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School of Electrical Engineering

Multi-energy System Planning and Operation (MESPO) Group

# Coordinated Operation of Multi-energy Microgrids Considering Green Hydrogen and Congestion Management via a Safe Policy Learning Approach


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# Personal Profile

Multi-energy System Planning and Operation (MESPO) Group

**Jia Xueyong**

## Education

- Sep. 2016 - Jul. 2020 NCUST Bachelor 's degree
- Sep. 2020 - Jul. 2023 Shandong University Master's degree
- Sep. 2023-present Aalto University PhD student

## Research Interests:

- Data-driven Operation of Multi-Energy systems.
- Safe/Distributional/Diffusion-based deep reinforcement learning
- Multi-energy Microgrids/Industrial Multi-energy Microgrids

**Google Scholar**: https://scholar.google.com/citations?user=blA_MDsAAAAJ&hl=en&oi=ao

# Outline



# 1-Background



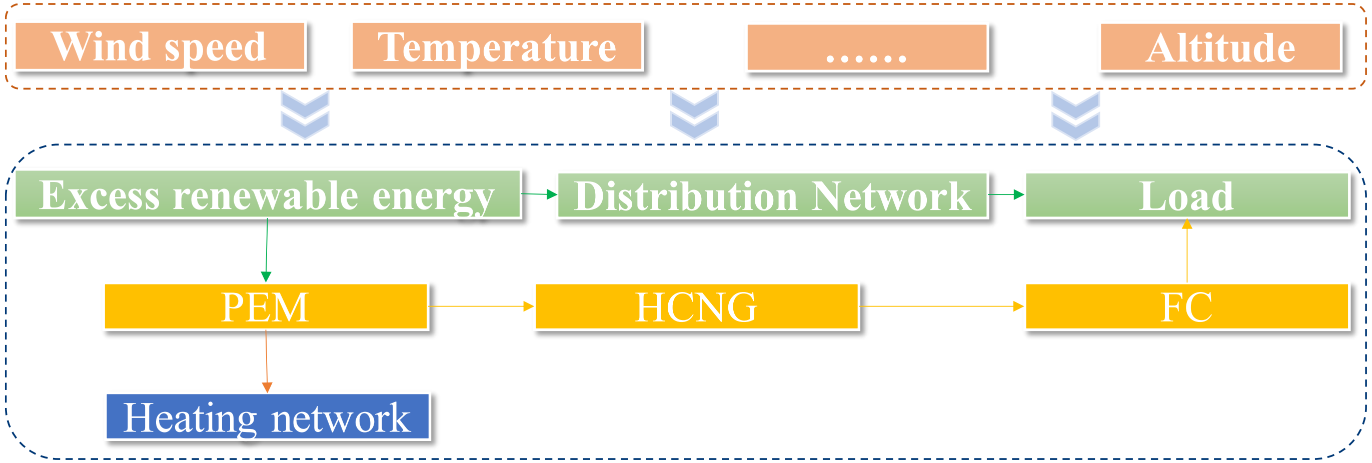
## 01 Multi-energy Coordination

**Why is it necessary to achieve coordinated operation in multi-energy microgrids (MEMGs)?**

- ✓ Multi-energy microgrids (MEMGs) have proven to be an effective solution to enhance energy efficiency and facilitate the transition to sustainable energy systems.

**Why should HCNG be considered as an alternative in MEMGs?**

- ✓ In practice, the high construction costs of hydrogen infrastructure and technological limitations hinder its integration into current MEMGs.




**Hydrogen compressed natural gas**

- ✓ **Production:** Excess renewable energy uses P2H to produce hydrogen.
- ✓ **Transportation:** Hydrogen is injected into the existing natural gas infrastructure.
- ✓ **Utilization:** Hydrogen uses H2P to produce electricity.

# 1-Background



## 02 Congestion Problems

**RES**

- High Proportion
- Clean Energy
- Uncertainties
- Intermittent

**Load**

**Electricity Demand**

- High Temperatures
- Zero-carbon
  - Electrical Vehicles
  - Heat Pumps

Temporal and Spatial Mismatch

**Congestion Problems**

- Balance of Power Demand and Supply
- Line Overload
- Voltage Drop

**Network**

The power system operating state is not only dependent on the electrical parameters but is also impacted by ambient factors. In addition, the **transfer capacity of network will be reduced** in high temperatures during summer.

# 1-Background



## 03 Data-driven method

**Challenges of Mathematical Methods in Energy Systems**

- ✓ Limited adaptability to dynamic environments
- ✓ Computational complexity grows rapidly with system scale
- ✓ Struggle to handle nonlinear and high-dimensional problems.

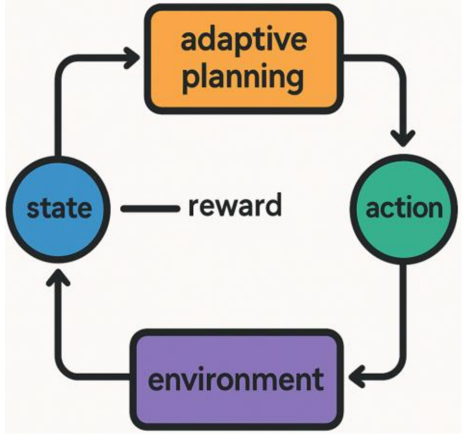
**Why Use Deep Reinforcement Learning (DRL)?**

- ✓ Learns directly from interaction without explicit system modeling.
- ✓ Avoids repeatedly solving complex optimization problems.

**Limitations of DRL:** Lack of Safety Guarantees.

Uncertainty of Renewable energy


Complex multi-energy microgrids




AI driven coordinated method

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# Outline

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1 Background

**2 Modelling**

3 Methodology

4 Case Study

5 Conclusions

# 2-Modeling



- A comprehensive operation model for a MEMG is proposed with electricity, green hydrogen, natural gas, and thermal flows.
- Congestion management scheme is involved as well.
- A safe deep reinforcement learning approach is developed to ensure the economic and secure operation of MEMGs.

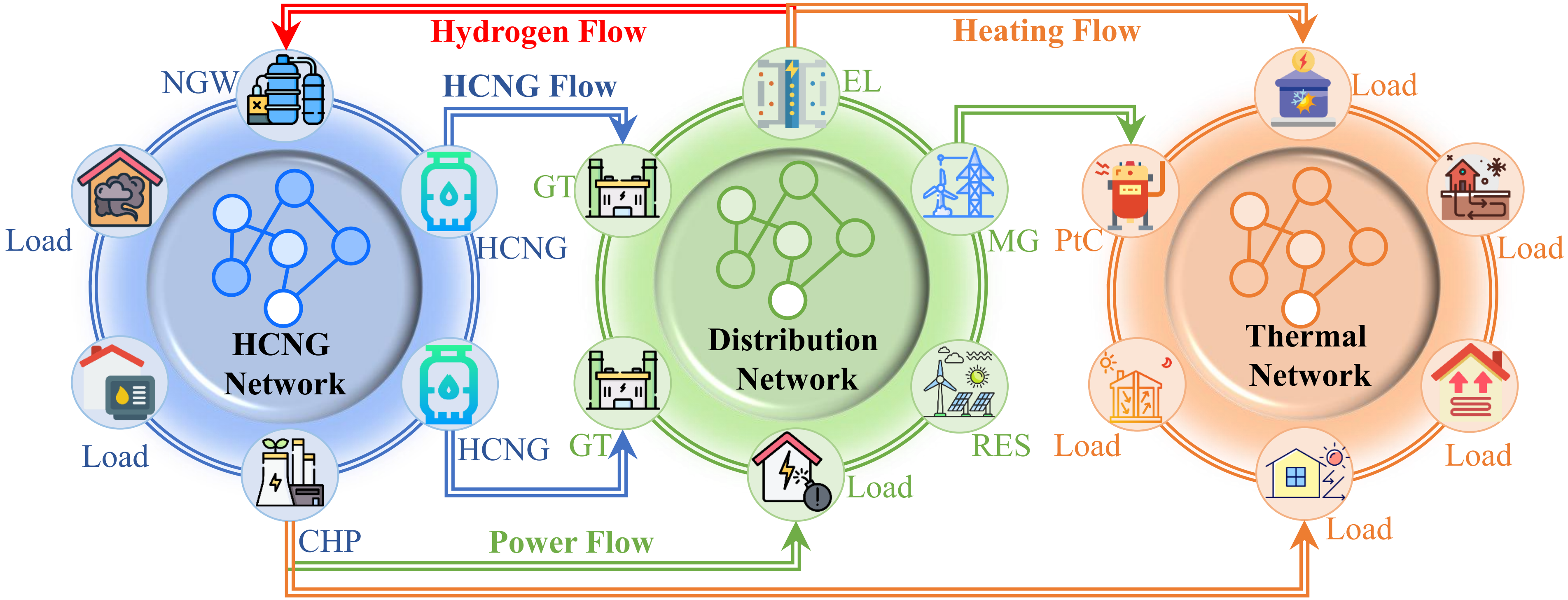



Fig. 1. The typical structure of a MEMG.

# 2-Modeling



## 01 Power flow model

$$\begin{cases} \Delta P_i = P_i - V_i^2 G_{ii} - V_i \sum\limits_{\substack{j=1 \\ j\neq i}}^{n} V_j (G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) \\ \Delta Q_i = Q_i + V_i^2 B_{ii} - V_i \sum\limits_{\substack{j=1 \\ j\neq i}}^{n} V_j (G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}) \\ \Delta I_l^2 = \dfrac{3L}{r_{(l)} S_b}[q_c + q_r - q_s] - \dfrac{V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}}{r_{(l)}^2 + X_{ij}^2} \end{cases}$$

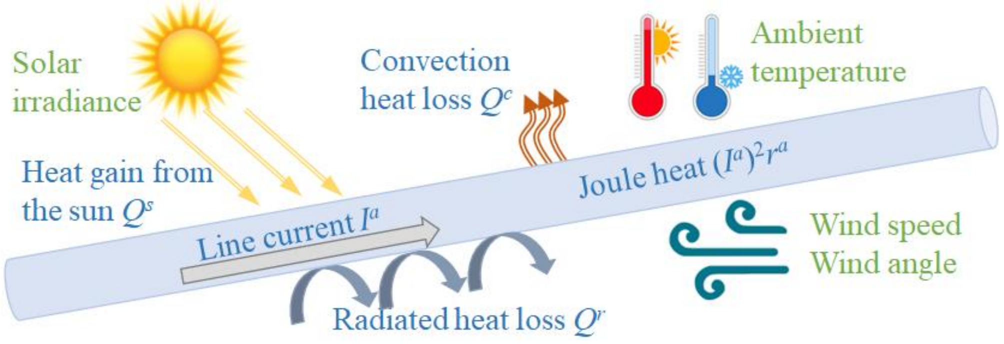



Fig. 2. Diagram of electro-thermal balance in OCs.

**Weather-dependent Power flow!**

## 02 HCNG flow model

$$p_j - p_i = \frac{\beta}{\alpha}\ln\left(\frac{\alpha p_j + \beta}{\alpha p_i + \beta}\right) - \alpha\frac{\lambda \mathcal{R} T^g L^p}{2D^p M (A^p)^2} f_l |f_l|$$

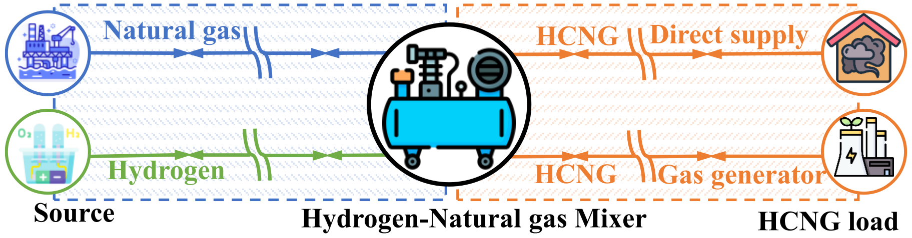



Fig. 3. A general structure of the HCNG network.

## 03 Thermal flow model

$$H^l_{i,t} = C^p m^s_{l,t}(T^s_{i,t} - T^h_0)$$

$$\begin{cases} T^{s/r}_{j,t} = (T^{s/r}_{i,t} - T^e_t) e^{-(\lambda/L^h_l)/(C^p\cdot m^{s/r}_{l,t})} + T^e_t \\ \sum_{n\in S^{(-)}_{s/r}} (m^{s/r}_{n,t}\cdot T^{s/r}_{n,t}) = \sum_{n\in S^{(+)}_{s/r}} (m^{s/r}_{n,t})\cdot T^{s/r}_{n,t} \end{cases}$$

# 2-Modeling



## 04 Coordinated Operation Model

- This study aims to coordinate the MEMG to minimize total operational costs while ensuring system security. The objective function and constraints are modeled as follows:

$$\min C^F = \sum\nolimits_{t\in N_T} (C_t^{om} + C_t^{e} + C_t^{ng})$$

$$C_t^{om} = (\xi^{chp}\cdot P_t^{chp} + \xi^{pem}\cdot P_t^{pem} + \xi^{gt}\cdot P_t^{gt} + \xi^{PtC}\cdot P_t^{PtC})\cdot \Delta t$$

$$C_t^{e} = \kappa^{e}\cdot P_t^{e,buy}\cdot \Delta t$$

$$C_t^{ng} = \kappa^{ng}\cdot m_t^{ng,buy} / \rho^{ng}\cdot 3600\cdot \Delta t$$

Equation. (1)-(30)

$$[H_{i,t}^{chp}, H_{i,t}^{PtC}] = [P_{i,t}^{chp}, P_{i,t}^{PtC}]\cdot[\eta^{chp}, \eta^{PtC}]$$

$$[P_{min}^{PtC}, P_{min}^{chp}, P_{i,min}^{gt}] \le [P_t^{PtC}, P_t^{chp}, P_{i,t}^{gt}] \le [P_{max}^{PtC}, P_{max}^{chp}, P_{i,max}^{gt}]$$

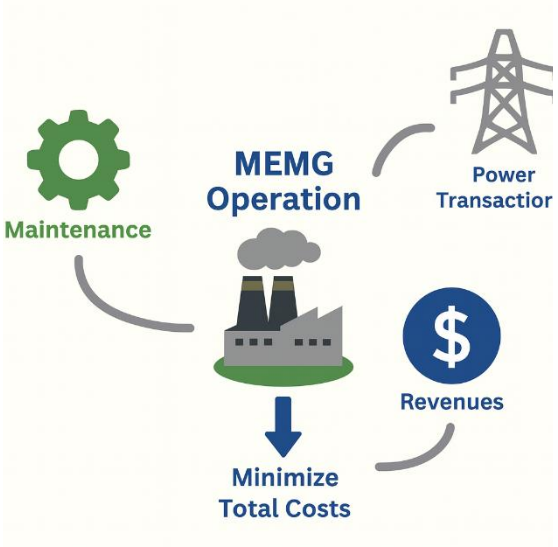
$$R^{chp}\cdot \Delta t \le P_t^{chp} - P_{t-1}^{chp} \le R^{chp}\cdot \Delta t$$

$$R_i^{gt}\cdot \Delta t \le P_{i,t}^{gt} - P_{i,t-1}^{gt} \le R_i^{gt}\cdot \Delta t$$

$$Q_{i,min}^{svc} \le Q_{i,t}^{svc} \le Q_{i,max}^{svc}$$

$$V_{i,\min} \le V_{i,t}^{b} \le V_{i,max}, \quad \forall i, \forall t$$

$$\left|P_{l,t}^{\ell}\right| \le P_{l,\max}, \forall l, \forall t$$

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# Outline

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1 Background

2 Modelling

3 **Methodology**

4 Case Study

5 Conclusions

# 3-Methodology



## 01 Constrained Markov Decision Process

- **State:** The state space is defined as:

$$s_t = \left\{ \begin{array}{l} t, \kappa_t^e, \boldsymbol{P}_t^{load}, \boldsymbol{Q}_t^{load}, \boldsymbol{H}_t^{load}, \boldsymbol{f}_t^{load}, P_t^{wt}, P_t^{pv} \\ \chi_t, P_{t-1}^{CHP}, P_{i,t-1}^{GT}, Q_{i,t-1}^{svc}, \Delta \boldsymbol{V}_{t-1}^{b}, \Delta \boldsymbol{P}_{t-1}^{line} \end{array} \right\}$$

- **Action:** The action set is defined as:

$$a_t = \{a_t^{CHP}, a_{i,t}^{GT}, a_{i,t}^{SVC}\}$$

- **Reward:** The reward is defined as follows:

$$r_t(s_t, a_t) = -(C_t^{om} + C_t^{e} + C_t^{ng})$$

- **Constraints:** The cost functions are as follows:

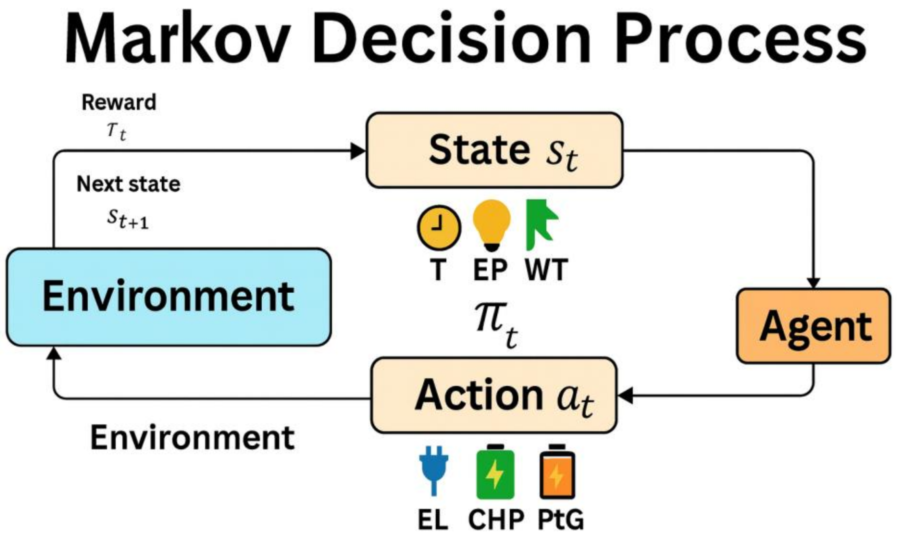
$$c_{1,t}(s_t, a_t) = \max([V_{min} - \boldsymbol{V}_t^b]^+ + [\boldsymbol{V}_t^b - V_{max}]^+)$$

$$c_{2,t}(s_t, a_t) = \max([\boldsymbol{P}_t^{\ell} - \boldsymbol{P}_{\max}^{\ell}]^+)$$

- **Objective Function:** The constrained objective function can be formulated as:

$$\max_{\pi_\phi} \mathop{\mathbb{E}}_{(s_t, a_t) \sim \rho_\pi} \left[ \sum_t \gamma \cdot r_t(s_t, a_t) \right]$$

$$s.t. \;\; c_{i,t}(s_t, a_t) \le d_i, \quad i \in \{1,2\}$$



# 3-Methodology



## 02 General Framework

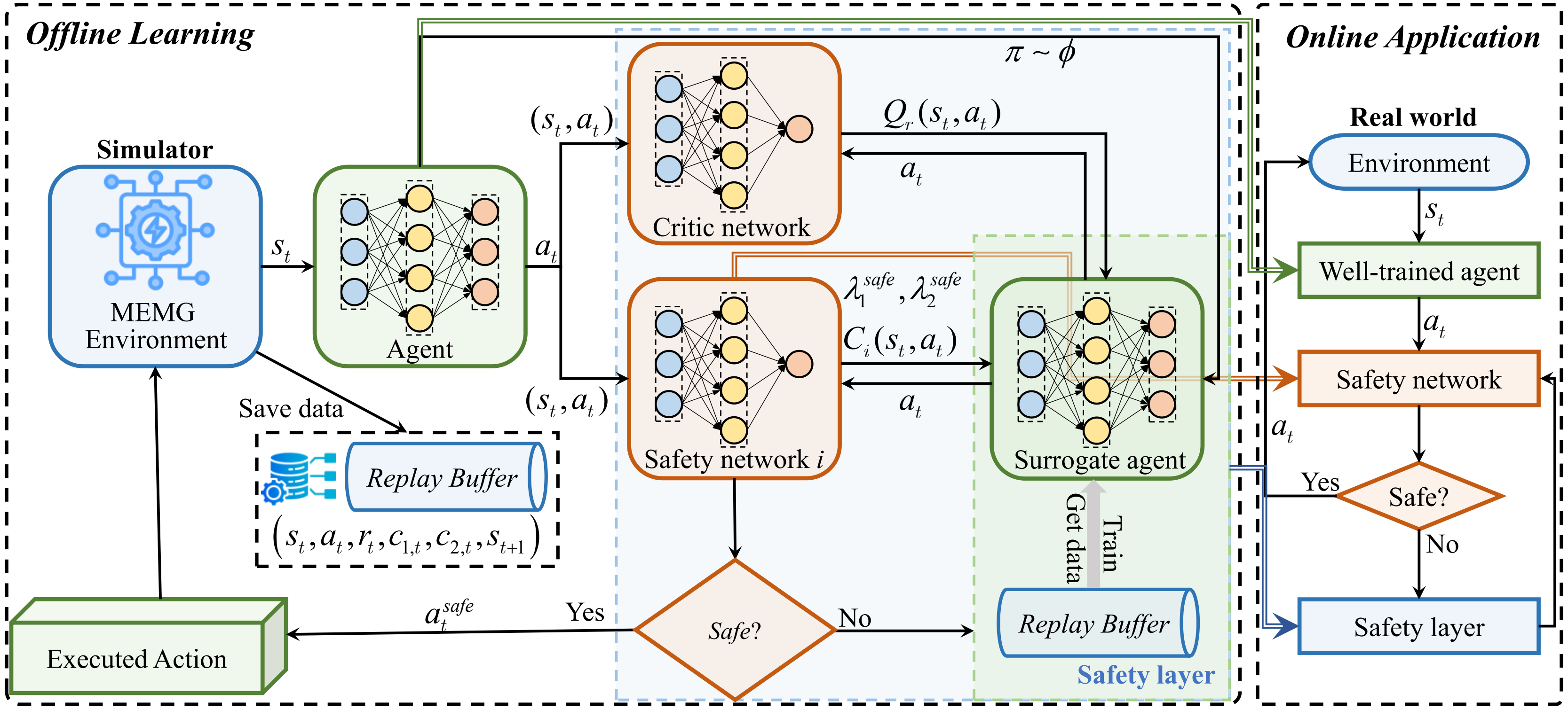



Fig. 4. Framework of the HS-SAC-based solution method.

- ✓ The proposed method is divided into two stages: offline learning and online application.
- ✓ To ensure actions do not violate safety constraints, two steps are implemented, utilizing both the **safety network** and **the safety layer**

# Outline





# 4-Case Study



## 01 Testing System

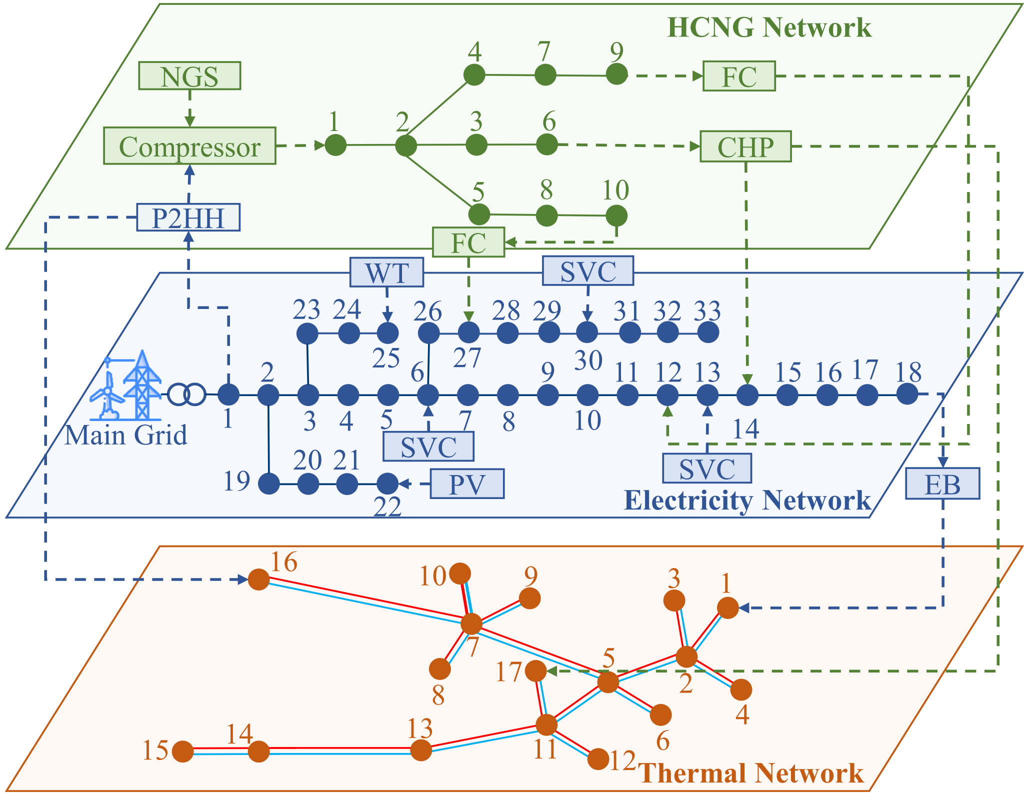



Fig. 5. Schematic diagram of the MEMG test system

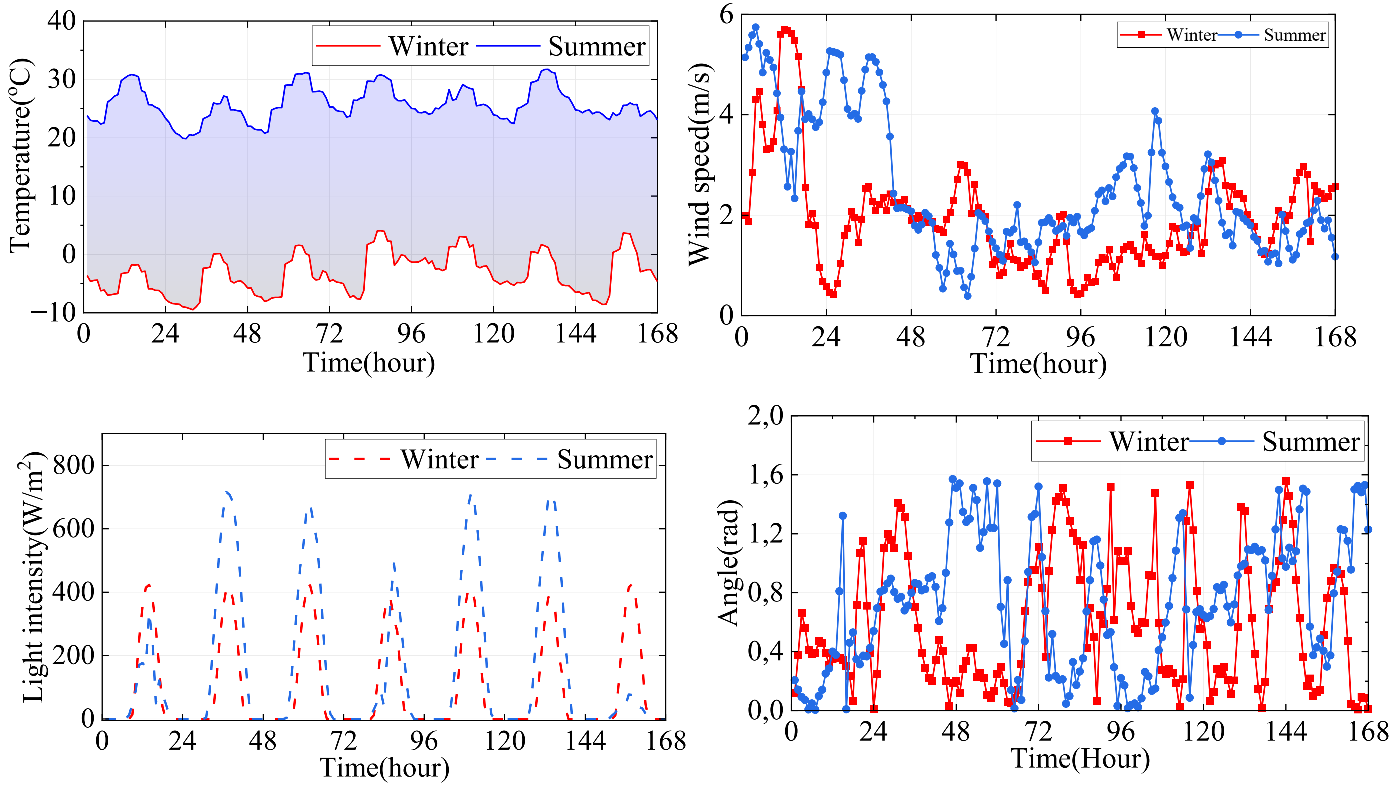



Fig.6 Variations of ambient factors in winter and summer.

H. Hersbach, et al., "ERA5 hourly data on single levels from 1979 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS)," 2018.

# 4-Case Study



## 02 Offline Training

- ✓ The safety networks are trained to minimize prediction errors related to safety constraint satisfaction.
- ✓ Fig.8 show the number of unsafe cases during offline training.
- ✓ Fig.9 compares the average rewards obtained using three different methods: SAC, SAC with Penalty, and the proposed method.

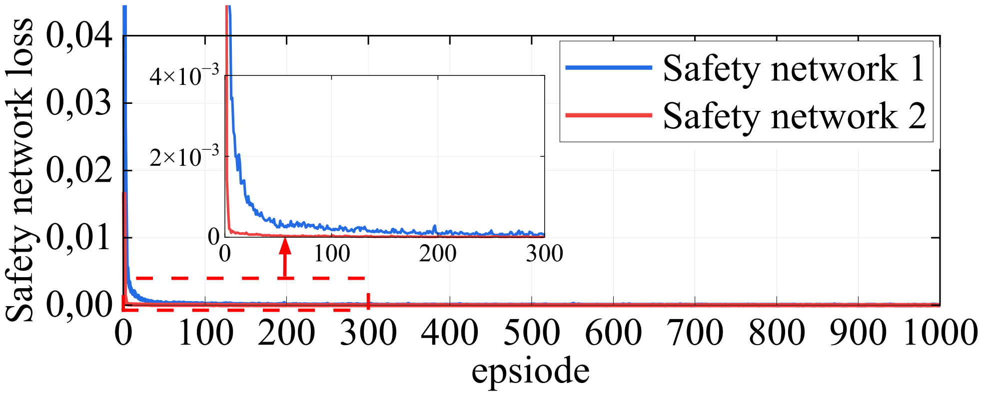



Fig. 7. Loss function values of safety networks.

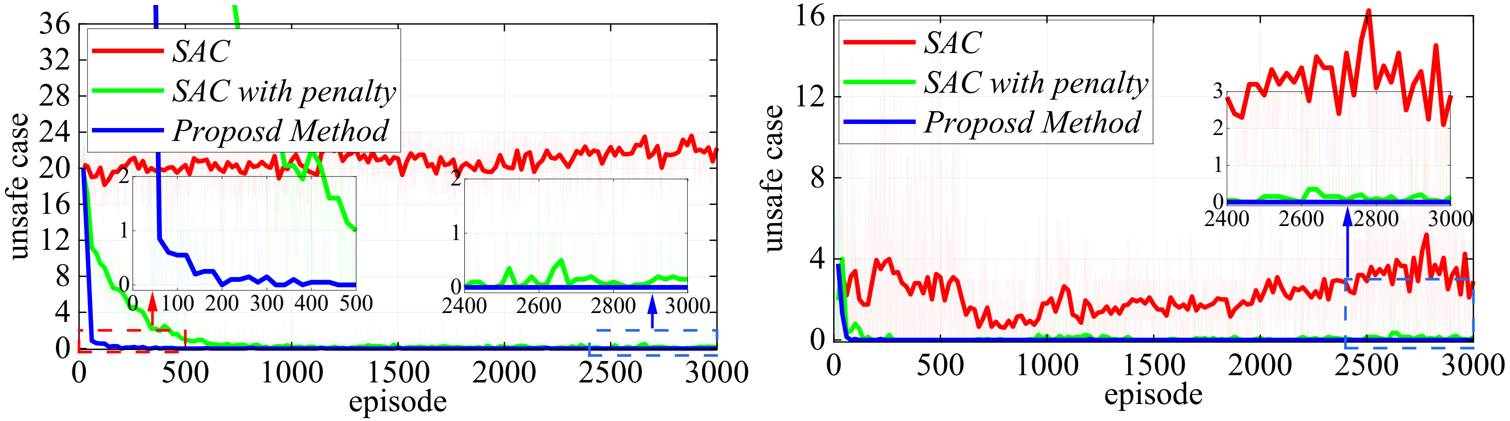



Fig. 8. Number of unsafe cases in offline training

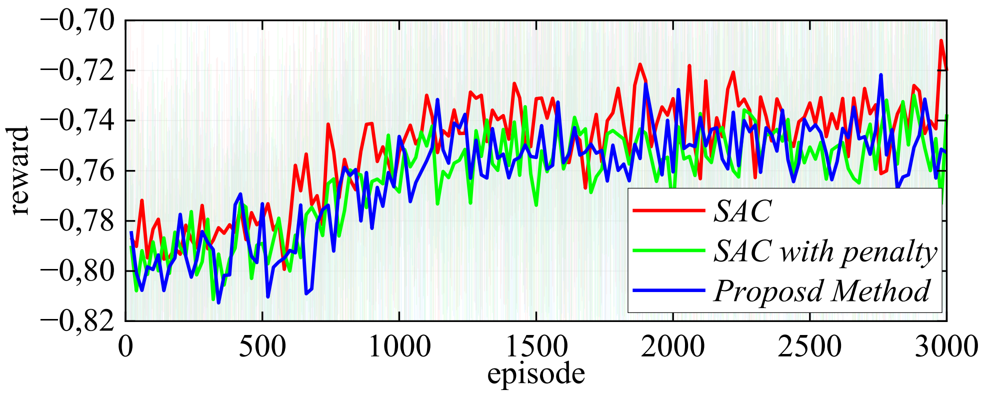


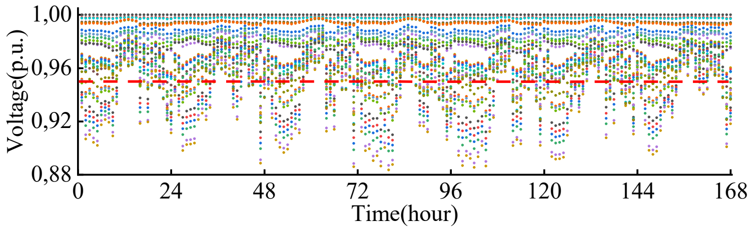

Fig. 9. Average rewards

# 4-Case Study

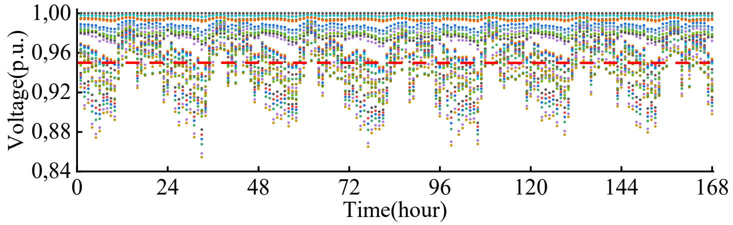


## 03 Test Results

- ✓ Tested over two weeks: Case 1 (August 22-28) and Case 2 (December 22-28).
- ✓ SAC leads to frequent violations of safety constraints in both cases.
- ✓ HSC-SAC demonstrates superior voltage regulation and congestion management.

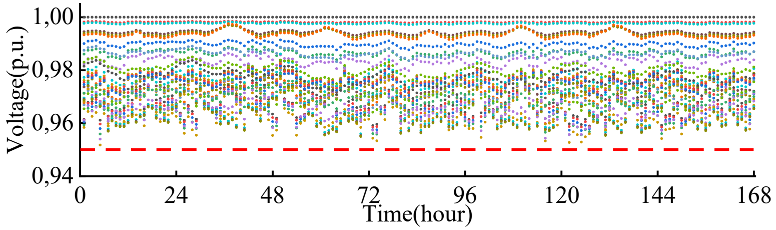



(a) SAC for case 1

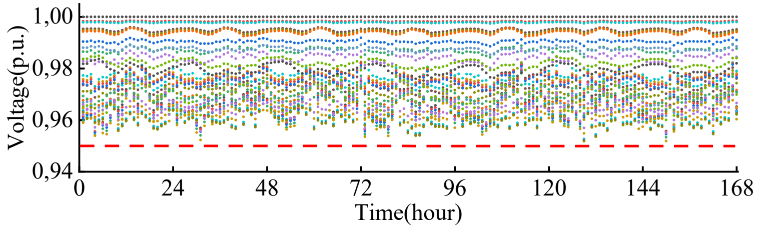



(b) SAC for case 2

**Bus voltage**

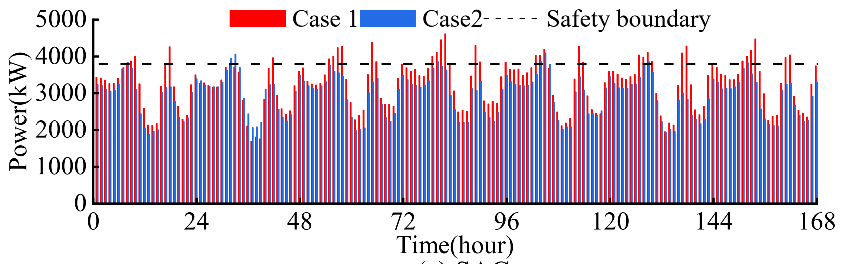



(a) HSC-SAC for case 1

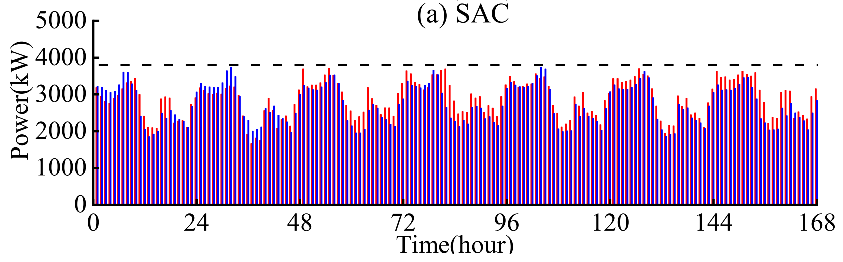



(b) HSC-SAC for case 2

**Bus voltage**




(a) SAC




(b) HSC-SAC

**Line congestion**

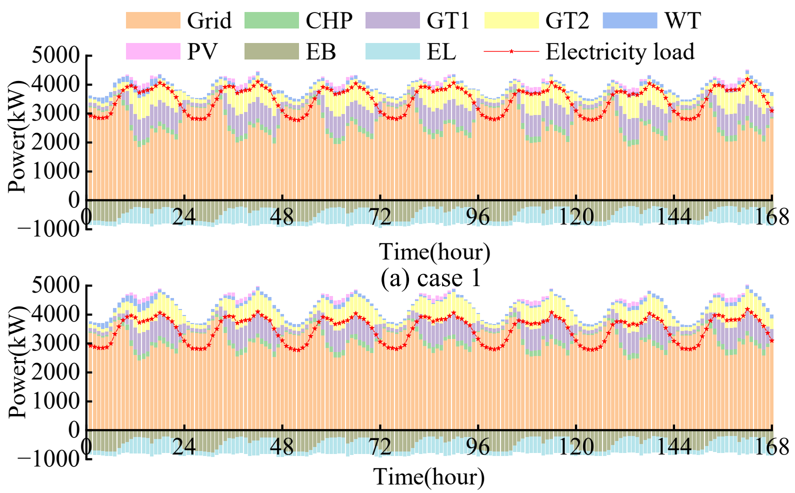
**Safety!**

# 4-Case Study

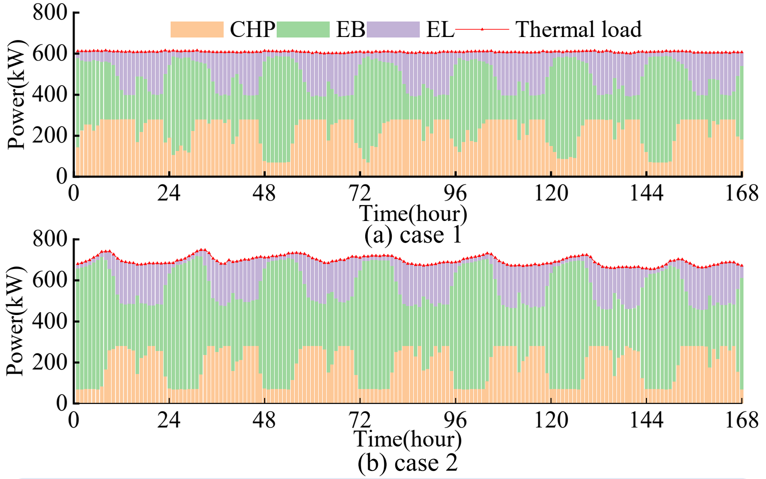


## 03 Test Results

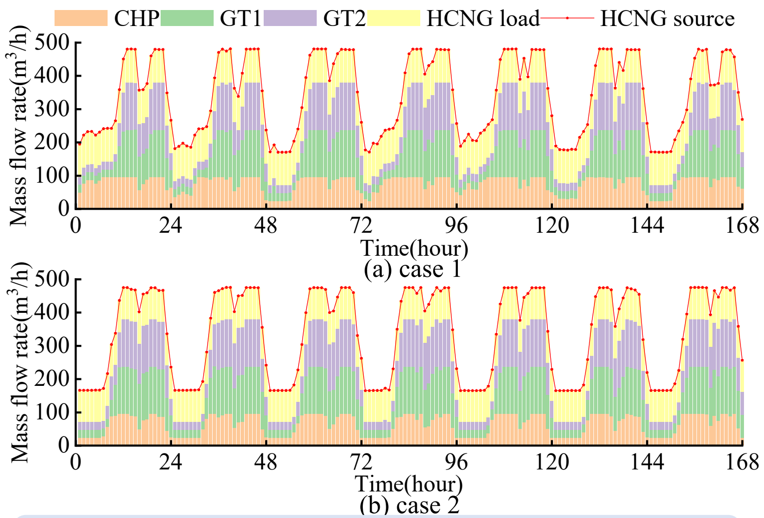
- ✓ Coordinated operation among diverse units maintains power, thermal, and gas flow balance.
- ✓ Proper coordination effectively mitigates congestion in the system.




Power balance condition for MEMG




Thermal balance condition for MEMG




HCNG balance condition for MEMG

**Coordinated Operation!**

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# Outline

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# Conclusions



## 01 A accuracy and comprehensive model

- Power flow model considering impacts of ambient factors
- Hydrogen compressed natural gas model
- Thermal flow model
- PEM model

## 02 A coordinated scheme

- Multi-energy systems
- Multiple energy conversion equipment

## 03 Considering multiple factors

- Line congestion
- Voltage constraints

## 04 Safe DRL

**Objectives**

✓ Economic, safe, and sustainable operation

# Thank you for your time!

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