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

Unlocking Reliable Flexibility from Generalized Energy Storage Resources

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1、Background and Motivation

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

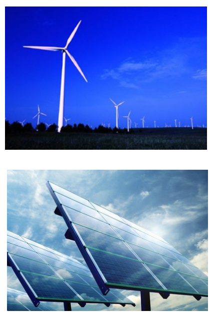
Ning Qi is a postdoctoral research scientist in Earth and Environmental Engineering at **Columbia University**. He received his Ph.D. degree in Electrical Engineering from **Tsinghua University** in 2023 (**Prof. Lin Cheng**). Before joining Columbia, he was the research associate at Digital Power System (DPS) lab at Department of Electrical Engineering, Tsinghua University (**Prof. Feng Liu**). He was a visiting scholar at **Technical University of Denmark** in 2022 (**Prof. Pierre Pinson & Prof. Mads R. Almassalkhi**). He received a B.E. degree in Electrical Engineering from **Tianjin University** in 2018 (**Prof. Yanxia Zhang**). My current research focuses on data-driven modeling, optimization under uncertainty and market design for **generalized energy storage.**

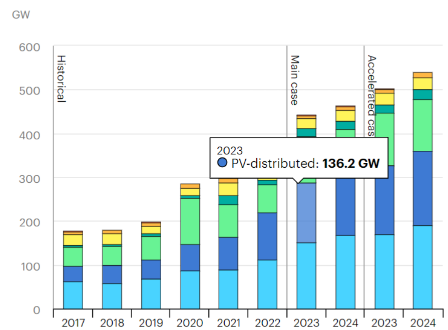
1. N. Qi, P. Pinson, M. R. Almassalkhi, et al, "Spatial–Temporal Capacity Credit Evaluation of Generalized Energy Storage Considering Decision-Dependent Uncertainty," *IEEE Transactions on Power Systems*, 2024.
2. N. Qi, L. Cheng, Kaidi Huang et al, "Reliability-Aware Probabilistic Reserve Procurement under Decision-Dependent Uncertainty," *IEEE PES General Meeting 2024*.
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. L. Cheng, Y. Wan, N. Qi et al, "Coordinated Operation Strategy of Distribution Network with the Multi-Station Integrated System Considering the Risk of Controllable Resources," *Int. J. Electr. Power Energy Syst.*, vol. 137, p. 107 793, 2022.
7. 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.

Contents

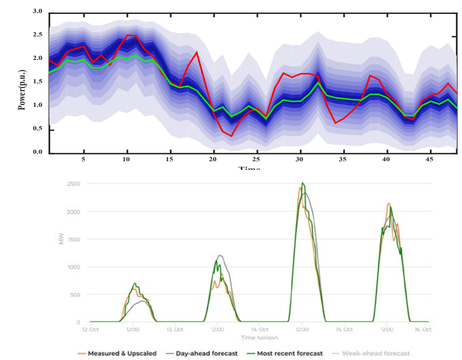
1、 Background and Motivation

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





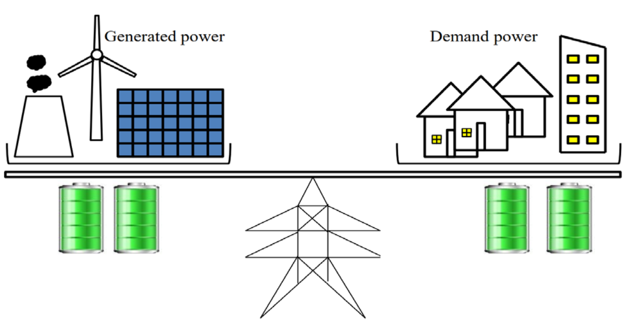
Rapidly Growing Renewables

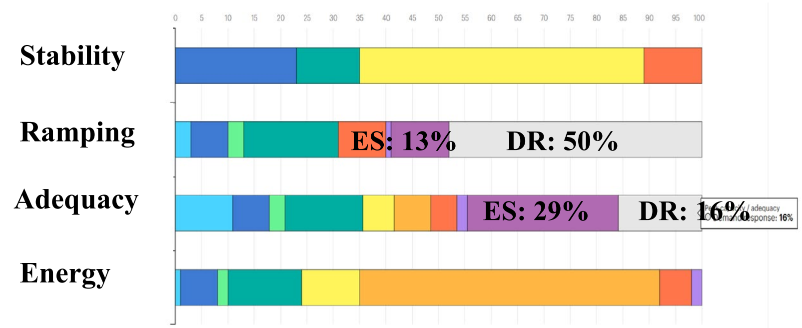


Increased Uncertainty and Flexibility requirements

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

Generation-Demand Power Balance

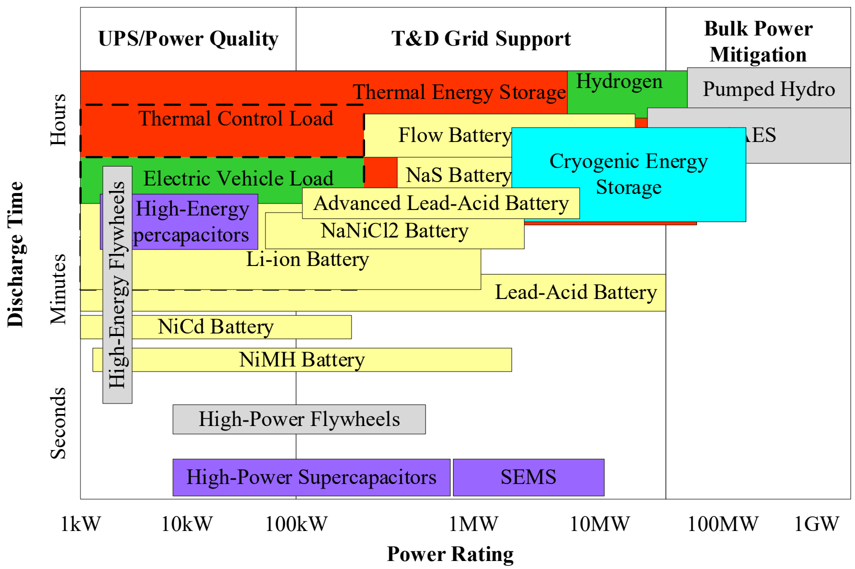




ES & DR Contribute Significantly

1、Background and Motivation

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



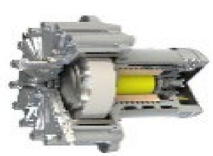
- **Flywheel → UPS (Expensive)**
- **Battery → Short-Term Dispatch (Security, Extreme Climate Conditions)**
- **Pumped-Hydro → Mid-Term/Long-Term Dispatch (Resource-Dependent, Expensive)**
- **CAES/Hydrogen → Low-efficiency, Expensive**
- **Virtual Energy Storage(VES) → Cheap (Unreliable)**

✓ **Q: Generate Reliable Flexibility from Unreliable 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

Pumped-hydro

Hydrogen

TCL

EV

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2、Physics-Informed Data-driven Modeling of GES

- **Non-Intrusively Extract/Disaggregate GES from Load (Behind-the-Meter) and Evaluate the Operational DR Potential 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," in 2019 IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia), IEEE, 2019, pp. 4334–4339.

⇕ **Coupling**

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

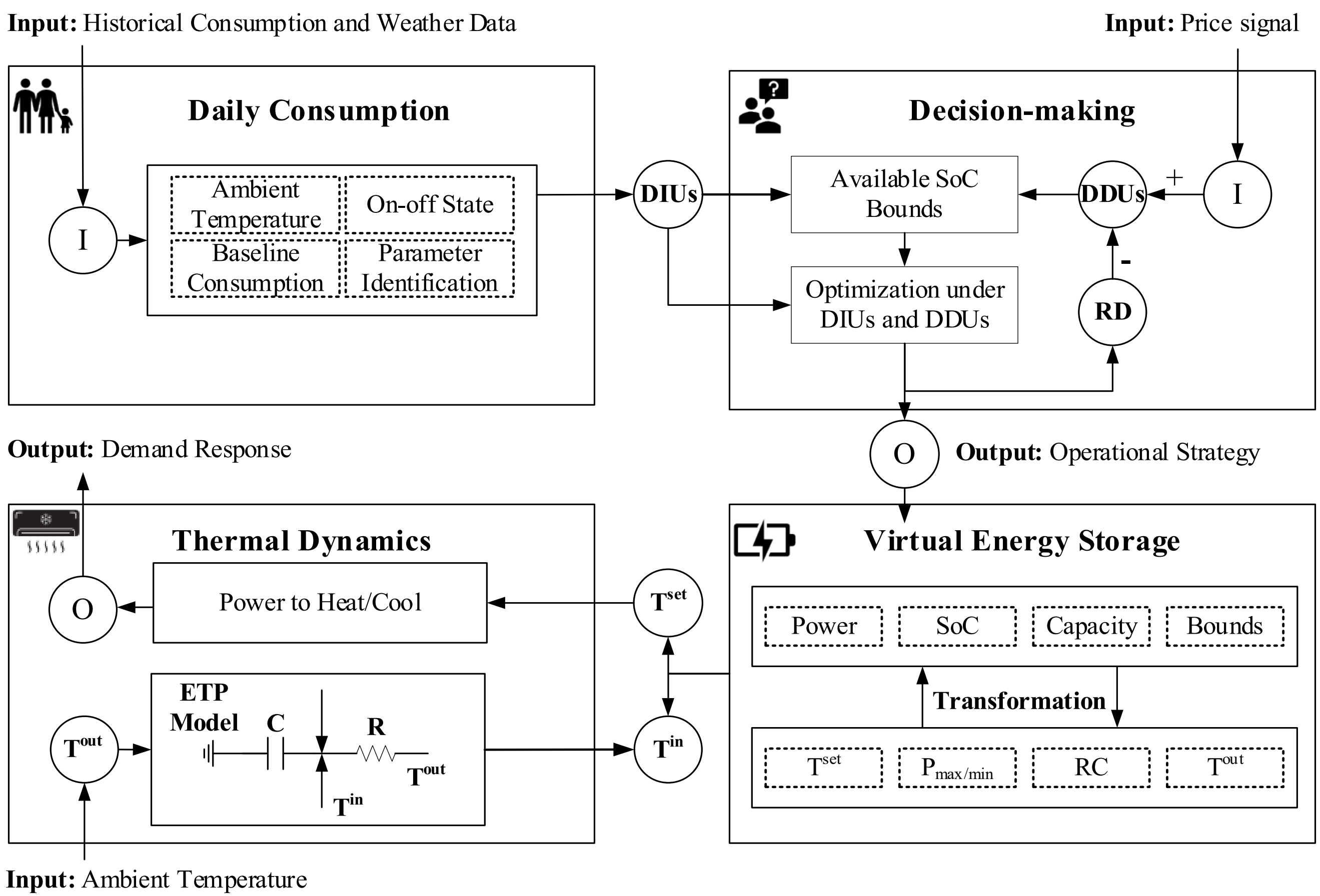
N. Qi*, P. Pinson, M. R. Almassalkhi et al, "Chance-Constrained Generic Energy Storage Operations under Decision-Dependent Uncertainty," IEEE Transactions on Sustainable Energy, vol. 14, no. 4, pp. 2234–2248, 2023.

N. Qi*, L. Cheng, Y. Wan, et al, "Risk assessment with generic energy storage under exogenous and endogenous uncertainty," in 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)



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

Dynamic

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

Steady

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

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

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

● Non-Intrusive + Unsupervised Learning

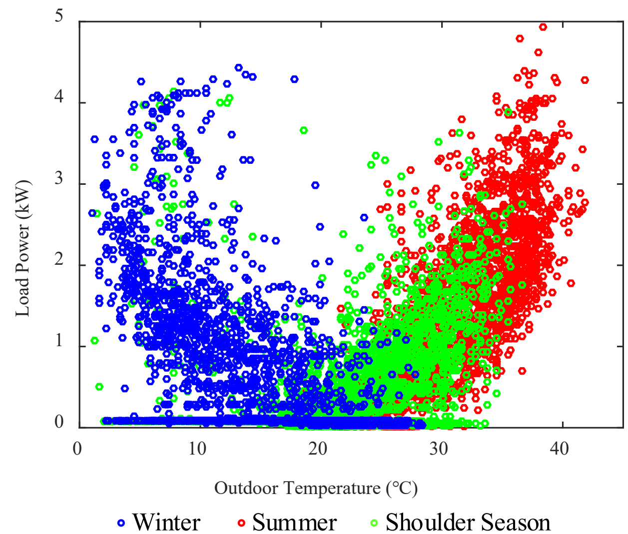
Step1 Data Acquisition
Smart meter data, temperature data

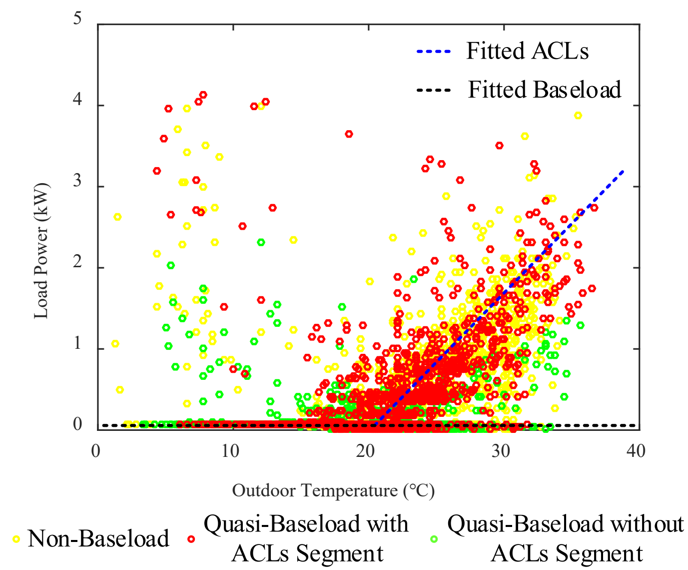
Step2 Data Cleaning
Missing readings, without TCL

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-baseload

Step5 Distribution Test
Distribution of baseload with seasonal variations





2、Physics-Informed Data-driven Modeling of GES

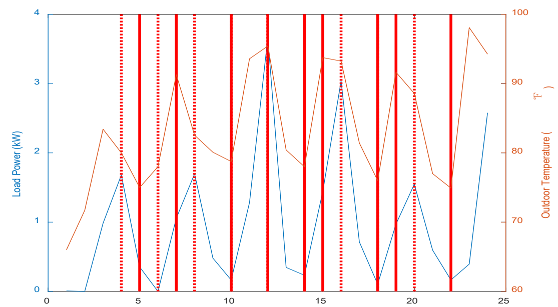
✓ **Behavior Analysis+ Load Disaggregation + Parameter identification**

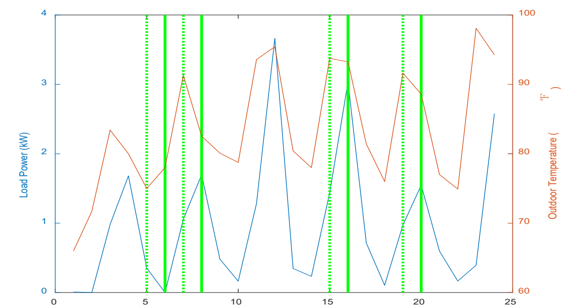
● ETP Model + Simulation + Recursively Estimation

Step1 Segment Decomposition

on-off segment static-dynamic segment

$$\left|P_t\right| \le \delta \qquad \mathrm{dPT}_t = \frac{d}{dt}\left(\frac{P_t}{T_{\mathrm{out},t}}\right) \le \sigma$$





Step2 Static Parameter Estimation

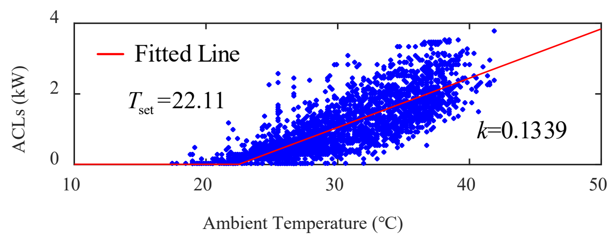
constrained regression

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

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

$$T_{\mathrm{set,min}} \le -b_t / k \le T_{\mathrm{set,max}}, \quad t \in \boldsymbol{\Omega}_{\text{on-static}}$$

$$k = 1/\eta_{\mathrm{eq}} R_{\mathrm{eq}} \qquad -\boldsymbol{b}/k = \boldsymbol{T}_{\mathrm{set}} = \{T_{\mathrm{set},t}\}$$



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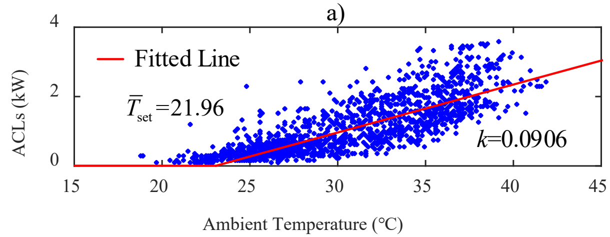

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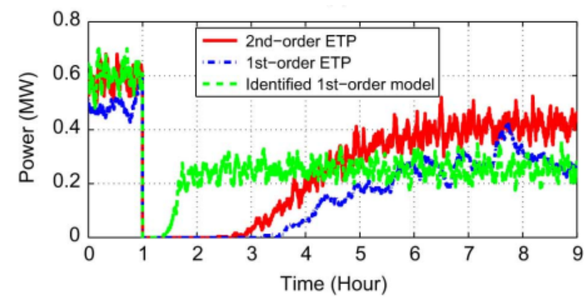
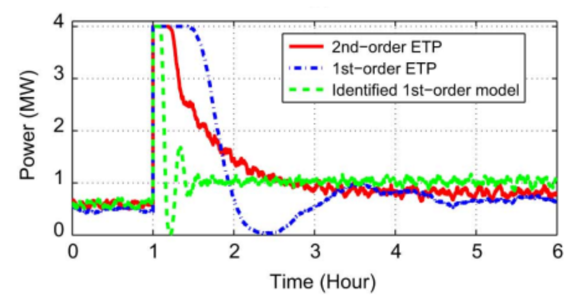




Step3 Dynamic Parameter Estimation

Simulation+PSO Recursively

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

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

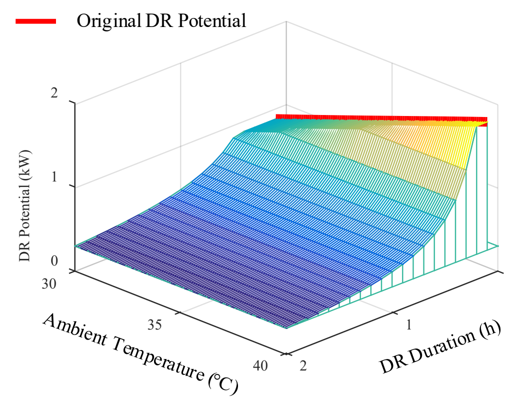
2、Physics-Informed Data-driven Modeling of GES

✓ Operational Demand Response Potential—State Dependent Flexibility

➢ **Redefined DR Potential:**

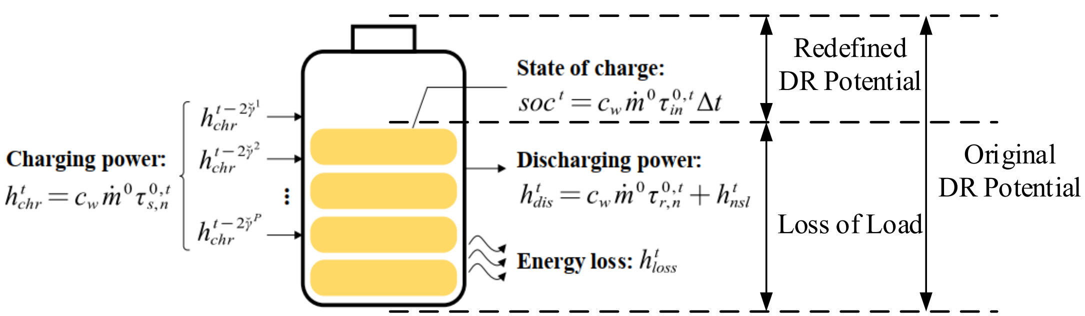
Multifaceted Factors: ambient temperature、setpoint temperature、equivalent thermal parameter、comfort

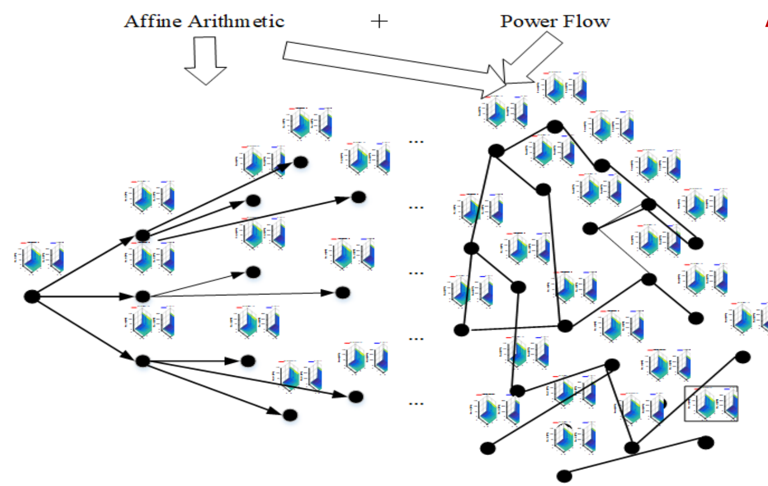
Multiple uncertainties: seasonal variation、temperature correlation、social behavior



Individual DR Potential

$$\mathrm{DR}_t = P_{\mathrm{eq},t} - P^*_{\mathrm{eq},t} = \begin{cases} \dfrac{M\Delta T}{\eta_{\mathrm{eq}} R_{\mathrm{eq}} (M-1)}, & t_{\mathrm{duration}} > R_{\mathrm{eq}} C_{\mathrm{eq}} \ln \dfrac{T_{\mathrm{out},t} - T_{\mathrm{in},t}}{T_{\mathrm{out},t} - T_{\mathrm{in},t} - \Delta T} \\ \dfrac{T_{\mathrm{out},t} - T_{\mathrm{in},t}}{\eta_{\mathrm{eq}} R_{\mathrm{eq}}}, & t_{\mathrm{duration}} \le R_{\mathrm{eq}} C_{\mathrm{eq}} \ln \dfrac{T_{\mathrm{out},t} - T_{\mathrm{in},t}}{T_{\mathrm{out},t} - T_{\mathrm{in},t} - \Delta T} \end{cases}$$





Affine Power Flow

Grid-aware DR Potential

2、Physics-Informed Data-driven Modeling of GES

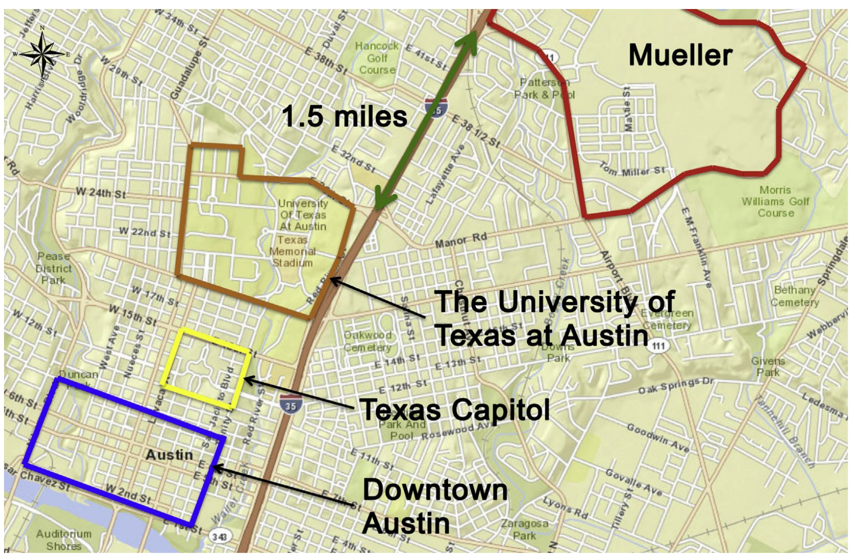
✓ Case Study (Ground-Truth Data)

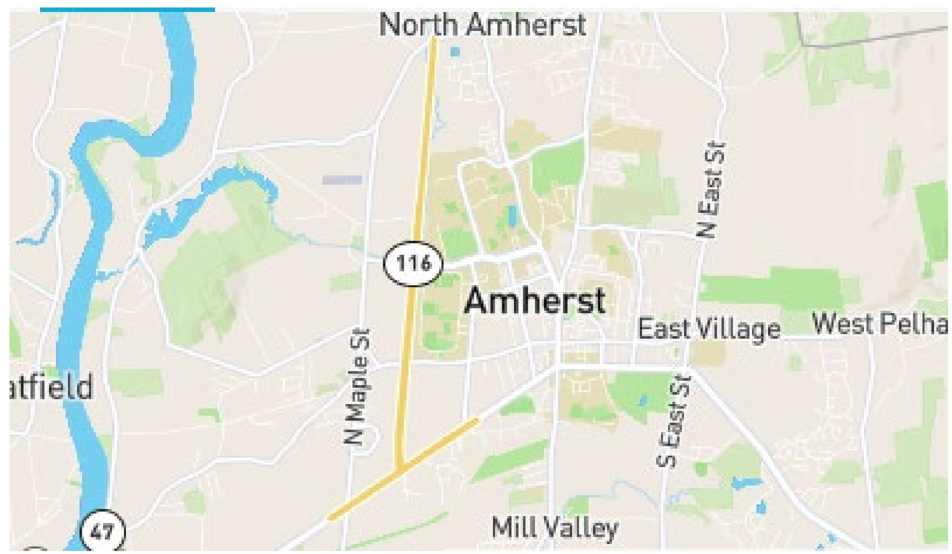
Austin Mueller Project

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





2、Physics-Informed Data-driven Modeling of GES

✓ 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

Hanzhou 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

✓ Case Study (Ground-Truth Data)

- **High Accuracy, High Robustness Highly-Transferable**

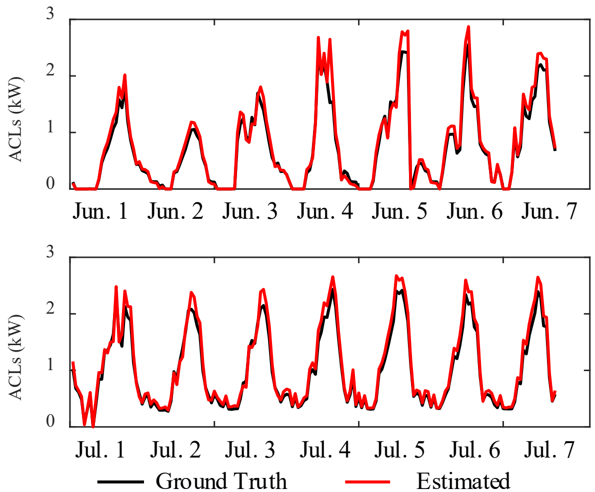


Fig Comparison of the ground truth and estimated data of customer #77

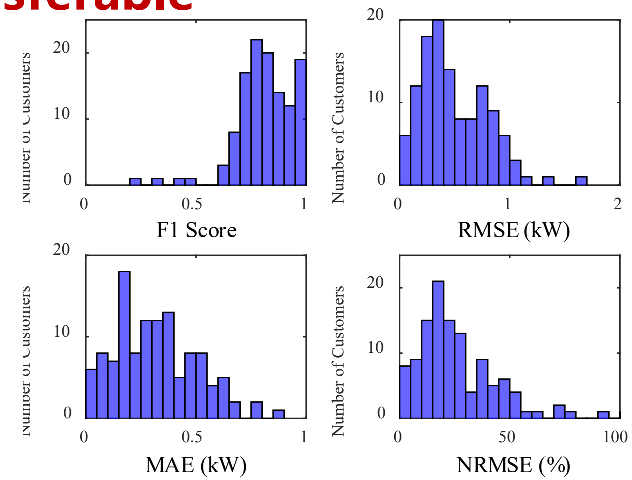
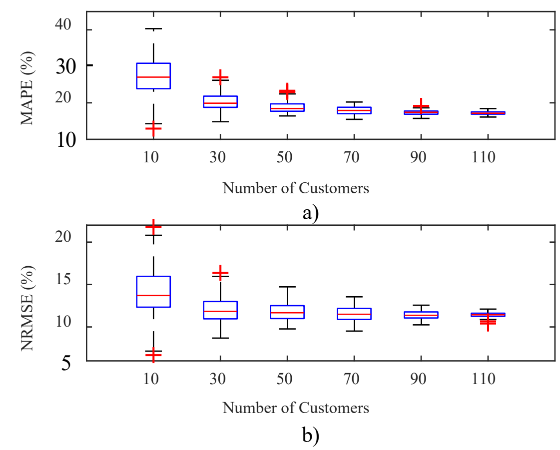


Fig Histogram of the important evaluation index across the 119 customers

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



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

✓ Case Study (Ground-Truth Data)

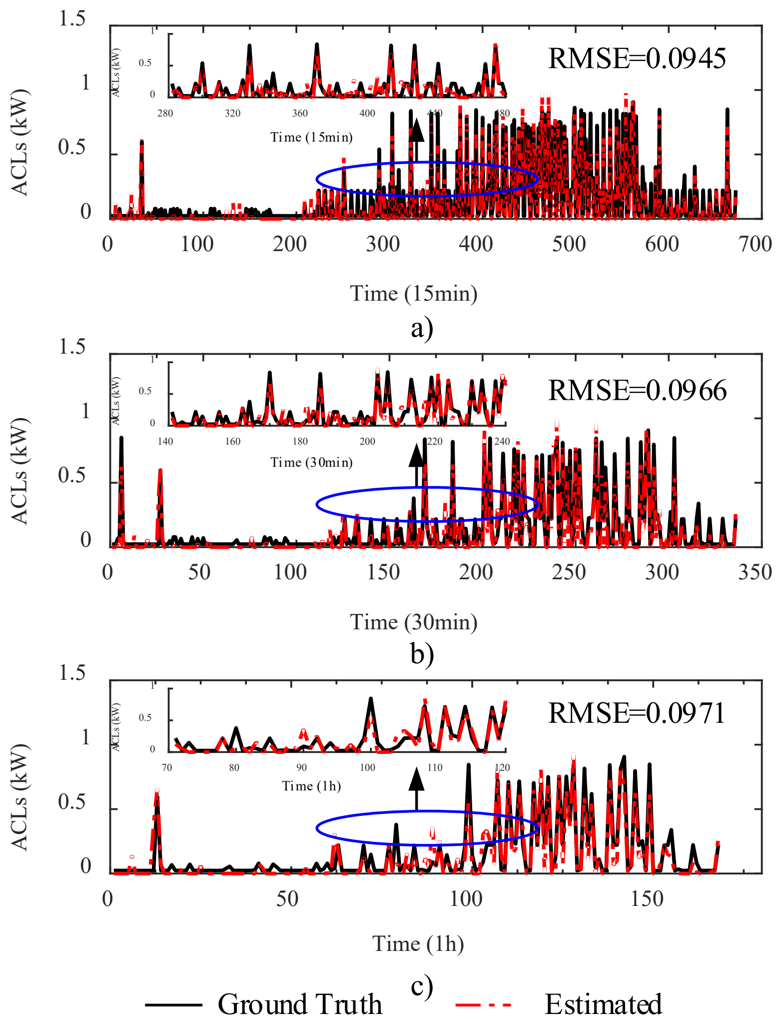


Fig load disaggregation test over different time-scales

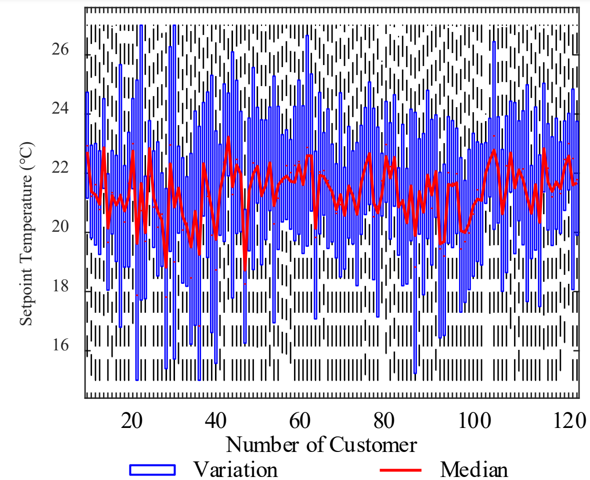


Fig setpoint temperature estimation

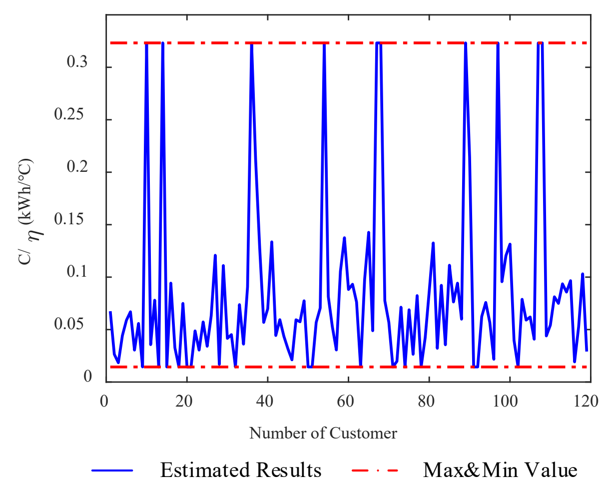
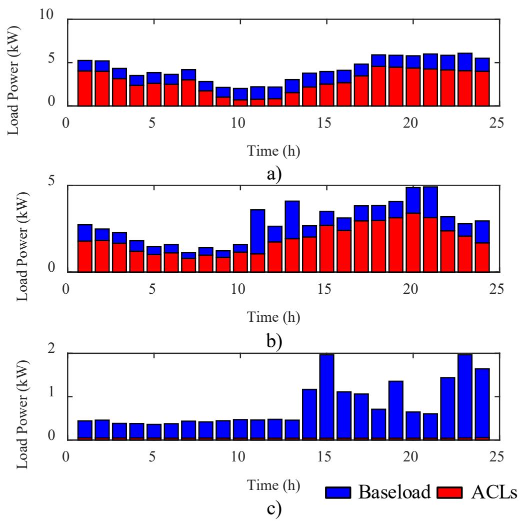


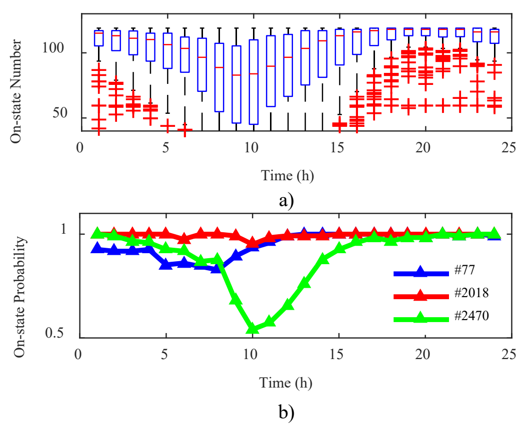
Fig thermal capacity estimation

2、Physics-Informed Data-driven Modeling of GES

✓ Case Study (Ground-Truth Data)

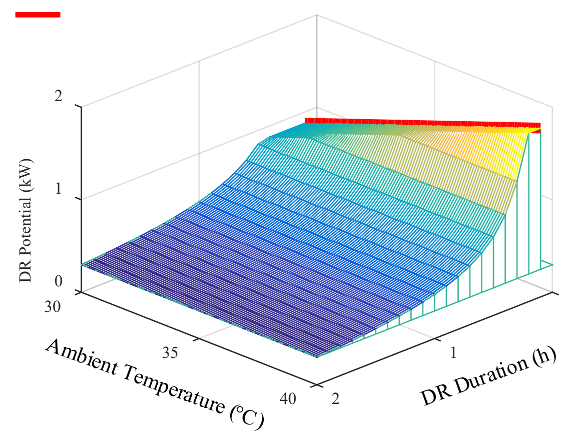
➢ Usage Pattern



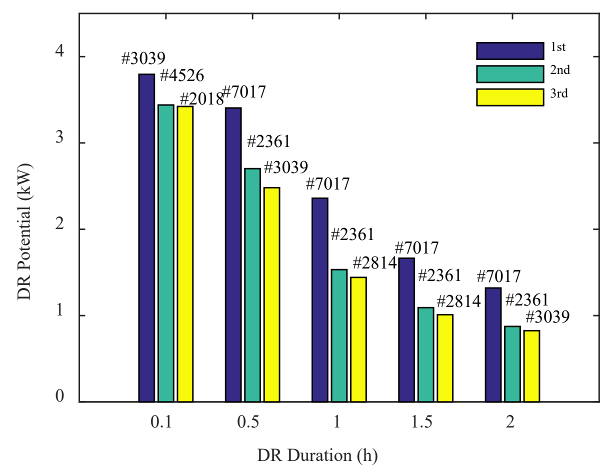


On-state

➢ DR Potential Distribution



➢ DR Customer Targeting



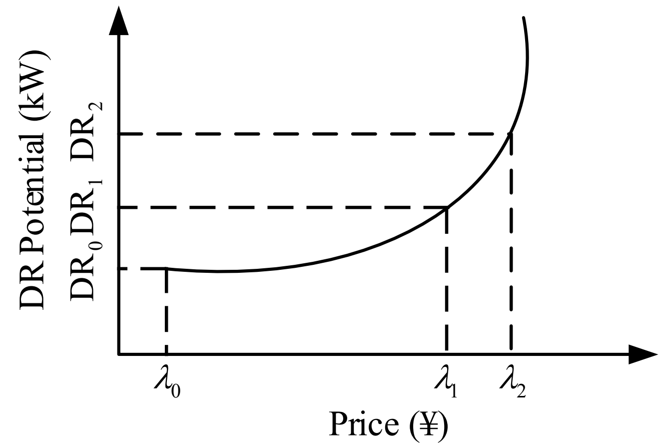
2、Physics-Informed Data-driven Modeling of GES

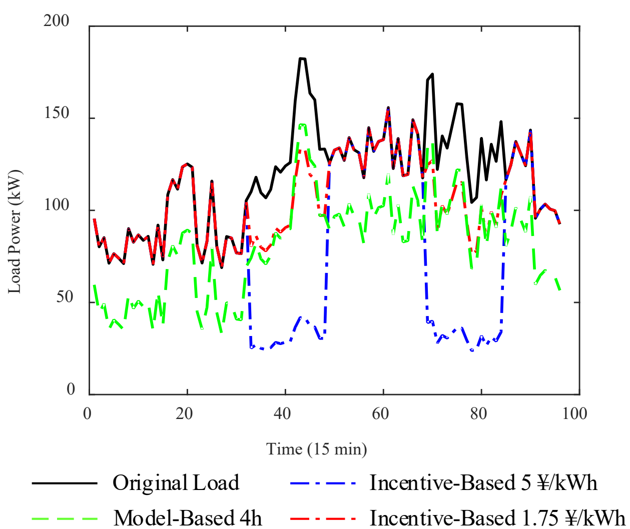
✓ Case Study (Ground-Truth Data)

- **Practical DR Potential= min (Physical DR Potential, Economic DR Potential)**

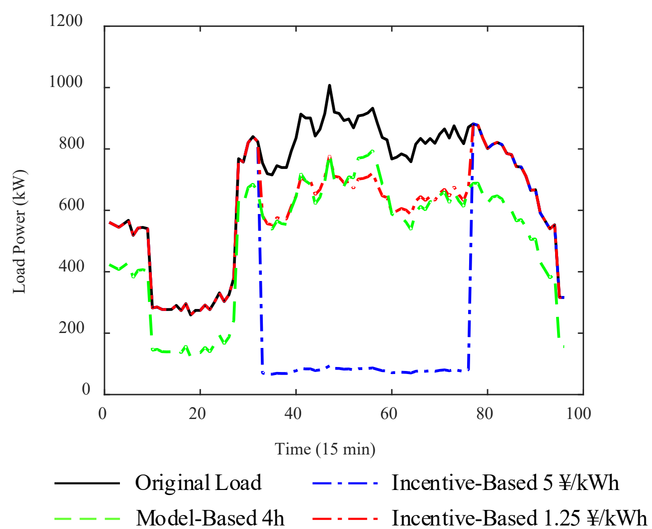
$$\mathrm{DP}_t^1 = \frac{\varphi E_t P^*_{\mathrm{total},t}}{\rho_t^*}(\rho_t - \rho_t^* + \eta\lambda_t) + \sum_{\substack{j=1 \\ j\neq t}} \frac{\varphi E_{t,j} P^*_{\mathrm{total},t}}{\rho_j^*}(\rho_j - \rho_j^* + \eta\lambda_j)$$

$$\mathrm{DP}_t^2 = \boldsymbol{f}(T_{\mathrm{out},t}, t_{\mathrm{duration}}, T_{\mathrm{in},t}, \Delta T, \boldsymbol{\theta}_{eq})$$

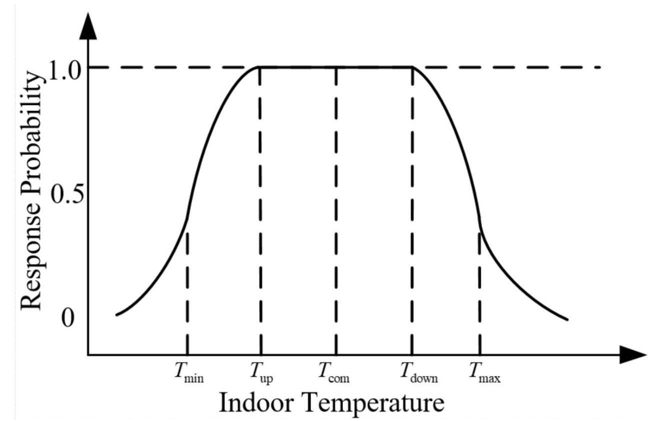




a)

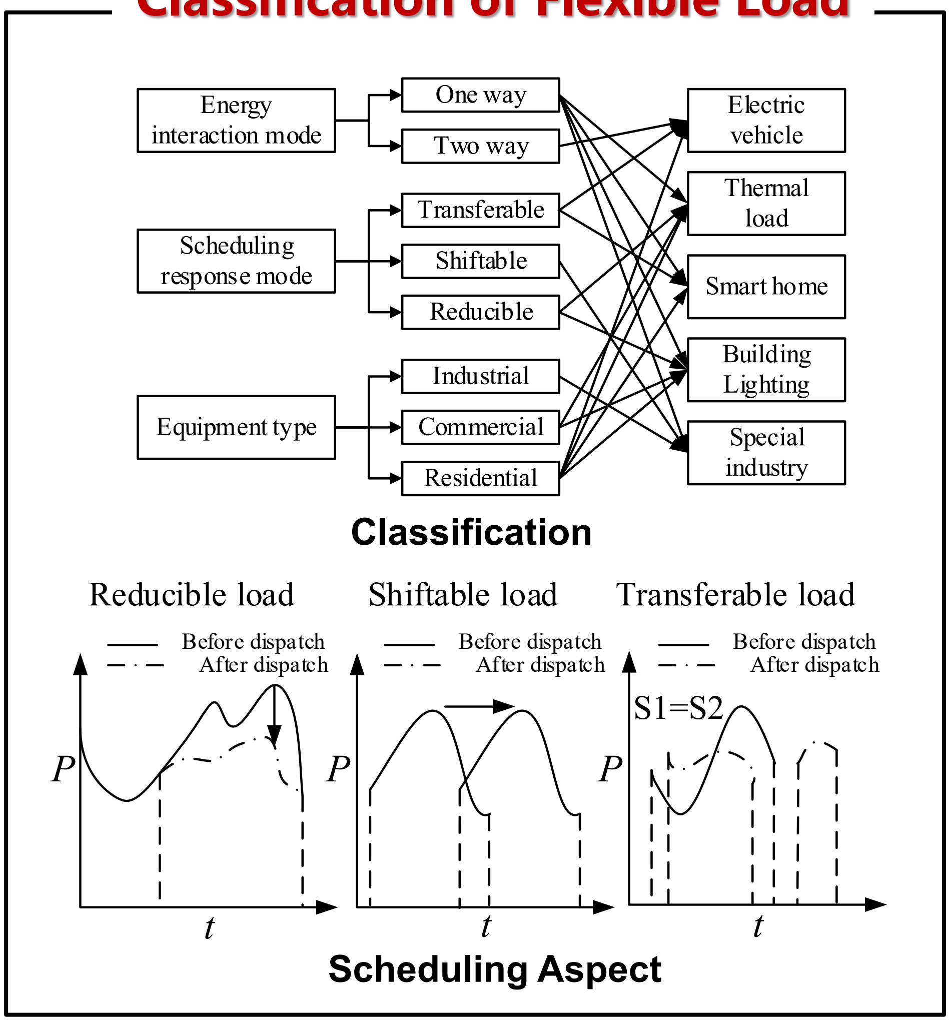


b)

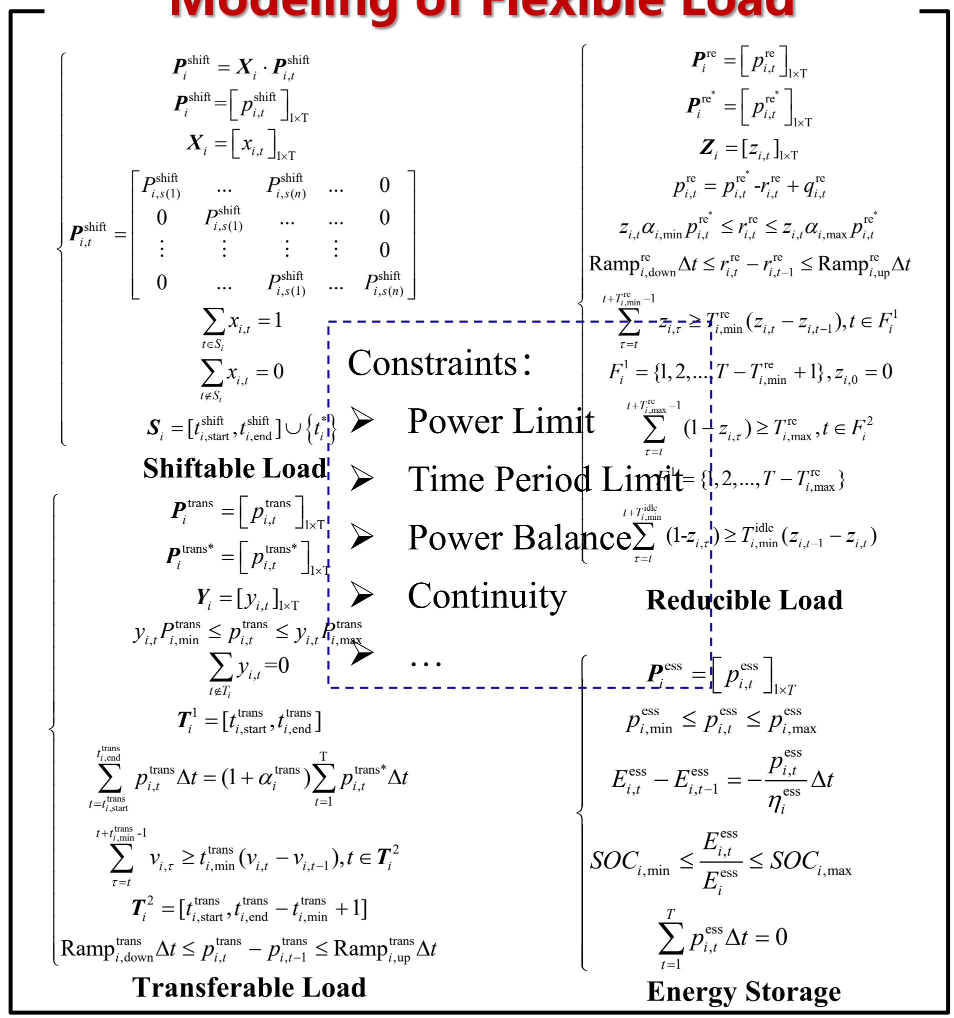


✓ Unified Modeling of GES Resources

Classification of Flexible Load



Modeling of Flexible Load



L. Cheng, **N. Qi***, and L. Tian, “Joint planning of generalized energy storage resource and distributed generator considering operation control strategy,” Automation of Electric Power Systems, no. 10, pp. 27–40, 2019.

✓ 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

$$0 \le P^{\rm GES}_{{\rm c},i,t} \le \overline{P}^{\rm GES}_{{\rm c},i,t}$$

$$0 \le P^{\rm GES}_{{\rm d},i,t} \le \overline{P}^{\rm GES}_{{\rm d},i,t}$$

Time-varying

$$\underline{SoC}^{\rm GES}_{i,t} \le SoC^{\rm GES}_{i,t} \le \overline{SoC}^{\rm GES}_{i,t}$$

Baseline Consumption

$$SoC^{\rm GES}_{i,t+1} = (1-\varepsilon^{\rm GES}_i)SoC^{\rm GES}_{i,t} + \frac{\eta^{\rm GES}_{{\rm c},i} P^{\rm GES}_{{\rm c},i,t}\Delta t}{S^{\rm GES}_i} - \frac{P^{\rm GES}_{{\rm d},i,t}\Delta t}{S^{\rm GES}_i \eta^{\rm GES}_{{\rm d},i}} + \alpha^{\rm GES}_{i,t}$$

$$SoC^{\rm GES}_{i,T} = SoC^{\rm GES}_{i,0}$$

SoC Ramping

$$-RD^{\rm GES}_i \Delta t \le SoC^{\rm GES}_{i,t+1} - SoC^{\rm GES}_{i,t} \le RU^{\rm GES}_i \Delta t$$

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

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

$$g = (\underline{SoC}_{i,t} - \underline{SoC}^{\rm DIU}_{i,t})\mathcal{N}(\mu_g, \sigma_g) + \underline{SoC}^{\rm DIU}_{i,t}$$

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

$$\mu_g = c^{\rm S}_{{\rm d},i,t}/\overline{c}^{\rm S}, \mu_h = \beta_i RD_{i,t},$$

Decision-dependent uncertainty (DDU)

1. Mapping GES Model to Physical Resources

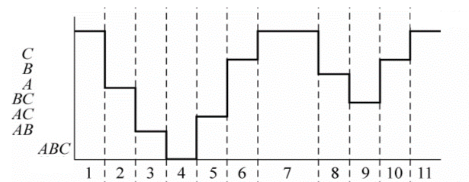
GES model parameters	Physical BES	Physical TCL (IVA/FFA)	Physical EV
SoC_t	SoC_t	$\frac{\overline{T}^{\rm in} - T^{\rm in}_t}{\overline{T}^{\rm in} - \underline{T}^{\rm in}}$	SoC_t
$\overline{P}_{{\rm c},t}$	$\overline{P}_{\rm c}$	$\overline{P} - P^{\rm B}_t$	$\overline{P}_{\rm c} - P^{\rm B}_{{\rm c},t}$
$\overline{P}_{{\rm d},t}$	$\overline{P}_{\rm d}$	$P^{\rm B}_t - \underline{P}$	$\overline{P}_{\rm d} - P^{\rm B}_{{\rm d},t}$
$\underline{SoC}_t$	$\underline{SoC}$	$\frac{\overline{T}^{\rm in} - \overline{T}^{\rm in}_t}{\overline{T}^{\rm in} - \underline{T}^{\rm in}}$	$\underline{SoC}_t$
$\overline{SoC}_t$	$\overline{SoC}$	$\frac{\overline{T}^{\rm in} - \underline{T}^{\rm in}_t}{\overline{T}^{\rm in} - \underline{T}^{\rm in}}$	$\overline{SoC}_t$
ε	ε	$1-e^{-\Delta t/RC}$	ε
S	S	$\frac{\Delta t(\overline{T}^{\rm in} - \underline{T}^{\rm in})}{KR(1-e^{-\Delta t/RC})}$	S
$\eta_{\rm c/d}$	$\eta_{\rm c/d}$	1	$\eta_{\rm c/d}$
α_t	0	$(1-e^{-\Delta t/RC})SoC^{\rm B}_t$	$\Delta SoC^{\rm B}_t$

2. Decision-independent Uncertainty→Data

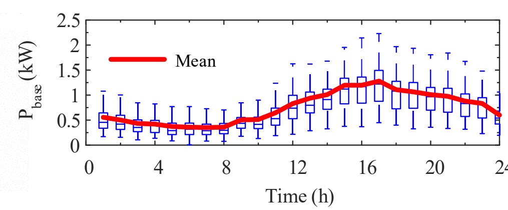
$$f(\omega^{\rm VES}_t) = \begin{cases} p^{\rm VES}_t & \omega_t = 1 \\ 1-p^{\rm VES}_t & \omega_t = 0 \end{cases}$$

$$P^{\rm B}_{i,t} \sim \mathcal{LN}\left(\mu_{P^{\rm B}_{i,t}}, \sigma_{P^{\rm B}_{i,t}}\right), \quad \forall t \in \Omega_T, \forall i \in \Omega_S$$

Operation States



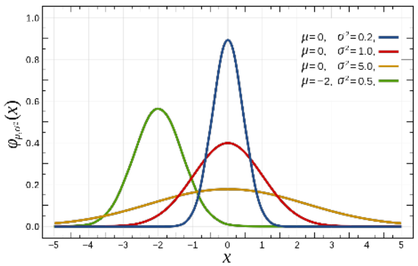
Baseline Consumption

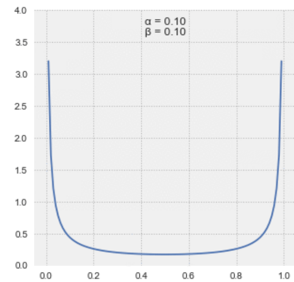


2、Physics-Informed Data-driven Modeling of GES

✓ Unified Modeling of GES Resources—DIUs and DDUs

- **DDU: Coupling Relationship Between Decisions & Uncertainty**

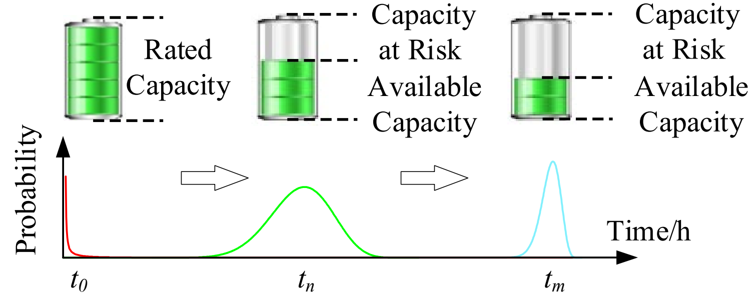




DIU (Static)

DDU (Dynamic)

Willingness & Capability to Response



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

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

$$g = (\underline{SoC}_{i,t} - \underline{SoC}_{i,t}^{\mathrm{DIU}})\mathcal{N}(\mu_g,\sigma_g) + \underline{SoC}_{i,t}^{\mathrm{DIU}}$$

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

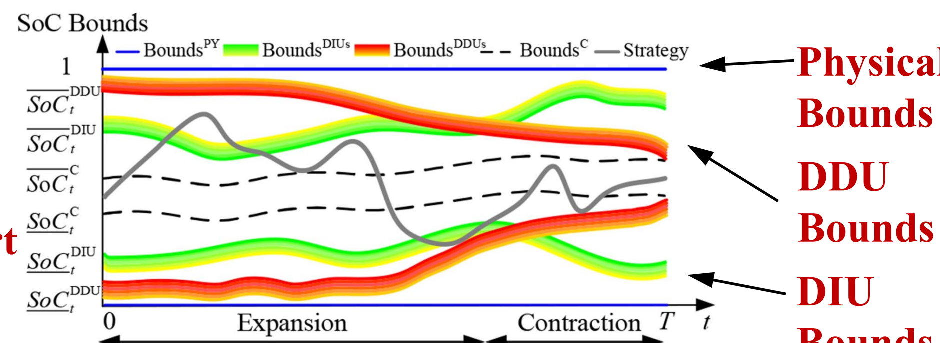
$$\mu_g = c_{\mathrm{d},i,t}^{\mathrm{S}}/\overline{c}^{\mathrm{S}}, \mu_h = \beta_i RD_{i,t},$$

DIU VS DDU

Discomfort Function

Incentive Effect

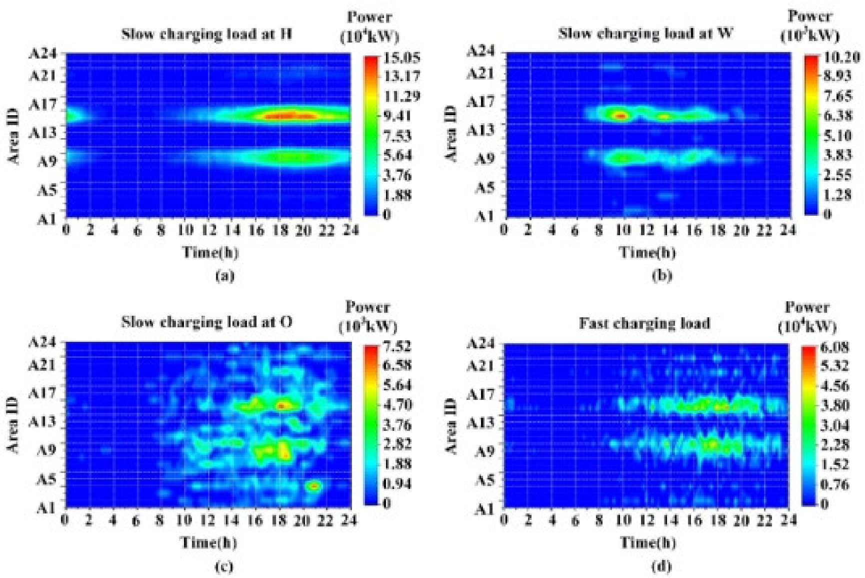
Discomfort Effect

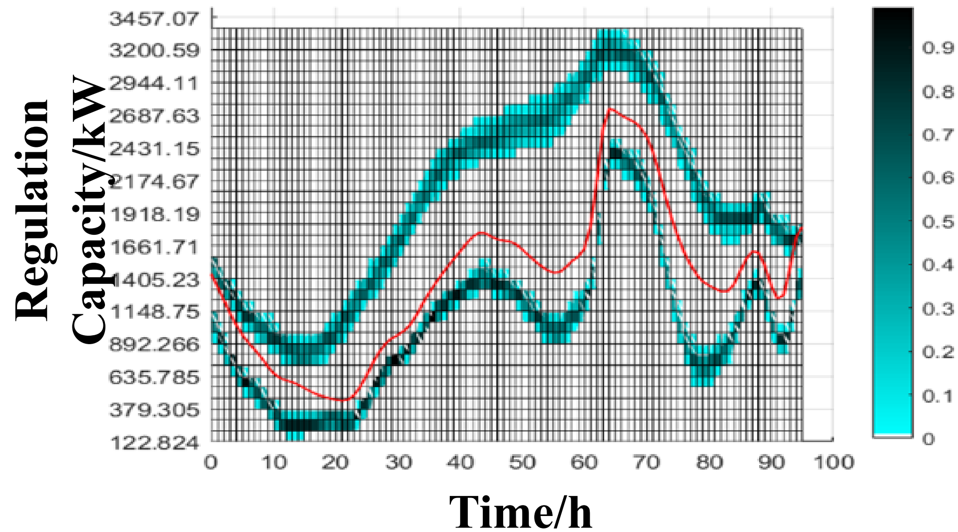


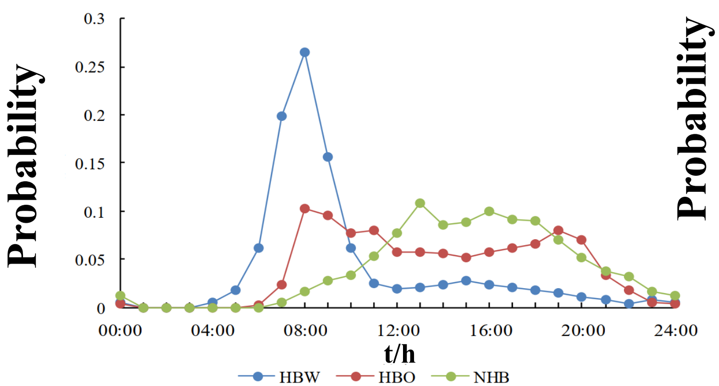
N. Qi*, P. Pinson, M. R. Almassalkhi et al, "Chance-Constrained Generic Energy Storage Operations under Decision-Dependent Uncertainty," IEEE Transactions on Sustainable Energy, vol. 14, no. 4, pp. 2234–2248, 2023.

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.

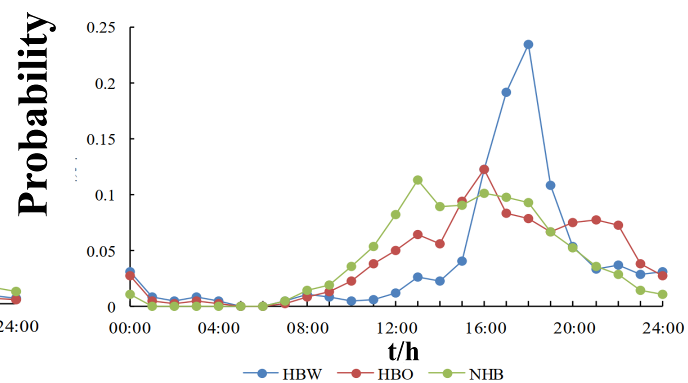
✓ Flexibility from EV—More Complex and Stochastic than TCL







Plug-in time



Plug-out times

2、Physics-Informed Data-driven Modeling of GES

✓ Learning DDU Remains a Challenging Issue!

1. Price/incentive

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

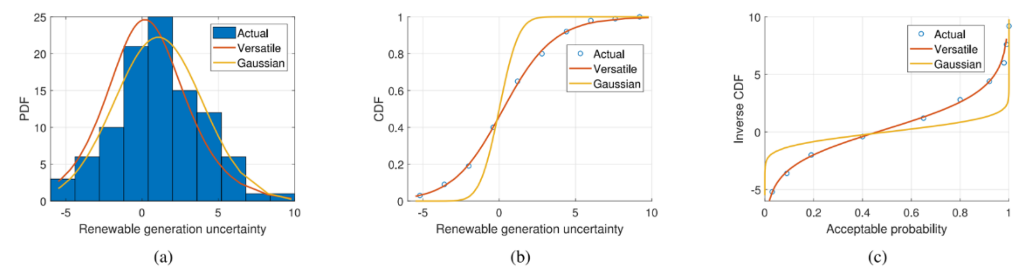
Ruan J, Liang G, Zhao J, et al. Graph Deep Learning-based Retail Dynamic Pricing for Demand Response[J]. IEEE Transactions on Smart Grid, 2023.

Versatile Mixture Distribution

PDF: $f(x \mid \alpha,\beta,\gamma) = \dfrac{\alpha\beta e^{-\alpha(x-\gamma)}}{\left(1+e^{-\alpha(x-\gamma)}\right)^{\beta+1}}$

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

CDF^{-1}: $F^{-1}(\varepsilon \mid \alpha,\beta,\gamma) = \gamma - \dfrac{1}{\alpha}\ln\left(\varepsilon^{-1/\beta}-1\right)$



2. Discomfort

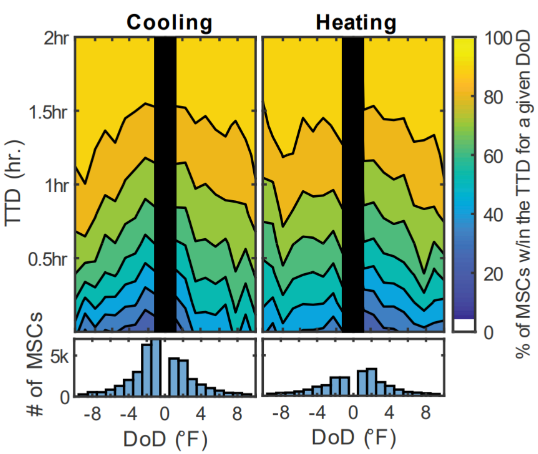


Fig. 9: Degree of discomfort vs Time to discomfort; during occupied periods (Single-occupant households; 30 min. filter)

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

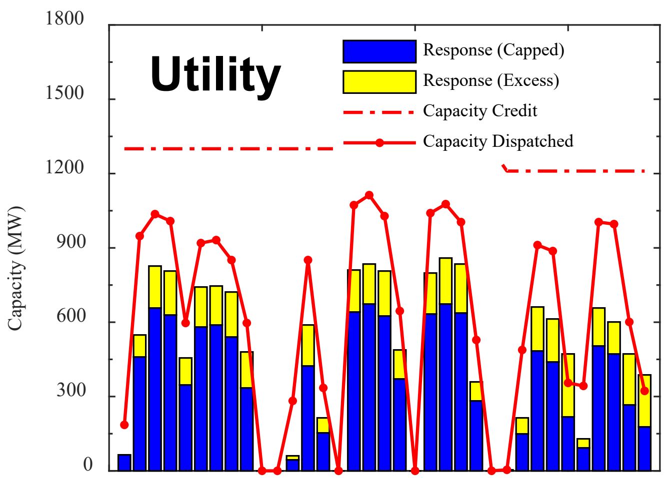
Differentiable, integrable, and convex

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.

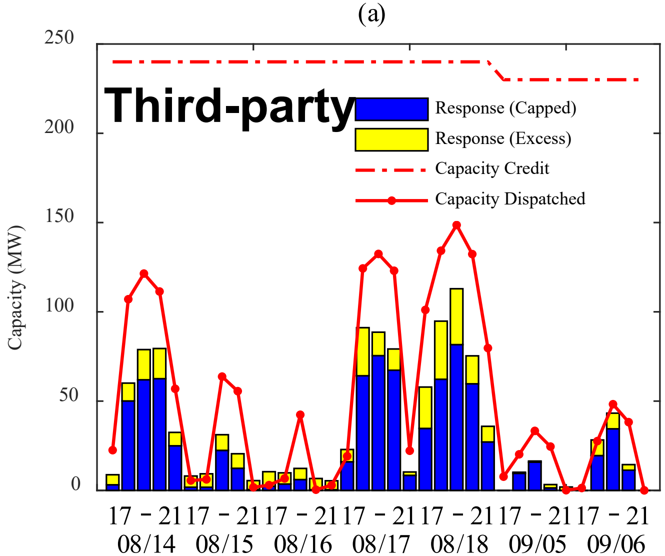
Contents

2、Chance-Constrained GES Operations under DDU

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



(a)



(b)

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)**

✓ **Reliability Commitment with Reserves**

2、Chance-Constrained GES Operations under DDU

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

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. 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.
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.

⇕ **Coordination**

- **Propose a Two-Stage Reliability Commitment Framework for Probabilistic Reserve Procurement (DA-DDU with Data-Driven Observation, RT-Reliability Allocation)**

N. Qi, L. Cheng, Feng Liu* et al, "Reliability-Aware Probabilistic Reserve Procurement under Decision-Dependent Uncertainty," IEEE PES General Meeting 2024.

✓ Chance-Constrained Optimization under DDU

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

$$\begin{cases} \mathbb{P}\left(c(y)^T \tilde{z} + d(y) \le e\right) \ge 1-\gamma \Rightarrow \\ c(y)^T \mu + d(y) + F^{-1}(1-\gamma)\left\|c(y)\sigma\right\|_2 \le e \end{cases}$$

$\tilde{z}$ Stochastic Parameters

y Decisions

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

✓ **Robust Estimation of $F_y^{-1}(1-\gamma)$ (Robust Approximation)**

✓ **Data-Driven Update of DDU by Real-Time Observation (Data-Driven Aproach)**

✓ **Iterative Update of DDU with Distribution (Iterative Algorithm)**

- **Joint Project (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 under DDU (Robust Approximation)

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

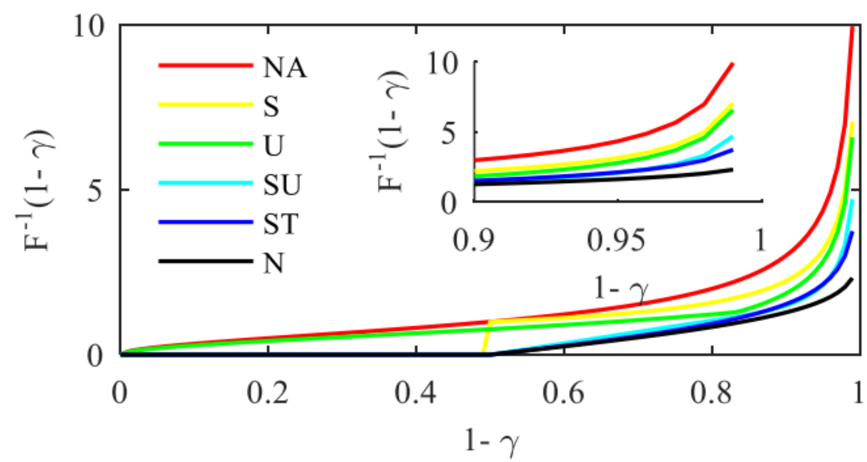
TABLE II APPROXIMATION OF WIDELY USED NORMALIZED INVERSE CUMULATIVE DISTRIBUTION

Type & Shape	$F^{-1}(1-\gamma)$	γ
1) No distribution assumption	$\sqrt{(1-\gamma)/\gamma}$	$0<\gamma\le 1$
2) Symmetric distribution	$\sqrt{1/2\gamma}$	$0<\gamma\le 1/2$
	0	$1/2<\gamma\le 1$
3) Unimodal distribution	$\sqrt{(4-9\gamma)/9\gamma}$	$0<\gamma\le 1/6$
	$\sqrt{(3-3\gamma)/(1+3\gamma)}$	$1/6<\gamma\le 1$
4) Symmetric & unimodal distribution	$\sqrt{2/9\gamma}$	$0<\gamma\le 1/6$
	$\sqrt{3}(1-2\gamma)$	$1/6<\gamma\le 1/2$
	0	$1/2<\gamma\le 1$
5) Student's t distribution	$t_{\upsilon,\sigma}^{-1}(1-\gamma)$	$0<\gamma\le 1$
6) Normal distribution	$\Phi^{-1}(1-\gamma)$	$0<\gamma\le 1$

3) VySoChanskij–Petunin inequality can be used with unimodal distribution of DDUs and infers the following conclusion.

$$F(k)=1-\sup_{P\in U}\mathbb{P}[\xi\ge k] = \begin{cases} 1-4/(9k^2+9) & k\ge\sqrt{5/3} \\ 1-(3-k^2)/(3+3k^2) & 0\le k\le\sqrt{5/3} \end{cases} \tag{20a}$$

$$F^{-1}(1-\gamma)=\begin{cases} \sqrt{2/9\gamma} & 0<\gamma\le 1/6 \\ \sqrt{3}(1-2\gamma) & 1/6<\gamma\le 1/2 \end{cases} \tag{20b}$$



✓ Chance-Constrained Optimization under DDU (Robust Approximation)

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

$$\mathbb{P}\Big(a_i(x)^{\mathrm{T}}\xi(x)\le b_i(x)\Big)\ge 1-\epsilon$$

$$a_i(x)^{\mathrm{T}}\mu(x)+b_i(x)+F_x^{-1}(1-\epsilon)\sqrt{a_i(x)^{\mathrm{T}}\Sigma a_i(x)}\le 0$$

$$\Downarrow$$

$$\begin{cases} a_i(x)^{\mathrm{T}}\mu(x)+b_i(x)+\psi_K\,\|r(x)\|_1+\pi_K\sqrt{1/\epsilon-1}\,\|y\|_2\le 0 \\ \sqrt{a_i(x)^{\mathrm{T}}\Sigma a_i(x)}\le y_1,\quad \sqrt{2\psi_K}\,\|r(x)\|_1\le y_2 \\ \psi_K=K^{(1/p-1/2)},\quad \pi_K=\Big(1-\frac{4}{\epsilon}\exp(-(K^{1/p}-2)^2/2)\Big)^{-1/2} \end{cases}$$

$r(x)$ is the radius of DDU, p, K should guarantee: $p\ge 2$, $K>(2+\sqrt{2\ln(4/\varepsilon)})^p$
y is the auxiliary decision matrix.

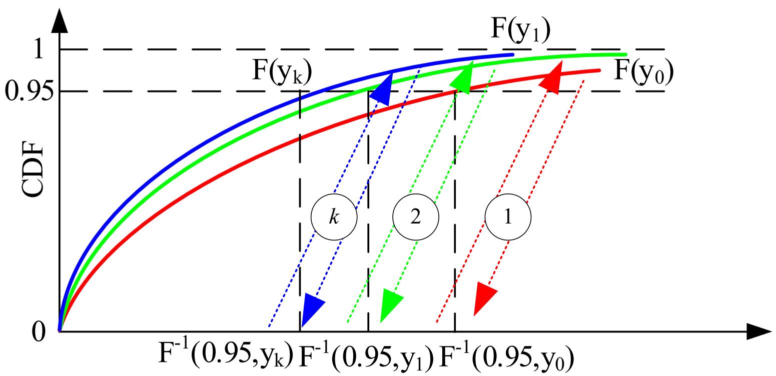
✓ Chance-Constrained Optimization under DDU (Robust Approximation)

● **Iteratively Update DDU and Solutions**

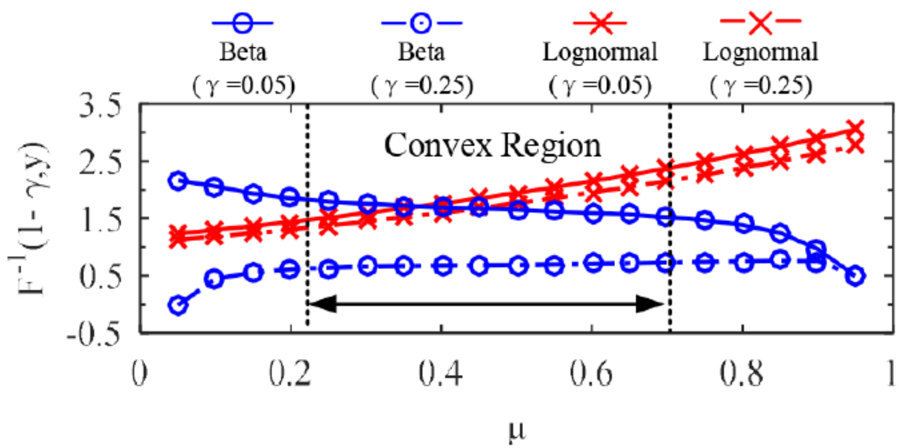
Algorithm 1 Iterative algorithm for CCO-DDUs

Input: Probability level γ, convergence criterion δ, deterministic and reformulated random parameters under DIUs.
Output: Decision variables $\boldsymbol{y}$ and cost function $F(\boldsymbol{y}, \boldsymbol{z})$.
Step1: Initialization
Set k=1, and $F^{-1}(1-\gamma, \boldsymbol{y}_0)$ with robust reformulation value referred to Table II. Compute CCO-DDUs with $F^{-1}(1-\gamma, \boldsymbol{y}_0)$ to obtain initial value of $\boldsymbol{y}_0$. Use $\boldsymbol{y}_0$ to update $F^{-1}(1-\gamma, \boldsymbol{y}_1)$ via MCS. Calculate eps $=\left|F^{-1}(1-\gamma, \boldsymbol{y}_1)-F^{-1}(1-\gamma, \boldsymbol{y}_0)\right|$.
Step2: Iteration
While eps$>\delta$ **do**
Compute CCO-DDUs with $F^{-1}(1-\gamma, \boldsymbol{y}_k)$ to obtain $\boldsymbol{y}_k$. Use $\boldsymbol{y}_k$ to update $F^{-1}(1-\gamma, \boldsymbol{y}_{k+1})$ via MCS. Calculate eps $=\left|F^{-1}(1-\gamma, \boldsymbol{y}_{k+1})-F^{-1}(1-\gamma, \boldsymbol{y}_k)\right|$.
$k \leftarrow k+1$
end
Step3: Return $\boldsymbol{y}=\boldsymbol{y}_k$, $G(\boldsymbol{y}, \boldsymbol{z})=G(\boldsymbol{y}_k, \boldsymbol{z})$

Starting Point of Robust Approximation



Convexity and Convergence Conditions
1) RD function; 2) g/h distribution



✓ Economic Dispatch in Microgrid with GES (Case 1—Normal)

Objective function

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

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

$$C_t^{\mathrm{G}}=c_t^{\mathrm{G}}P_t^{\mathrm{G}}\Delta t$$

a) GES chance constraints:

$$\mathbb{P}(P_{\mathrm{c},i,t}\le\overline{P}_{\mathrm{c},i,t})\ge 1-\gamma$$

$$\mathbb{P}(P_{\mathrm{d},i,t}\le\overline{P}_{\mathrm{d},i,t})\ge 1-\gamma$$

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

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

b) Power balance chance constraints:

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

c) GES other constraints:

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

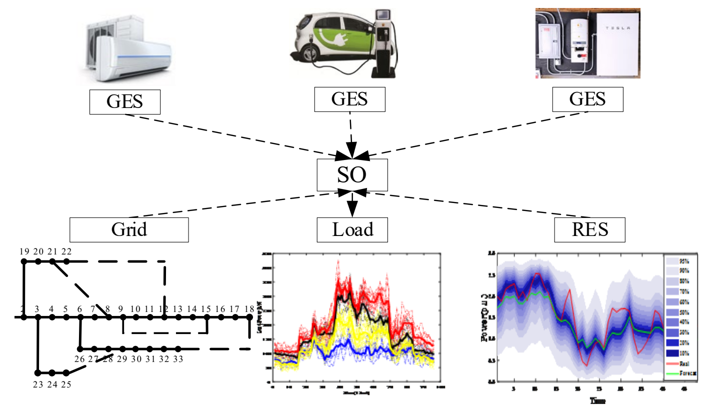
$$-SoC_{i,\mathrm{RD}}\le SoC_{i,t+1}-SoC_{i,t}\le SoC_{i,\mathrm{RU}}$$

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

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

$$0\le P_{\mathrm{c},i,t}\le\overline{P}_{\mathrm{c},i,t}$$

$$0\le P_{\mathrm{d},i,t}\le\overline{P}_{\mathrm{d},i,t}$$



d) DDU constraints:

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

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

$$RD_{i,t}=\lambda\sum_{\tau=1}^{t}(P_{\mathrm{c},i,\tau}/\overline{P}_{\mathrm{c},i}+P_{\mathrm{d},i,\tau}/\overline{P}_{\mathrm{d},i})/T+(1-\lambda)\max\{|SoC_{i,t}-SoC_{i,t}^{\mathrm{B,av}}|-SoC_{i,t}^{\mathrm{DB}}/2,0\}$$

e) other constraints:

$$0\le P_t^{\mathrm{G}}\le\overline{P}^{\mathrm{G}}.$$

2、Chance-Constrained GES Operations under DDU

✓ Economic Dispatch in Microgrid with GES (Case 1—Normal)

- **Deterministic(Blue), DIU(Green), DDU(Red)**

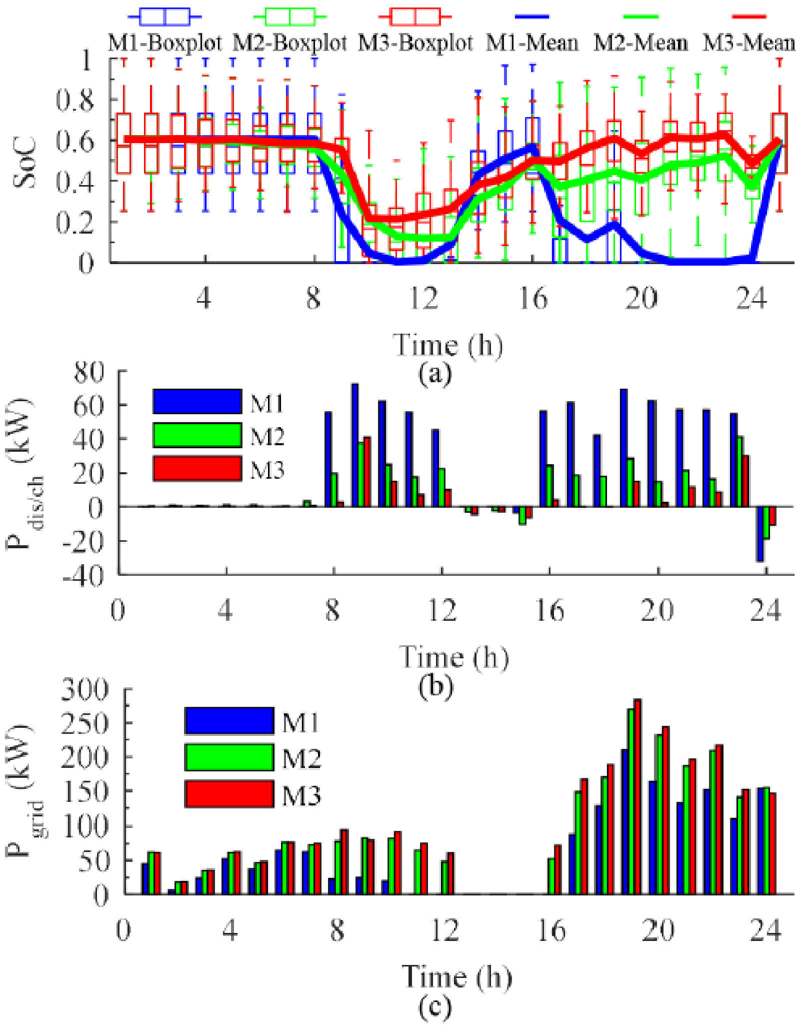
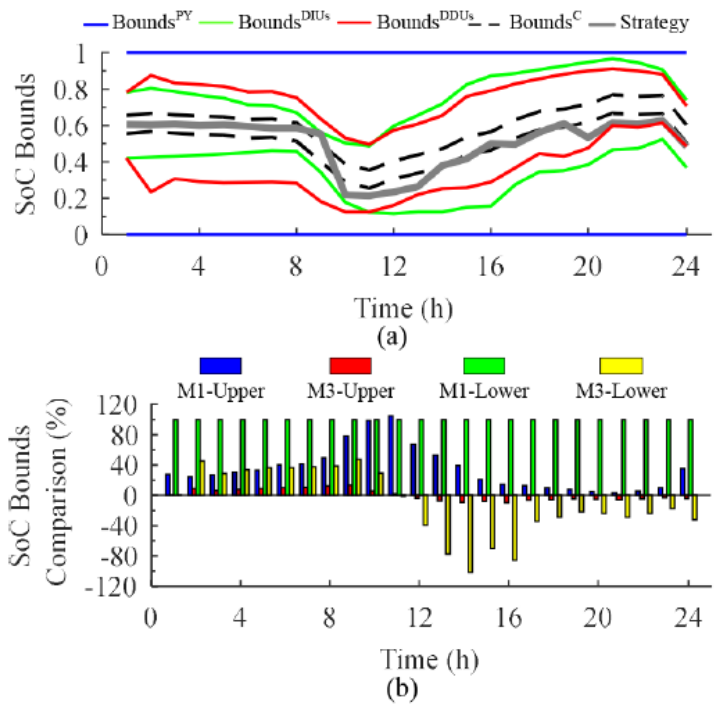


TABLE III

OPTIMIZATION RESULTS WITH DIFFERENT MODELS AND UNCERTAINTIES

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



Most Conservative

Flexibility Contracted

2、Chance-Constrained GES Operations under DDU

✓ Economic Dispatch in Microgrid with GES (Case 1—Normal State)

- **Deterministic(Blue), DIU(Green), DDU(Red)**

Best Performance in Real-time Availability

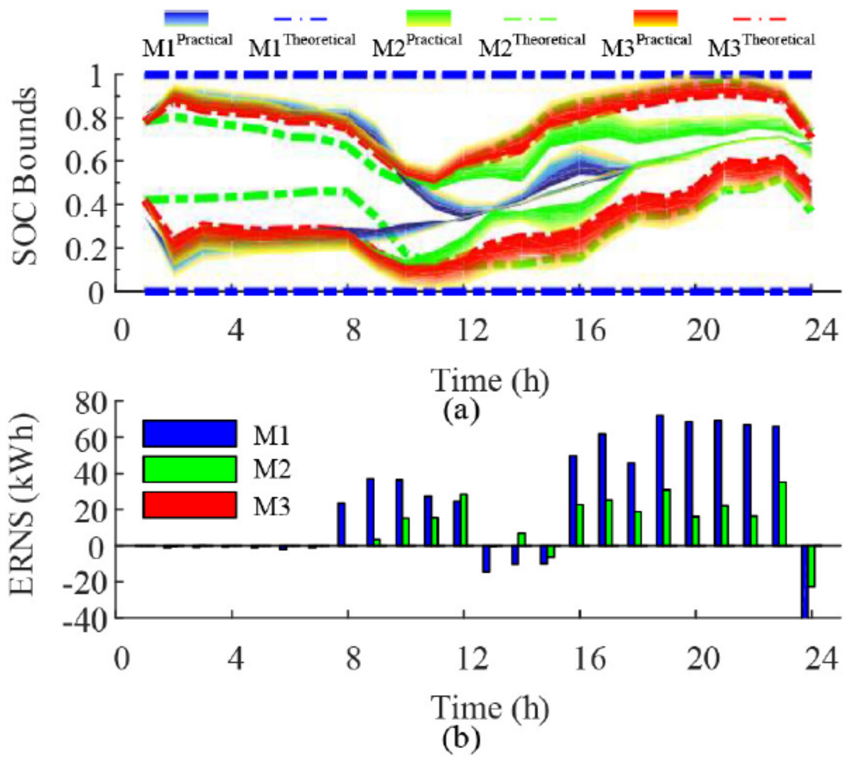


Fig. 6. Reliability performance comparison with respect to (a) practical and theoretical SoC bounds (95%) and (b) ERNS.

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

γ	Indices	M1	M2	M3
0.05	*LORP* / *ERNS*		0.3 / 12.0	0.0 / 0.0
	$Cost^{RT}$ / $Cost^{TC}$	*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
	$Cost^{RT}$ / $Cost^{TC}$	$Cost^{RT}$ 1057.9	440.0 / 2909.0	0.0 / 2799.7
0.45	*LORP* / *ERNS*	$Cost^{TC}$ 3088.3	0.4 / 15.2	0.2 / 3.6
	$Cost^{RT}$ / $Cost^{TC}$		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	$Cost^{TC}$ (CNY)	$\sum P_{d,i,t}\Delta t$ (kWh)	$\sum P_{c,i,t}\Delta t$ (kWh)	$\overline{EP}$ (%)	$\underline{EP}$ (%)	$\overline{CT}$ (%)	$\underline{CT}$ (%)
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

✓ Economic Dispatch in Microgrid with GES (Case 1—Normal)

● **Convergence and Scalability Performance**

It converges quickly!

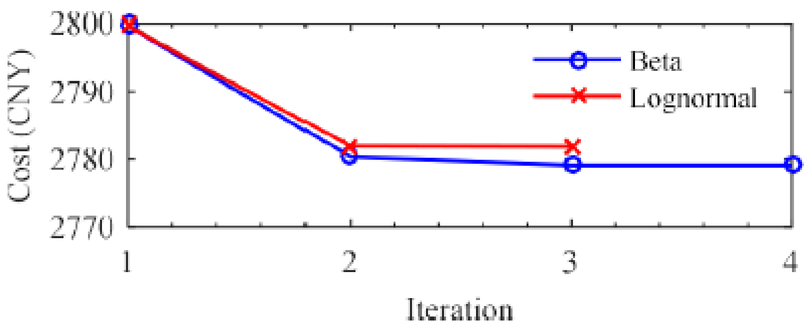


Fig. 8. Convergence performance under Beta and Lognormal distribution (95%)

TABLE VI
OPERATIONS COMPARED WITH DIFFERENT REFORMULATION METHODS

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

Aggregator or Robust approximation or Stop Indices

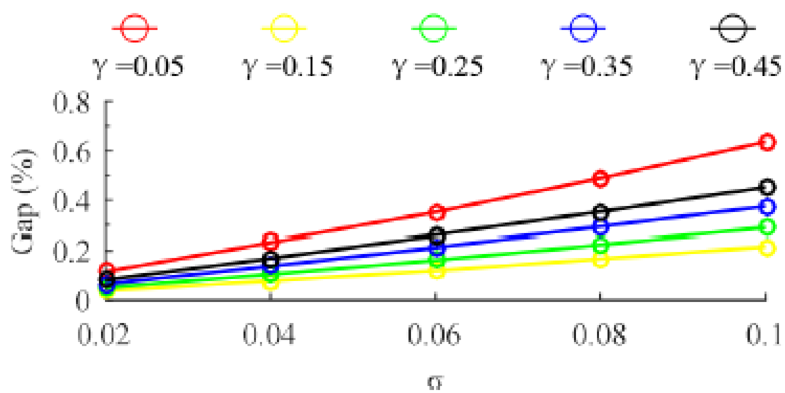


Fig. 7. Sensitivity of gap with probability level and standard deviations

TABLE VII
OPERATIONS COMPARED WITH DIFFERENT ACCELERATION METHODS

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

✓ Reliability Improvement of Distribution System with GES (Case 2—Emergency)

Objective function(load curtailment)

$$\begin{cases} C^{\mathrm{LC}} = \sum_{t\in\mathbf{\Omega}_{\mathrm{T}}}\sum_{i\in\mathbf{E}_{\mathrm{s}}} c_t^{\mathrm{LC}} P_{i,t}^{\mathrm{LC}}\Delta t \\ C^{\mathrm{Grid}} = \sum_{t\in\mathbf{\Omega}_{\mathrm{T}}} c_t^{\mathrm{Grid}} P_t^{\mathrm{Grid}} \\ C^{\mathrm{VES}} = \sum_{t\in\mathbf{\Omega}_{\mathrm{T}}}\sum_{s\in\mathbf{\Omega}_{\mathrm{V}}} (P_{\mathrm{dis},s,t}^{\mathrm{VES}} c_{\mathrm{dis},s,t}^{\mathrm{VES}} + P_{\mathrm{ch},s,t}^{\mathrm{VES}} c_{\mathrm{ch},s,t}^{\mathrm{VES}})\Delta t \end{cases}$$

a) GES chance constraints:

$$\mathbb{P}(P_{\mathrm{c},i,t} \le \overline{P}_{\mathrm{c},i,t}) \ge 1-\gamma$$

$$\mathbb{P}(P_{\mathrm{d},i,t} \le \overline{P}_{\mathrm{d},i,t}) \ge 1-\gamma$$

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

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

d) DDU constraints:

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

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

$$RD_{i,t} = \lambda\sum_{\tau=1}^{t}(P_{\mathrm{c},i,\tau}/\overline{P}_{\mathrm{c},i} + P_{\mathrm{d},i,\tau}/\overline{P}_{\mathrm{d},i})/T + (1-\lambda)\max\{|SoC_{i,t} - SoC_{i,t}^{\mathrm{B,av}}| - SoC_{i,t}^{\mathrm{DB}}/2$$

c) GES other constraints:

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

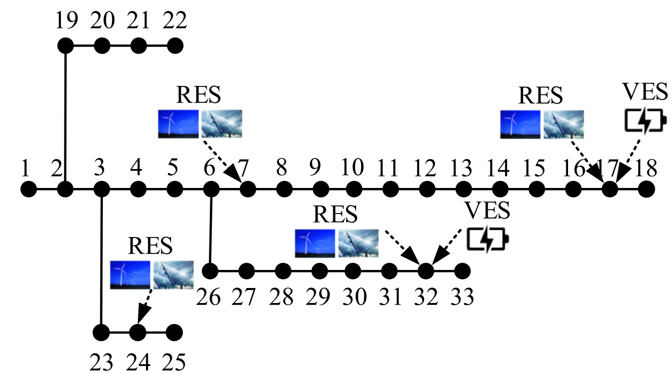
$$-SoC_{i,\mathrm{RD}} \le SoC_{i,t+1} - SoC_{i,t} \le SoC_{i,\mathrm{RU}}$$

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

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

$$0 \le P_{\mathrm{c},i,t} \le \overline{P}_{\mathrm{c},i,t}$$

$$0 \le P_{\mathrm{d},i,t} \le \overline{P}_{\mathrm{d},i,t}$$



e) other constraints:

$$\sum_{ik\in\mathbf{\Omega}_L(i)} P_{ik,t} + P_{i,t}^{\mathrm{R}} + \sum_{s\in\mathbf{\Omega}_S}(P_{\mathrm{d},s,t}^{\mathrm{GES}} - P_{\mathrm{c},s,t}^{\mathrm{GES}}) + P_{i,t}^{\mathrm{LC}} = P_{i,t}^{\mathrm{L}} + \sum_{ji\in\mathbf{\Omega}_L(i)}\left(P_{ji,t} - r_{ij}I_{ji,t}\right)$$

$$\sum_{ik\in\mathbf{\Omega}_L(i)} Q_{ik,t} + Q_{i,t}^{\mathrm{R}} + \sum_{s\in\mathbf{\Omega}_S}(Q_{\mathrm{d},s,t}^{\mathrm{GES}} - Q_{\mathrm{c},s,t}^{\mathrm{GES}}) + Q_{i,t}^{\mathrm{LC}} = Q_{i,t}^{\mathrm{L}} + \sum_{ji\in\mathbf{\Omega}_L(i)}\left(Q_{ji,t} - x_{ij}I_{ji,t}\right)$$

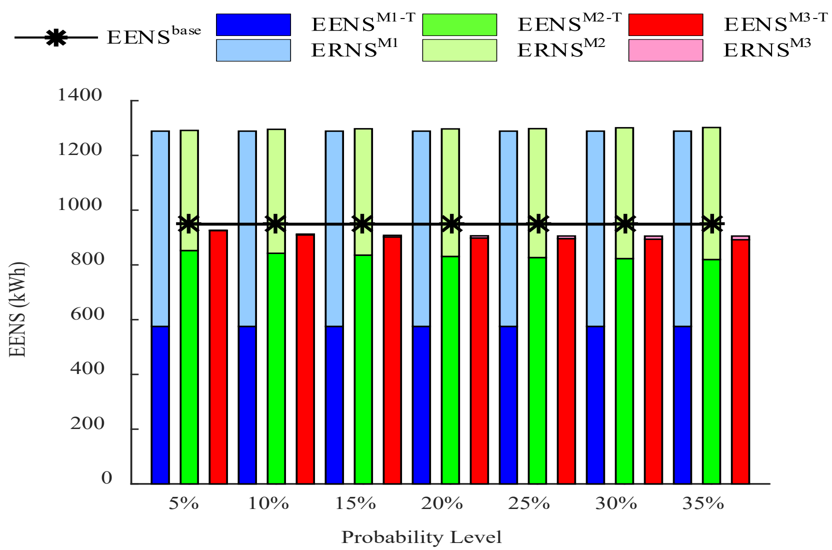
$$U_{i,t} - U_{j,t} + \left(r_{ij}^2 + x_{ij}^2\right)I_{ij,t} - 2\left(r_{ij}P_{ij,t} + x_{ij}Q_{ij,t}\right) = 0$$

$$\underline{U}_i \le U_{i,t} \le \overline{U}_i,\ 0 \le I_{ij,t} \le \overline{I}_{ij}$$

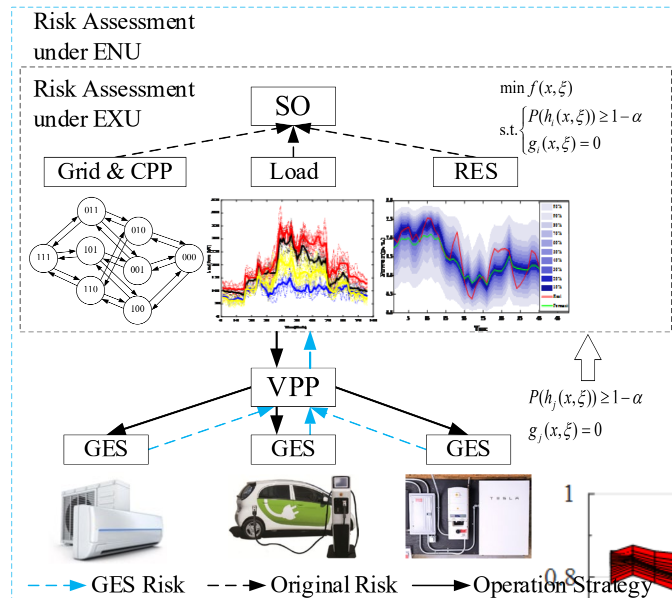
$$\left\|\begin{bmatrix}2P_{ij,t} & 2Q_{ij,t} & I_{ij,t} - U_{i,t}\end{bmatrix}^T\right\|_2 \le I_{ij,t} + U_{i,t}$$

✓ Reliability Improvement of Distribution System with GES (Case 2—Emergency)

- **DDU Cause Conservative but Reliable Response**



Additional risk from DDU



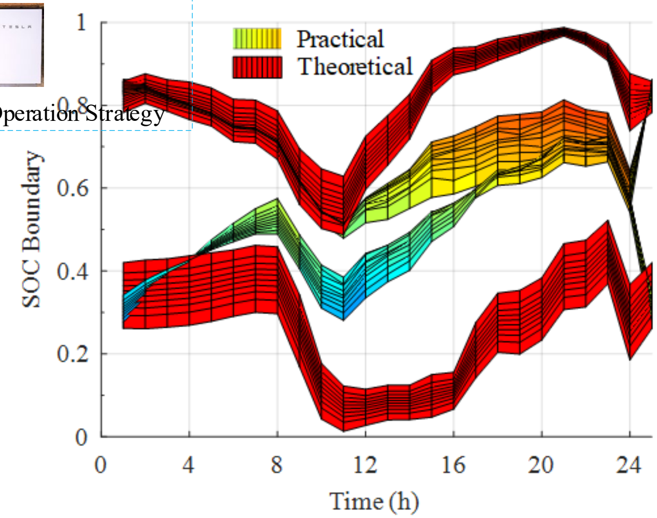


TABLE III Reliability Indices Compared with Different Models

Index	M0	M1	M2	M3
LORP	0.000	0.252	0.340	0.001
ERNS	0.00	713.35	438.80	0.05
$LOLP^T$	0.023	0.013	0.016	0.018
$EENS^T$	948.76	575.32	852.41	925.85
$LOLP^P$	0.023	0.028	0.037	0.018
$EENS^P$	948.76	1288.67	1291.22	925.90

theoretical

practical

✓ Reliability Improvement of Distribution System with GES (Case 2—Emergency)

● Impact factor of Reliability Improvement with DDU

① Confidence Level (65%-70%)

TABLE IV RELIABILITY IMPROVEMENT COMPARED WITH DIFFERENT MODELS AND PROBABILITY LEVEL

Method	Probability Level						
	5%	10%	15%	20%	25%	30%	35%
M1-T	39.4	39.4	39.4	39.4	39.4	39.4	39.4
M1-P	-35.8	-35.8	-35.8	-35.8	-35.8	-35.8	-35.8
M2-T	10.2	11.2	11.9	12.4	12.9	13.2	13.6
M2-P	-36.1	-36.5	-36.7	-36.7	-36.8	-37.1	-37.2
M3-T	2.41	4.13	4.91	5.31	5.56	5.80	6.01
M3-P	2.41	3.82	4.30	4.48	4.55	4.59	4.58

② Dispatch Period (short with valley)

TABLE VI OPTIMIZATION PERFORMANCE COMPARED WITH DIFFERENT DISPATCH TIME PERIODS

Time Period	Cost (10^3 CNY)	EENS (kWh)	$\overline{EP}$ (%)	$\underline{EP}$ (%)	$\overline{CT}$ (%)	$\underline{CT}$ (%)
S: 1 am E: 12 am	511.01	926.0	5.22	23.94	-3.91	-36.81
S: 3 pm E: 8 pm	488.38	879.5	0.00	25.80	-3.45	-35.02
S: 8 am E: 8 pm	482.96	867.1	6.85	26.54	-5.46	-66.69

③ DDU Level (discomfort > incentive)

TABLE V OPTIMIZATION PERFORMANCE COMPARED WITH DIFFERENT DDUS LEVEL

DDUs Level	Cost (10^3 CNY)	EENS (kWh)	$\overline{EP}$ (%)	$\underline{EP}$ (%)	$\overline{CT}$ (%)	$\underline{CT}$ (%)
I-1 D-1	511.01	926.0	5.22	23.94	-3.91	-36.81
I-0.5 D-1	515.25	937.13	1.94	10.16	-5.93	-44.61
I-1.5 D-1	508.32	917.76	7.51	40.32	-2.85	-35.96
I-1 D-0.5	484.24	869.03	5.97	26.14	-3.14	-28.08
I-1 D-1.5	523.44	951.67	5.30	27.03	-5.43	-60.18

④ Locating（RES）

TABLE VII OPTIMIZATION PERFORMANCE COMPARED WITH DIFFERENT LOCATIONS OF VES UNITS

VES Location	Cost (10^3 CNY)	EENS (kWh)	$\overline{EP}$ (%)	$\underline{EP}$ (%)	$\overline{CT}$ (%)	$\underline{CT}$ (%)
Buses: 17 & 32	511.01	926.0	5.22	23.94	-3.91	-36.81
Buses: 18 & 32	510.94	925.9	5.25	23.27	-3.93	-38.13
Buses: 18 & 30	517.40	938.9	5.09	24.05	-3.94	-37.57
Buses: 7 & 32	526.41	956.2	5.91	24.68	-4.87	-54.04

✓ Portfolio Optimization in GES-VPP(Case 3—Profit VS Risk)

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

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

CVaR

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

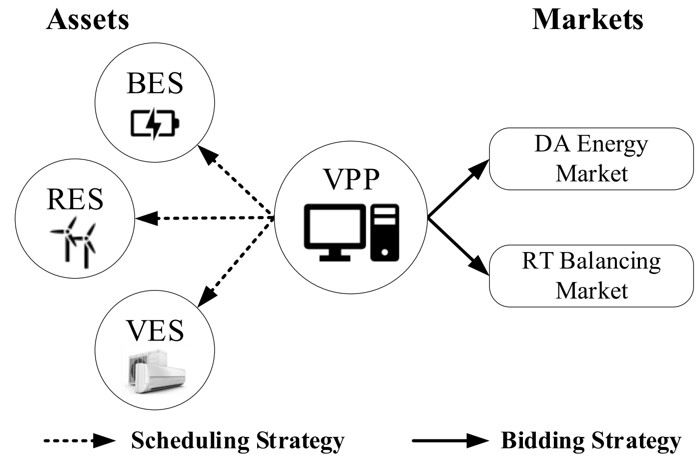
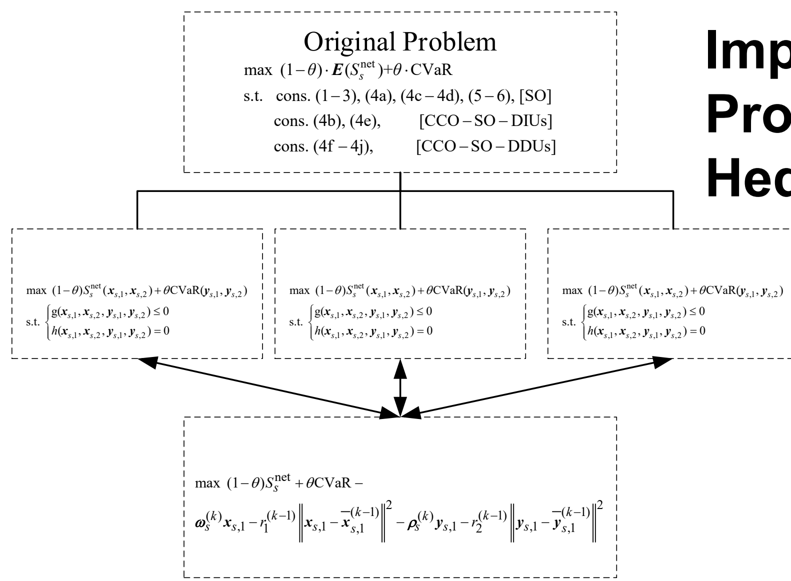


TABLE I DESCRIPTION AND REFORMULATION OF UNCERTAINTIES

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

Improved Progressive Hedging



✓ Portfolio Optimization in GES-VPP(Case 3—Profit VS Risk)

- **Without DDU, M1 is more aggressive with higher TCL, DA trading and average profit**

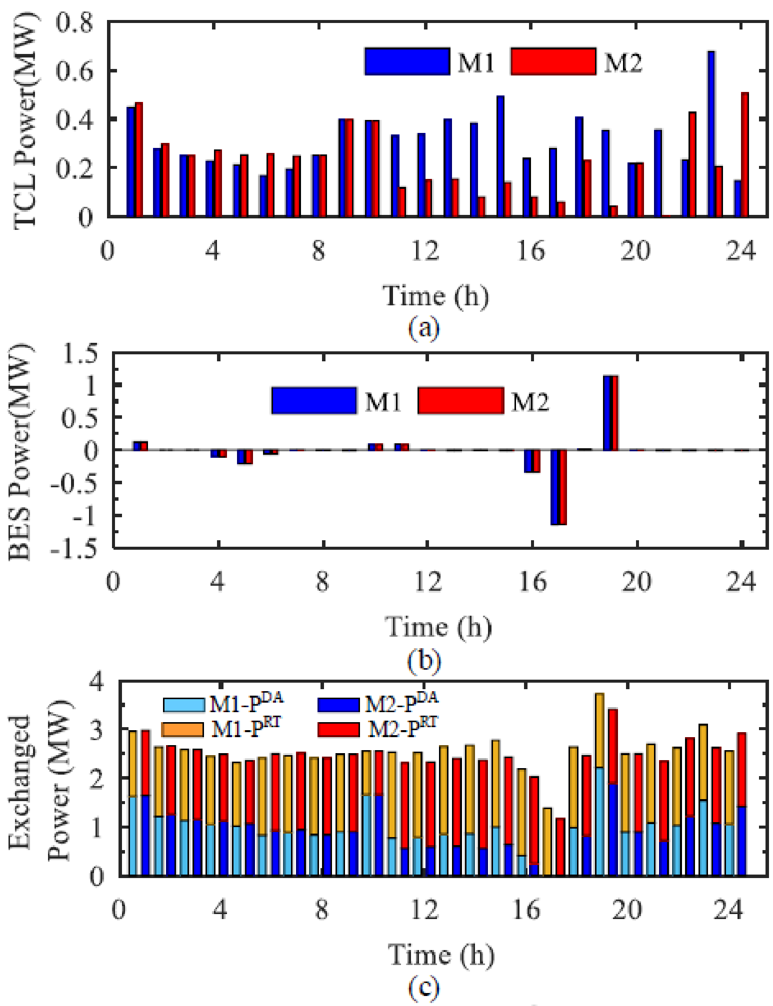


TABLE II OPTIMIZATION RESULTS COMPARED WITH DIFFERENT MODELS

Metric/ method	$E(S_s^{net})$ /CVaR($)	$\sum P_t^{DA}$ / $P_t^{R\pm}\Delta t$ (MWh)	$\sum P_{d/c,t}^{BES}\Delta t$ (MWh)	$\sum P_{d/c,t}^{TCL}\Delta t$ (MWh)
M1	2257.8/993.6	24.7/37.7/0.5	1.5/2.0	7.7/0.0
M2	2110.9/848.8	22.8/37.5/0.6	1.4/2.0	5.5/0.0

Larger gap under higher risk preference

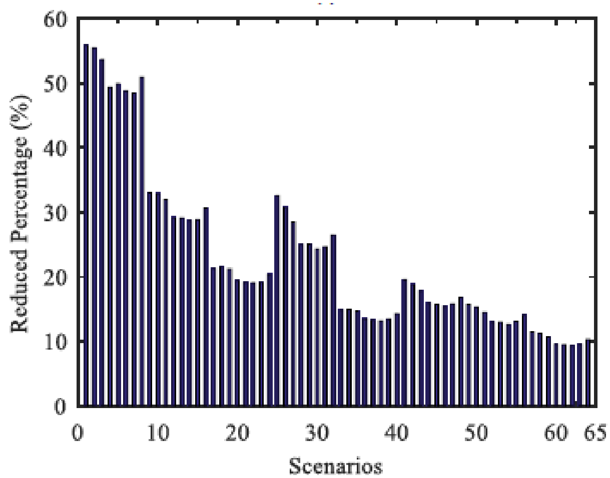
TABLE III OPTIMIZATION RESULTS COMPARED WITH DIFFERENT MODELS

Metric/ method	$E(S_s^{net})$ /CVaR($)	$\sum P_t^{DA}$ / $P_t^{R\pm}\Delta t$ (MWh)	$\sum P_{d/c,t}^{BES}\Delta t$ (MWh)	$\sum P_{d/c,t}^{TCL}\Delta t$ (MWh)
M1-0.1	2341.5/672.9	44.4/25.4/8.2	1.7/2.3	7.7/0.0
M1-0.9	2245.1/1007.3	23.1/38.6/0.0	1.6/2.2	7.7/0.0
M2-0.1	2194.2/528.2	42.5/25.3/8.3	1.7/2.3	5.5/0.0
M2-0.9	2090.8/863.4	20.5/38.9/0.0	1.8/2.5	5.5/0.0

✓ Portfolio Optimization in GES-VPP(Case 3—Profit VS Risk)

- **What's the benefit from considering DDU?**

Maximum of 60% profit loss



Portfolio Allocation by DDU not by capacity

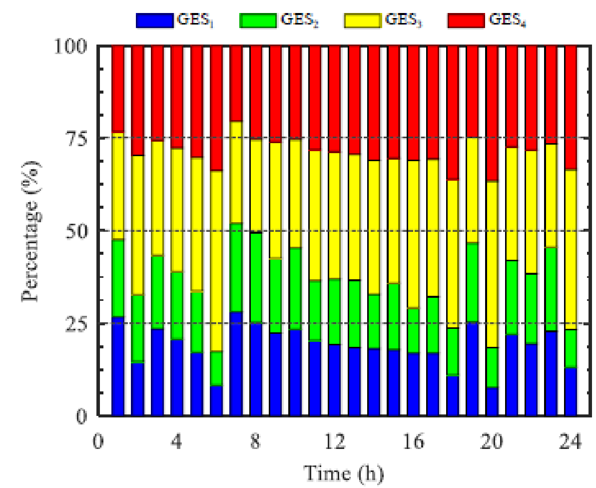
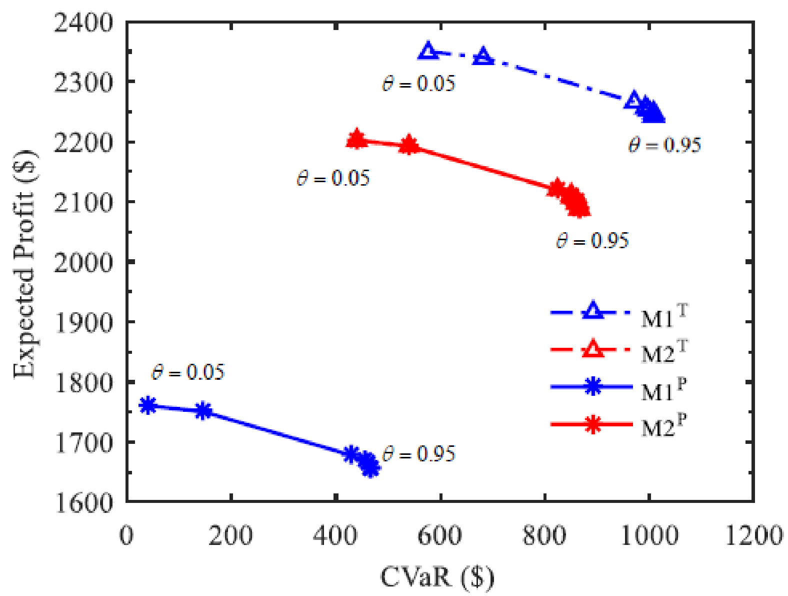


Fig. 10. Power composition of different GES portfolios

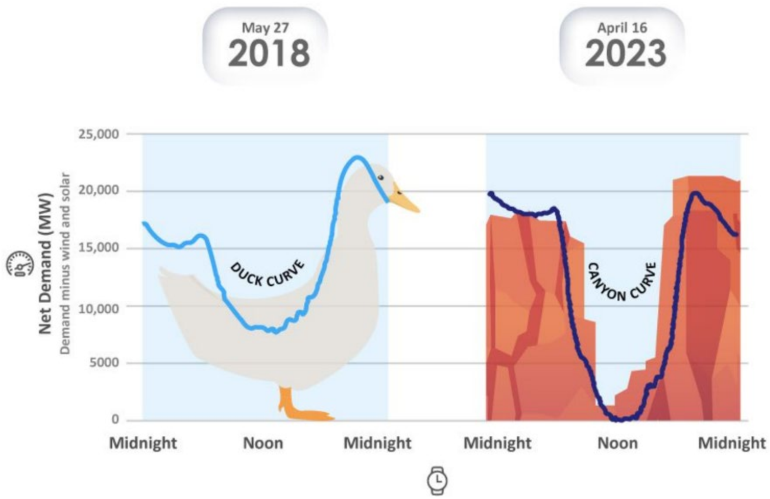
maximum of 93.2% and minimum of 54.0% reduction have been witnessed in CVaR for the lowest and highest risk aversion decisions



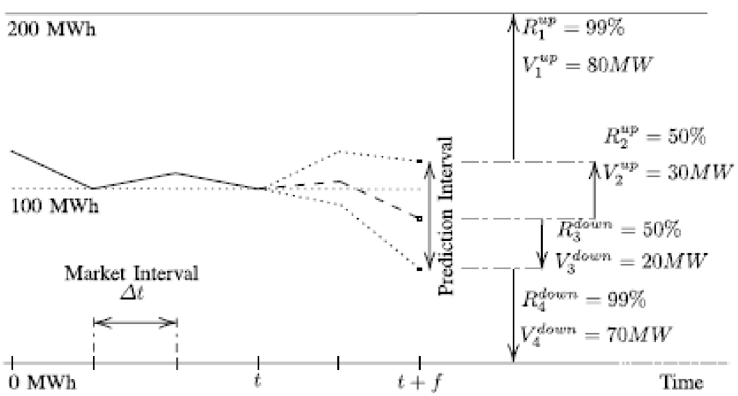
Expected profit bears a relatively stable reduction (25%~26%)

✓ Reliability-Aware Probabilistic Reserve Procurement

- **Proposed the probabilistic reserve and enhance the liquidity of reserve offers**



Canyon Curve



Probabilistic Forecast

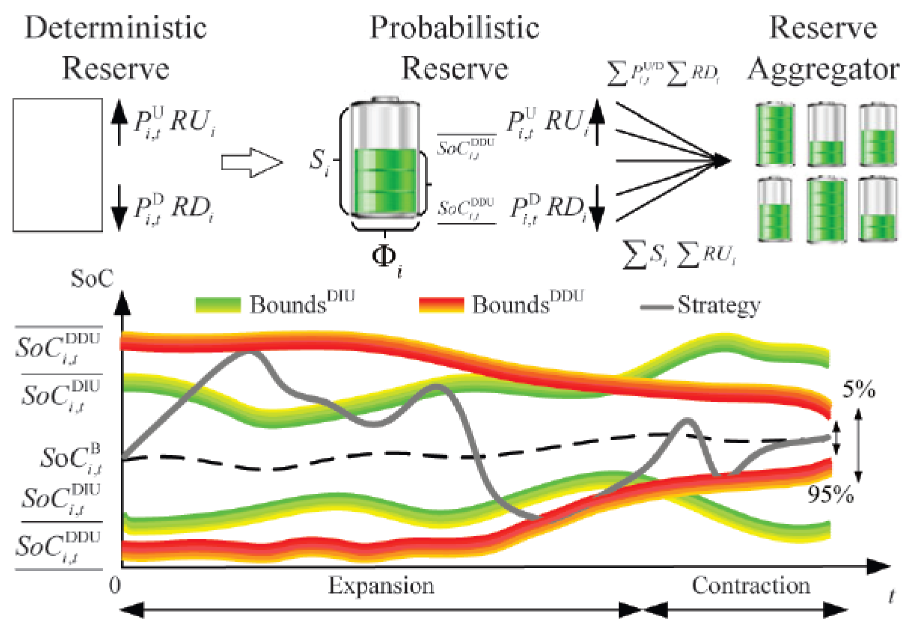


Fig. 1. Illustration of probabilistic reserve model.

Probabilistic Reserve

- **Ramping**
- **SoC**
- **Reliabitliy (＜100%)**

✓ **Reliability-Aware Probabilistic Reserve Procurement**

- **Two-stage Probabilistic Reserve Procurement under DDU**

DA-Joint Chance-Constrained Optimization under DDU

$$\min_{P_{i,t}^{\mathrm{U}},P_{i,t}^{\mathrm{D}},SoC_{i,t}} \sum_{t\in\Omega_{\mathrm{T}}}\sum_{i\in\Omega_{\mathrm{A}}}(c_t^{\mathrm{U}}P_{i,t}^{\mathrm{U}}+c_t^{\mathrm{D}}P_{i,t}^{\mathrm{D}})\Delta t$$

subject to: (1a)−(1h)

$$\mathbb{P}\left(\sum_{i\in\Omega_{\mathrm{A}}}(P_{i,t}^{\mathrm{D}}-P_{i,t}^{\mathrm{U}})\ge \mathrm{P}_t^{\mathrm{S,DIU}}\right)\ge 1-\epsilon \quad \forall t\in\Omega_{\mathrm{T}}$$

$$\mathbb{P}\left(a_i(x)^{\mathrm{T}}\xi(x)\le b_i(x),\quad i=1,2,\cdots,N\right)\ge 1-\epsilon \tag{4a}$$

$$\mathbb{P}\left(a_i(x)^{\mathrm{T}}\xi(x)\le b_i(x)\right)\ge 1-\epsilon_i,\quad i=1,2,\cdots,N \tag{4b}$$

$$\epsilon_i=\frac{1}{2}\left(1+erf\left(\beta_i erf^{-1}(2\epsilon-1)\right)\right),\quad \beta_i=\frac{\sqrt{\sum_{i=1}^N\sigma_i^2}}{\sum_{i=1}^N\sigma_i} \tag{4c}$$

RT-Reliability Commitment

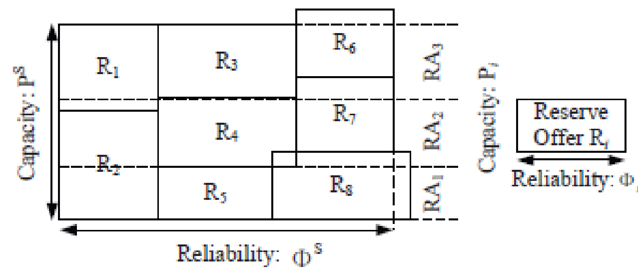


Fig. 2. Illustration of unit and reliability commitment.

$$\min_{P_i,P_{i,j},z_{i,j},\phi_i}\sum_{i\in\Omega_{\mathrm{A}}}\sum_{j\in\Omega_{\mathrm{R}}}\rho_j P_{i,j}$$

subject to:

$$\phi_i=1-\prod\nolimits_j(1-\Phi_j z_{i,j}) \quad \forall i\in\Omega_{\mathrm{A}}$$

$$P_i-P_{i,j}\le \mathrm{M}(1-z_{i,j}) \quad \forall i\in\Omega_{\mathrm{A}},\forall j\in\Omega_{\mathrm{R}}$$

$$\Phi^{\mathrm{S}}\le\prod\nolimits_i\phi_i$$

$$\mathrm{P}^{\mathrm{S}}\le\sum\nolimits_i P_i$$

$$\sum\nolimits_i P_{i,j}\le \mathrm{P}_j \quad \forall j\in\Omega_{\mathrm{R}}$$

$$z_{i,j}\in\{0,1\} \quad \forall i\in\Omega_{\mathrm{A}},\forall j\in\Omega_{\mathrm{R}}$$

$$P_{i,j}P_i\ge 0 \quad \forall i\in\Omega_{\mathrm{A}},\forall j\in\Omega_{\mathrm{R}}$$

$$P_i\ge\underline{\mathrm{P}}^{\mathrm{A}} \quad \forall i\in\Omega_{\mathrm{A}}$$

$$\phi_i\ge\underline{\Phi}^{\mathrm{A}} \quad \forall i\in\Omega_{\mathrm{A}}$$

✓ Reliability-Aware Probabilistic Reserve Procurement

- **Two-stage Probabilistic Reserve Procurement under DDU**

Relaxation of Product Function

IM1: Log Function
IM2: Taylor Approximation
IM3: Piecewise Linear
IM4: Equal Reliability Allocation

$$\ln(1-\phi_i)=\sum_j \ln(1-\Phi_j)z_{i,j}, \quad \ln(\Phi^S)\le\sum_i \ln(\phi_i)$$

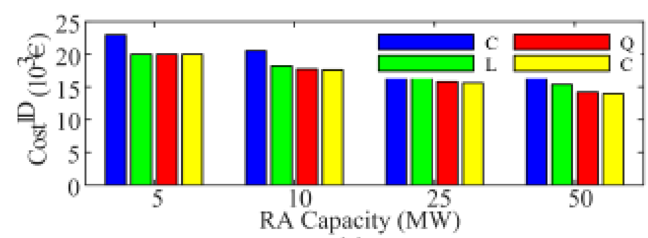
$$f(x)\approx f(x_0)+\nabla f(x_0)(x-x_0)+\nabla^2 f(x_0)(x-x_0)^2/2$$

$$f(x)=\sum_i w_i f(b_i), \quad x=\sum_i w_i b_i$$

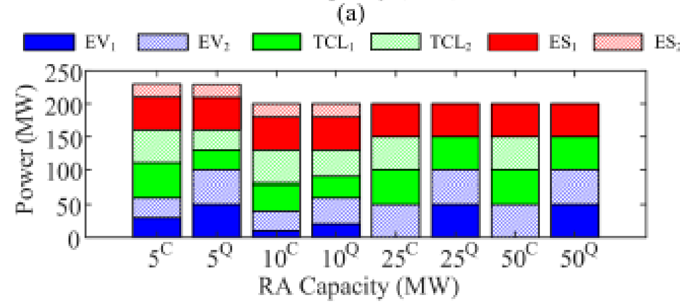
$$\phi_i=\Phi^{S^{1/L}}, \quad \ln(1-\Phi^{S^{1/L}})=\sum_j \ln(1-\Phi_j)z_{i,j}$$

TABLE II
REAL-TIME OPTIMIZATION RESULTS WITH DIFFERENT METHODS

Method	P^A (MW)	$Cost^{RT}$ (10^3 €)	Overall Reliability	Time (s)	P^A (MW)	$Cost^{RT}$ (10^3 €)	Overall Reliability	Time (s)
IM1	5	-	-	Infeasible	25	15.97	99.991%	58.03
IM2		17.16	99.987%	1200.00		16.28	99.993%	0.22
IM3		18.54	99.994%	0.28		15.85	99.990%	0.14
IM4		18.54	99.994%	0.20		15.85	99.990%	0.13
IM1	10	17.56	99.990%	979.05	50	15.66	99.994%	9.72
IM2		16.07	99.989%	0.96		16.28	99.996%	0.25
IM3		16.75	99.992%	0.33		15.66	99.994%	0.12
IM4		17.44	99.994%	0.17		15.66	99.994%	0.15



(a)



(b)

Contents

✓ Sequential Coordinated Dispatch of GES Incorporating DDU (GES Simulation)

① Normal Status: Day-ahead Energy Arbitrage

$$\max \sum_t c_t^{\mathrm{DA}}(P_{\mathrm{d},i,t}^{\mathrm{DA}} - P_{\mathrm{c},i,t}^{\mathrm{DA}})$$

$$s.t.\quad SoC_{i,t+1}^{\mathrm{DA}} = (1-\varepsilon_i)SoC_{i,t}^{\mathrm{DA}} + \frac{\eta_{\mathrm{c},i}\eta_{\mathrm{d},i}P_{\mathrm{c},i,t}^{\mathrm{DA}} - P_{\mathrm{d},i,t}^{\mathrm{DA}}}{\eta_{\mathrm{d},i}S_i}\Delta t$$

$$\underline{SoC}_{i,t} \le SoC_{i,t}^{\mathrm{DA}} \le \overline{SoC}_{i,t}$$

$$SoC_{i,T}^{\mathrm{DA}} = SoC_{i,0}^{\mathrm{DA}}$$

$$0 \le P_{\mathrm{c},i,t}^{\mathrm{DA}} \le \overline{P}_{\mathrm{c},i}$$

$$0 \le P_{\mathrm{d},i,t}^{\mathrm{DA}} \le \overline{P}_{\mathrm{d},i}$$

② Emergency Status: Real-time Adequacy Support

$$\min \sum_i P_{i,t}^{\mathrm{LC}}$$

$$s.t.\quad P_{ij,t} = (\theta_{i,t} - \theta_{j,t})/X_{ij}$$

$$-\overline{P}_{ij} \le P_{ij,t} \le \overline{P}_{ij}$$

$$0 \le P_{i,t}^{\mathrm{CG}} \le P_{i,t}^{\mathrm{CG,AV}}$$

$$(1-r_i)P_{i,t}^{\mathrm{RG,AV}} \le P_{i,t}^{\mathrm{RG}} \le P_{i,t}^{\mathrm{RG,AV}}$$

$$0 \le P_{i,t}^{\mathrm{LC}} \le P_{i,t}^{\mathrm{LD}}$$

$$0 \le P_{\mathrm{d},i,t}^{\mathrm{RT}} \le \overline{P}_{\mathrm{d},i}$$

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

DDU

$$\mathbb{P}(\underline{SoC}_{i,t}^{\mathrm{DDU}} \le SoC_{i,t}^{\mathrm{RT}}) \ge 1-\gamma$$

$$P_{i,t}^{\mathrm{CG/RG}} + P_{i,t}^{\mathrm{LC}} + P_{\mathrm{d},i,t}^{\mathrm{RT}} = \sum_{ij \in \Omega_{\mathrm{L}}^i} P_{ij,t} + P_{i,t}^{\mathrm{LD}}$$

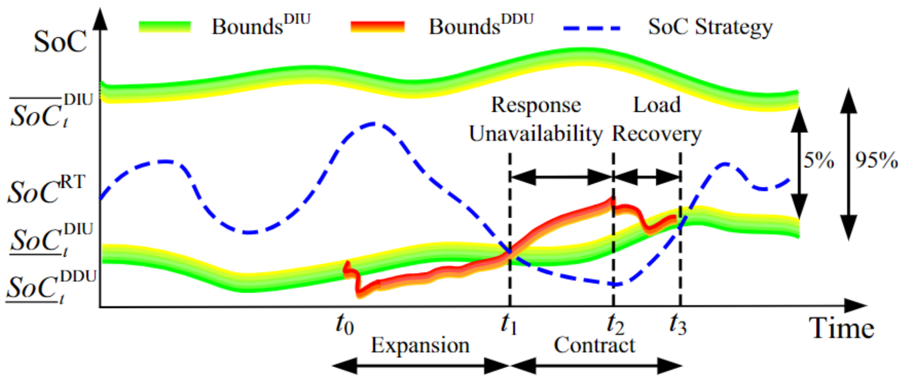
③ Recovery Status: Real-time Capacity Recovery

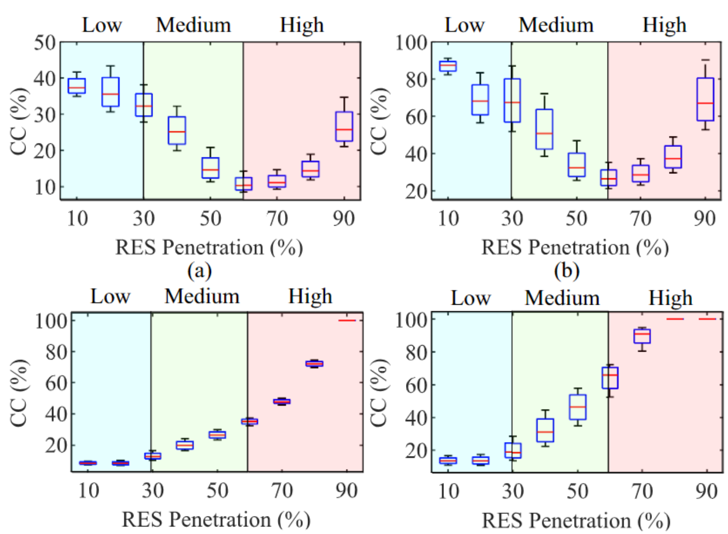
$$RC_t = \sum_i (P_{i,t}^{\mathrm{CG/RG,AV}} - P_{i,t}^{\mathrm{LD}}) \tag{6a}$$

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

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

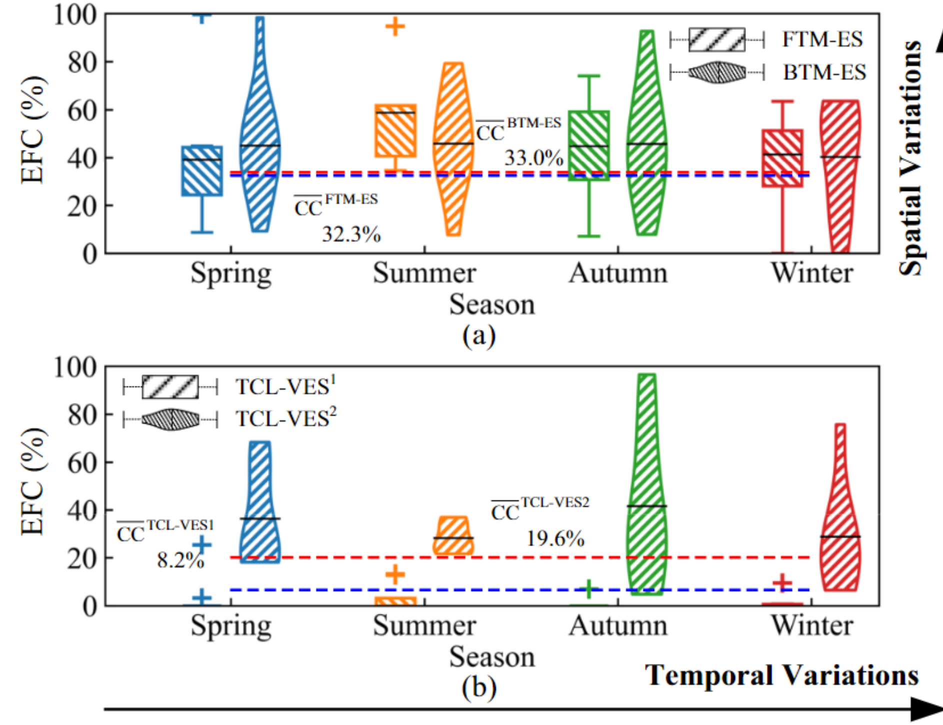
✓ DDU Consequence Calculation (Response Unavailability & Load Recovery)





Decarbonization Effort

Fig. 7. CC of ES and VES with different RES penetration: (a) 4-h FTM-ES, (b) 12-h FTM-ES, (c) 4-h TCL-VES[1] and (d) 12-h TCL-VES[1]



Spatial-Temporal Variations

Future Works

✓ Extension and Enhancement

- **Learning DDU of GES VS Utility Function (Real Data)**
- **Design Effective Pricing and Penalty Market Mechanism for GES (DR/Reserve/CM)**
- **Extend GES to hydrogen, PHS, CAES**

✓ Other Works

- **Problem-Driven Scenario Reduction Framework--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.***

- **Online Optimization Method—Real-Time Control Policy**

Kaidi Huang, L. Cheng, N. Qi* et al, "Prediction-Free Coordinated Dispatch of Microgrid: A Data-Driven Online Optimization Approach," ***IEEE Transactions on Smart Grid, 2024.***

N. Qi, Kaidi Huang, Zhiyuan Fan et al, "Long-Term Resilient Operation of Microgrid with Hybrid Hydrogen-Battery Energy Storage: A Data-Driven Online Optimization Approach," ***Applied energy, 2024.***

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Unlocking Reliable Flexibility from Generalized Energy Storage Resources

Thank You!

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