:00–23:00	110.6	64.2	100.9
	On-peak	10:00–12:00 13:00–17:00	163.6	68.1	138.7

- heuristic-based selection are aware of real-time electricity prices
  - Low Price : opts to charge
  - Medium Price : randomly select
  - High Price : decides to discharge

Case Study_Total Costs and Battery usage



Simulation of the charging cost for all the models.



Average battery usage time

- RL had the lowest cost (left) and longest usage of EV battery (right)

limitations

1. 매 타임 스텝마다 0.8의 확률로 driving, 0.2의 확률로 parking 으로 전이한다고 가정함

RL Environment Data	Value/Distribution
Electricity prices ($10)	KEPCO's EV charging tariff (as of April 2022)
Maximum battery capacity E_{max} (kWh)	24
Initial energy ($\times E_{max}$)	$N(0.5, 0.01^2)$
Required distance (km)	0, 5, 10, 15, 20, 25, 30
Cost of battery	800
Event probabilities $P_{driving}$, $P_{station}$	0.8, 0.2

- 이는 **(1). 전기차가 대부분 주차된 상태**로 있다는 사실을 반영하지 못하며, **(2). 데이터로부터 생성된 시뮬레이션과는 괴리가 있는 에피소드**를 기반으로 함
    - According to Yilmaz and Krein, the average personal car in the US is only on the road approximately 4-5% of the time

2. EV는 이동수단이기 때문에, **random하게 충전량을 선택한다는 baselines 들의 action 은 현실적이지 못함**

Abstract_Second Paper

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Uncertainty analysis of the electric vehicle potential for a household to enhance robustness in decision on the EV/V2H technologies

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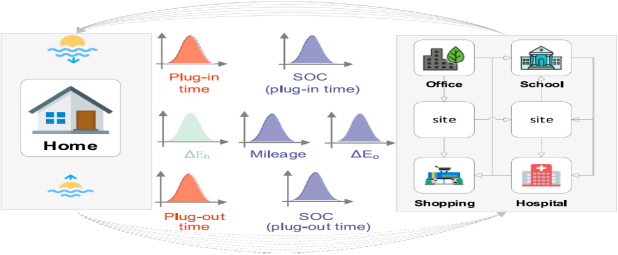
- EV travel behavior stochasticity is considered
- annual costs optimization by Mixed Integer Linear Programming (MILP)

Motivation

1. As the government subsidy program for EV purchases are being withdrawn, it needs to be carefully **assessed benefits to households by V2H**
2. potential **benefits of V2H** is strictly related to the **travel behavior**
3. conventional approach of modeling travel behavior is to define a fixed travel pattern, insufficient **consideration in the stochasticity of travel behavior**

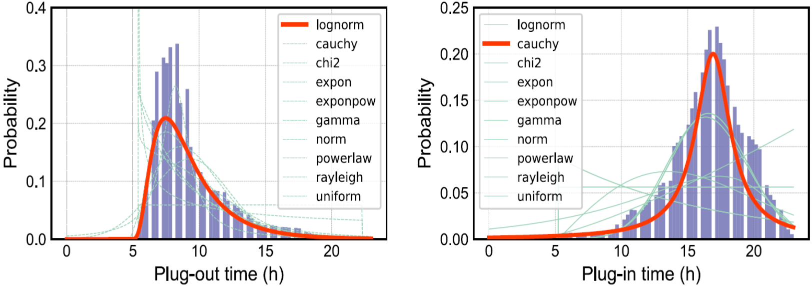
Vehicle usage model

Three uncertain sources, **1. travel behavior**, **2. charging strategy**, **3. battery charge state** affect the potential benefits of V2H



1. travel behavior
   - plug-in/out time
2. charging strategy
   - charge/discharge at home/outside
3. battery charge state
   - plug-in/out SoC
   - trip distance

Uncertainty in travel behavior



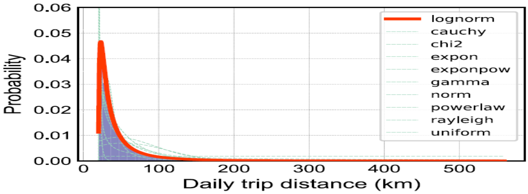
- By using `North China Intelligent Travel Data` and `Python fitter package`, fitting probability distributions to **plug-out time** and **plug-in time**
  - plug-out time is expressed as lognormal distribution
  - plug-in time is expressed as Cauchy distribution

Uncertainty in charging strategy

- **charging/discharging at home/outside** are stochastic variables which are affected by various influences, will be determined by MILP
  - plug-in/out time
  - charge state
  - electricity price

Uncertainty in charge state

- **daily trip distance** is expressed as lognormal distribution



- **plug-out SoC** are stochastic variables, which are affected by price of electricity, travel distance, so will be determined by MILP

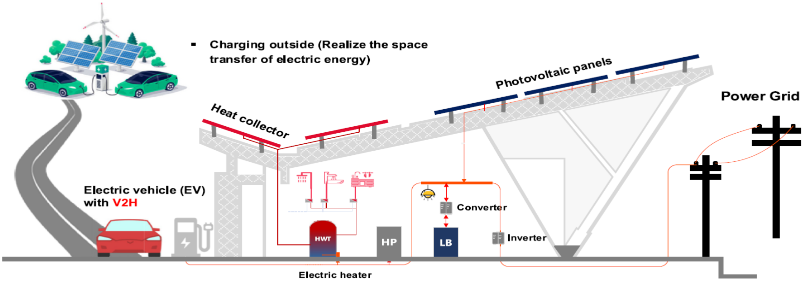
- **plug-in SoC** is determined by plug-out SoC, travel distance and charging/discharging amount at outside

Modeling of vehicle travel behavior

The study generates episodes using a 7 stochastic parameters,

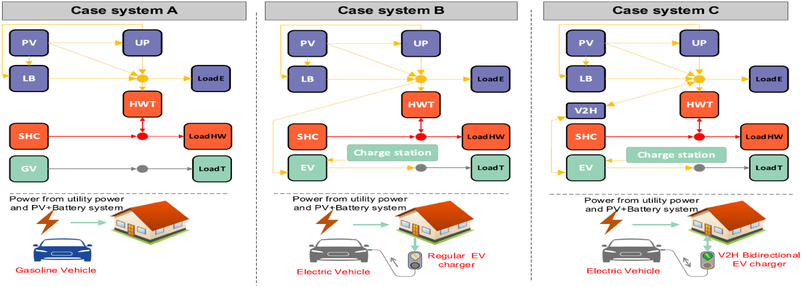
1. parameters such as **plug-in time, plug-out time, and daily trip distance**, which have probability distributions, are generated via Monte Carlo simulations
2. remaining parameters, **charging/discharging electricity at home/outside, and SoC at plug-in/out times**, are determined through a MILP

Household test systems



- annual cost minimization under Household grid that contains solar heat collector, PV and V2H

three distinct case systems



- system A : no EV
- system B : no V2H (only charge)
- system C : V2H

Objective Function

The objective function for minimizing the Equivalent Annual Cost (EAC_s) is defined as:

$$\min EAC_s = Inv_s + RC_s^{EVB} + Op_s^{grid} + Op_s^{Tr} - Op_s^{PV}$$

where:

- Inv_s: Investment cost.
- RC_s^{EVB}: battery degradation cost
- Op_s^{grid}: electricity purchasing cost
- Op_s^{Tr}: charging cost
- Op_s^{PV}: Revenue from selling excess PV power

Degardation function

The equation for battery degradation cost RC_s^{EVB} is given by:

$$RC_s^{EVB} = \left\lceil \frac{Q_s^{EVB}}{2 \cdot Cy^{EVB} \cdot Ca_s^{EVB}} - 1 \right\rceil \cdot up_j \cdot v_j$$

where:

- Q_s^{EVB}: Total charge/discharge amount
- Cy^{EVB}: Charge cycle
- Ca_s^{EVB}: Capacity of battery
- up_j: Unit price of battery
- v_j: capacity recovery factor

limitations in settings

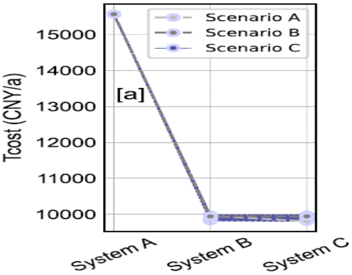
1. **V2H를 통해 여분의 전기를 판매할 수 없으며**, 다른 저장 장치로의 방전만 허용됨

- V2H 경제적 이점 제한

2. degradation model 에서 **충/방전량과 충전 주기의 수만을 고려함**

- 온도, 충전 속도, SoC 등 degradatoin에 영향을 미치는 다른 변수들을 고려하지 않음

Results



- Scenario A
  - assumes fixed travel behavior (previous studies)
- Scenarios B and C
  - consider stochastic travel behavior (Monte Carlo)

- Given significant limitations in settings related to V2H cost optimization
- the paper concludes that the randomness of travel behavior does not impact total cost
  - This conclusion has limitations

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