



Department of Electrical Engineering  
Tsinghua University

COLUMBIA | ENGINEERING  
The Fu Foundation School of Engineering and Applied Science

# Chance-Constrained Generalized Energy Storage Operations under Decision-Dependent Uncertainty

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# Biography

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Research Interest: Data-Driven Modeling, Optimization under Uncertainty and Market Design for Power System with Generalized Energy Storage Resources



B.S. EE, Tianjin University, 2018  
Prof. Yanxia Zhang

PhD. EE, Tsinghua University, 2023  
Prof. Lin Cheng

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Prof. Mads R. Almassalkhi



Research Associate,  
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2023 Prof. Feng Liu



Columbia University  
2024 Prof. Bolun Xu

1. N. Qi, P. Pinson, M. R. Almassalkhi, et al, “Capacity Credit Evaluation of Generalized Energy Storage under Endogenous Uncertainty,” *IEEE Transactions on Power Systems*, 2024.
2. N. Qi, L. Cheng, Kaidi Huang et al, “Reliability-Aware Probabilistic Reserve Procurement under Decision-Dependent Uncertainty,” *2024 IEEE PES General Meeting* (Best Paper Award).
3. N. Qi\*, P. Pinson, M. R. Almassalkhi et al, “Chance-Constrained Generic Energy Storage Operations under Decision-Dependent Uncertainty,” *IEEE Transactions on Sustainable Energy*, vol. 14, no. 4, pp. 2234–2248, 2023.
4. N. Qi\*, L. Cheng, H. Li et al, “Portfolio Optimization of Generic Energy Storage-Based Virtual Power Plant under Decision-Dependent Uncertainties,” *Journal of Energy Storage*, vol. 63, p. 107 000, 2023.
5. N. Qi\*, L. Cheng, Y. Zhuang et al, “Reliability Assessment and Improvement of Distribution System with Virtual Energy Storage under Exogenous and Endogenous Uncertainty,” *Journal of Energy Storage*, vol. 56, p. 105 993, 2022.
6. N. Qi\*, L. Cheng, H. Xu et al, “Smart meter data-driven evaluation of operational demand response potential of residential air conditioning loads,” *Applied Energy*, vol. 279, p. 115 708, 2020.



## **Background and Motivation**



## **Physics-Informed Data-driven Modeling of GES ---how much reliable flexibility is available?**

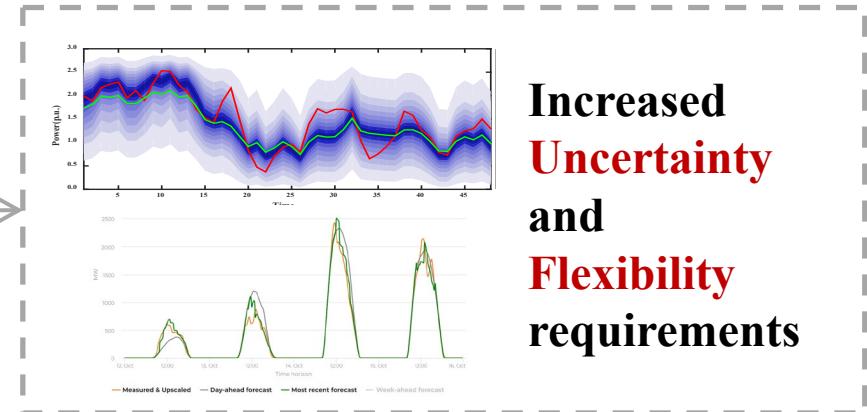


## **Chance-Constrained GES Operations under DDU ---how to better utilize this reliable flexibility?**

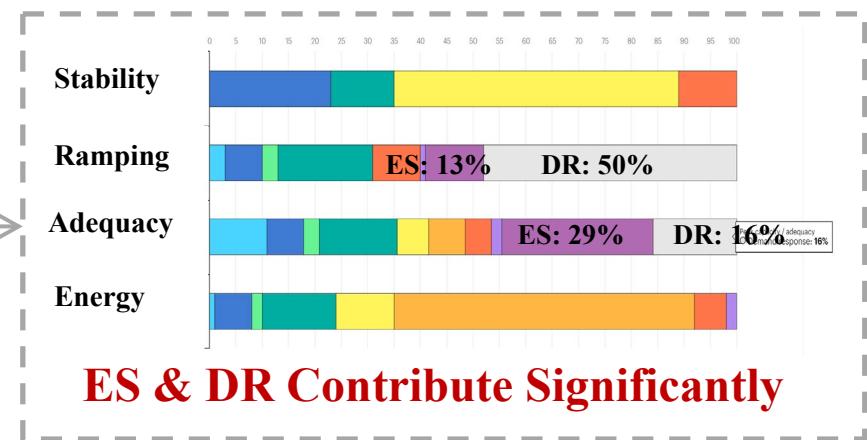
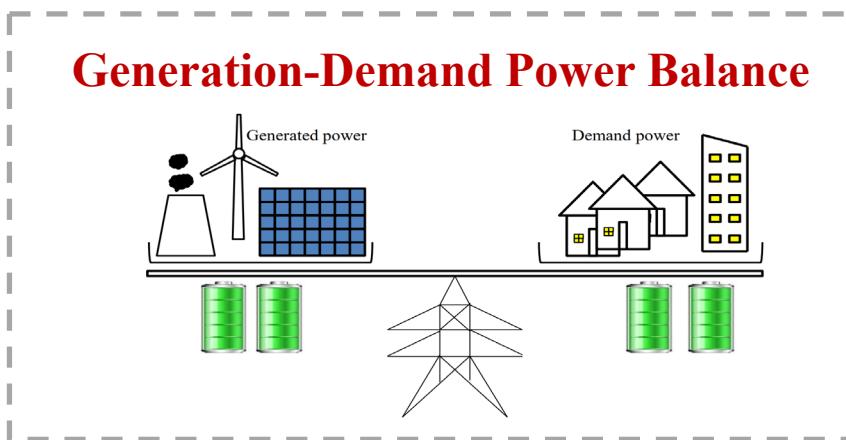
## **Conclusion and Current Work**

# 1. Background and Motivation

- Climate Change → Carbon Neutrality Policies → Vigorously Development of Renewables → Increased Uncertainty → Increased Flexibility Requirements

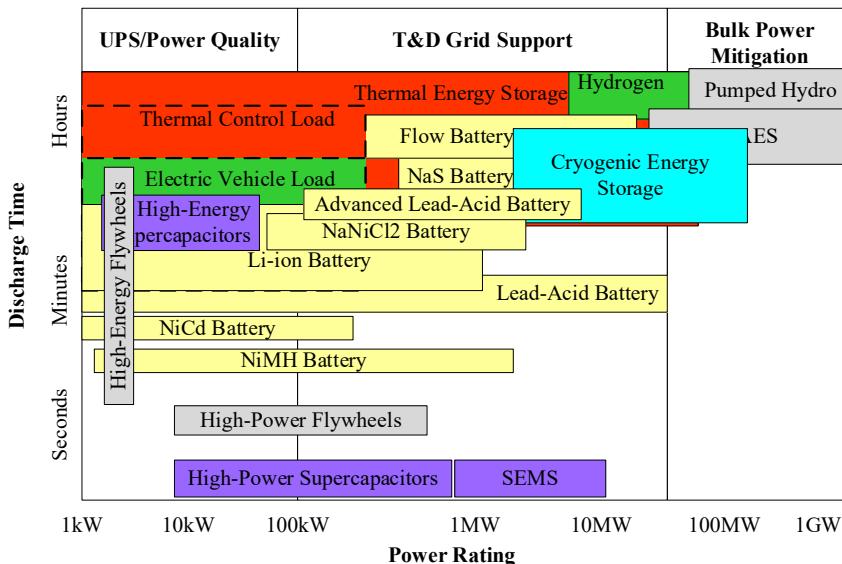


- Ensure Power Balance → Four Basic Flexibility Requirements → Declined Flexibility from Generation → Unlock flexibility from Energy Storage and Demand Response



# 1. Background and Motivation

- Extensive Types of Energy Storage and Demand Response Resources → Large Power and Energy Ranges → Limitations in **Reliability and Economy**



- Flywheel → UPS (Expensive)
- Battery → Short-Term Dispatch (Security, Extreme Climate Conditions)
- Pumped-Storage Hydro → Long-Term Dispatch (Resource-Dependent, Expensive)
- CAES/Hydrogen → Low-efficiency, Expensive
- Virtual Energy Storage(VES) → Cheap (Unreliable)

- ✓ Q: Generate Reliable Flexibility from Heterogeneous Resources?
- ✓ Q: Guarantee both Reliability and Economy with Less ES and More VES?
- Generalized Energy Storage (GES): physical energy storage + virtual energy storage



Battery



Flywheel



PSH



Hydrogen



TCL



EV



## Background and Motivation



## Physics-Informed Data-driven Modeling of GES ---how much reliable flexibility is available?



## Chance-Constrained GES Operations under DDU ---how to better utilize this reliable flexibility?

## Conclusion and Current Work

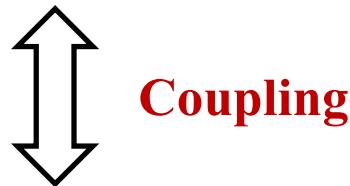
## 2. Physics-Informed Data-driven Modeling of GES

- Non-Intrusively Extract/Disaggregate GES from Load (Behind-the-Meter) and Evaluate the Operational Flexibility of GES Resources—Flexibility Learning

N. Qi\*, L. Cheng, H. Xu et al, “Smart meter data-driven evaluation of operational demand response potential of residential air conditioning loads,” *Applied Energy*, vol. 279, p. 115 708, 2020.

N. Qi\*, L. Cheng, H. Xu, Z. Wang, and X. Zhou, “Practical demand response potential evaluation of air-conditioning loads for aggregated customers,” *Energy Reports*, vol. 6, pp. 71–81, 2020.

L. Cheng, N. Qi\*, Y. Guo, et al, “Potential evaluation of distributed energy resources with affine arithmetic,” *2019 IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia)*, IEEE, 2019, pp. 4334–4339.



- Propose a Unified GES Model with Various Decision-Independent Uncertainties (DIUs) and Decision-Dependent Uncertainties (DDUs)—Flexibility Modeling

N. Qi\*, P. Pinson, M. R. Almassalkhi et al, “Chance-Constrained Generic Energy Storage Operations under Decision-Dependent Uncertainty,” *IEEE Transactions on Sustainable Energy*, vol. 14, no. 4, pp. 2234–2248, 2023.

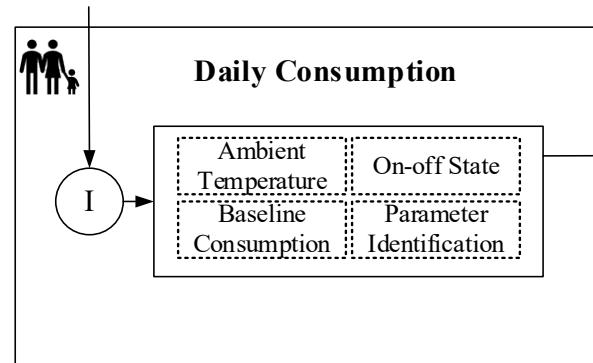
N. Qi\*, L. Cheng, Y. Wan, et al, “Risk assessment with generic energy storage under exogenous and endogenous uncertainty,” *2022 IEEE Power & Energy Society General Meeting (PESGM)*, IEEE, 2022, pp. 1–5.

## 2. Physics-Informed Data-driven Modeling of GES

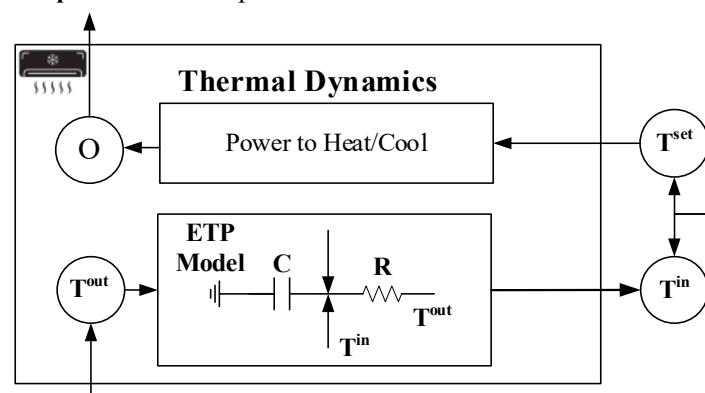
✓ Behavior Analysis + Load Disaggregation + Parameter identification

- Thermostatically Controlled Load (TCL)

**Input:** Historical Consumption and Weather Data

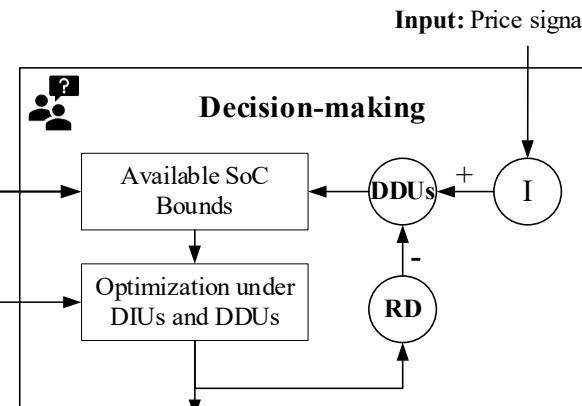


**Output:** Demand Response



**Input:** Ambient Temperature

**Input:** Price signal

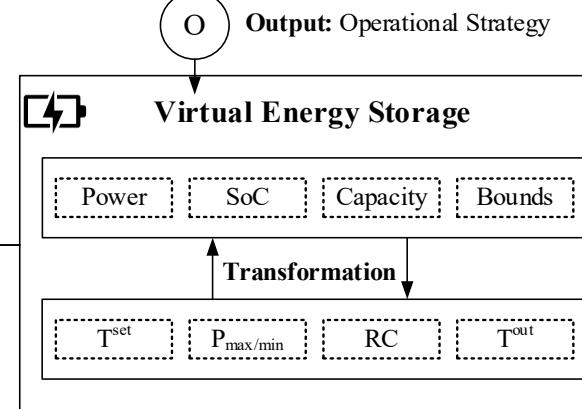


- **States:** cooling, heating, off
- **Physic Model:** equivalent thermal parameter(ETP)

$$\text{Dynamic} \quad C_{eq} \frac{dT_{in}(t)}{dt} = -\eta_{eq} P_{eq} + \frac{T_{out}(t) - T_{in}(t)}{R_{eq}}$$

$$\text{Steady} \quad P_{eq} = \frac{T_{out}(t) - T_{set}(t)}{\eta_{eq} R_{eq}}$$

- **Impact Factors:** temperature (ambient & indoor), price, time



## 2. Physics-Informed Data-driven Modeling of GES

✓ Behavior Analysis+ **Load Disaggregation** + Parameter identification

- Non-Intrusive + Unsupervised Learning

**Step1 Data Acquisition**

Smart meter data, temperature data

**Step2 Data Cleaning**

Missing readings, without TCL

**Step3 Load Level Clustering (Kmeans++ DTW)**

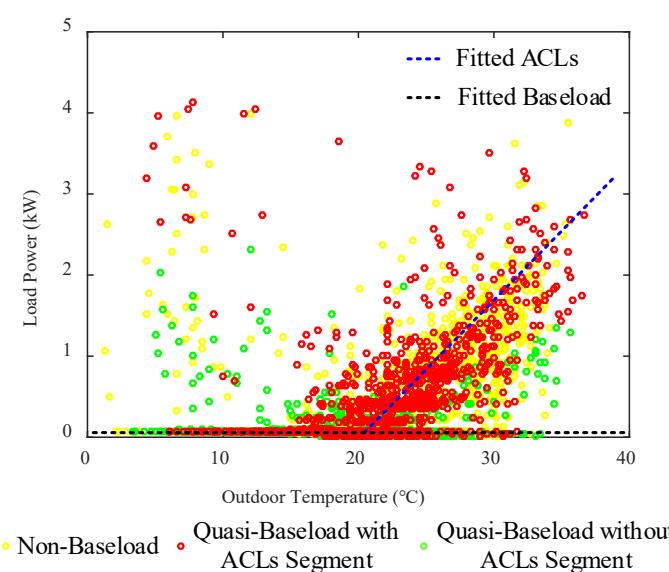
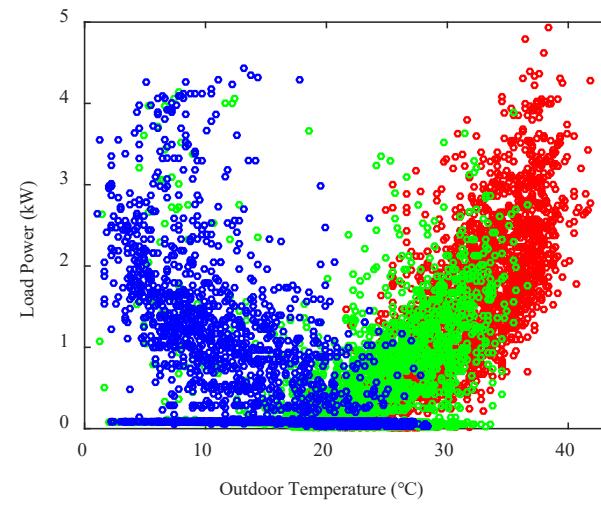
Identification of different consumption levels:  
weekday load without or with fewer ACLs,  
weekday load with ACLs, weekend load without or  
with fewer ACLs, and weekend load with ACLs

**Step4 Correlation Analysis (Temperature)**

Remove the ACLs segments in the quasi-baselload

**Step5 Distribution Test**

Distribution of baseload with seasonal variations



## 2. Physics-Informed Data-driven Modeling of GES

✓ Behavior Analysis+ Load Disaggregation + Parameter identification

### ● ETP Model + Simulation + Recursively Estimation

**Step1 Segment Decomposition**  
on-off segment static-dynamic segment

$$|P_t| \leq \delta \quad dPT_t = \frac{d}{dt} \left( \frac{P_t}{T_{out,t}} \right) \leq \sigma$$

**Step2 Static Parameter Estimation**  
constrained regression

$$[k, b] = \arg \min_{k, b_t} \sum_{t \in \Omega_{\text{on-static}}} (P_t - kT_{out,t} - b_t)^2$$

$$\text{s.t. } K_{\min} \leq k \leq K_{\max}$$

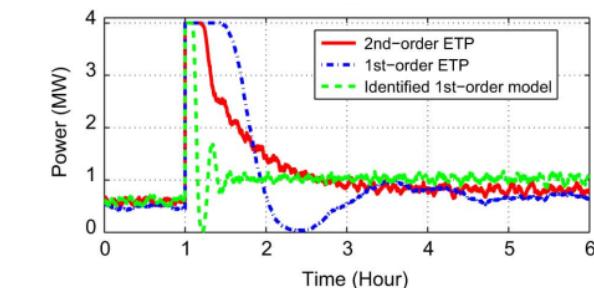
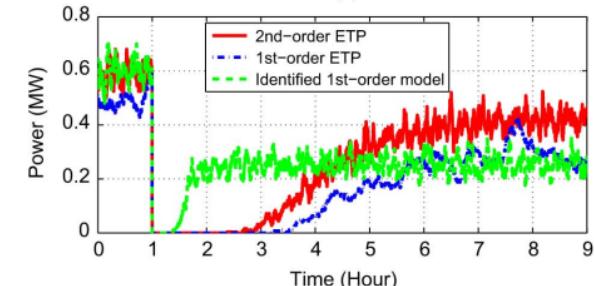
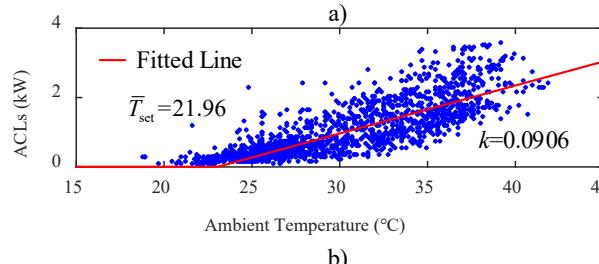
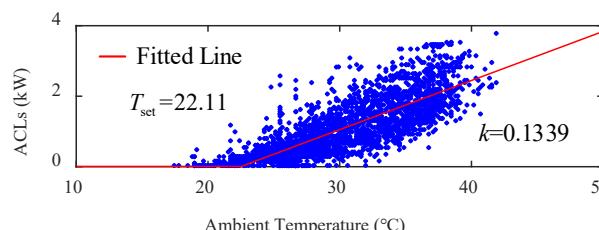
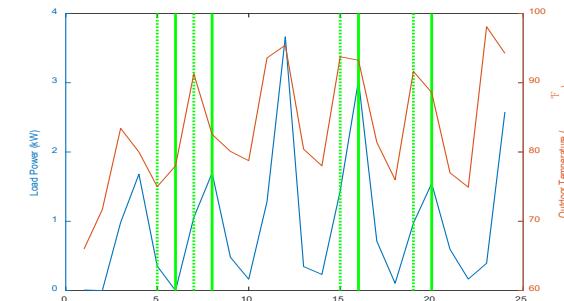
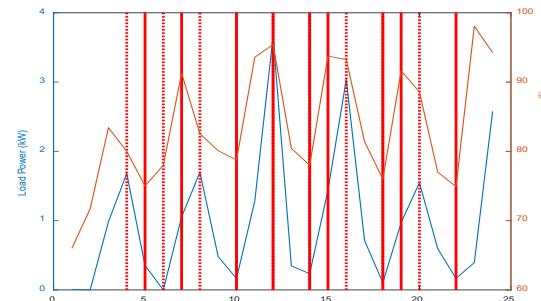
$$T_{set,min} \leq -b_t / k \leq T_{set,max}, \quad t \in \Omega_{\text{on-static}}$$

$$k = 1 / \eta_{eq} R_{eq} \quad -b / k = T_{set} = \{T_{set,t}\}$$

**Step3 Dynamic Parameter Estimation**  
Simulation+PSO Recursively

$$\frac{C_{eq}}{\eta_{eq}} = \frac{t_3 - t_2}{\eta_{eq} R_{eq} \ln[(P_2 - P_4) / (P_3 - P_4)]}$$

$$\left(\frac{C_{eq}}{\eta_{eq}}\right)_{\max} = \left(\frac{\sum C_i}{\eta_{eq}}\right)_{\max} = \left(\frac{\sum c \rho h_i S_i}{\eta_{eq}}\right)_{\max} = c_{air} \rho_{air} P_{max} \frac{h}{Q}$$



## 2. Physics-Informed Data-driven Modeling of GES

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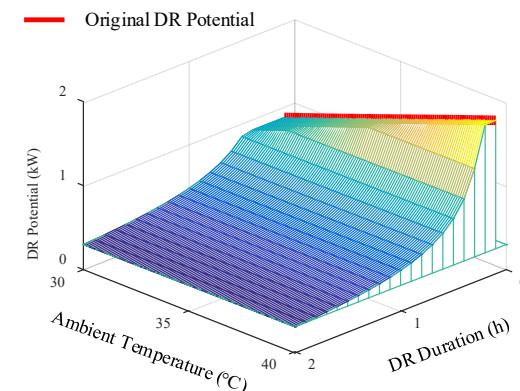
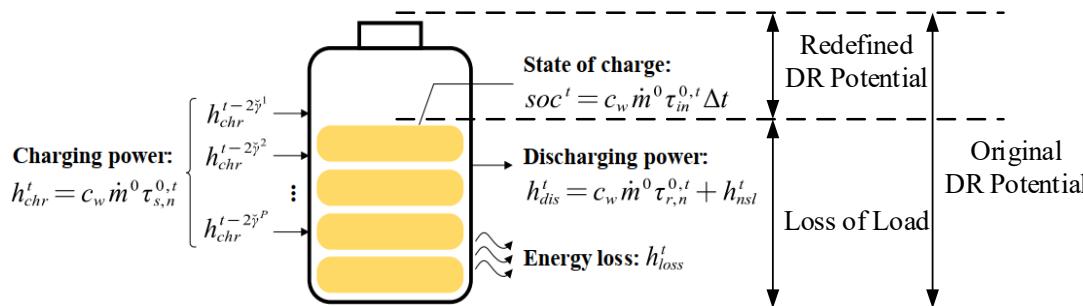
### ✓ Operational Flexibility—State-Dependent

**Multiple Factors:** ambient temperature、setpoint temperature、equivalent thermal parameter、comfort

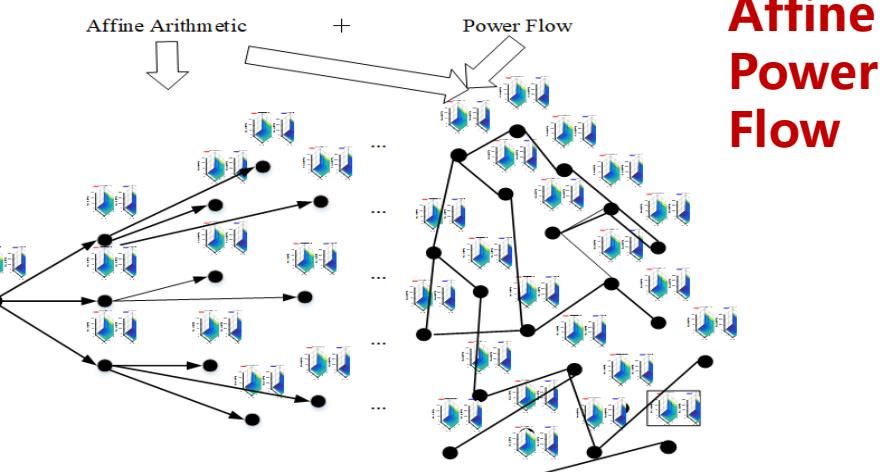
**Multiple Uncertainties:** seasonal variation、temperature correlation、social behavior

$$DR_t = P_{eq,t} - P_{eq,t}^*$$

$$= \begin{cases} \frac{M\Delta T}{\eta_{eq} R_{eq}(M-1)}, & t_{duration} > R_{eq} C_{eq} \ln \frac{T_{out,t} - T_{in,t}}{T_{out,t} - T_{in,t} - \Delta T} \\ \frac{T_{out,t} - T_{in,t}}{\eta_{eq} R_{eq}}, & t_{duration} \leq R_{eq} C_{eq} \ln \frac{T_{out,t} - T_{in,t}}{T_{out,t} - T_{in,t} - \Delta T} \end{cases}$$



**Individual Flexibility**



**Grid-aware Flexibility**

## 2. Physics-Informed Data-driven Modeling of GES

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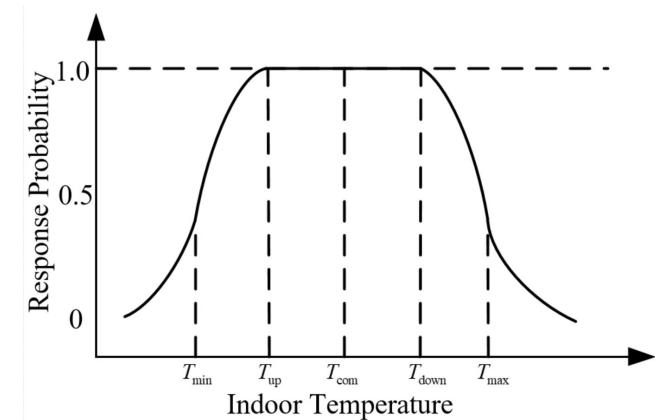
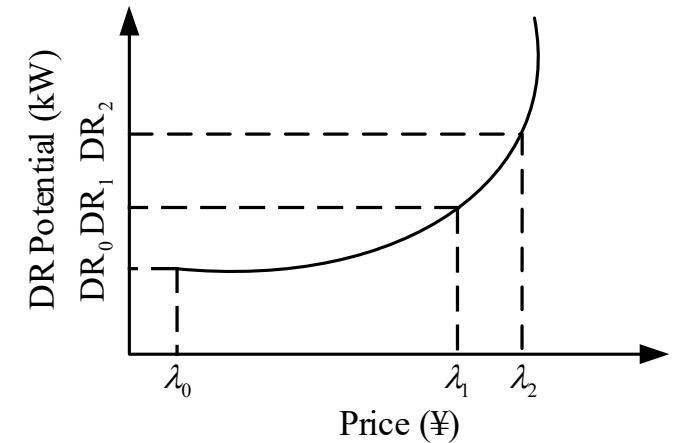
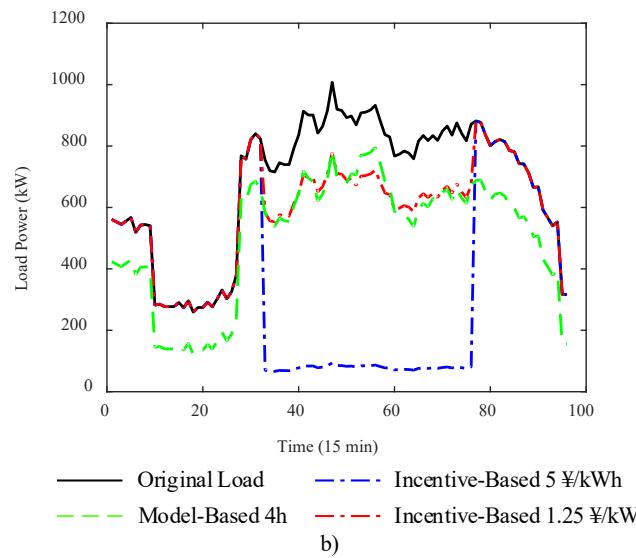
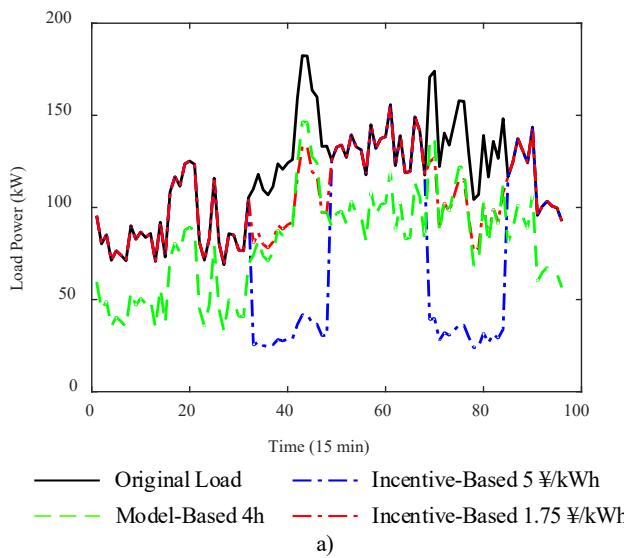
✓ Practical Flexibility= min (Physical Flexibility, Economic Flexibility)

Economic Flexibility: price elasticity model

$$DP_t^1 = \frac{\varphi E_t P_{\text{total},t}^*}{\rho_t^*} (\rho_t - \rho_t^* + \eta \lambda_t) + \sum_{j=1, j \neq t} \frac{\varphi E_{t,j} P_{\text{total},t}^*}{\rho_j^*} (\rho_j - \rho_j^* + \eta \lambda_j)$$

Physical Flexibility: data-driven model

$$DP_t^2 = f(T_{\text{out},t}, t_{\text{duration}}, T_{\text{in},t}, \Delta T, \theta_{eq})$$



### ✓ Case Study (Ground-Truth Data)

#### Austin Mueller Project

##### Smart Meter Data

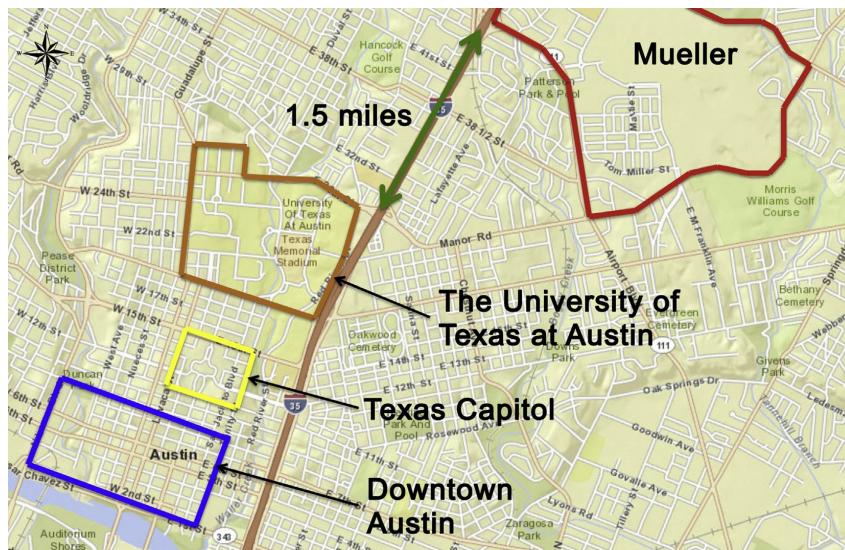
Downtown Austin residential customer,  
whole-house, sub-meter

August 2015 to July 2016, 1min

##### Weather Data

Mueller weather station

August 2015 to July 2016, 1h



#### Smart Home Project

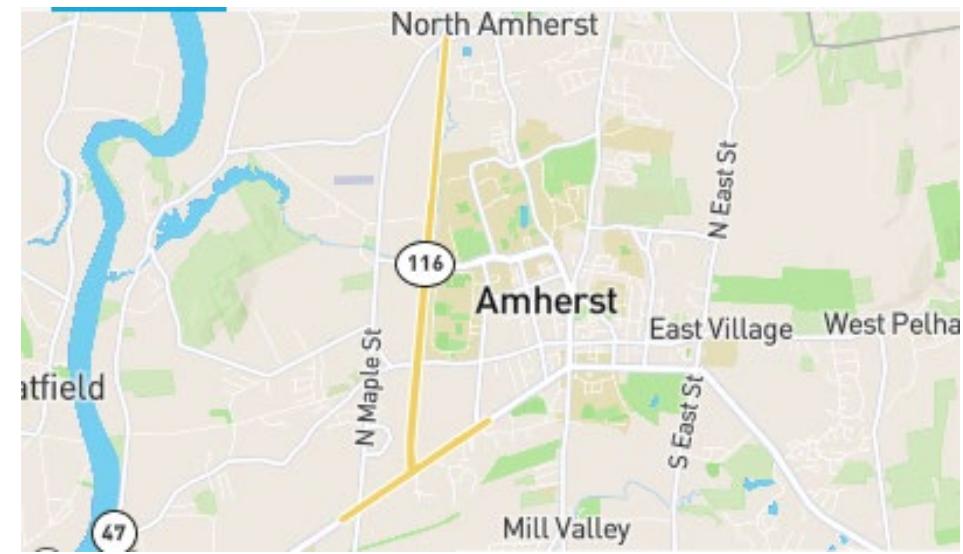
##### Smart Meter Data

Smart Home , Mississippi state  
whole-house, sub-meter

2016.01~2016.12, 15min/30min/1h

##### Weather Data

2016.01~2016.12, 1h



### ✓ Case Study (Ground-Truth Data)

#### Nanjing Project

##### Low-Voltage Distribution Substation Data

Aggregated customers

garment factory, hotel, hospital

2017.01~ 2018.12, 15min

##### Weather Data

2017.01~ 2018.12, 1h



#### Hangzhou Project

##### Low-Voltage Distribution Substation Data

Aggregated customers

Office building, rural area, hotel

2020.01~ 2021.12, 15min

##### Weather Data

2020.01~ 2021.12, 1h

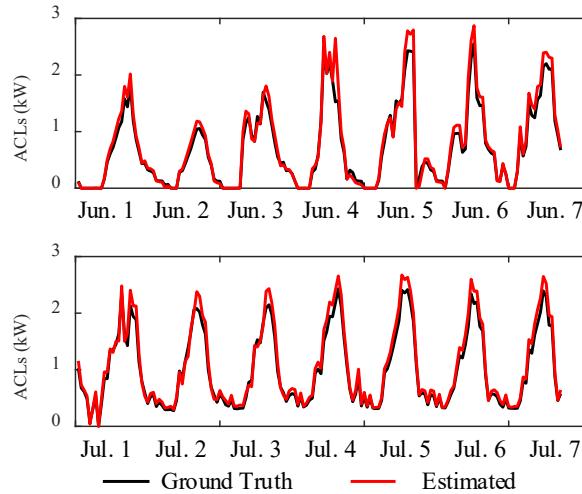


## 2. Physics-Informed Data-driven Modeling of GES

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### ✓ Case Study (Ground-Truth Data)

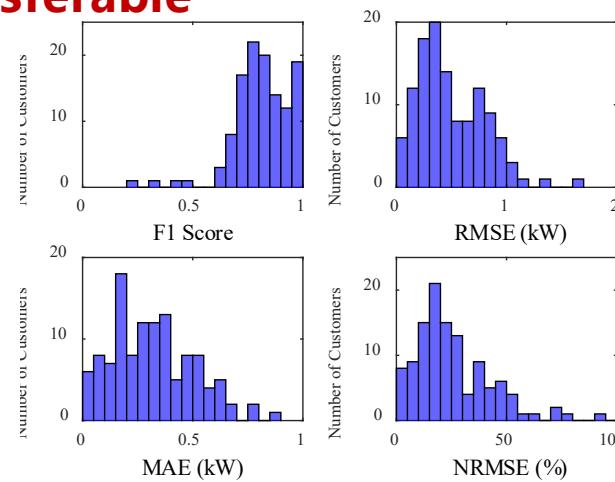
#### ● High Accuracy, High Robustness Highly-Transferable



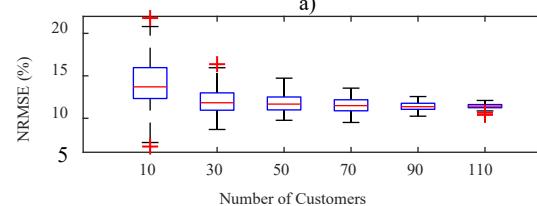
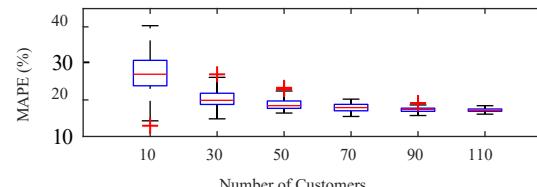
**Fig Comparison of the ground truth and estimated data of customer #77**

**Table Comparison of the average performance evaluation index**

Index	Hybrid Method	Linear Regression [18]	HMM [13]
F1 Score	0.77	0.67	0.71
MAE (kW)	0.26	0.34	0.28
RMSE (kW)	0.48	0.51	0.42
MAPE (%)	29.09	50.06	31.29
NRMSE (%)	21.36	23.91	19.73



**Fig Histogram of the important evaluation index across the 119 customers**

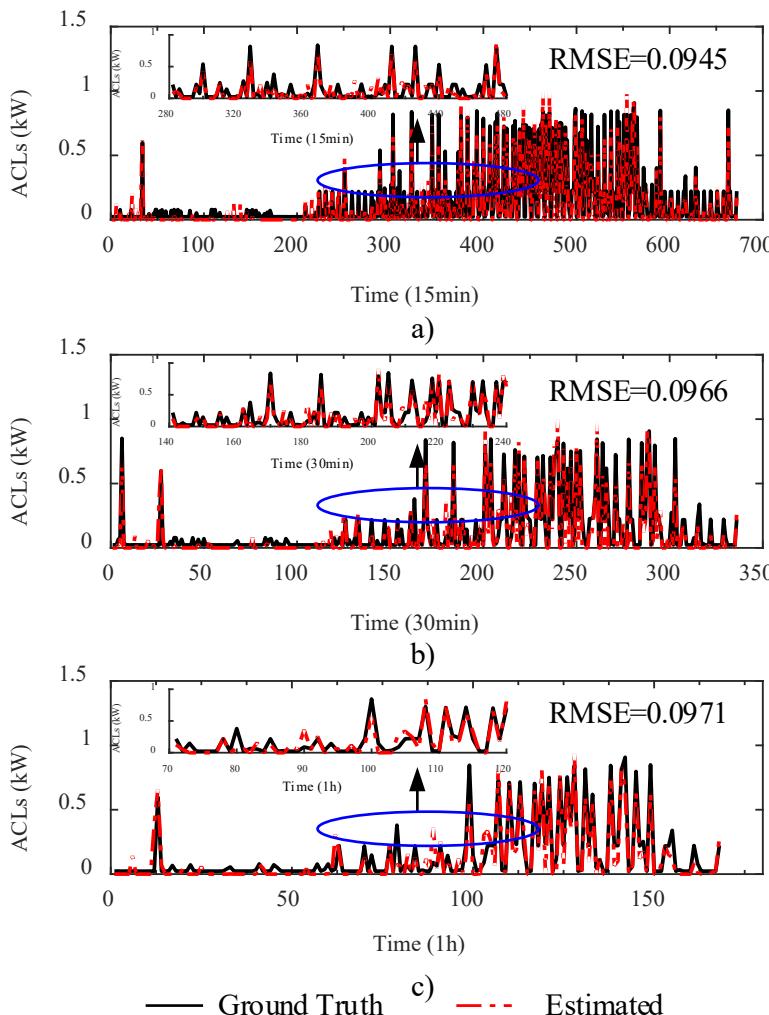


**Distribution of a) MAPE and b) NRMSE considering different number of customers**

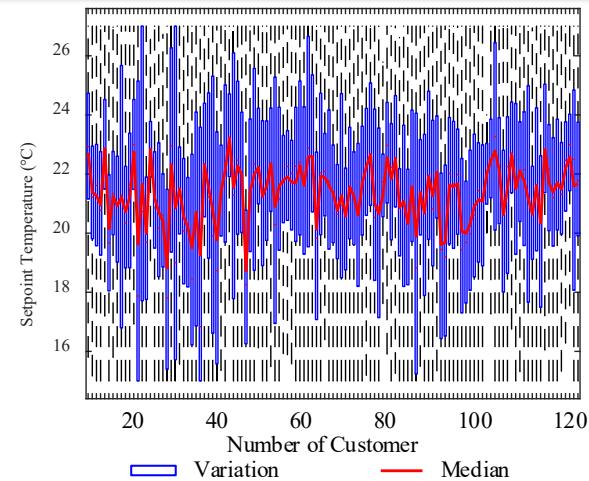
## 2. Physics-Informed Data-driven Modeling of GES

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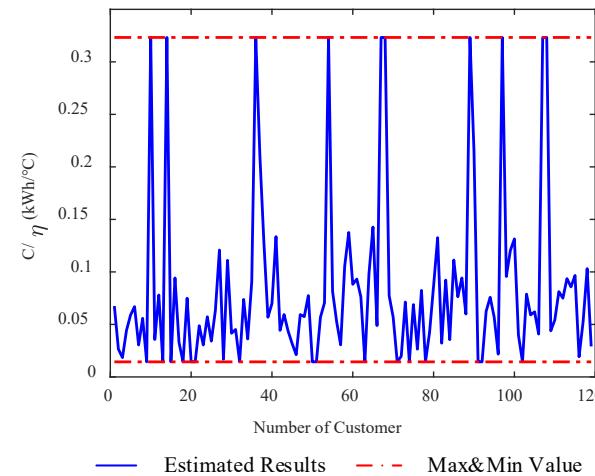
### ✓ Case Study (Ground-Truth Data)



**Fig load disaggregation test over different time-scales**



**Fig setpoint temperature estimation**



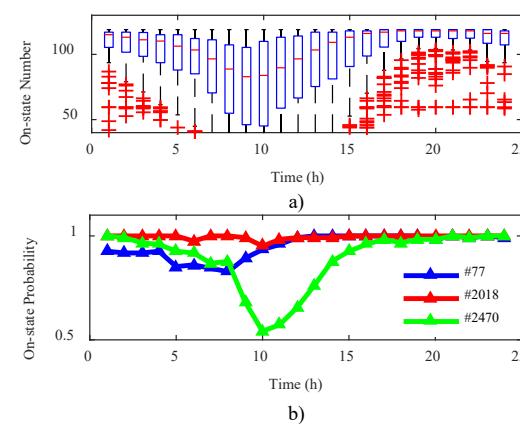
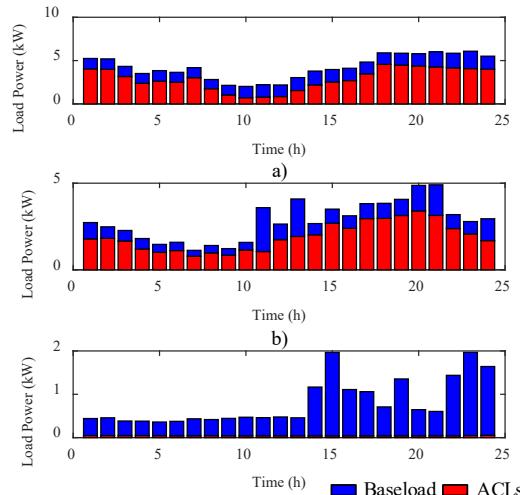
**Fig thermal capacity estimation**

## 2. Physics-Informed Data-driven Modeling of GES

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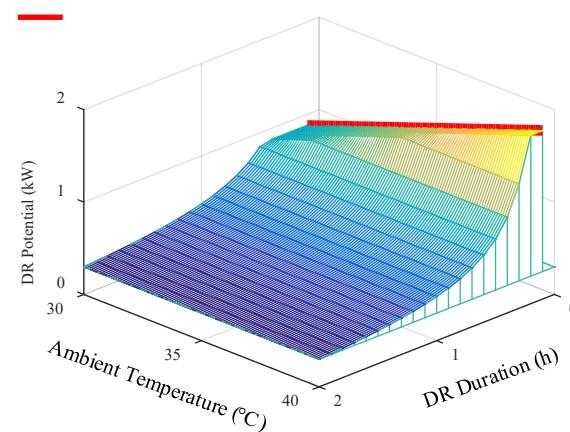
### ✓ Case Study (Ground-Truth Data)

#### ➤ Usage Pattern

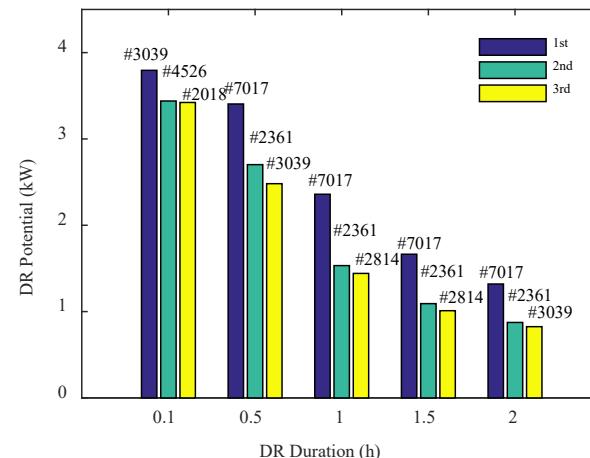


**On-state**

#### ➤ Distribution of Flexibility

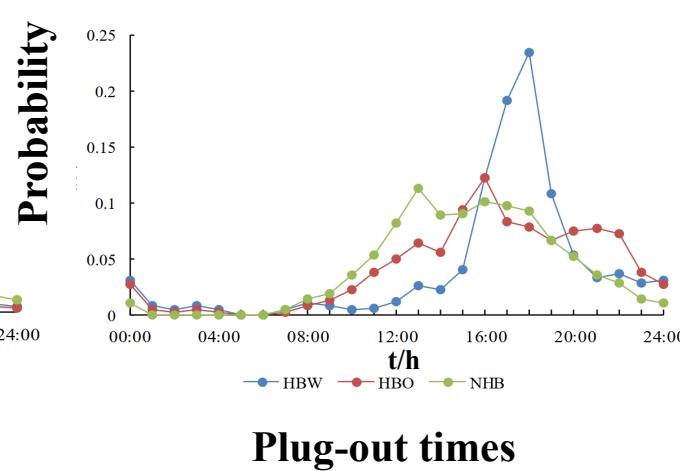
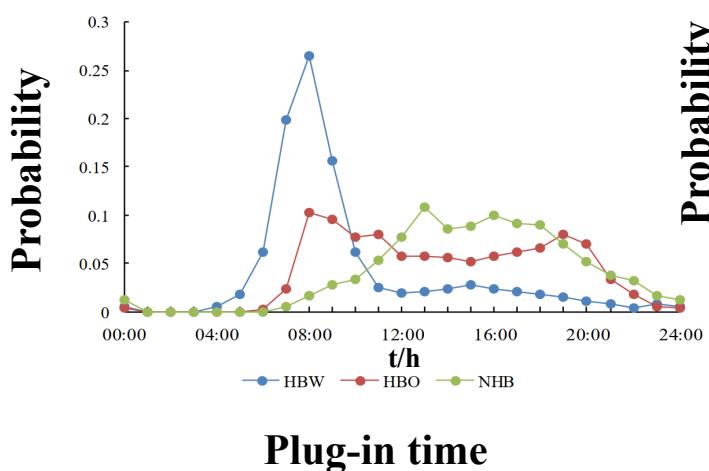
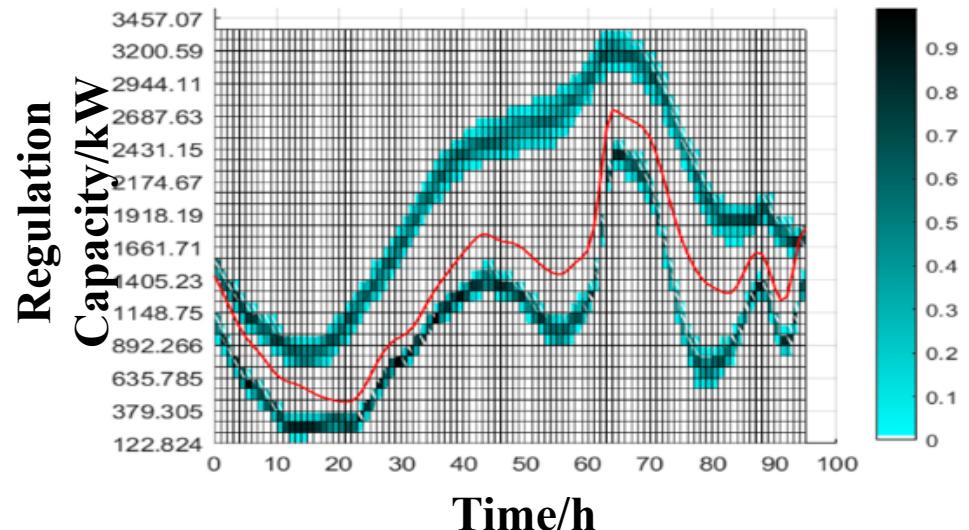
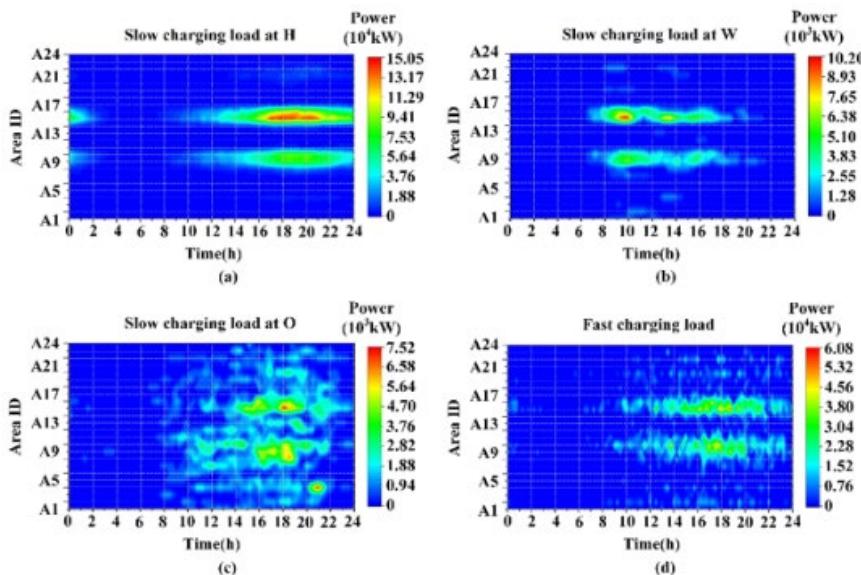


#### ➤ DR Customer Targeting



## 2. Physics-Informed Data-driven Modeling of GES

✓ Flexibility from EV—More Complex and Stochastic than TCL

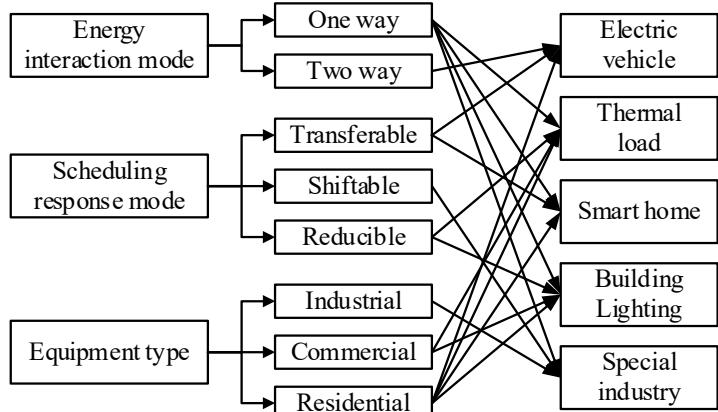


## 2. Physics-Informed Data-driven Modeling of GES

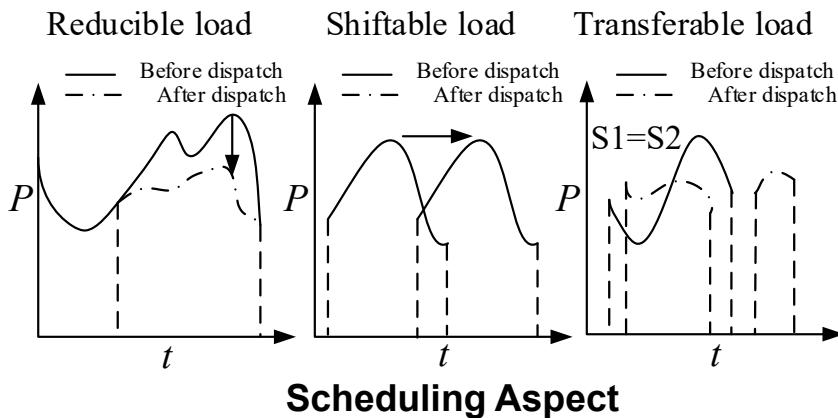
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### ✓ Unified Modeling of GES Resources

#### Classification of Flexible Load



#### Classification



#### Modeling of Flexible Load

$$\begin{aligned}
 & \mathbf{P}_i^{\text{shift}} = \mathbf{X}_i \cdot \mathbf{P}_{i,t}^{\text{shift}} \\
 & \mathbf{P}_i^{\text{shift}} = \left[ p_{i,t}^{\text{shift}} \right]_{1 \times T} \\
 & \mathbf{X}_i = \left[ x_{i,t} \right]_{1 \times T} \\
 & \mathbf{P}_{i,t}^{\text{shift}} = \begin{bmatrix} P_{i,s(1)}^{\text{shift}} & \dots & P_{i,s(n)}^{\text{shift}} & \dots & 0 \\ 0 & P_{i,s(1)}^{\text{shift}} & \dots & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & P_{i,s(1)}^{\text{shift}} & \dots & P_{i,s(n)}^{\text{shift}} \end{bmatrix} \\
 & \sum_{t \in S_i} x_{i,t} = 1 \\
 & \sum_{t \in S_i} x_{i,t} = 0 \\
 & S_i = [t_{i,\text{start}}^{\text{shift}}, t_{i,\text{end}}^{\text{shift}}] \cup \{t_i^*\} \\
 & \mathbf{P}_i^{\text{re}} = \left[ p_{i,t}^{\text{re}} \right]_{1 \times T} \\
 & \mathbf{P}_i^{\text{re}*} = \left[ p_{i,t}^{\text{re}*} \right]_{1 \times T} \\
 & \mathbf{Z}_i = \left[ z_{i,t} \right]_{1 \times T} \\
 & p_{i,t}^{\text{re}} = p_{i,t}^{\text{re}*} \cdot r_{i,t}^{\text{re}} + q_{i,t}^{\text{re}} \\
 & z_{i,t} \alpha_{i,\min} p_{i,t}^{\text{re}*} \leq r_{i,t}^{\text{re}} \leq z_{i,t} \alpha_{i,\max} p_{i,t}^{\text{re}*} \\
 & \text{Ramp}_{i,\text{down}}^{\text{re}} \Delta t \leq r_{i,t}^{\text{re}} - r_{i,t-1}^{\text{re}} \leq \text{Ramp}_{i,\text{up}}^{\text{re}} \Delta t \\
 & \sum_{\tau=t}^{t+T_{i,\text{min}}^{\text{re}}-1} z_{i,\tau} \geq T_{i,\min}^{\text{re}} (z_{i,t} - z_{i,t-1}), t \in F_i^1 \\
 & F_i^1 = \{1, 2, \dots, T - T_{i,\min}^{\text{re}} + 1\}, z_{i,0} = 0 \\
 & \sum_{\tau=t}^{t+T_{i,\text{max}}^{\text{re}}-1} (1 - z_{i,\tau}) \geq T_{i,\max}^{\text{re}}, t \in F_i^2 \\
 & F_i^2 = \{1, 2, \dots, T - T_{i,\max}^{\text{re}}\} \\
 & \sum_{\tau=t}^{t+T_{i,\text{idle}}^{\text{re}}-1} (1 - z_{i,\tau}) \geq T_{i,\min}^{\text{idle}} (z_{i,t-1} - z_{i,t}) \\
 & \boxed{\text{Constraints:}}
 \end{aligned}$$

- Power Limit
- Time Period Limit
- Power Balance
- Continuity
- Reducible Load

$$\begin{aligned}
 & \mathbf{P}_i^{\text{trans}} = \left[ p_{i,t}^{\text{trans}} \right]_{1 \times T} \\
 & \mathbf{P}_i^{\text{trans}*} = \left[ p_{i,t}^{\text{trans}*} \right]_{1 \times T} \\
 & \mathbf{Y}_i = \left[ y_{i,t} \right]_{1 \times T} \\
 & y_{i,t} P_{i,\min}^{\text{trans}} \leq p_{i,t}^{\text{trans}} \leq y_{i,t} P_{i,\max}^{\text{trans}} \\
 & \sum_{t \in T_i} y_{i,t} = 0 \\
 & T_i^1 = [t_{i,\text{start}}^{\text{trans}}, t_{i,\text{end}}^{\text{trans}}] \\
 & T_i^2 = [t_{i,\text{start}}^{\text{trans}}, t_{i,\text{end}}^{\text{trans}} - t_{i,\min}^{\text{trans}} + 1] \\
 & \sum_{t=t_{i,\text{start}}^{\text{trans}}}^{t_{i,\text{end}}^{\text{trans}}} p_{i,t}^{\text{trans}} \Delta t = (1 + \alpha_i^{\text{trans}}) \sum_{t=1}^T p_{i,t}^{\text{trans}*} \Delta t \\
 & \sum_{\tau=t}^{t+T_{i,\min}^{\text{trans}}-1} v_{i,\tau} \geq t_{i,\min}^{\text{trans}} (v_{i,t} - v_{i,t-1}), t \in T_i^2 \\
 & T_i^2 = [t_{i,\text{start}}^{\text{trans}}, t_{i,\text{end}}^{\text{trans}} - t_{i,\min}^{\text{trans}} + 1] \\
 & \text{Ramp}_{i,\text{down}}^{\text{trans}} \Delta t \leq p_{i,t}^{\text{trans}} - p_{i,t-1}^{\text{trans}} \leq \text{Ramp}_{i,\text{up}}^{\text{trans}} \Delta t
 \end{aligned}$$

#### Transferable Load

## 2. Physics-Informed Data-driven Modeling of GES

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### ✓ Unified Modeling of GES Resources—DIUs and DDUs

- GES model involves: **Battery, TCL and EV**
- Q: What's the **difference** between GES model and battery model?

#### GES Model

$$0 \leq P_{c,i,t}^{\text{GES}} \leq \bar{P}_{c,i,t}^{\text{GES}}$$

Time-varying

$$0 \leq P_{d,i,t}^{\text{GES}} \leq \bar{P}_{d,i,t}^{\text{GES}}$$

Baseline Consumption

$$SoC_{i,t+1}^{\text{GES}} = (1 - \varepsilon_i^{\text{GES}}) SoC_{i,t}^{\text{GES}} + \frac{\eta_{c,i}^{\text{GES}} P_{c,i,t}^{\text{GES}} \Delta t}{S_i^{\text{GES}}} - \frac{P_{d,i,t}^{\text{GES}} \Delta t}{S_i^{\text{GES}} \eta_{d,i}^{\text{GES}}} + \alpha_{i,t}^{\text{GES}}$$

SoC Ramping

$$SoC_{i,T}^{\text{GES}} = SoC_{i,0}^{\text{GES}}$$

$$-RD_i^{\text{GES}} \Delta t \leq SoC_{i,t+1}^{\text{GES}} - SoC_{i,t}^{\text{GES}} \leq RU_i^{\text{GES}} \Delta t$$

$$SoC_{i,t}^{\text{DDU}} = h(g(SoC_{i,t}^{\text{DIU}}, c_{d,i,t}^{\text{S}}), RD_{i,t})$$

$$RD_{i,t} = \lambda \sum_{\tau=1}^t P_{d,i,\tau} / (\bar{P}_{d,i} T) + (1 - \lambda) |SoC_{i,t} - SoC_{i,t}^{\text{B}}|$$

$$g = (SoC_{i,t} - SoC_{i,t}^{\text{DIU}}) \mathcal{N}(\mu_g, \sigma_g) + SoC_{i,t}^{\text{DIU}}$$

$$h = (SoC_{i,t}^{\text{B}} - Q_g) \mathcal{L}\mathcal{N}(\mu_h, \sigma_h) + Q_g$$

$$\mu_g = c_{d,i,t}^{\text{S}} / \bar{c}^{\text{S}}, \mu_h = \beta_i RD_{i,t},$$

Decision-dependent uncertainty (DDU)

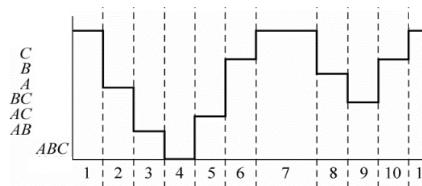
#### 1. Mapping GES Model to Physical Resources

GES model parameters	Physical BES	Physical TCL (IVA/FFA)	Physical EV
$SoC_t$	$SoC_t$	$\frac{\bar{T}^{\text{in}} - T_t^{\text{in}}}{\bar{T}^{\text{in}} - \bar{T}^{\text{in}}}$	$SoC_t$
$\bar{P}_{c,t}$	$\bar{P}_c$	$\bar{P} - P_t^{\text{B}}$	$\bar{P}_c - P_{c,t}^{\text{B}}$
$\bar{P}_{d,t}$	$\bar{P}_d$	$P_t^{\text{B}} - P$	$\bar{P}_d - P_{d,t}^{\text{B}}$
$SoC_t$	$SoC$	$\frac{\bar{T}^{\text{in}} - T_t^{\text{in}}}{\bar{T}^{\text{in}} - \bar{T}^{\text{in}}}$	$SoC_t$
$SoC_t$	$SoC$	$\frac{\bar{T}^{\text{in}} - T_t^{\text{in}}}{\bar{T}^{\text{in}} - \bar{T}^{\text{in}}}$	$SoC_t$
$\varepsilon$	$\varepsilon$	$1 - e^{-\Delta t / RC}$	$\varepsilon$
$S$	$S$	$\frac{\Delta t (\bar{T}^{\text{in}} - T^{\text{in}})}{KR(1 - e^{-\Delta t / RC})}$	$S$
$\eta_{c/d}$	$\eta_{c/d}$	1	$\eta_{c/d}$
$\alpha_t$	0	$(1 - e^{-\Delta t / RC}) SoC_t^{\text{B}}$	$\Delta SoC_t^{\text{B}}$

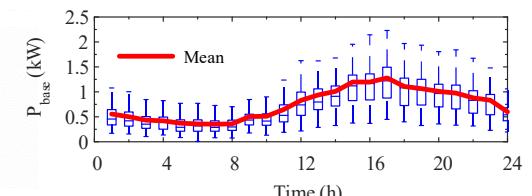
#### 2. Decision-independent Uncertainty→Data

$$f(\omega_t^{\text{VES}}) = \begin{cases} p_t^{\text{VES}} & \omega_t = 1 \\ 1 - p_t^{\text{VES}} & \omega_t = 0 \end{cases} \quad P_{i,t}^{\text{B}} \sim \mathcal{LN} \left( \mu_{P_{i,t}^{\text{B}}}, \sigma_{P_{i,t}^{\text{B}}} \right), \quad \forall t \in \Omega_T, \forall i \in \Omega_S$$

##### Operation States



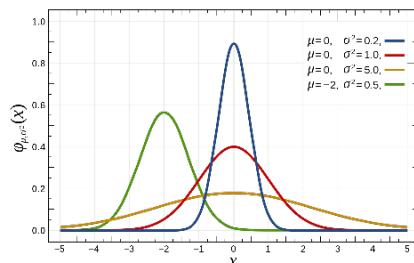
##### Baseline Consumption



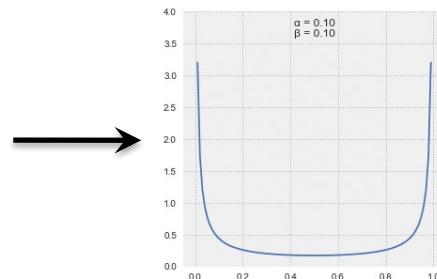
## 2. Physics-Informed Data-driven Modeling of GES

### ✓ Unified Modeling of GES Resources—DIUs and DDUs

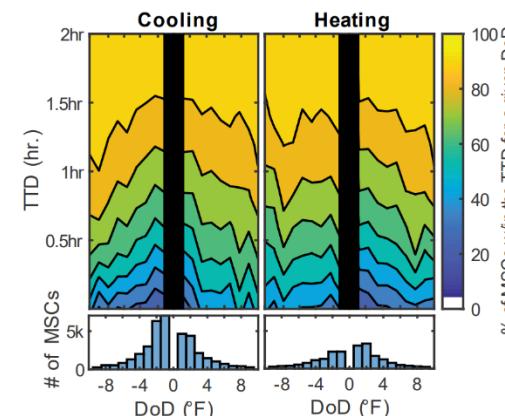
#### ● DDU: Coupling Relationship Between Decisions & Uncertainty



**DIU  
(Static)**

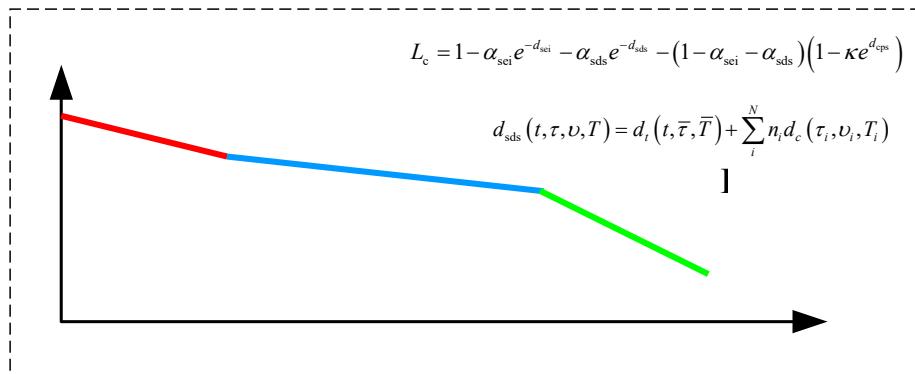


**DDU  
(Dynamic)**

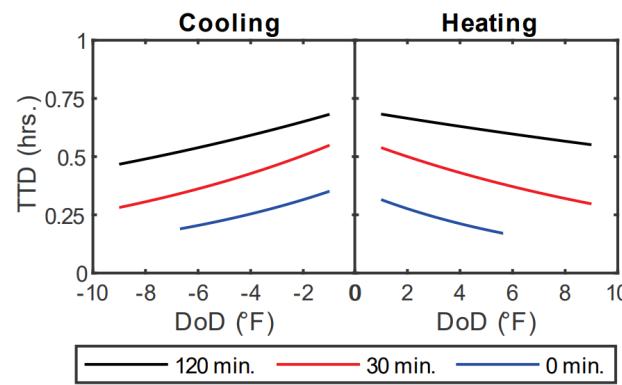


**Occupant  
Discomfort**

**Manual Overrides**



**Capacity Degradation**



**Fig. 10:** Effect occupancy filter on the relationship between degree of discomfort and time to discomfort

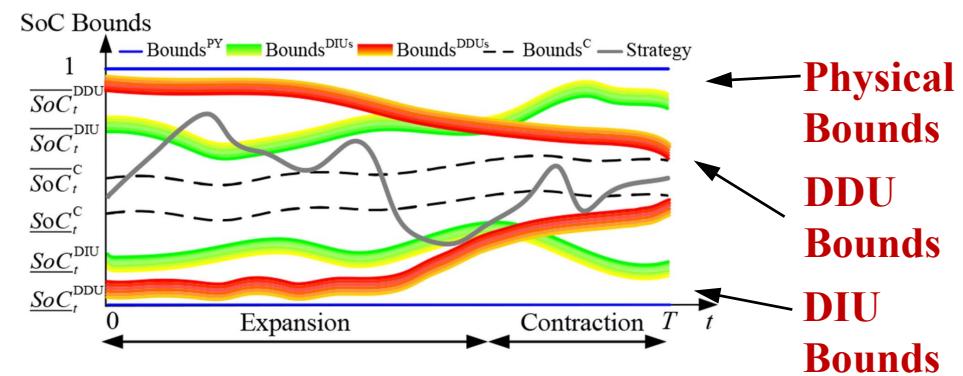
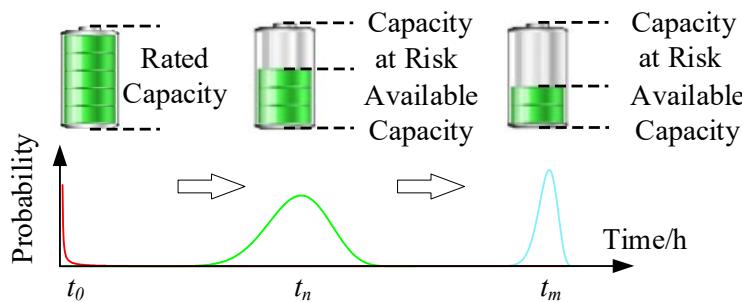
## 2. Physics-Informed Data-driven Modeling of GES

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### ✓ Unified Modeling of GES Resources—DIUs and DDUs

#### ● DDU: Coupling Relationship Between Decisions & Uncertainty

#### Willingness & Capability to Response



$$SoC_{i,t}^{\text{DDU}} = h(g(SoC_{i,t}^{\text{DIU}}, c_{d,i,t}^S), RD_{i,t})$$

**DIU VS DDU**

$$RD_{i,t} = \lambda \sum_{\tau=1}^t P_{d,i,\tau} / (\bar{P}_{d,i} T) + (1-\lambda) |SoC_{i,t} - SoC_{i,t}^B|$$

**Discomfort Function**

$$g = (SoC_{i,t} - SoC_{i,t}^{\text{DIU}}) \mathcal{N}(\mu_g, \sigma_g) + SoC_{i,t}^{\text{DIU}}$$

**Incentive Effect Distribution**

$$h = (SoC_{i,t}^B - Q_g) \mathcal{LN}(\mu_h, \sigma_h) + Q_g$$

**Discomfort Effect Distribution**

$$\mu_g = c_{d,i,t}^S / \bar{c}^S, \mu_h = \beta_i RD_{i,t},$$

N. Qi\*, P. Pinson, M. R. Almassalkhi et al, “Chance-Constrained Generic Energy Storage Operations under Decision-Dependent Uncertainty,” IEEE Transactions on Sustainable Energy, vol. 14, no. 4, pp. 2234–2248, 2023.

N. Qi\*, L. Cheng, Y. Wan, et al, “Risk assessment with generic energy storage under exogenous and endogenous uncertainty,” in 2022 IEEE Power & Energy Society General Meeting (PESGM), IEEE, 2022, pp. 1–5.

## 2. Physics-Informed Data-driven Modeling of GES

23

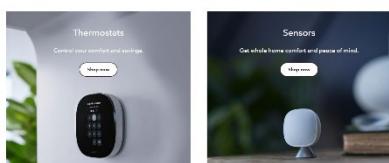
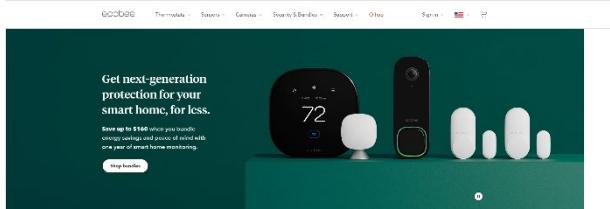
### ✓ Learning DDU Remains a Challenging Issue!

#### 1. Price/Incentive-Synthetic Data

$$\begin{bmatrix} \Delta Q_1/Q_1 \\ \Delta Q_2/Q_2 \\ \vdots \\ \Delta Q_{24}/Q_{24} \end{bmatrix} = \begin{bmatrix} \varepsilon_{1,1} & \varepsilon_{1,2} & \cdots & \varepsilon_{1,24} \\ \varepsilon_{2,1} & \varepsilon_{2,2} & \cdots & \varepsilon_{2,24} \\ \vdots & \vdots & \ddots & \vdots \\ \varepsilon_{24,1} & \varepsilon_{24,2} & \cdots & \varepsilon_{24,24} \end{bmatrix} \begin{bmatrix} \Delta P_1/P_1 \\ \Delta P_2/P_2 \\ \vdots \\ \Delta P_{24}/P_{24} \end{bmatrix} \quad (1)$$

Ruan J, Liang G, Zhao J, et al. Graph Deep Learning-based Retail Dynamic Pricing for Demand Response[J]. IEEE Transactions on Smart Grid, 2023.

#### 2. Discomfort-Utility data



Kane M B, Sharma K. Data-driven identification of occupant thermostat-behavior dynamics[J]. arXiv preprint arXiv:1912.06705, 2019.

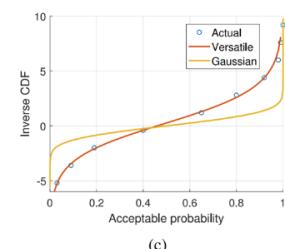
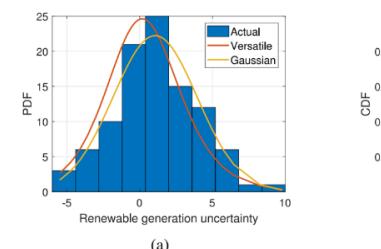
#### 3. Distribution

##### Versatile Mixture Distribution

$$\text{PDF: } f(x | \alpha, \beta, \gamma) = \frac{\alpha \beta e^{-\alpha(x-\gamma)}}{(1+e^{-\alpha(x-\gamma)})^{\beta+1}}$$

$$\text{CDF: } F(x | \alpha, \beta, \gamma) = (1+e^{-\alpha(x-\gamma)})^{-\beta}$$

$$\text{CDF}^{-1}: F^{-1}(x | \alpha, \beta, \gamma) = \gamma - \frac{1}{\alpha} \ln(x^{-1/\beta} - 1)$$



Differentiable, integrable, and convex

Zhang Z S, Sun Y Z, Gao D W, et al. A versatile probability distribution model for wind power forecast errors and its application in economic dispatch[J]. IEEE transactions on power systems, 2013, 28(3): 3114-3125.



## Background and Motivation



## Physics-Informed Data-driven Modeling of GES ---how much reliable flexibility is available?



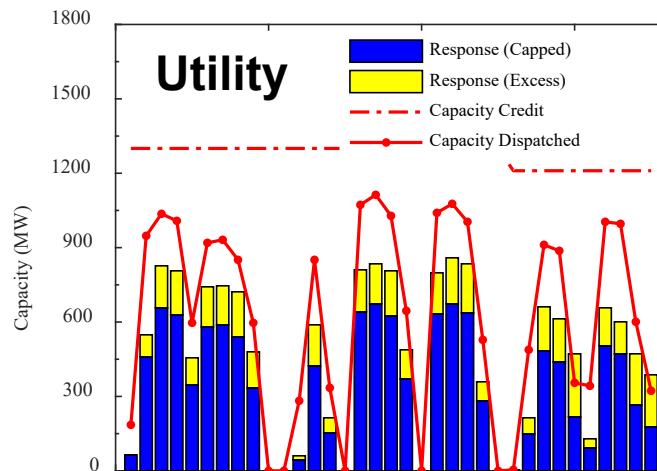
## Chance-Constrained GES Operations under DDU ---how to better utilize this reliable flexibility?

## Conclusion and Current Work

## 2. Chance-Constrained GES Operations under DDU

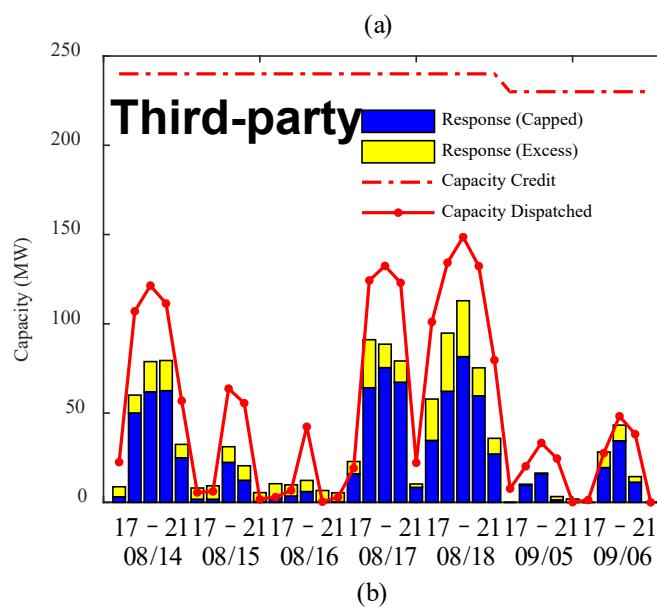
25

- DR Performance of CAISO- **1/3 of DR is unavailable** especially during peaks



What causes the DR unavailability  
during load Peak?

- Modeling Error (Detailed Occupant Behavior)
- Uncertainty Consideration (Overlook DDU)
- Incentive Mechanism (Fairness)



Solutions?

- ✓ DDU Risk Hedging (Chance-Constrained)

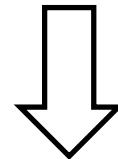
## 2. Chance-Constrained GES Operations under DDU

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- Propose Three **General Solution Methodologies** for Chance-Constrained Optimization (CCO) under DDU (Ambiguous Information & Complete Distribution & Online Data)

N. Qi\*, P. Pinson, M. R. Almassalkhi et al, “Chance-Constrained Generic Energy Storage Operations under Decision-Dependent Uncertainty,” *IEEE Transactions on Sustainable Energy*, vol. 14, no. 4, pp. 2234–2248, 2023.

N. Qi, P. Pinson, M. R. Almassalkhi, et al, “Capacity Credit Evaluation of Generalized Energy Storage under Endogenous Uncertainty,” *IEEE Transactions on Power Systems*, 2024.



### Variants and Applications

- Microgrid, Virtual Power Plant, Reserve and Adequacy Provision  
Portfolio Optimization, Unit & Reliability Commitment, Capacity Credit Evaluation

N. Qi\*, L. Cheng, H. Li et al, “Portfolio Optimization of Generic Energy Storage-Based Virtual Power Plant under Decision-Dependent Uncertainties,” *Journal of Energy Storage*, vol. 63, p. 107 000, 2023.

N. Qi, L. Cheng, Kaidi Huang et al, “Reliability-Aware Probabilistic Reserve Procurement under Decision-Dependent Uncertainty,” *2024 IEEE PES General Meeting* (Best Paper Award).

N. Qi\*, L. Cheng, Y. Zhuang et al, “Reliability Assessment and Improvement of Distribution System with Virtual Energy Storage under Exogenous and Endogenous Uncertainty,” *Journal of Energy Storage*, vol. 56, p. 105 993, 2022.

- ✓ **Chance-Constrained Optimization under DDU**

- **Joint Funding (UNSFC) on DDU—RO/DRO/SO/MARO**

Y. Su, F. Liu, Z. Wang, Y. Zhang, B. Li and Y. Chen, "Multi-Stage Robust Dispatch Considering Demand Response Under Decision-Dependent Uncertainty," IEEE Transactions on Smart Grid, vol. 14, no. 4, pp. 2786-2797, July 2023.

Y. Zhang, F. Liu, Z. Wang, Y. Su, W. Wang and S. Feng, "Robust Scheduling of Virtual Power Plant Under Exogenous and Endogenous Uncertainties," in IEEE Transactions on Power Systems, vol. 37, no. 2, pp. 1311-1325, March 2022.

Y. Li, S. Lei, W. Sun, C. Hu and Y. Hou, "A Distributionally Robust Resilience Enhancement Strategy for Distribution Networks Considering Decision-Dependent Contingencies," IEEE Transactions on Smart Grid, vol. 15, no. 2, pp. 1450-1465, March 2024

C. Pan, C. Shao, B. Hu, K. Xie, C. Li and J. Ding, "Modeling the Reserve Capacity of Wind Power and the Inherent Decision-Dependent Uncertainty in the Power System Economic Dispatch," IEEE Transactions on Power Systems, vol. 38, no. 5, pp. 4404-4417, Sept. 2023

- **Chance-Constrained Optimization (CCO)**

- ◆ **Challenge: Coupling Relationship between Decisions and Parameters (non-convex)**

### Reformulation under DIU

$$\mathbb{P}(a_i(\mathbf{x})^T \boldsymbol{\xi} \leq b_i(\mathbf{x})) \geq 1 - \epsilon$$

$$a_i(\mathbf{x})^T \boldsymbol{\mu} + b_i(\mathbf{x}) + F^{-1}(1 - \epsilon) \sqrt{a_i(\mathbf{x})^T \boldsymbol{\Sigma} a_i(\mathbf{x})} \leq 0$$

$\boldsymbol{\xi}$  Stochastic Parameters  
 $\mathbf{x}$  Decisions

### Reformulation under DDU

$$\mathbb{P}(a_i(\mathbf{x})^T \boldsymbol{\xi}(\mathbf{x}) \leq b_i(\mathbf{x})) \geq 1 - \epsilon$$

$$a_i(\mathbf{x})^T \boldsymbol{\mu}(\mathbf{x}) + b_i(\mathbf{x}) + F_{\mathbf{x}}^{-1}(1 - \epsilon) \sqrt{a_i(\mathbf{x})^T \boldsymbol{\Sigma}(\mathbf{x}) a_i(\mathbf{x})} \leq 0$$

$F_{\mathbf{x}}^{-1}(1 - \epsilon)$  Unknown

## ✓ Solution Methodology (I-Distributionally Robust Approximation)

- Obtain Robust Value of inversed CDF from generations of Cantelli's inequality

## 1. Without Distribution Assumption (NA)    2. Symmetric Distribution (S)

$$F(k) = 1 - \sup_{P \in \mathcal{N}A} \mathbb{P}[\xi \geq k] = k^2 / (1 + k^2)$$

$$F^{-1}(1 - \gamma) = \sqrt{(1 - \gamma)/\gamma}$$

### **3. Unimodal Distribution (U)**

$$F(k) = 1 - \sup_{P \in \mathcal{U}} \mathbb{P}[\xi \geq k]$$

$$= \begin{cases} 1 - 4/(9k^2 + 9) & k \geq \sqrt{5/3} \\ 1 - (3 - k^2)/(3 + 3k^2) & 0 \leq k \leq \sqrt{5/3} \end{cases}$$

$$F^{-1}(1-\gamma) = \begin{cases} \sqrt{2/9\gamma} & 0 < \gamma \leq 1/6 \\ \sqrt{3}(1-2\gamma) & 1/6 < \gamma \leq 1/2 \end{cases}$$

## 5. Student's t (ST) & Normal Distribution (N)

$$t_{\nu,\sigma}^{-1}(1-\gamma)$$

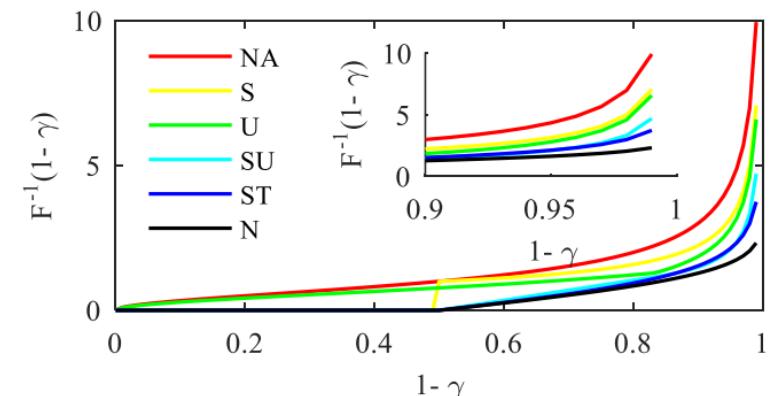
$$\Phi^{-1}(1 - \gamma)$$

## 4. Symmetric & Unimodal Distribution (SU)

$$F(k) = 1 - \sup_{P \in \mathcal{S}^{II}} \mathbb{P}[\xi \geq k] = 1 - \frac{1}{2} \sup_{P \in \mathcal{U}} \mathbb{P}[|\xi| \geq k]$$

$$= \begin{cases} 1 - 2/9k^2 & k \geq 2/\sqrt{3} \\ 1/2 + k/2\sqrt{3} & 0 \leq k \leq 2/\sqrt{3} \end{cases}$$

$$F^{-1}(1 - \gamma) = \begin{cases} \sqrt{2/9\gamma} & 0 < \gamma \leq 1/6 \\ \sqrt{3}(1 - 2\gamma) & 1/6 < \gamma \leq 1/2 \end{cases}$$

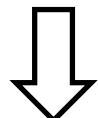


- ✓ Solution Methodology (**II-Data-Driven Online Optimization**)

- Observe the DDU and Update DDU in Real-Time Operation

$$\mathbb{P}(a_i(\mathbf{x})^T \boldsymbol{\xi}(\mathbf{x}) \leq b_i(\mathbf{x})) \geq 1 - \epsilon$$

$$a_i(\mathbf{x})^T \boldsymbol{\mu}(\mathbf{x}) + b_i(\mathbf{x}) + F_{\mathbf{x}}^{-1}(1 - \epsilon) \sqrt{a_i(\mathbf{x})^T \boldsymbol{\Sigma}(\mathbf{x}) a_i(\mathbf{x})} \leq 0$$



$$\begin{cases} a_i(\mathbf{x})^T \boldsymbol{\mu}(\mathbf{x}) + b_i(\mathbf{x}) + \psi_K \|\mathbf{r}(\mathbf{x})\|_1 + \pi_K \sqrt{1/\epsilon - 1} \|\mathbf{y}\|_2 \leq 0 \\ \sqrt{a_i(\mathbf{x})^T \boldsymbol{\Sigma} a_i(\mathbf{x})} \leq y_1, \sqrt{2\psi_K} \|\mathbf{r}(\mathbf{x})\|_1 \leq y_2 \\ \psi_K = K^{(1/p-1/2)}, \pi_K = \left(1 - \frac{4}{\epsilon} \exp\left(-\left(K^{1/p} - 2\right)^2/2\right)\right)^{-1/2} \\ p \geq 2, K > (2 + \sqrt{2 \ln(4/\epsilon)})^p \end{cases}$$

**r(x)** is the radius of DDU,  
**y** is the auxiliary decision matrix.

**p, K** should guarantee:  $p \geq 2, K > (2 + \sqrt{2 \ln(4/\epsilon)})^p$

## 2. Chance-Constrained GES Operations under DDU

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### ✓ Solution Methodology (III-Iterative Approach)

#### ● Iteratively Update DDU and Solutions

---

##### Algorithm 1 Iterative algorithm for CCO-DDUs

---

**Input:** Probability level  $\gamma$ , convergence criterion  $\delta$ , deterministic and reformulated random parameters under DIUs.

**Output:** Decision variables  $y$  and cost function  $F(y, z)$ .

#### Step1: Initialization

Set  $k=1$ , and  $F^{-1}(1 - \gamma, y_0)$  with robust reformulation value referred to Table II. Compute CCO-DDUs with  $F^{-1}(1 - \gamma, y_0)$  to obtain initial value of  $y_0$ . Use  $y_0$  to update  $F^{-1}(1 - \gamma, y_1)$  via MCS. Calculate  $\text{eps} = |F^{-1}(1 - \gamma, y_1) - F^{-1}(1 - \gamma, y_0)|$ .

#### Step2: Iteration

While  $\text{eps} > \delta$  do

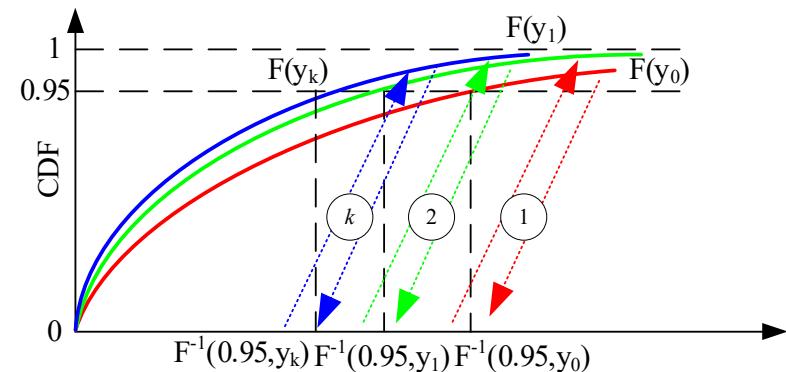
Compute CCO-DDUs with  $F^{-1}(1 - \gamma, y_k)$  to obtain  $y_k$ . Use  $y_k$  to update  $F^{-1}(1 - \gamma, y_{k+1})$  via MCS. Calculate  $\text{eps} = |F^{-1}(1 - \gamma, y_{k+1}) - F^{-1}(1 - \gamma, y_k)|$ .  
 $k \leftarrow k + 1$

end

**Step3: Return**  $y = y_k$ ,  $G(y, z) = G(y_k, z)$

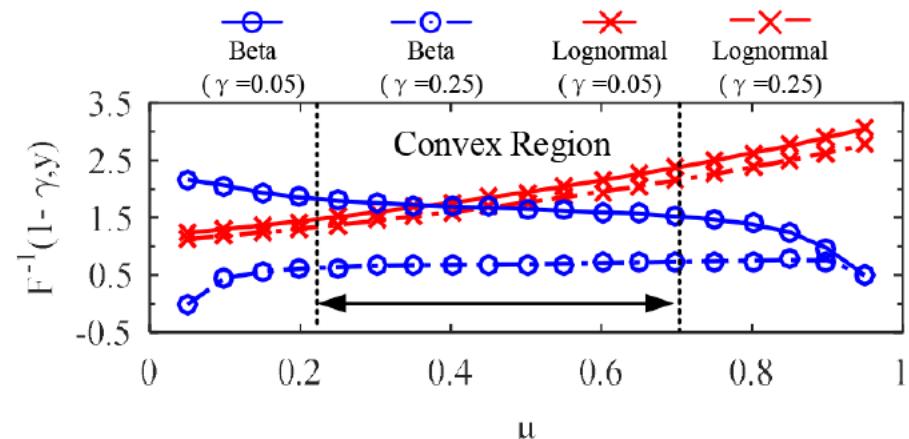
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#### Starting Point of Robust Approximation



#### Convexity and Convergence Conditions

##### 1) RD function; 2) g/h distribution



## 2. Chance-Constrained GES Operations under DDU

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### ✓ Economic Dispatch in Microgrid with GES (Case 1)

#### Objective function

$$\min_y G(y, z) = \sum_{t \in \Omega_T} (C_t^S + C_t^G)$$

$$C_t^S = \sum_{i \in \Omega_S} (c_{d,i,t}^S P_{d,i,t} + c_{c,i,t}^S P_{c,i,t}) \Delta t$$

$$C_t^G = c_t^G P_t^G \Delta t$$

#### a) GES chance constraints:

$$\mathbb{P}(P_{c,i,t} \leq \bar{P}_{c,i,t}) \geq 1 - \gamma$$

$$\mathbb{P}(P_{d,i,t} \leq \bar{P}_{d,i,t}) \geq 1 - \gamma$$

$$\mathbb{P}(\underline{SoC}_{i,t} \leq SoC_{i,t}) \geq 1 - \gamma$$

$$\mathbb{P}(SoC_{i,t} \leq \overline{SoC}_{i,t}) \geq 1 - \gamma,$$

#### b) Power balance chance constraints:

$$\mathbb{P}\left(\sum_{i \in \Omega_R} P_{i,t}^R + \sum_{i \in \Omega_S} (P_{d,i,t} - P_{c,i,t}) + P_t^G \geq P_t^L\right) \geq 1 - \gamma$$

#### c) GES other constraints:

$$SoC_{i,t+1} = (1 - \varepsilon_i) SoC_{i,t} + \eta_{c,i} P_{c,i,t} \Delta t / S_i - P_{d,i,t} \Delta t / (\eta_{d,i} S_i) + \alpha_{i,t}$$

$$-\underline{SoC}_{i,RD} \leq SoC_{i,t+1} - SoC_{i,t} \leq \overline{SoC}_{i,RU}$$

$$\underline{SoC}_{i,t} \leq SoC_{i,t} \leq \overline{SoC}_{i,t}$$

$$SoC_{i,T} = SoC_{i,0}$$

$$0 \leq P_{c,i,t} \leq \bar{P}_{c,i,t}$$

$$0 \leq P_{d,i,t} \leq \bar{P}_{d,i,t}$$

#### d) DDU constraints:

$$\overline{SoC}_{i,t}^{DDU} = h(g(\overline{SoC}_{i,t}^{DIU}, c_{c,i,t}^S), \beta_i^U RD_{i,t})$$

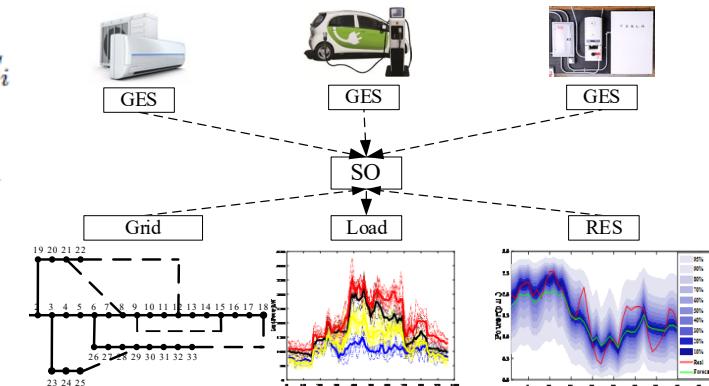
$$\underline{SoC}_{i,t}^{DDU} = h(g(\underline{SoC}_{i,t}^{DIU}, c_{d,i,t}^S), \beta_i^L RD_{i,t})$$

$$RD_{i,t} = \lambda \sum_{\tau=1}^t (P_{c,i,\tau} / \bar{P}_{c,i} + P_{d,i,\tau} / \bar{P}_{d,i}) / T$$

$$+ (1 - \lambda) \max\{|SoC_{i,t} - SoC_{i,t}^{B,av}| - SoC_{i,t}^{DB} / 2, 0\}$$

#### e) other constraints:

$$0 \leq P_t^G \leq \bar{P}_t^G$$



## 2. Chance-Constrained GES Operations under DDU

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### ✓ Economic Dispatch in Microgrid with GES (Case 1)

- M1 : Deterministic(Blue), M2: DIU(Green), M3:DDU(Red)

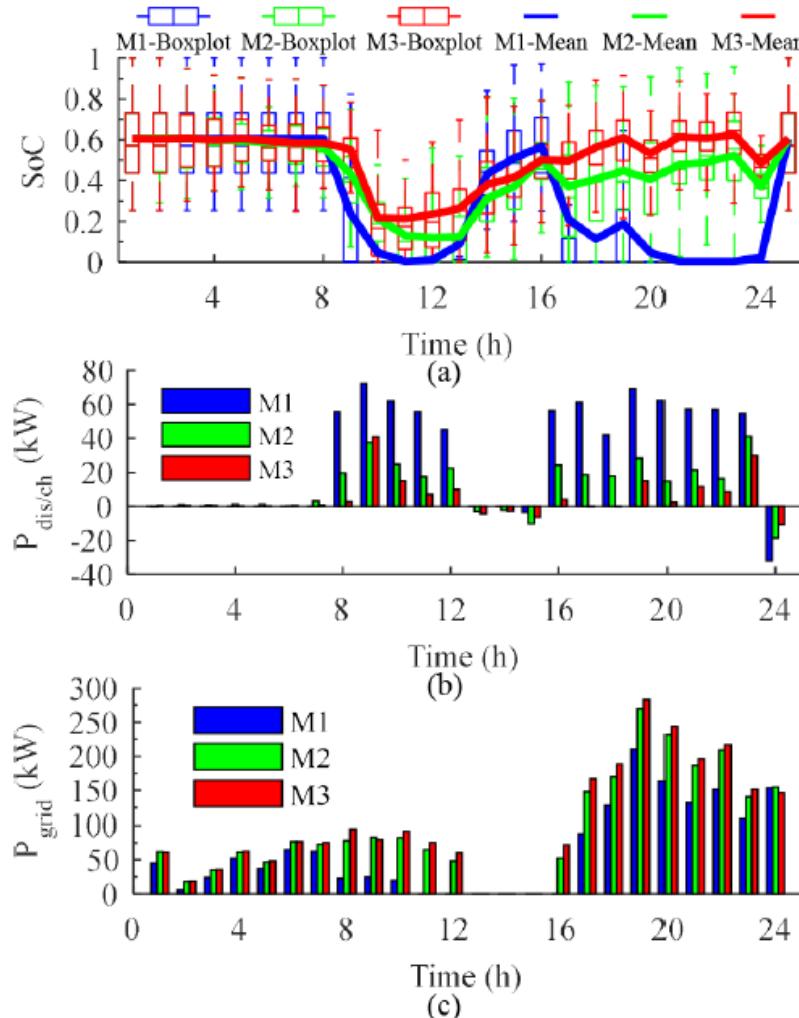
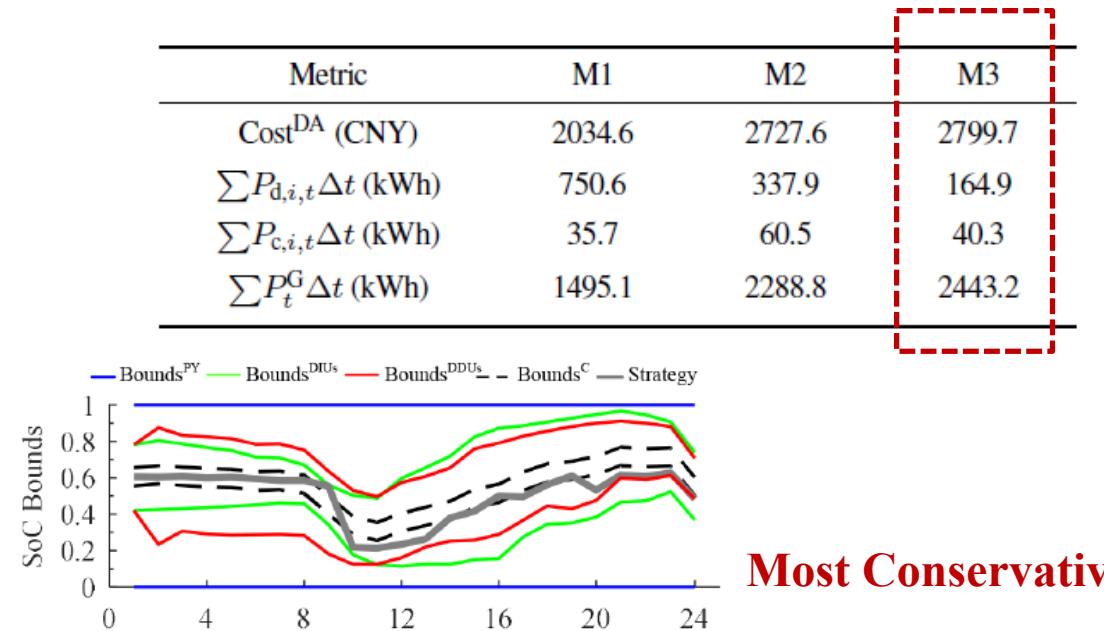
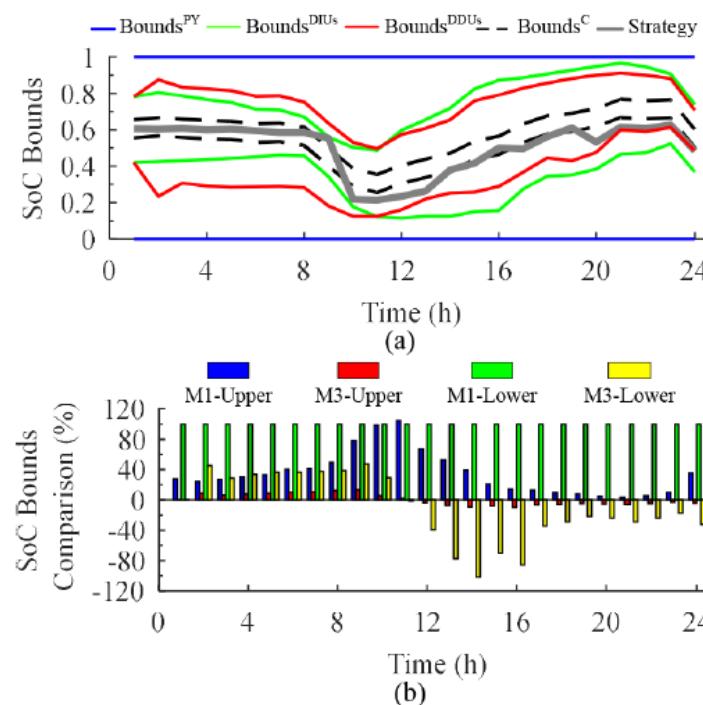


TABLE III  
OPTIMIZATION RESULTS WITH DIFFERENT MODELS AND UNCERTAINTIES

Metric	M1	M2	M3
$\text{Cost}^{\text{DA}} \text{ (CNY)}$	2034.6	2727.6	2799.7
$\sum P_{d,i,t} \Delta t \text{ (kWh)}$	750.6	337.9	164.9
$\sum P_{c,i,t} \Delta t \text{ (kWh)}$	35.7	60.5	40.3
$\sum P_t^G \Delta t \text{ (kWh)}$	1495.1	2288.8	2443.2



Most Conservative

Flexibility Contracted

## 2. Chance-Constrained GES Operations under DDU

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### ✓ Economic Dispatch in Microgrid with GES (Case 1)

- M1 : Deterministic(Blue), M2: DIU(Green), M3:DDU(Red)

**Best Performance in Real-time Availability**

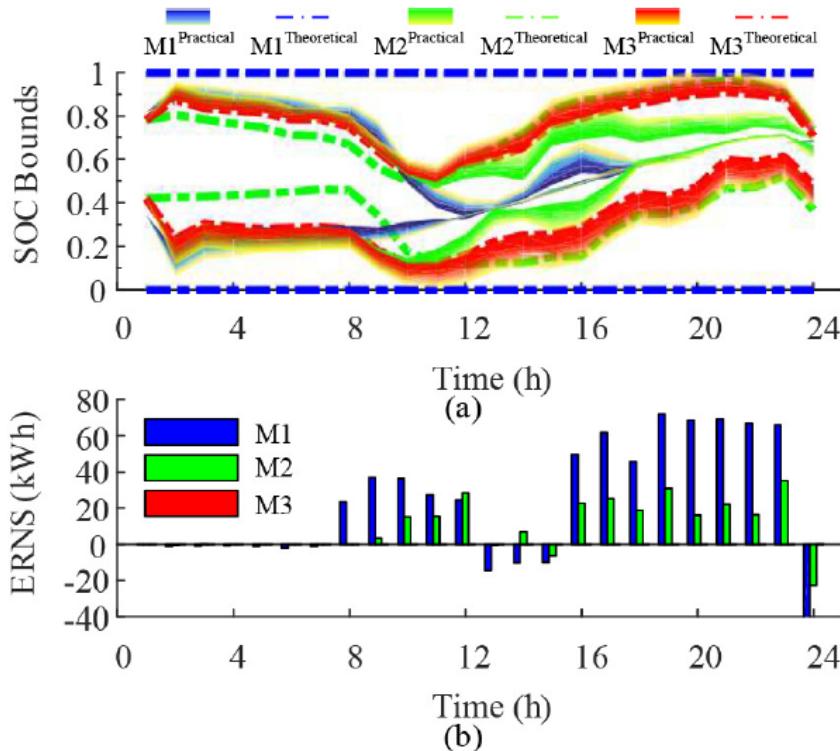


Fig. 6. Reliability performance comparison with respect to (a) practical and theoretical SoC bounds (95%) and (b) ERNS.

TABLE IV  
RELIABILITY AND ECONOMIC PERFORMANCE OF DIFFERENT MODELS AND PROBABILITY LEVEL

$\gamma$	Indices	M1	M2	M3
0.05	LORP / ERNS		0.3 / 12.0	0.0 / 0.0
	Cost <sup>RT</sup> / Cost <sup>TC</sup>	LORP 0.6	365.6 / 3039.1	0.0 / 2799.7
0.25	LORP / ERNS	ERNS 30.8	0.4 / 14.0	0.1 / 3.0
	Cost <sup>RT</sup> / Cost <sup>TC</sup>	Cost <sup>RT</sup> 1057.9	440.0 / 2909.0	0.0 / 2799.7
0.45	LORP / ERNS	Cost <sup>TC</sup> 3088.3	0.4 / 15.2	0.2 / 3.6
	Cost <sup>RT</sup> / Cost <sup>TC</sup>		487.4 / 2810.4	0.0 / 2407.7

### DDU Impact on GES Types and DR Duration

TABLE V  
OPERATIONS WITH DISPATCH MODES AND DDUS STRUCTURE

DDUs Structure	Dispatch Mode	Cost <sup>TC</sup> (CNY)	$\sum P_{d,i,t} \Delta t$ (kWh)	$\sum P_{c,i,t} \Delta t$ (kWh)	EP (%)	EP (%)	CT (%)	CT (%)
F1	D1	2772.4	187.8	31.7	9.4	37.9	-4.2	-26.7
	D2	2749.2	174.3	0.8	0.0	7.5	-0.4	-0.7
F2	D1	2799.7	164.9	40.3	8.6	37.0	-5.9	-42.0
	D2	2766.5	152.7	0.9	2.6	28.8	-3.1	-13.3
F3	D1	2785.4	171.2	32.1	9.4	39.8	-4.8	-31.2
	D2	2755.8	167.1	1.4	0.2	13.2	-1.8	-5.4

**Impact Less for Battery and Short-time Duration**

## 2. Chance-Constrained GES Operations under DDU

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### ✓ Economic Dispatch in Microgrid with GES (Case 1)

#### ● Convergence and Scalability Performance

**It converges quickly!**

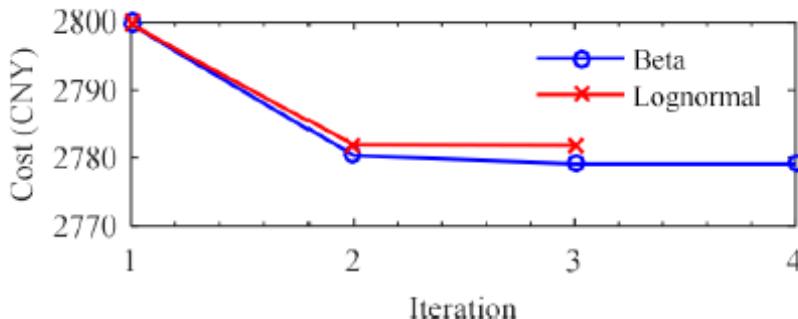


Fig. 8. Convergence performance under Beta and Lognormal distribution (95%)

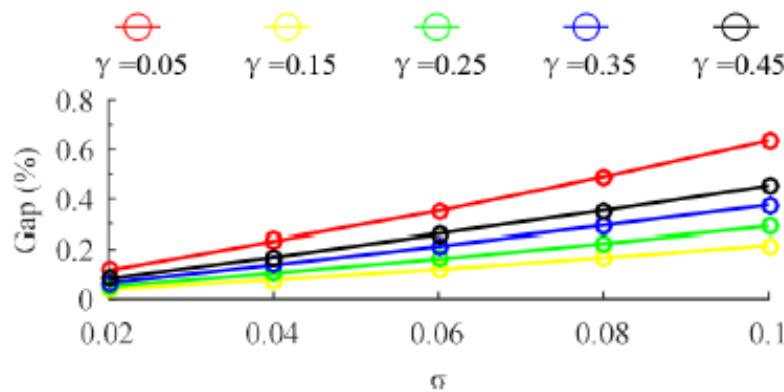


Fig. 7. Sensitivity of gap with probability level and standard deviations

TABLE VI  
OPERATIONS COMPARED WITH DIFFERENT REFORMULATION METHODS

DDUs Structure	Distribution Type	R1		R2	
		Cost <sup>TC</sup> (CNY)	Time (s)	Cost <sup>TC</sup> (CNY)	Time (s)
F1	Beta Distribution	2772.4	24.6	2750.0	2751.0
		2799.7	211.3	2779.1	6406.7
		2785.4	28.0	2764.3	3032.2
F2	Lognormal Distribution	2772.4	24.6	2752.3	132.1
		2799.7	211.3	2781.9	1039.9
		2785.4	28.0	2766.6	103.9
F3					

#### Aggregator or Robust approximation or Stop Indices

TABLE VII  
OPERATIONS COMPARED WITH DIFFERENT ACCELERATION METHODS

Acceleration Method	Distribution Type	100 GES units		1000 GES units	
		Gap (%)	Time (s)	Gap (%)	Time (s)
A1	Beta Distribution	-0.90	27.0	-1.24	28.1
		0.04	2113.6	0.04	128802.7
		0.74	211.3	0.81	5792.6
A2	Lognormal Distribution	-0.92	3.8	-1.08	4.0
		0.01	471.9	0.02	8845.3
		0.64	211.3	0.76	5792.6
A3					

## 2. Chance-Constrained GES Operations under DDU

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✓ Portfolio Optimization(Profit VS Risk) in VPP(Case 2)

● SO(DIU)+CCO(DDU)+**CVaR(worst-case)**+IPH(decomposition)

Average Profit

$$\max \left(1-\theta\right) \sum_{s \in \Omega_S} \pi_s S_s^{\text{net}} - \theta \left(\psi - \frac{1}{1-\alpha} \sum_{s \in \Omega_S} \pi_s \xi_s\right)$$

$$S_s^{\text{net}} = \Delta t \left[ \sum_{\forall t \in \Omega_T} \lambda_{s,t}^{\text{DA}} P_t^{\text{DA}} + \sum_{\forall t \in \Omega_T} (\lambda_{s,t}^{\text{R+}} P_{s,t}^{\text{R+}} - \lambda_{s,t}^{\text{R-}} P_{s,t}^{\text{R-}}) \right. \\ \left. - \sum_{\forall i \in \Omega_R} \sum_{\forall t \in \Omega_T} C_i^{\text{RES}} P_{s,i,t}^{\text{RES}} - \sum_{\forall i \in \Omega_G} \sum_{\forall t \in \Omega_T} C_{d/c,i}^{\text{GES}} P_{d/c,s,i,t}^{\text{GES}} \right]$$

**CVaR**

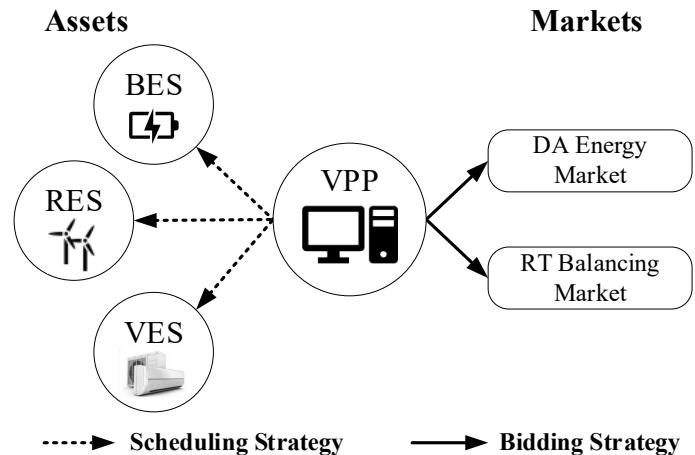


TABLE I DESCRIPTION AND REFORMULATION OF UNCERTAINTIES

Assets/ Resources	Probabilistic Parameters	Types of Uncertainty	Reformulation Method
Market price	$\lambda_{s,t}^{\text{DA}}, \lambda_{s,t}^{\text{R+}}, \lambda_{s,t}^{\text{R-}}$	DIUs	Scenarios
RES	$P_{s,i,t}^{\text{RES},\text{AW}}$	DIUs	Scenarios
GES	$\underline{P}_{c/d,i,t}^{\text{GES}}, \underline{SoC}_{i,t}^{\text{GES,DIU}},$ $\underline{SoC}_{i,t}^{\text{GES,DIU}}, \beta_{i,t}^{\text{GES}}$	DIUs	Explicit Quantiles
GES	$\underline{SoC}_{i,t}^{\text{GES,DDU}},$ $\underline{SoC}_{i,t}^{\text{GES,DDU}}$	DDUs	Iterative Quantiles

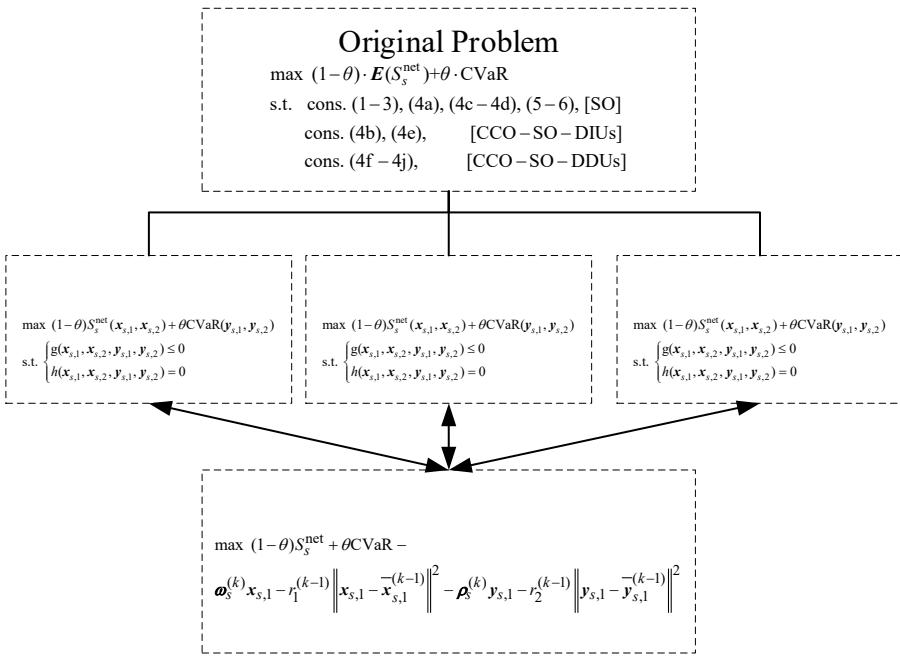
Hybrid Uncertainty Reformulations

## 2. Chance-Constrained GES Operations under DDU

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### ✓ Portfolio Optimization(Profit VS Risk) in VPP(Case 2)

- SO(DIU)+CCO(DDU)+CVaR(worst-case)+IPH(decomposition)



### Improved Progressive Hedging

#### External Loop: Decomposition and Coordination

**Sep 1** Set  $k=0$ , compute all the subproblems (8),  $\omega_s^{(0)}=0$ ,  $\rho_s^{(0)}=0$ ,  
 $k \leftarrow k+1$

**Sep 2** While  $\text{eps1} > \delta_1$  do

$$x_{s,1}^{(k-1)} = \sum_{s \in \Omega_S} \pi_s x_{s,1}^{(k-1)}, \quad \omega_s^{(k)} = \omega_s^{(k-1)} + r_1^{(k-1)} (x_{s,1}^{(k-1)} - \bar{x}_{s,1}^{(k-1)})$$

$$\bar{y}_{s,1}^{(k-1)} = \text{VaR}(S_s^{\text{net},(k-1)}), \quad \rho_s^{(k)} = \rho_s^{(k-1)} + r_2^{(k-1)} (y_{s,1}^{(k-1)} - \bar{y}_{s,1}^{(k-1)})$$

Add penalty to the objective function:  $\max (1-\theta) S_s^{\text{net}} + \theta \text{CVaR} -$

$$\omega_s^{(k)} x_{s,1} - r_1^{(k-1)} \|x_{s,1} - \bar{x}_{s,1}^{(k-1)}\|^2 - \rho_s^{(k)} y_{s,1} - r_2^{(k-1)} \|y_{s,1} - \bar{y}_{s,1}^{(k-1)}\|^2$$

Update  $[x_{s,1}^{(k)}, y_{s,1}^{(k)}]$ ,  $\text{eps1} = \left\| x_{s,1}^{(k)} - \bar{x}_{s,1}^{(k)} \right\|^2 + \left\| y_{s,1}^{(k)} - \bar{y}_{s,1}^{(k)} \right\|^2$

$$+ 1/r_1^{(k)2} \left\| \omega_s^{(k)} - \bar{\omega}_s^{(k)} \right\|^2 + 1/r_2^{(k)2} \left\| \rho_s^{(k)} - \bar{\rho}_s^{(k)} \right\|^2$$

$k \leftarrow k+1$

**End**

**Sep 3** Return  $x_{s,1} = x_{s,1}^{(k)}$ ,  $y_{s,1} = y_{s,1}^{(k)}$

### Asymmetric From Decomposition Method X

## 2. Chance-Constrained GES Operations under DDU

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### ✓ Reliability-Aware Probabilistic Reserve Procurement(Case 3)

- Uncertainty Increased while Reserve Decreased → Probabilistic Reserve
- Reserve: Assume 100% Reliability or DIU while overlooks DDU → Availability Risk

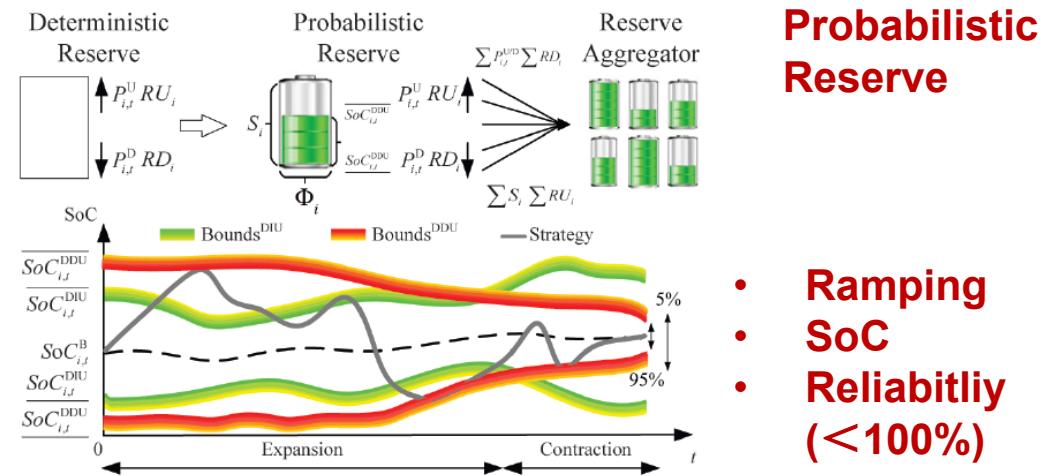
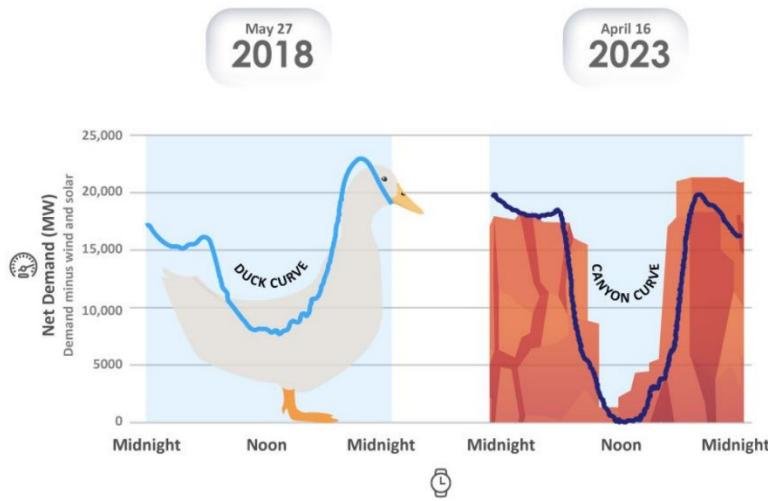
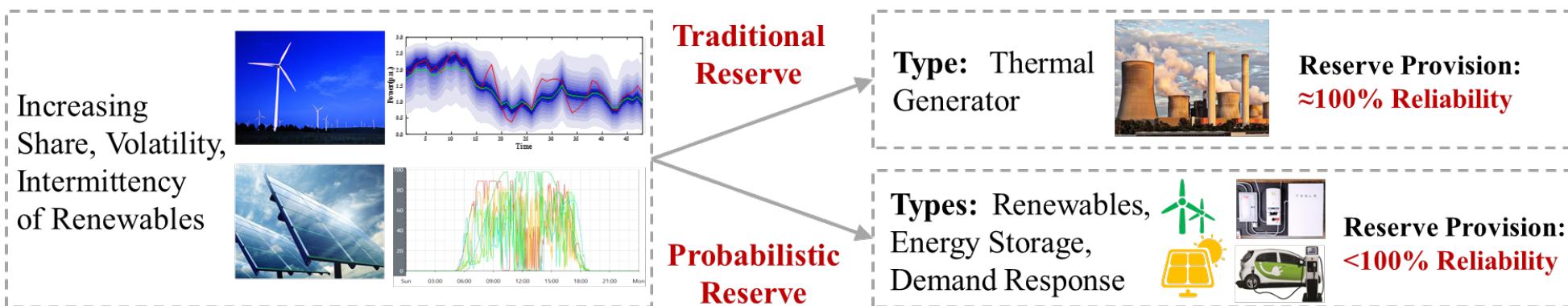


Fig. 1. Illustration of probabilistic reserve model.

- Ramping
- SoC
- Reliability ( $<100\%$ )

### ✓ Reliability-Aware Probabilistic Reserve Procurement (Case 3)

#### ● Two-stage Probabilistic Reserve Procurement under DDU

#### DA-Joint Chance-Constrained Optimization under DDU

$$\min_{P_{i,t}^U, P_{i,t}^D, SoC_{i,t}} \sum_{t \in \Omega_T} \sum_{i \in \Omega} (c_t^U P_{i,t}^U + c_t^D P_{i,t}^D) \Delta t \quad (2a)$$

subject to: (1a)–(1h) (2b)

$$\mathbb{P}\left(\sum_{i \in \Omega_A} (P_{i,t}^D - P_{i,t}^U) \geq P_t^{S,DIU}\right) \geq 1 - \epsilon \quad \forall t \in \Omega_T \quad (2c)$$

$$0 \leq P_{i,t}^U, 0 \leq P_{i,t}^D \quad (1a)$$

$$\mathbb{P}(P_{i,t}^U \leq \bar{P}_{i,t}^{U,DIU}) \geq 1 - \epsilon, \mathbb{P}(P_{i,t}^D \leq \bar{P}_{i,t}^{D,DIU}) \geq 1 - \epsilon \quad (1b)$$

$$P_{i,t+1}^U - P_{i,t}^U \leq RU_i, P_{i,t+1}^D - P_{i,t}^D \leq RD_i \quad (1c)$$

$$\begin{aligned} SoC_{i,t+1} = & (1 - \varepsilon_i) SoC_{i,t} + \eta_{c,i} P_{i,t}^U \Delta t / S_i \\ & - P_{i,t}^D \Delta t / (\eta_{d,i} S_i) + \alpha_{i,t}^{DIU} \end{aligned} \quad (1d)$$

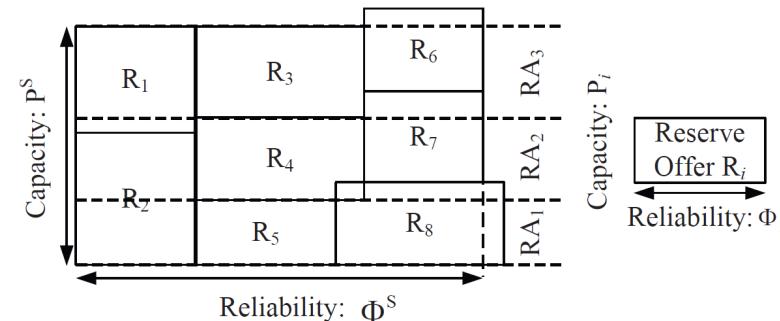
$$\mathbb{P}(\underline{SoC}_{i,t}^{DDU} \leq SoC_{i,t} \leq \overline{SoC}_{i,t}^{DDU}) \geq 1 - \epsilon \quad (1e)$$

$$\underline{SoC}_{i,t}^{DDU} = h(g(\overline{SoC}_{i,t}^{DIU}, c_t^U), \beta_i^U RD_{i,t}) \quad (1f)$$

$$\overline{SoC}_{i,t}^{DDU} = h(g(\underline{SoC}_{i,t}^{DIU}, c_t^D), \beta_i^D RD_{i,t}) \quad (1g)$$

$$\begin{aligned} RD_{i,t} = & \lambda \sum_{\tau=1}^t \left( P_{i,\tau}^U / \bar{P}_i^U + P_{i,\tau}^D / \bar{P}_i^D \right) / T \\ & + (1 - \lambda) |SoC_{i,t} - SoC_{i,t}^B| \end{aligned} \quad (1h)$$

#### RT-Reliability Commitment



$$\min_{P_{i,j}, z_{i,j}, \phi_i} \sum_{i \in \Omega_A} \sum_{j \in \Omega_R} \rho_j P_{i,j} \quad (3a)$$

$$\phi_i = 1 - \prod_j (1 - \Phi_j z_{i,j}) \quad \forall i \in \Omega_A \quad (3b)$$

$$P_i - P_{i,j} \leq M(1 - z_{i,j}) \quad \forall i \in \Omega_A, \forall j \in \Omega_R \quad (3c)$$

$$\Phi^S \leq \prod_i \phi_i \quad (3d)$$

$$P^S \leq \sum_i P_i \quad (3e)$$

$$\sum_i P_{i,j} \leq P_j \quad \forall j \in \Omega_R \quad (3f)$$

$$z_{i,j} \in \{0,1\} \quad \forall i \in \Omega_A, \forall j \in \Omega_R \quad (3g)$$

$$P_{i,j} P_i \geq 0 \quad \forall i \in \Omega_A, \forall j \in \Omega_R \quad (3h)$$

$$P_i \geq \underline{P}^A \quad \forall i \in \Omega_A \quad (3i)$$

$$\phi_i \geq \underline{\Phi}^A \quad \forall i \in \Omega_A \quad (3j)$$

#### Reformulation with Log Function

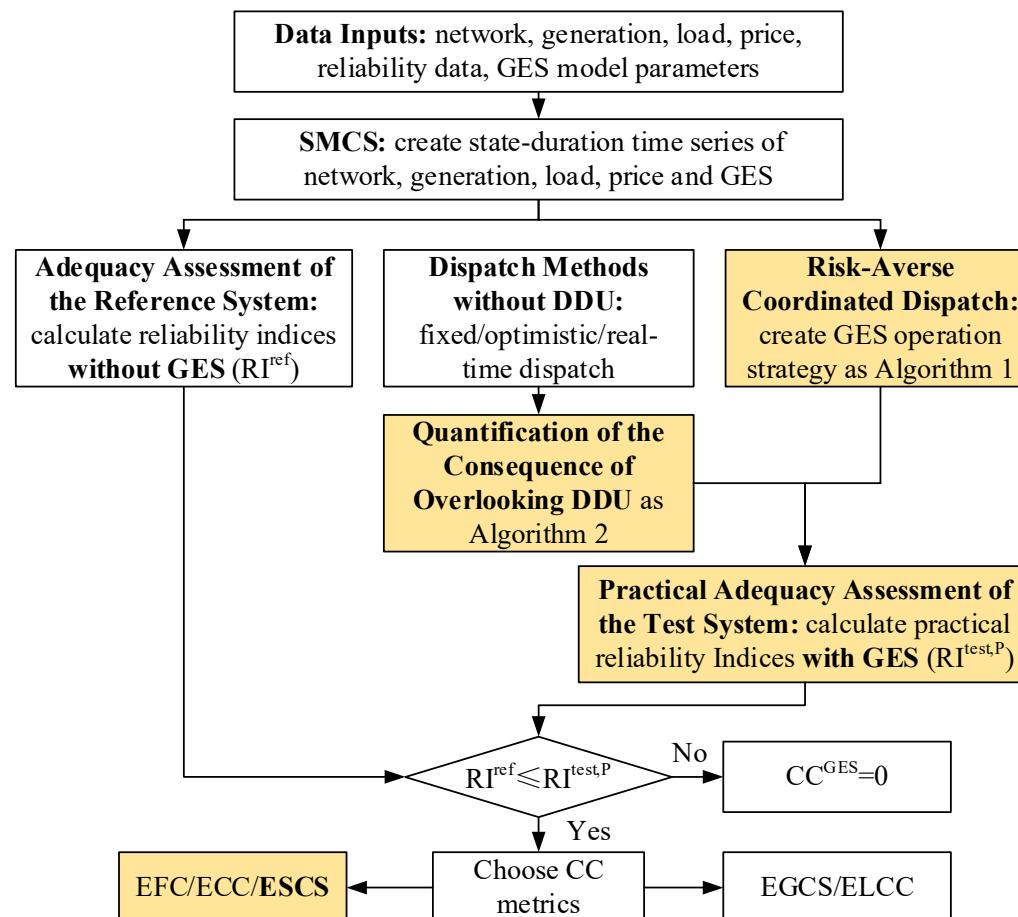
#### Piecewise Linear Approximation

### 3. Capacity Credit Evaluation of GES under DDU

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#### ✓ Capacity Credit Evaluation of GES (Case 4)

- Capacity Credit (CC) Evaluation: Provide a fair basis of comparison between resources and conventional generation in terms of their adequacy contribution



#### 1. Dispatch Simulation of GES

- ◆ Adequacy-Oriented Optimization
- ✗ Coordination between Short-Term Market and Long-Term Capacity Market Operation

#### 2. Availability of GES

- ◆ DIU & 100% Availability
- ✗ Decision-Dependent Response Unavailability

### 3. Capacity Credit Evaluation of GES under DDU

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#### ✓ Capacity Credit Evaluation of GES (Case 4)

##### ● Risk-Averse Coordinated Dispatch of GES (Market Simulation)

###### ① Normal Status: Day-ahead Energy Arbitrage

$$\begin{aligned} & \max_t c_t^{\text{DA}} (P_{d,i,t}^{\text{DA}} - P_{c,i,t}^{\text{DA}}) \\ \text{s.t. } & SoC_{i,t+1}^{\text{DA}} = (1 - \varepsilon_i) SoC_{i,t}^{\text{DA}} + \frac{\eta_{c,i} \eta_{d,i} P_{c,i,t}^{\text{DA}} - P_{d,i,t}^{\text{DA}}}{\eta_{d,i} S_i} \Delta t \\ & \underline{SoC}_{i,t} \leq SoC_{i,t}^{\text{DA}} \leq \overline{SoC}_{i,t} \\ & SoC_{i,T}^{\text{DA}} = SoC_{i,0}^{\text{DA}} \\ & 0 \leq P_{c,i,t}^{\text{DA}} \leq \overline{P}_{c,i} \\ & 0 \leq P_{d,i,t}^{\text{DA}} \leq \overline{P}_{d,i} \end{aligned}$$



###### ② Emergency Status: Real-time Adequacy Support

$$\begin{aligned} & \min_i \sum_i P_{i,t}^{\text{LC}} \\ \text{s.t. } & P_{ij,t} = (\theta_{i,t} - \theta_{j,t}) / X_{ij} \\ & -\overline{P}_{ij} \leq P_{ij,t} \leq \overline{P}_{ij} \\ & 0 \leq P_{i,t}^{\text{CG}} \leq P_{i,t}^{\text{CG,AV}} \\ & (1 - r_i) P_{i,t}^{\text{RG,AV}} \leq P_{i,t}^{\text{RG}} \leq P_{i,t}^{\text{RG,AV}} \\ & 0 \leq P_{i,t}^{\text{LC}} \leq P_{i,t}^{\text{LD}} \\ & 0 \leq P_{d,i,t}^{\text{RT}} \leq \overline{P}_{d,i} \\ & SoC_{i,t+1}^{\text{RT}} = (1 - \varepsilon_i) SoC_{i,t}^{\text{RT}} - P_{d,i,t}^{\text{RT}} \Delta t / \eta_{d,i} S_i \text{ DDU} \\ & \mathbb{P}(\underline{SoC}_{i,t}^{\text{DDU}} \leq SoC_{i,t}^{\text{RT}}) \geq 1 - \gamma \\ & P_{i,t}^{\text{CG/RG}} + P_{i,t}^{\text{LC}} + P_{d,i,t}^{\text{RT}} = \sum_{ij \in \Omega_L^i} P_{ij,t} + P_{i,t}^{\text{LD}} \end{aligned}$$

###### ③ Recovery Status: Real-time Capacity Recovery

$$RC_t = \sum_i (P_{i,t}^{\text{CG/RG,AV}} - P_{i,t}^{\text{LD}}) \quad (6a)$$

$$P_{c,i,t}^{\text{RT}} = \min\{\overline{P}_{c,i}, [SoC_{i,t}^{\text{DA}} - (1 - \varepsilon_i) SoC_{i,t-1}^{\text{RT}}] S_i / (\eta_{c,i} \Delta t), \varphi_i RC_t\} \quad (6b)$$

$$P_{d,i,t}^{\text{RT}} = \min\{\overline{P}_{d,i}, [(1 - \varepsilon_i) SoC_{i,t-1}^{\text{RT}} - SoC_{i,t}^{\text{DA}}] S_i \eta_{d,i} / \Delta t\} \quad (6c)$$





## Background and Motivation



## Physics-Informed Data-driven Modeling of GES ---how much reliable flexibility is available?



## Chance-Constrained GES Operations under DDU ---how to better utilize this reliable flexibility?

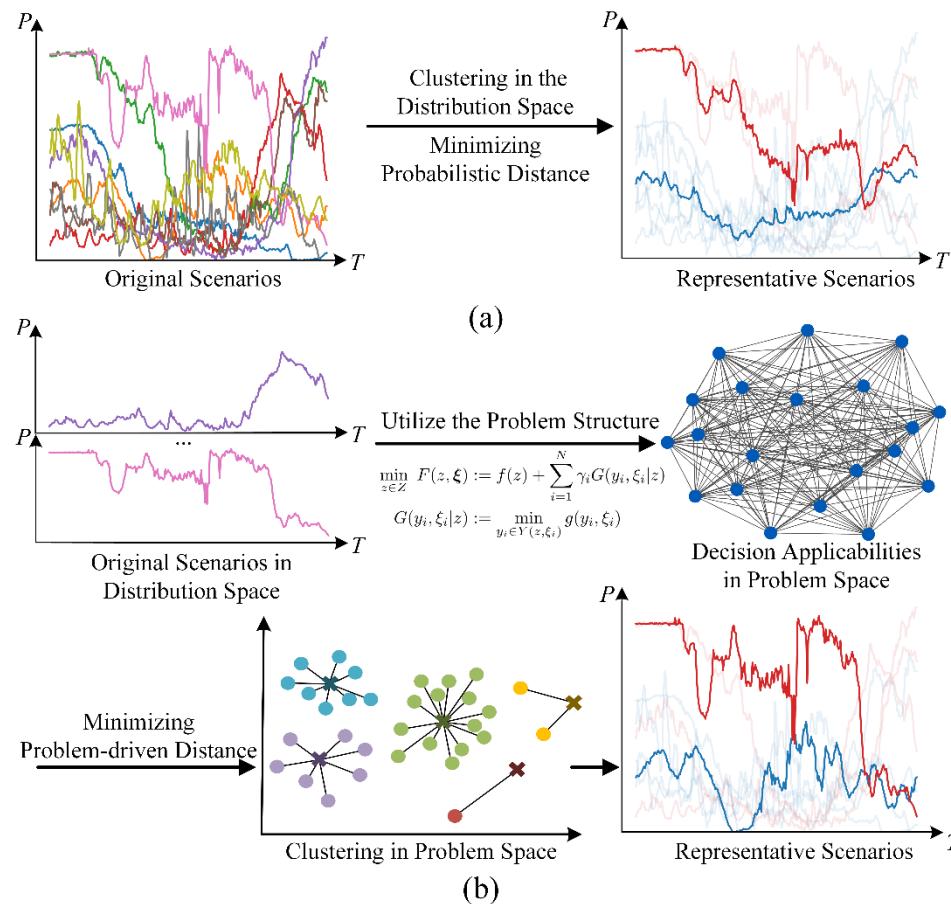
## Conclusion and Current Work

- ✓ GES Model: Better Capture the Stochasticity of Flexible Resources (DERs) by Physics-Informed Flexibility Learning and Incorporating Decision-Dependent Occupant Behavior
- ✓ Chance-Constrained Optimization under DDU: Tractable & Scalable Solutions to Hedging Risk from DDU, Improve the Availability and Performance of Coordinated GES Units, Enhanced Reliability and Economic Efficiency of the Power System.
- ✓ Industrial Applications: Learning DDU with Real-World Data?

## ✓ Problem-Driven Scenario Reduction—Stochastic Optimization

### ● Focus on the Implementation Performance & Representativeness of Scenarios

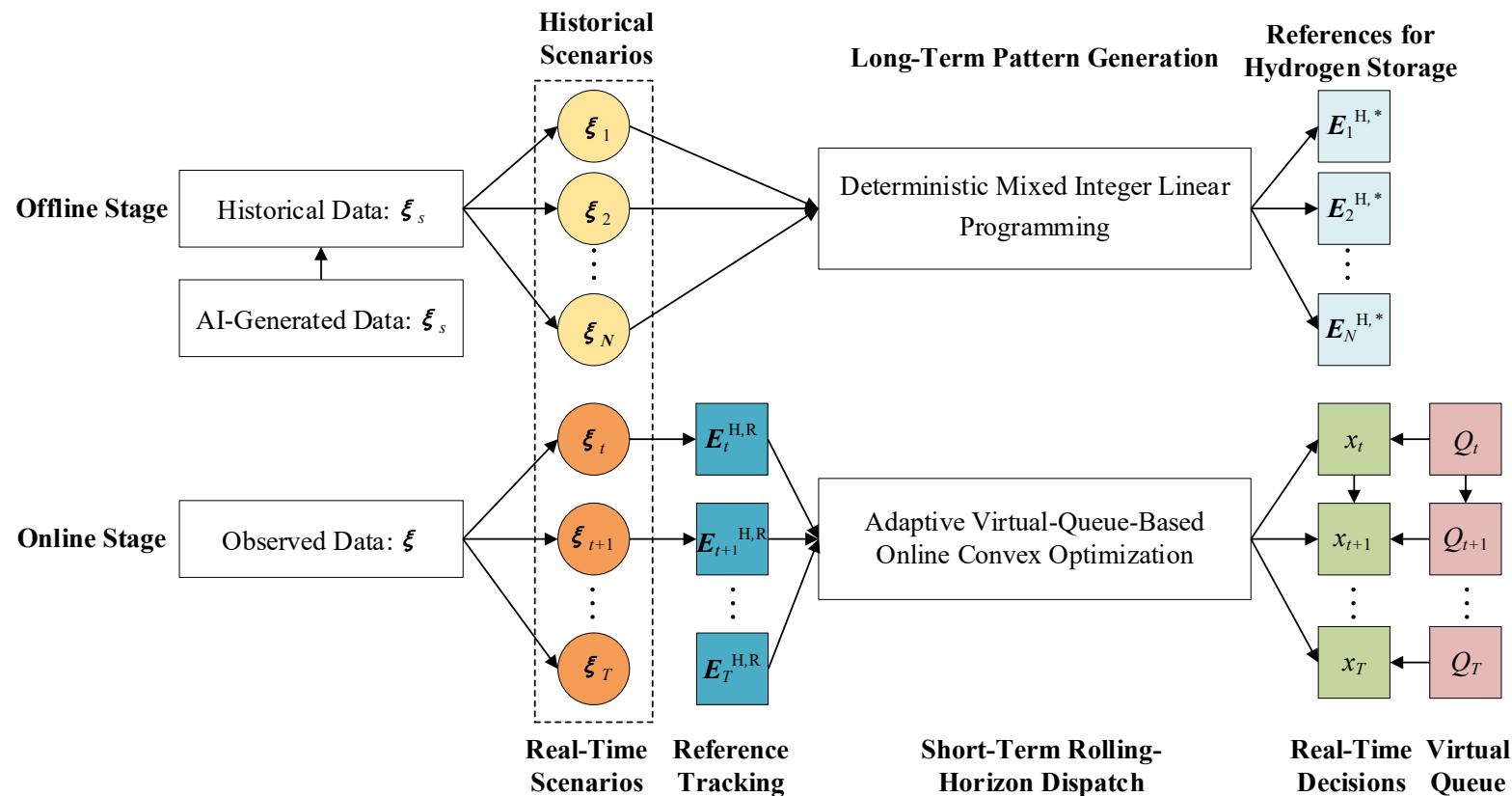
Y. Zhuang, L. Cheng, N. Qi et al, “Problem-Driven Scenario Reduction Framework for Power System Stochastic Operation,” *IEEE Transactions on Power Systems*, 2024.



## ✓ Prediction-Free Coordinated Dispatch—Long-Duration Storage

### ● Long-Term SoC Tracking + Online Convex Optimization

N. Qi\*, Kaidi Huang, Zhiyuan Fan et al, “Long-Term Energy Management for Microgrid with Hybrid Hydrogen-Battery Energy Storage: A Prediction-Free Coordinated Optimization Framework,” *Applied Energy*, 2024.



## ✓ Pricing for Social-Welfare Maximization—Storage Pricing

### ● Chance-Constrained Storage Opportunity Pricing: Default Storage Bid

**N. Qi, N. Zheng, B. Xu, “Chance-Constrained Energy Storage Pricing for Social Welfare Maximization,” IEEE Transactions on Energy Markets, Policy and Regulation, 2024.**

$$\min \mathbb{E} \sum_t (G(g_t + \varphi_t d_t) + M(p_t + \psi_t d_t))$$

$$g_t + p_t - b_t = D_t : \lambda_t \quad \text{Electricity Price}$$

$$e_{t+1} - e_t = -p_t/\eta + b_t\eta : \theta_t \quad \text{Storage Opportunity Price}$$

$$\varphi_t + \psi_t = 1 : \pi_t \quad \text{Reserve Price}$$

$$0 \leq \varphi_t, \psi_t \leq 1$$

$$\mathbb{P}(G \leq g_t + \varphi_t d_t \leq \bar{G}) \geq 1 - \epsilon : \underline{\nu}_t, \bar{\nu}_t$$

$$b_t p_t = 0$$

$$0 \leq b_t, \mathbb{P}(b_t - \psi_t d_t \leq \bar{P}) \geq 1 - \epsilon : \underline{\alpha}_t, \bar{\alpha}_t$$

$$0 \leq p_t, \mathbb{P}(p_t + \psi_t d_t \leq \bar{P}) \geq 1 - \epsilon : \underline{\beta}_t, \bar{\beta}_t$$

$$\mathbb{P}((\psi_t d_t + p_t)/\eta \leq e_t \leq \bar{E} - (b_t - \psi_t d_t)\eta) \geq 1 - \epsilon : \underline{\iota}_t, \bar{\iota}_t \quad (1j)$$

(1a)

$\times 10^5$

\$

Storage Profit (\$)

Scale Factor of  $\sigma$

(1b)

$\times 10^6$

\$

Generation Cost (\$)

Scale Factor of  $\sigma$

(1c)

$\times 10^6$

\$

System Cost (\$)

Scale Factor of  $\sigma$

(1d)

$\times 10^6$

\$

Electricity Payment (\$)

Scale Factor of  $\sigma$

(1e)

$\times 10^6$

\$

Storage Profit (\$)

Scale Factor of  $\sigma$

(1f)

$\times 10^6$

\$

Generation Cost (\$)

Scale Factor of  $\sigma$

(1g)

$\times 10^6$

\$

System Cost (\$)

Scale Factor of  $\sigma$

(1h)

$\times 10^6$

\$

Electricity Payment (\$)

Scale Factor of  $\sigma$

(1i)

$\times 10^6$

\$

Storage Profit (\$)

Scale Factor of  $\sigma$

(c)

$\downarrow$

-25.4%

$\downarrow$

-3.9%

$\downarrow$

-17.4%

$\downarrow$

-

(d)

$\downarrow$

-

-

-

-

-

-

-



Department of Electrical Engineering  
Tsinghua University

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The Fu Foundation School of Engineering and Applied Science

# Chance-Constrained Generalized Energy Storage Operations under Decision-Dependent Uncertainty

## Thank You!

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