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

Ning Qi

Columbia University, New York, NY
Email: nq2176@columbia.edu

Sep. 19th, 2024, Caltech

Biography

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

Name: Ning Qi **Title: Postdoctoral Research Scientist**
Affiliation: Earth & Environmental Engineering, Columbia University
Contact: nq2176@columbia.edu **Homepage: https://thuqining.github.io**
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

Technical University of Denmark, 2022

IMPERIAL
Imperial College London Prof. Pierre Pinson

University of Vermont Prof. Mads R. Almassalkhi

Research Associate, Tsinghua University, 2023 Prof. Feng Liu

Columbia University 2024 Prof. Bolun Xu

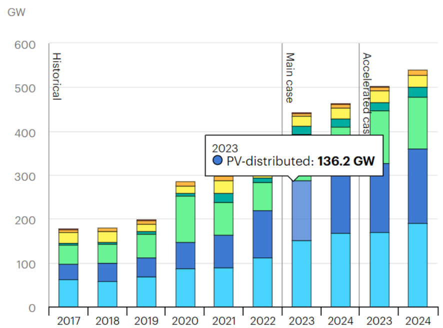
1. **N. Qi**, P. Pinson, M. R. Almassalkhi, et al, "Capacity Credit Evaluation of Generalized Energy Storage under Endogenous Uncertainty," *IEEE Transactions on Power Systems*, 2024.
2. **N. Qi**, L. Cheng, Kaidi Huang et al, "Reliability-Aware Probabilistic Reserve Procurement under Decision-Dependent 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.

Contents

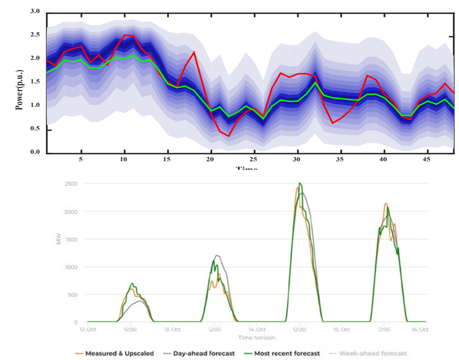
1、 Background and Motivation

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





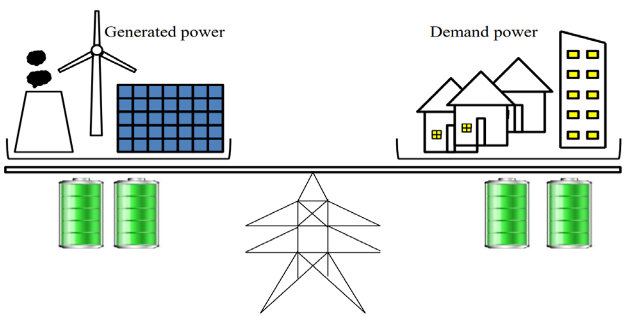
Rapidly Growing Renewables

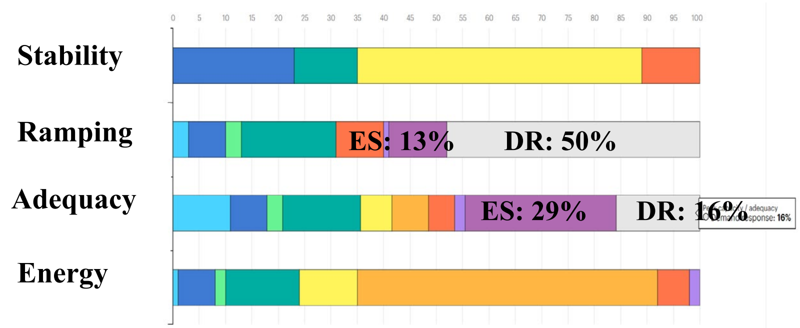


Increased Uncertainty and Flexibility requirements

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

Generation-Demand Power Balance

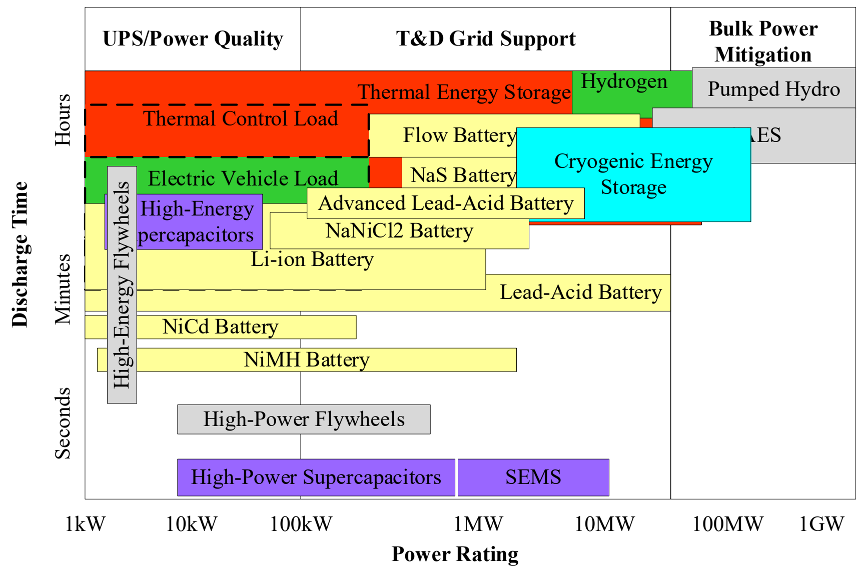




ES & DR Contribute Significantly

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-StorageHydro → 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

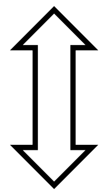
TCL

EV

Contents

- **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.



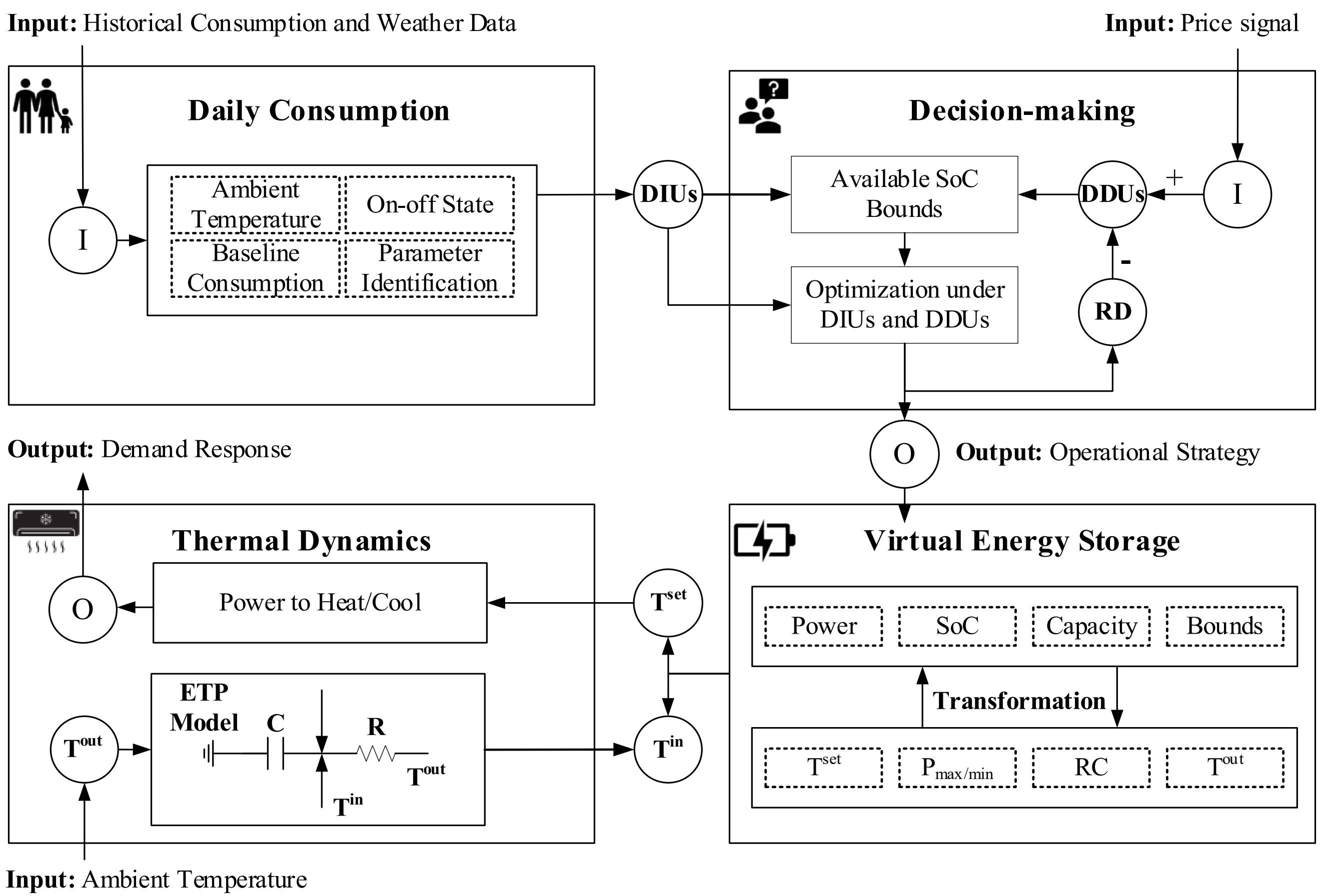
- **Propose a Unified GES Model with Various Decision-Independent Uncertainties (DIUs) and Decision-Dependent Uncertainties (DDUs)—Flexibility Modeling**

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)



- **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**

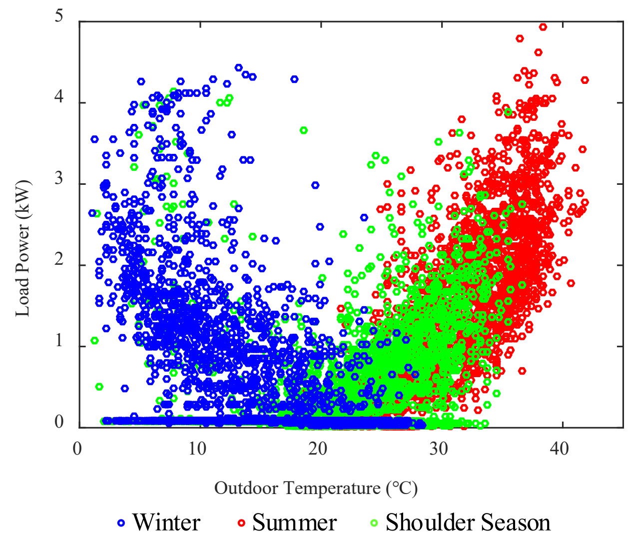
Step1 Data Acquisition
Smart meter data, temperature data

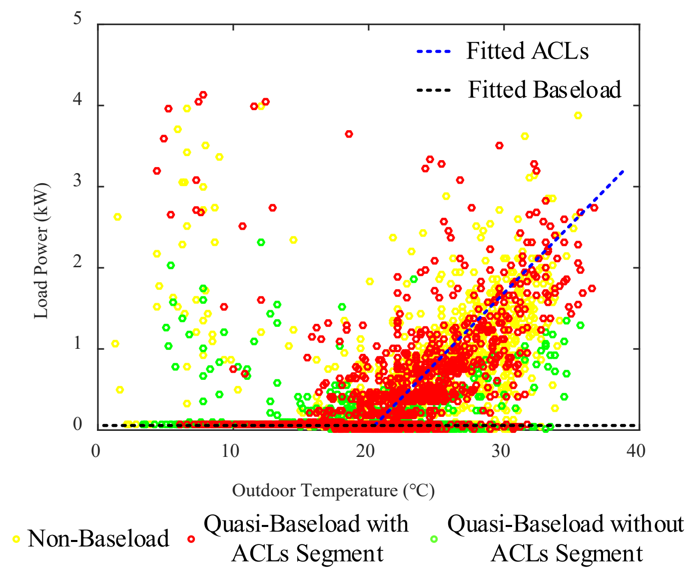
Step2 Data Cleaning
Missing readings, without TCL

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

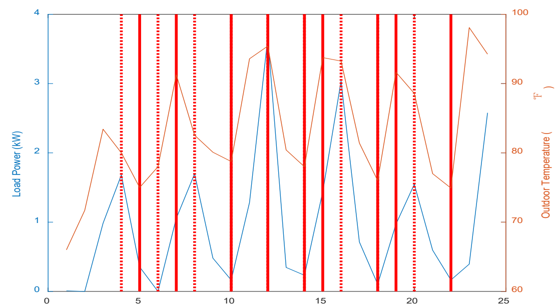
✓ **Behavior Analysis+ Load Disaggregation + Parameter identification**

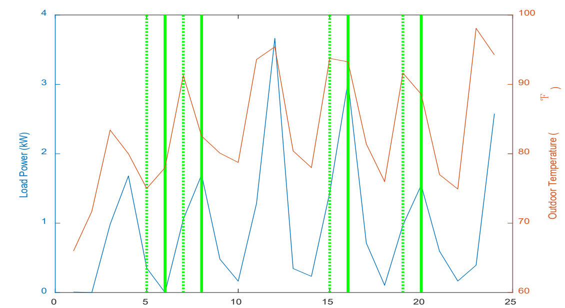
● ETP Model + Simulation + Recursively Estimation

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

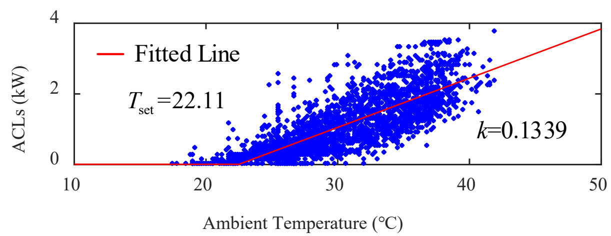
constrained regression

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

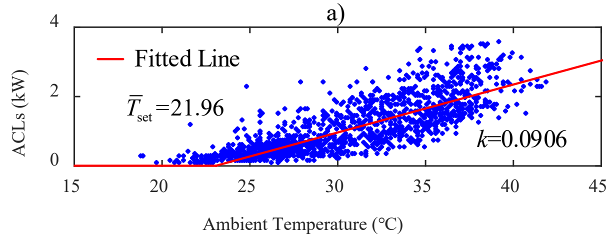
$$\text{s.t.} \qquad K_{\min} \le k \le K_{\max}$$

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

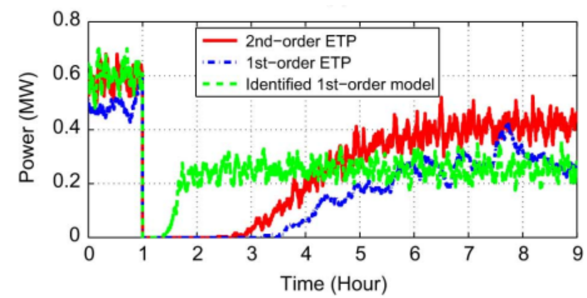
$$k = 1/\eta_{\mathrm{eq}} R_{\mathrm{eq}} \qquad -\boldsymbol{b}/k = \boldsymbol{T}_{\mathrm{set}} = \{T_{\mathrm{set},t}\}$$

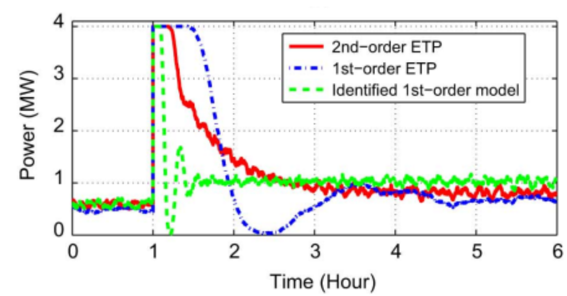


a)



b)





Step3 Dynamic Parameter Estimation

Simulation+PSO Recursively

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

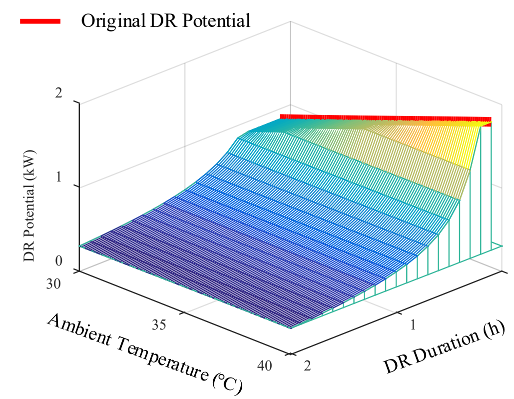
$$\left(\frac{C_{eq}}{\eta_{eq}}\right)_{\max} = \left(\frac{\sum_i C_i}{\eta_{eq}}\right)_{\max} = \left(\frac{\sum_i c\rho h_i S_i}{\eta_{eq}}\right)_{\max} = c_{\mathrm{air}}\rho_{\mathrm{air}} P_{max} \frac{h}{Q}$$

✓ Operational Flexibility—State-Dependent

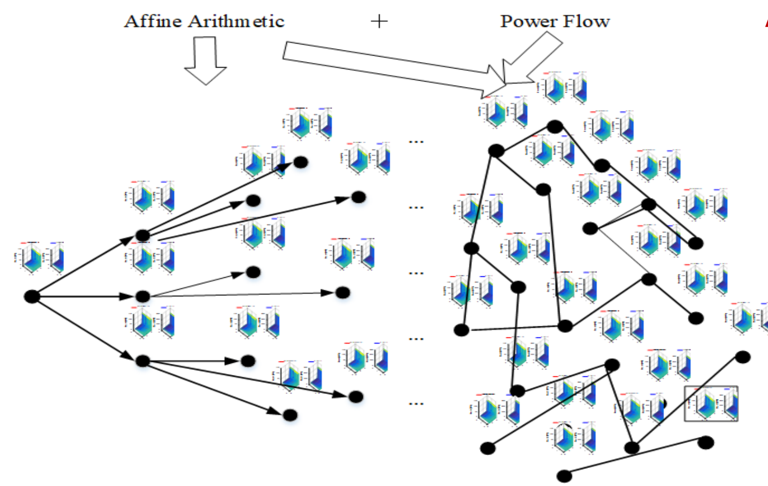
Multiple Factors: ambient temperature、setpoint temperature、equivalent thermal parameter、comfort

Multiple Uncertainties: seasonal variation、temperature correlation、social behavior

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

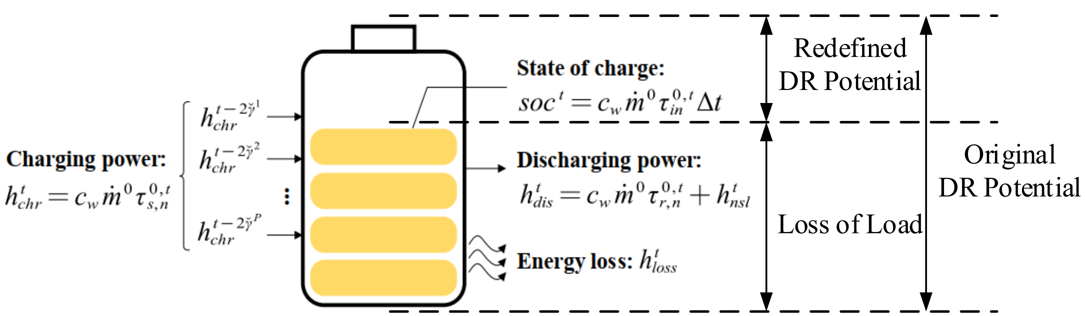


Individual Flexibility



Affine Power Flow

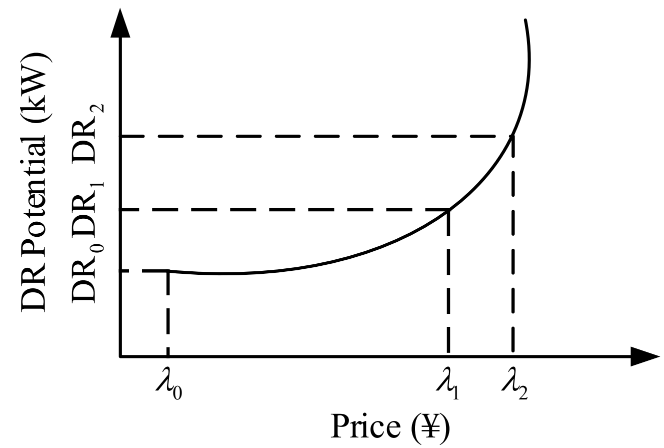
Grid-aware Flexibility



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

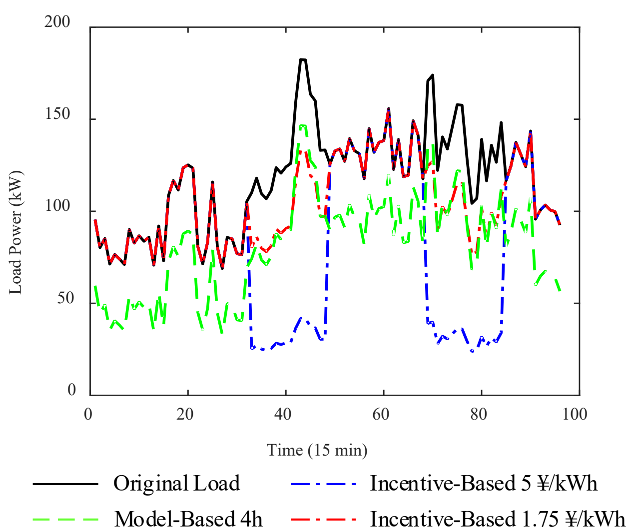
Economic Flexibility: price elasticity model

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

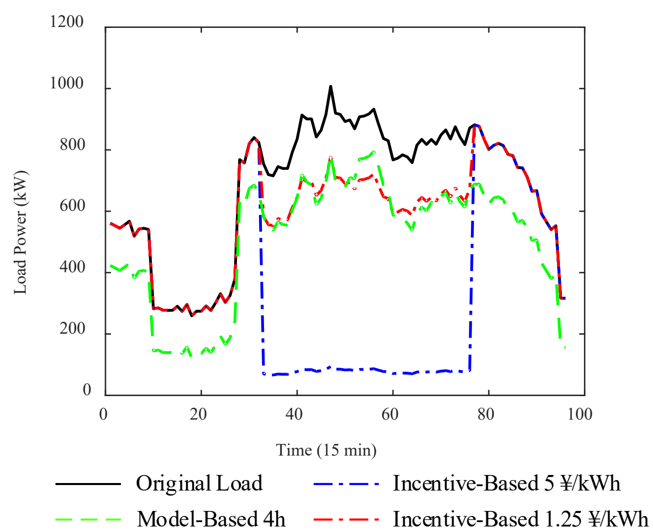


Physical Flexibility: data-driven model

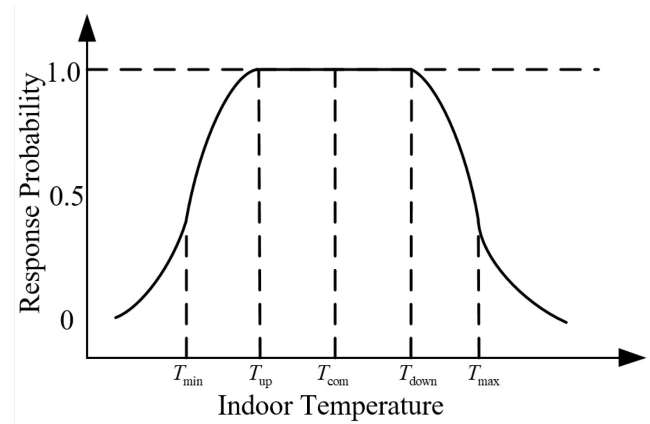
$$\mathrm{DP}_t^2=\boldsymbol{f}(T_{\mathrm{out},t},t_{\mathrm{duration}},T_{\mathrm{in},t},\Delta T,\boldsymbol{\theta}_{eq})$$



a)



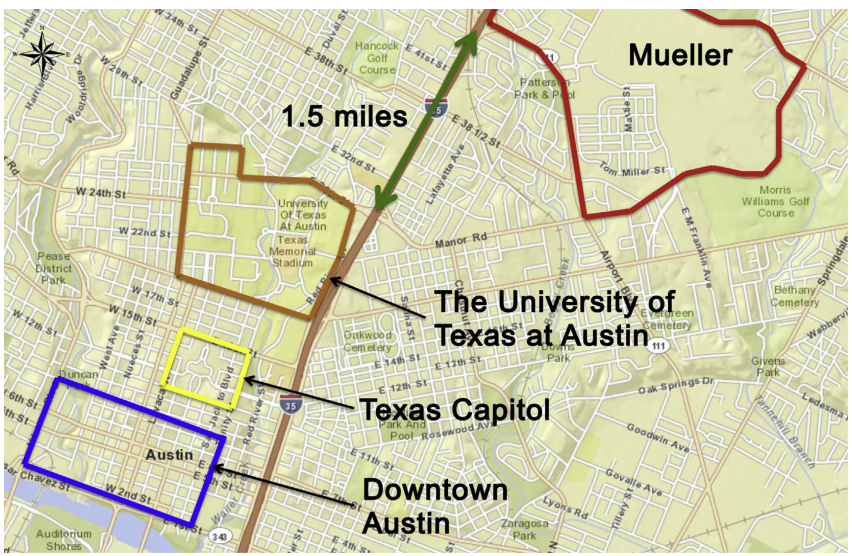
b)



✓ Case Study (Ground-Truth Data)

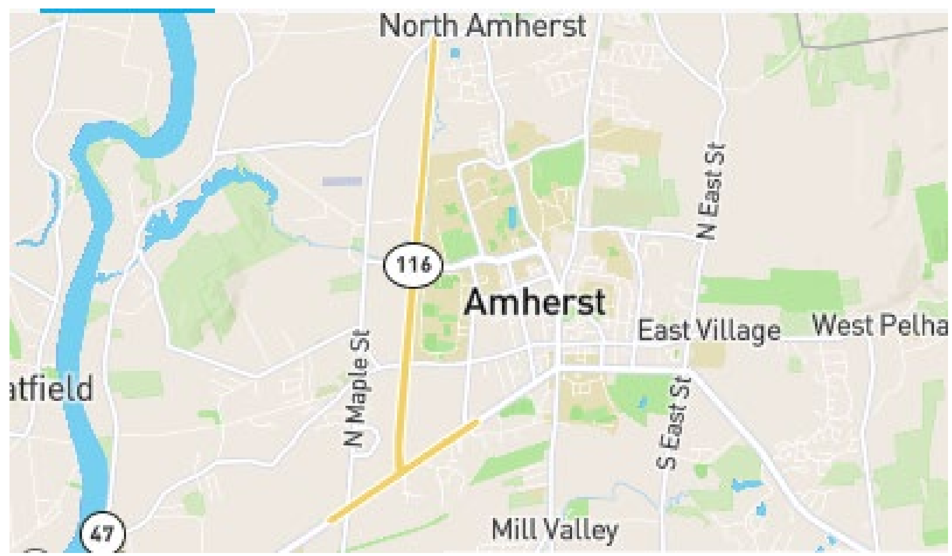
Austin Mueller Project

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

✓ Case Study (Ground-Truth Data)

● High Accuracy, High Robustness Highly-Transferable

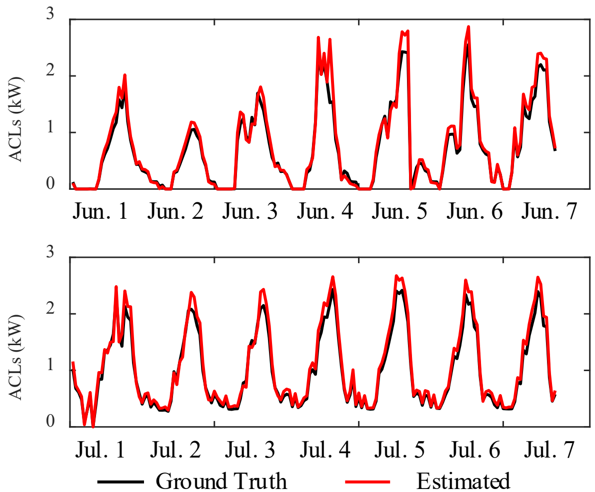


Fig Comparison of the ground truth and estimated data of customer #77

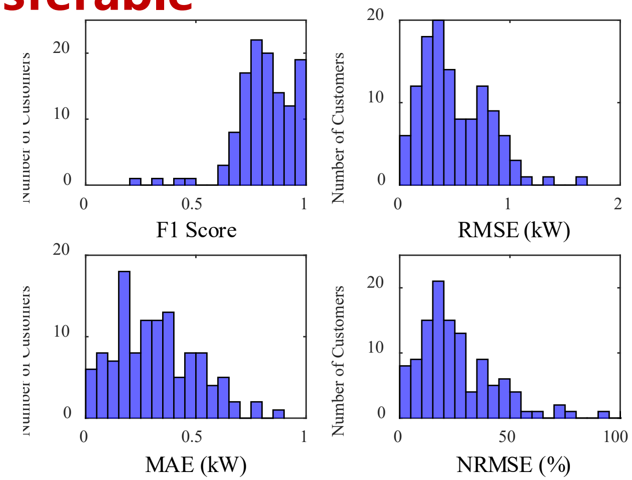
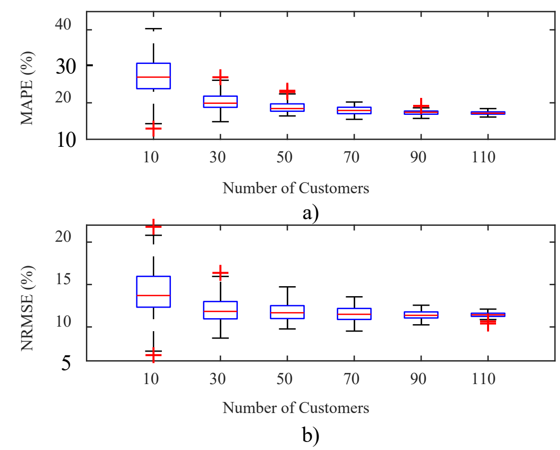


Fig Histogram of the important evaluation index across the 119 customers

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

2、Physics-Informed Data-driven Modeling of GES

✓ Case Study (Ground-Truth Data)

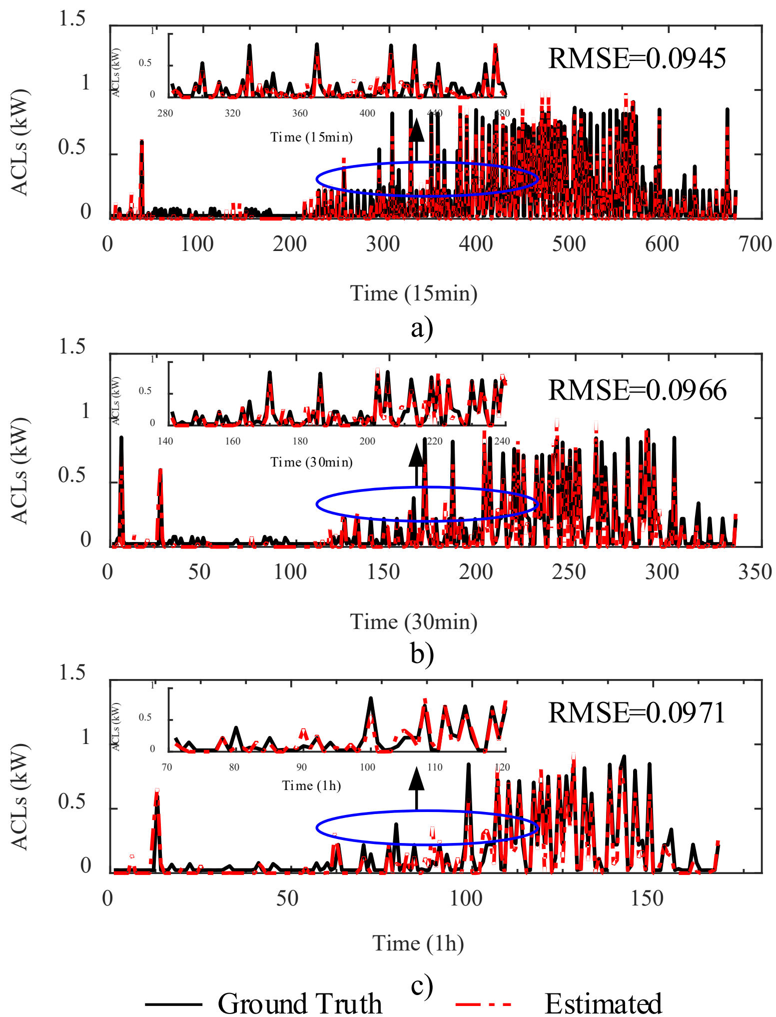


Fig load disaggregation test over different time-scales

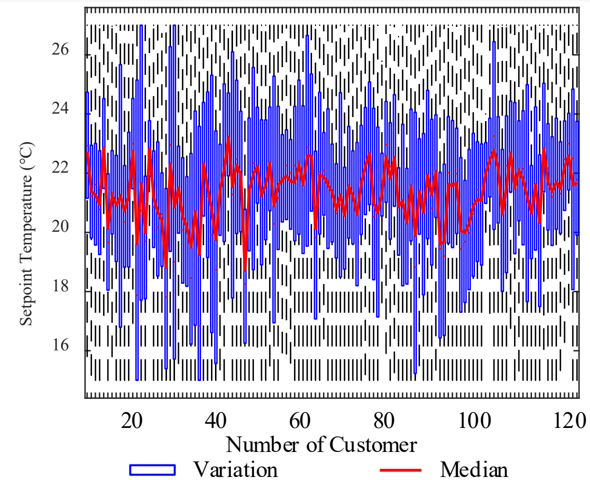


Fig setpoint temperature estimation

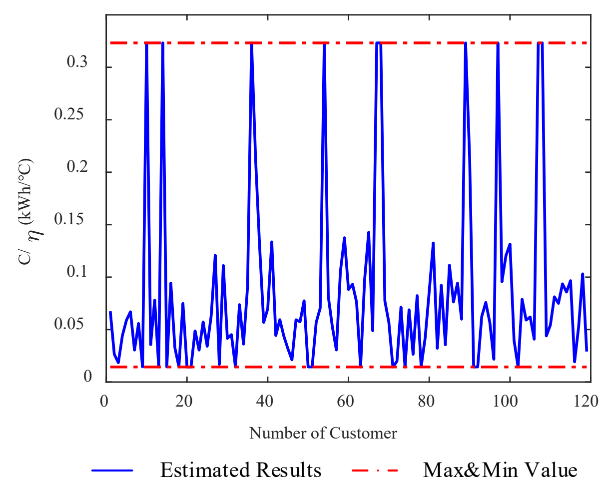
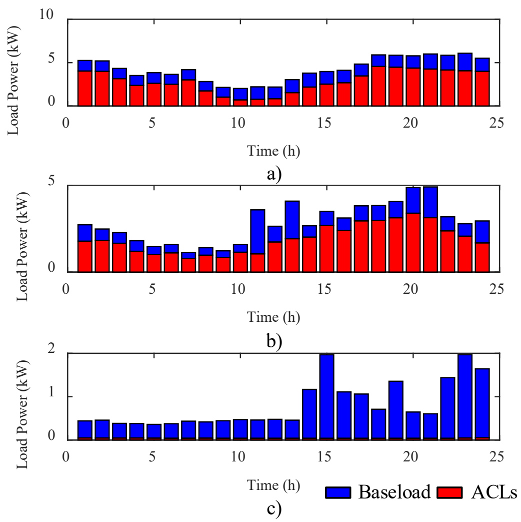


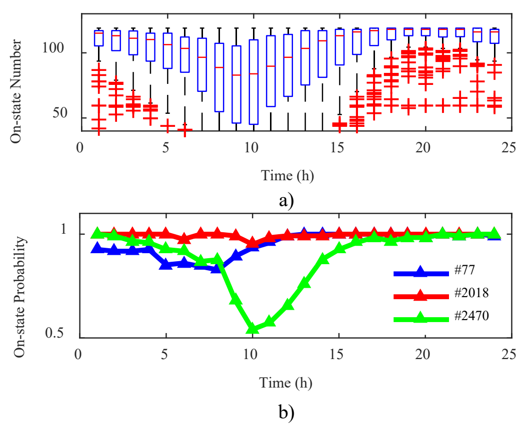
Fig thermal capacity estimation

2、Physics-Informed Data-driven Modeling of GES

✓ Case Study (Ground-Truth Data)

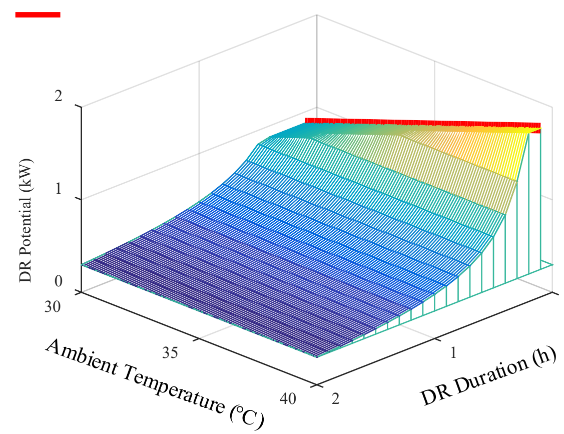
➢ Usage Pattern



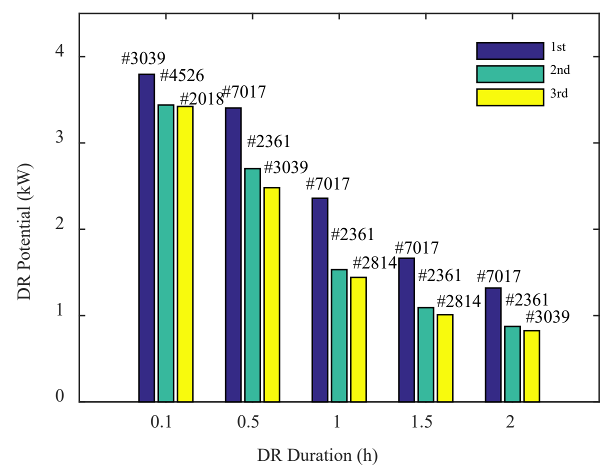


On-state

➢ Distribution of Flexibility

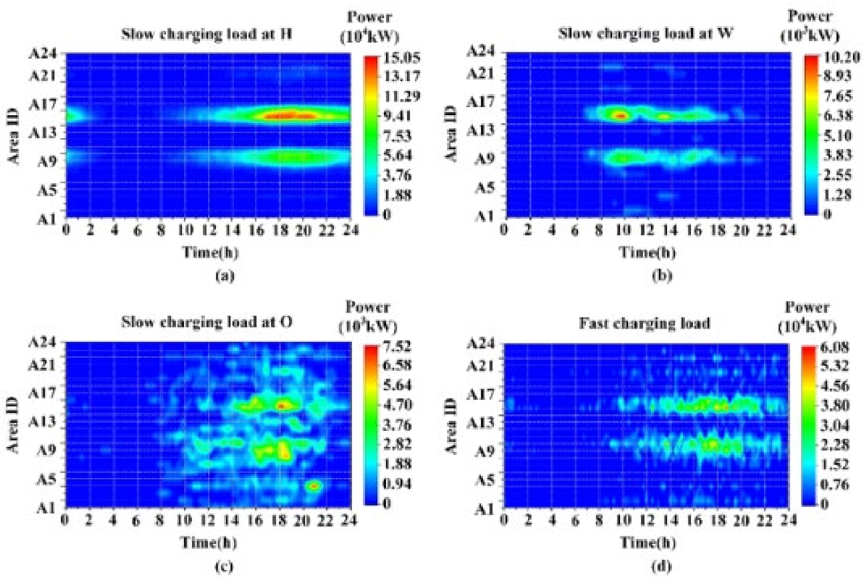


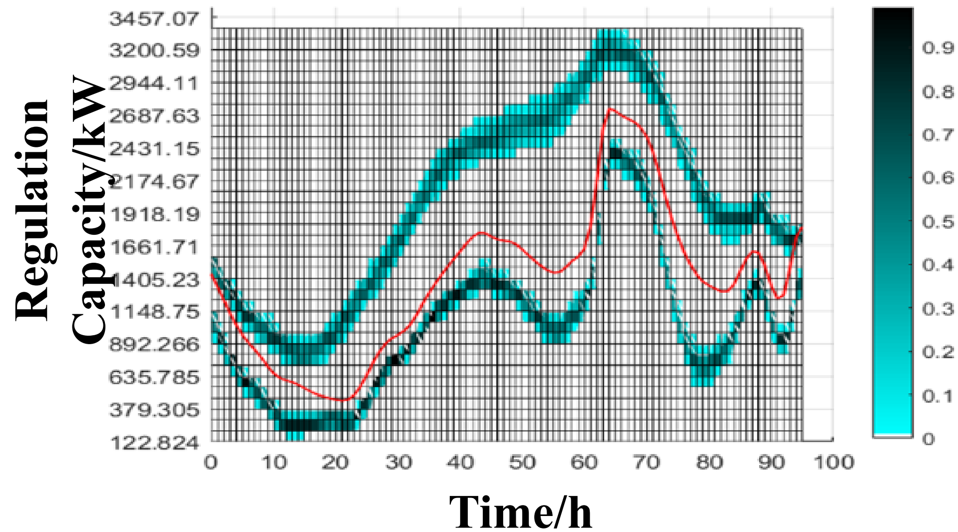
➢ DR Customer Targeting

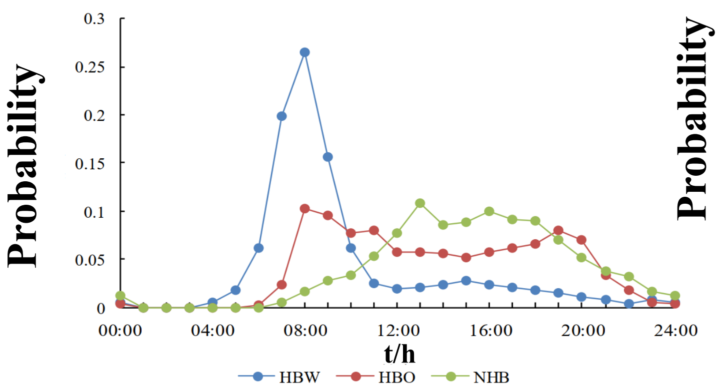


2、Physics-Informed Data-driven Modeling of GES

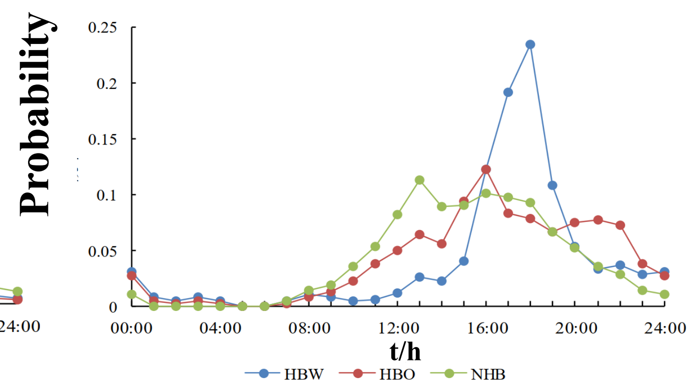
✓ Flexibility from EV—More Complex and Stochastic than TCL







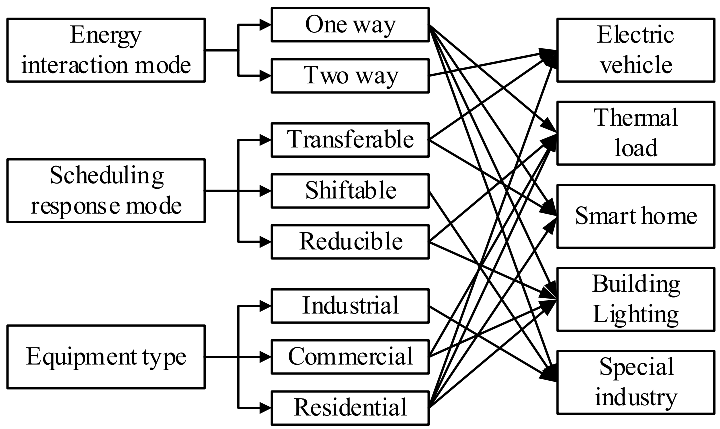
Plug-in time



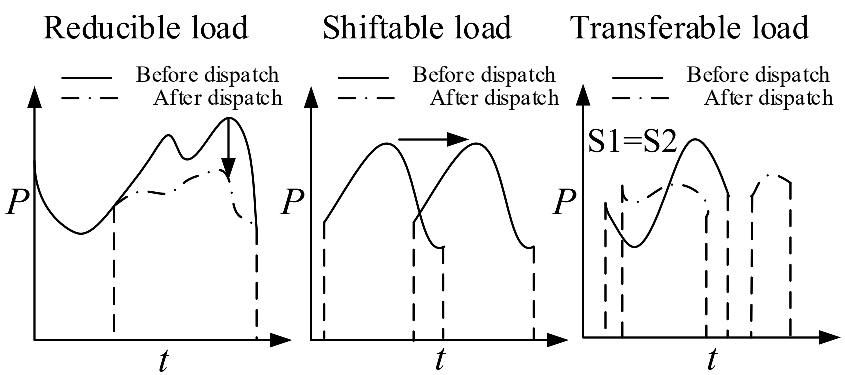
Plug-out times

✓ Unified Modeling of GES Resources

Classification of Flexible Load



Classification



Scheduling Aspect

Modeling of Flexible Load

$$
\begin{cases}
\boldsymbol{P}_i^{\text{shift}} = \boldsymbol{X}_i \cdot \boldsymbol{P}_{i,t}^{\text{shift}} \\
\boldsymbol{P}_i^{\text{shift}} = \left[p_{i,t}^{\text{shift}} \right]_{1\times \mathrm{T}} \\
\boldsymbol{X}_i = \left[x_{i,t} \right]_{1\times \mathrm{T}} \\
\boldsymbol{P}_{i,t}^{\text{shift}} = \begin{bmatrix} P_{i,s(1)}^{\text{shift}} & \dots & P_{i,s(n)}^{\text{shift}} & \dots & 0 \\ 0 & P_{i,s(1)}^{\text{shift}} & \dots & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & 0 \\ 0 & \dots & P_{i,s(1)}^{\text{shift}} & \dots & P_{i,s(n)}^{\text{shift}} \end{bmatrix} \\
\sum_{t\in S_i} x_{i,t} = 1 \\
\sum_{t\notin S_i} x_{i,t} = 0 \\
\boldsymbol{S}_i = [t_{i,\text{start}}^{\text{shift}}, t_{i,\text{end}}^{\text{shift}}] \cup \{t_i^*\}
\end{cases}
$$

Shiftable Load

$$
\begin{cases}
\boldsymbol{P}_i^{\text{re}} = \left[p_{i,t}^{\text{re}} \right]_{1\times \mathrm{T}} \\
\boldsymbol{P}_i^{\text{re}^*} = \left[p_{i,t}^{\text{re}^*} \right]_{1\times \mathrm{T}} \\
\boldsymbol{Z}_i = [z_{i,t}]_{1\times \mathrm{T}} \\
p_{i,t}^{\text{re}} = p_{i,t}^{\text{re}^*} - r_{i,t}^{\text{re}} + q_{i,t}^{\text{re}} \\
z_{i,t}\alpha_{i,\min} p_{i,t}^{\text{re}^*} \le r_{i,t}^{\text{re}} \le z_{i,t}\alpha_{i,\max} p_{i,t}^{\text{re}^*} \\
\text{Ramp}_{i,\text{down}}^{\text{re}}\Delta t \le r_{i,t}^{\text{re}} - r_{i,t-1}^{\text{re}} \le \text{Ramp}_{i,\text{up}}^{\text{re}}\Delta t \\
\sum_{\tau=t}^{t+T_{i,\min}^{\text{re}}-1} z_{i,\tau} \ge T_{i,\min}^{\text{re}}(z_{i,t} - z_{i,t-1}), t \in F_i^1 \\
F_i^1 = \{1,2,\dots,T - T_{i,\min}^{\text{re}} + 1\}, z_{i,0} = 0 \\
\sum_{\tau=t}^{t+T_{i,\max}^{\text{re}}-1} (1 - z_{i,\tau}) \ge T_{i,\max}^{\text{re}}, t \in F_i^2 \\
F_i^1 = \{1,2,\dots,T - T_{i,\max}^{\text{re}}\} \\
\sum_{\tau=t}^{t+T_{i,\min}^{\text{idle}}} (1 - z_{i,\tau}) \ge T_{i,\min}^{\text{idle}}(z_{i,t-1} - z_{i,t})
\end{cases}
$$

Reducible Load

Constraints：

- ➢ Power Limit
- ➢ Time Period Limit
- ➢ Power Balance
- ➢ Continuity
- ➢ …

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

Transferable Load

$$
\begin{cases}
\boldsymbol{P}_i^{\text{ess}} = \left[p_{i,t}^{\text{ess}} \right]_{1\times T} \\
p_{i,\min}^{\text{ess}} \le p_{i,t}^{\text{ess}} \le p_{i,\max}^{\text{ess}} \\
E_{i,t}^{\text{ess}} - E_{i,t-1}^{\text{ess}} = -\dfrac{p_{i,t}^{\text{ess}}}{\eta_i^{\text{ess}}}\Delta t \\
SOC_{i,\min} \le \dfrac{E_{i,t}^{\text{ess}}}{E_i^{\text{ess}}} \le SOC_{i,\max} \\
\sum_{t=1}^{T} p_{i,t}^{\text{ess}}\Delta t = 0
\end{cases}
$$

Energy Storage

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

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

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

Time-varying

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

Baseline Consumption

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

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

SoC Ramping

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

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

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

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

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

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

Decision-dependent uncertainty (DDU)

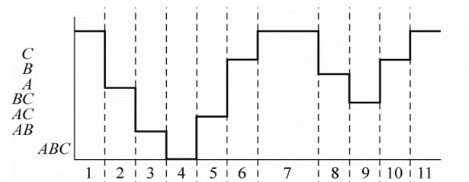
1. Mapping GES Model to Physical Resources

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

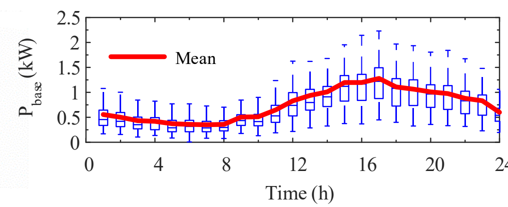
2. Decision-independent Uncertainty→Data

$$f(\omega^{\mathrm{VES}}_t) = \begin{cases} p^{\mathrm{VES}}_t & \omega_t = 1 \\ 1 - p^{\mathrm{VES}}_t & \omega_t = 0 \end{cases} \qquad P^{\mathrm{B}}_{i,t} \sim \mathcal{LN}\left(\mu_{P^{\mathrm{B}}_{i,t}}, \sigma_{P^{\mathrm{B}}_{i,t}}\right), \quad \forall t \in \mathbf{\Omega}_T, \forall i \in \mathbf{\Omega}_S$$

Operation States

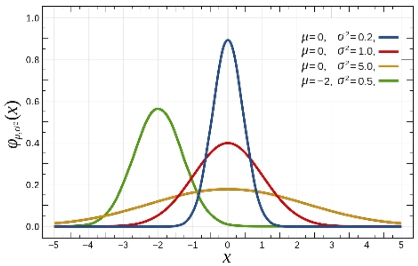


Baseline Consumption

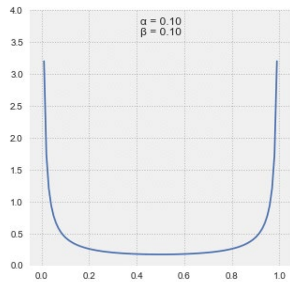


✓ Unified Modeling of GES Resources—DIUs and DDUs

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



DIU (Static)



DDU (Dynamic)

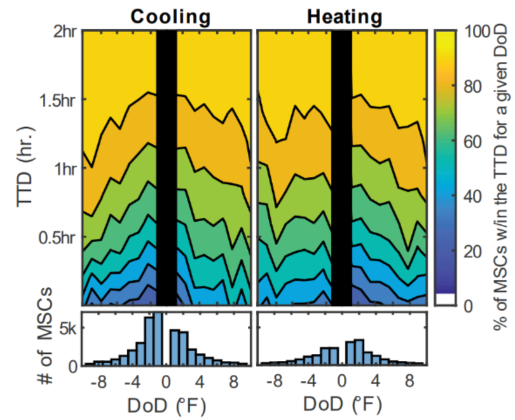


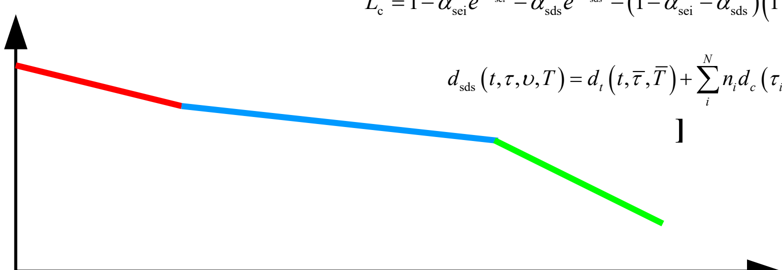
Fig. 9: Degree of discomfort vs Time to discomfort; during occupied periods (Single-occupant households; 30 min. filter)

Occupant Discomfort

Manual Overrides

$$L_c = 1 - \alpha_{sei} e^{-d_{sei}} - \alpha_{sds} e^{-d_{sds}} - (1 - \alpha_{sei} - \alpha_{sds})(1 - \kappa e^{d_{cps}})$$

$$d_{sds}(t, \tau, \upsilon, T) = d_t(t, \bar{\tau}, \bar{T}) + \sum_{i}^{N} n_i d_c(\tau_i, \upsilon_i, T_i)$$



Capacity Degradation

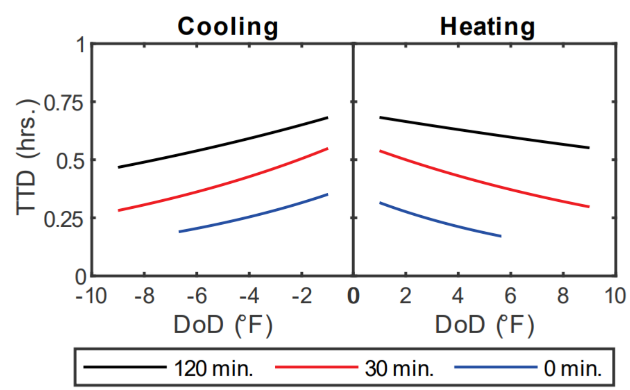
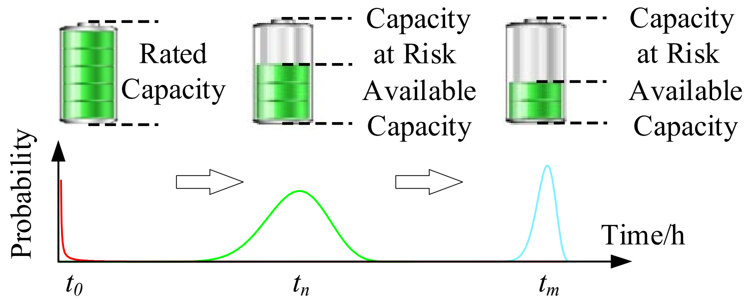


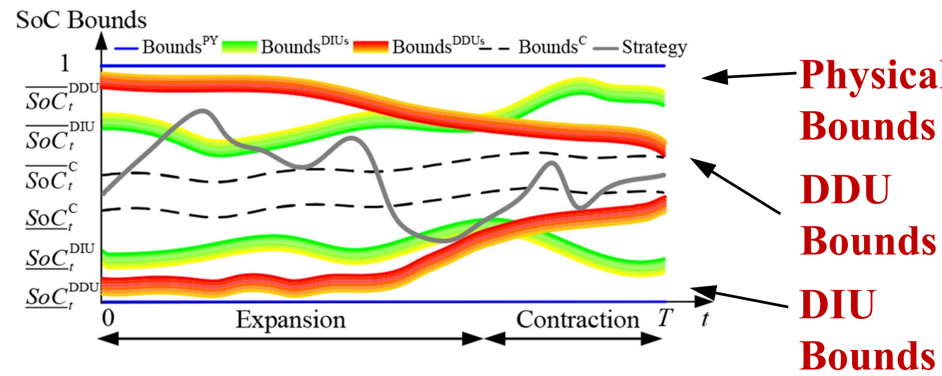
Fig. 10: Effect occupancy filter on the relationship between degree of discomfort and time to discomfort

✓ Unified Modeling of GES Resources—DIUs and DDUs

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

Willingness & Capability to Response





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

DIU VS DDU

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

Discomfort Function

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

Incentive Effect Distribution

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

Discomfort Effect Distribution

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

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.

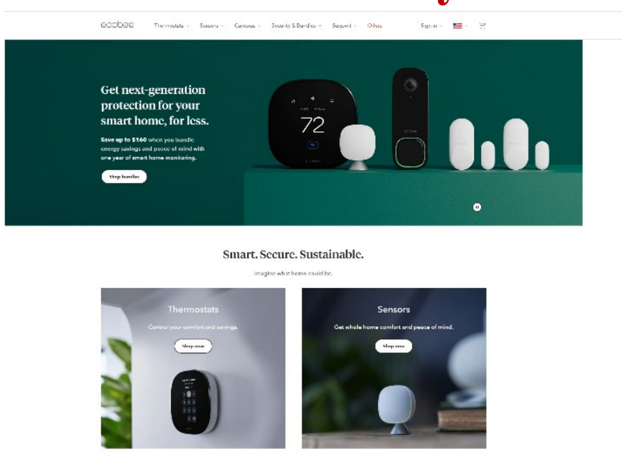
✓ **Learning DDU Remains a Challenging Issue!**

1. Price/Incentive-Synthetic Data

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

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.

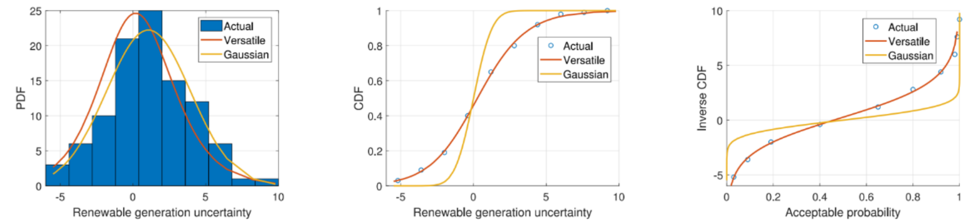
3. Distribution

Versatile Mixture Distribution

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



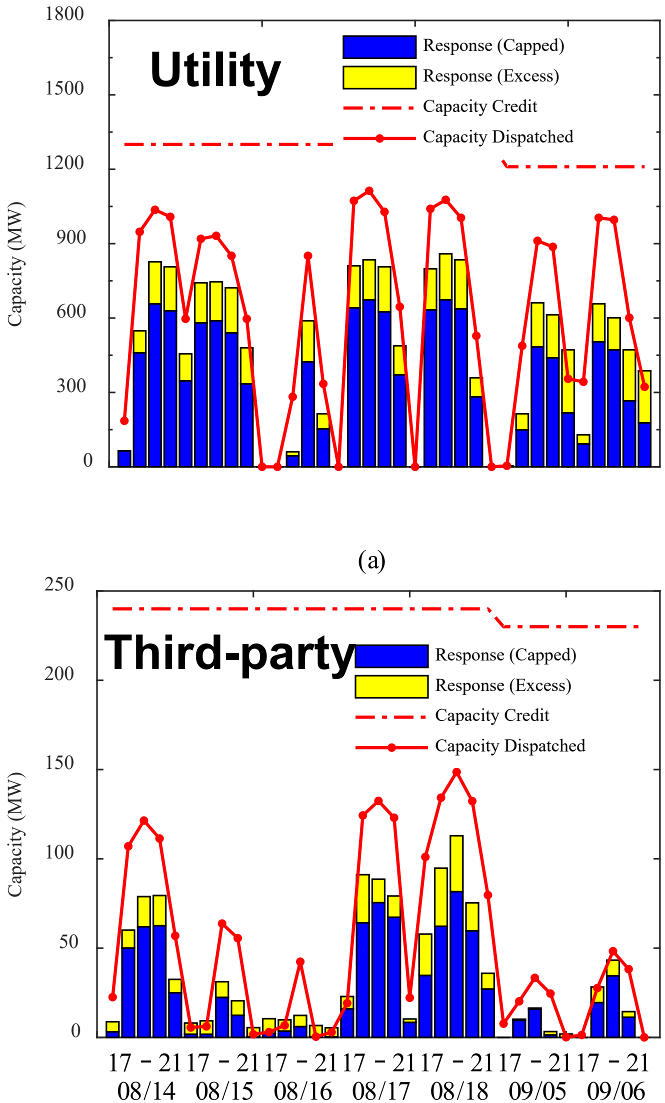
(a) (b) (c)

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

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



(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)**

2、Chance-Constrained GES Operations under DDU

- **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

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

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

ξ **Stochastic Parameters**

x **Decisions**

Reformulation under DDU

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

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

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

✓ Solution Methodology (I-Distributionally Robust Approximation)

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

1. Without Distribution Assumption (NA)

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

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

2. Symmetric Distribution (S)

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

$$F^{-1}(1-\gamma) = \sqrt{1/2\gamma}$$

3. Unimodal Distribution (U)

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

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

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

4. Symmetric & Unimodal Distribution (SU)

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

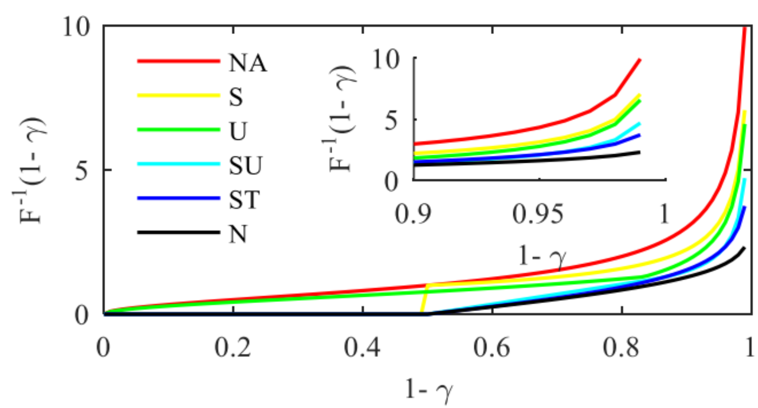
$$= \begin{cases} 1 - 2/9k^2 & k \geq 2/\sqrt{3} \\ 1/2 + k/2\sqrt{3} & 0 \leq k \leq 2/\sqrt{3} \end{cases}$$

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

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

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

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



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

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

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

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

$$\Downarrow$$

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

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

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

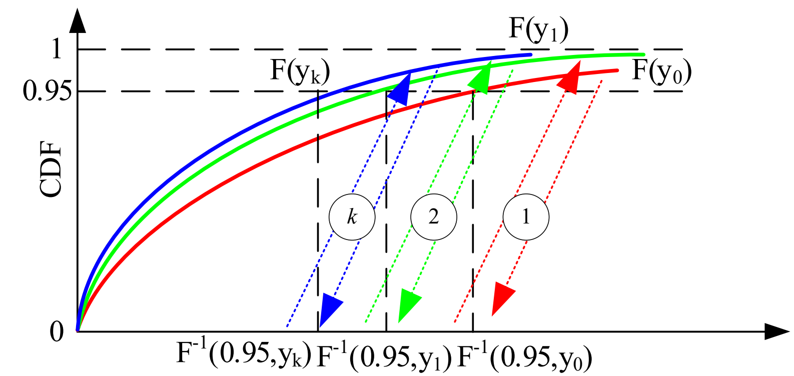
✓ Solution Methodology (III-Iterative Approach)

● Iteratively Update DDU and Solutions

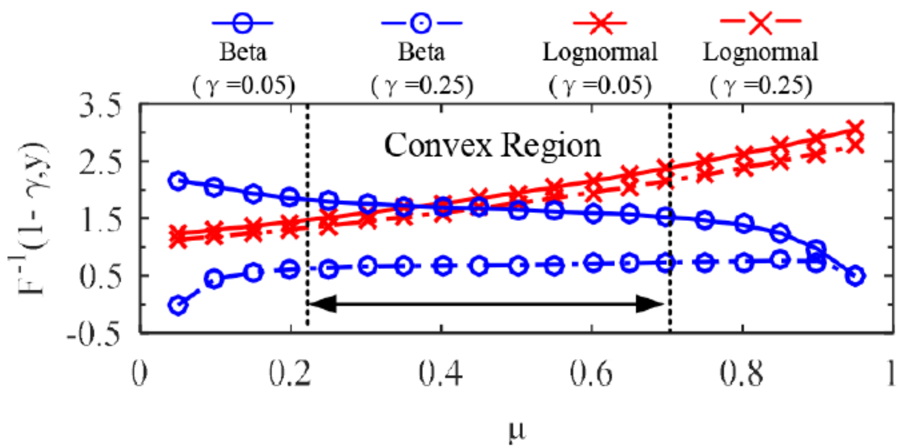
Algorithm 1 Iterative algorithm for CCO-DDUs

Input: Probability level γ, convergence criterion δ, deterministic and reformulated random parameters under DIUs.
Output: Decision variables 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 eps $=\left|F^{-1}(1-\gamma, y_1) - F^{-1}(1-\gamma, y_0)\right|$.
Step2: Iteration
While 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 eps $=\left|F^{-1}(1-\gamma, y_{k+1}) - F^{-1}(1-\gamma, y_k)\right|$.
  $k \leftarrow k+1$
end
Step3: Return $y = y_k$, $G(y, z) = G(y_k, z)$

Starting Point of Robust Approximation



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



2、Chance-Constrained GES Operations under DDU

✓ Economic Dispatch in Microgrid with GES (Case 1)

Objective function

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

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

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

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:

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

c) GES other constraints:

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

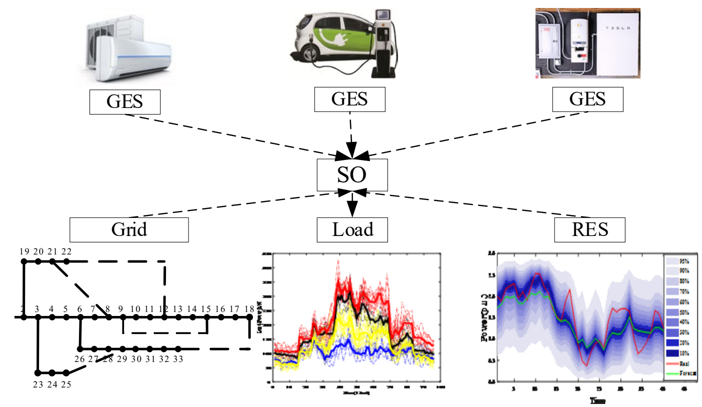
$$-SoC_{i,\mathrm{RD}} \le SoC_{i,t+1} - SoC_{i,t} \le SoC_{i,\mathrm{RU}}$$

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

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

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

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



d) DDU constraints:

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

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

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

e) other constraints:

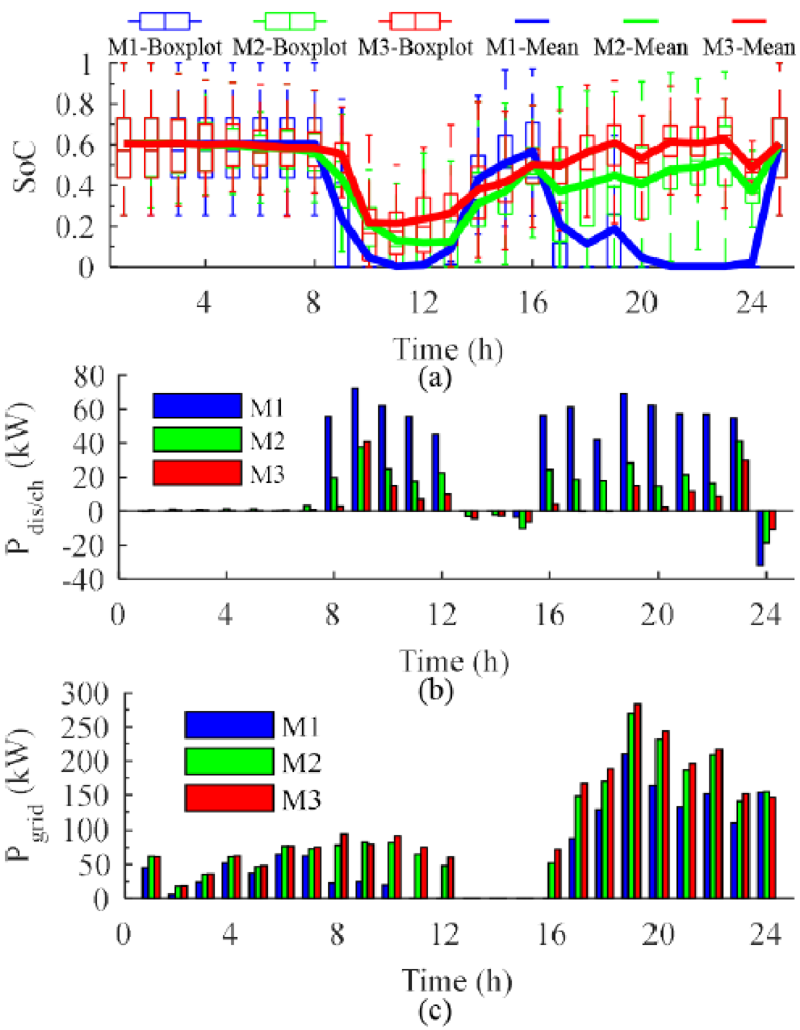
$$0 \le P_t^{\mathrm{G}} \le \overline{P}^{\mathrm{G}}.$$

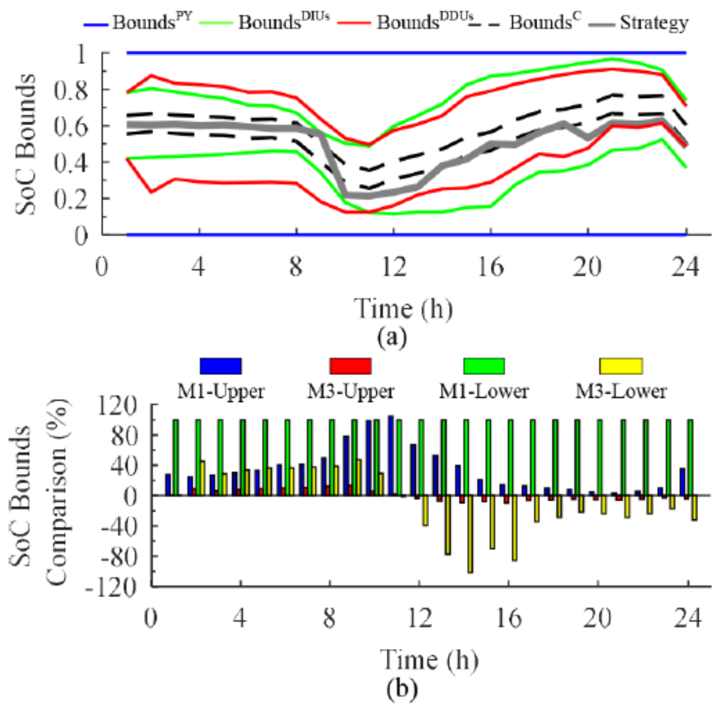
✓ Economic Dispatch in Microgrid with GES (Case 1)

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

TABLE III
OPTIMIZATION RESULTS WITH DIFFERENT MODELS AND UNCERTAINTIES

Metric	M1	M2	M3
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

✓ Economic Dispatch in Microgrid with GES (Case 1)

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

Best Performance in Real-time Availability

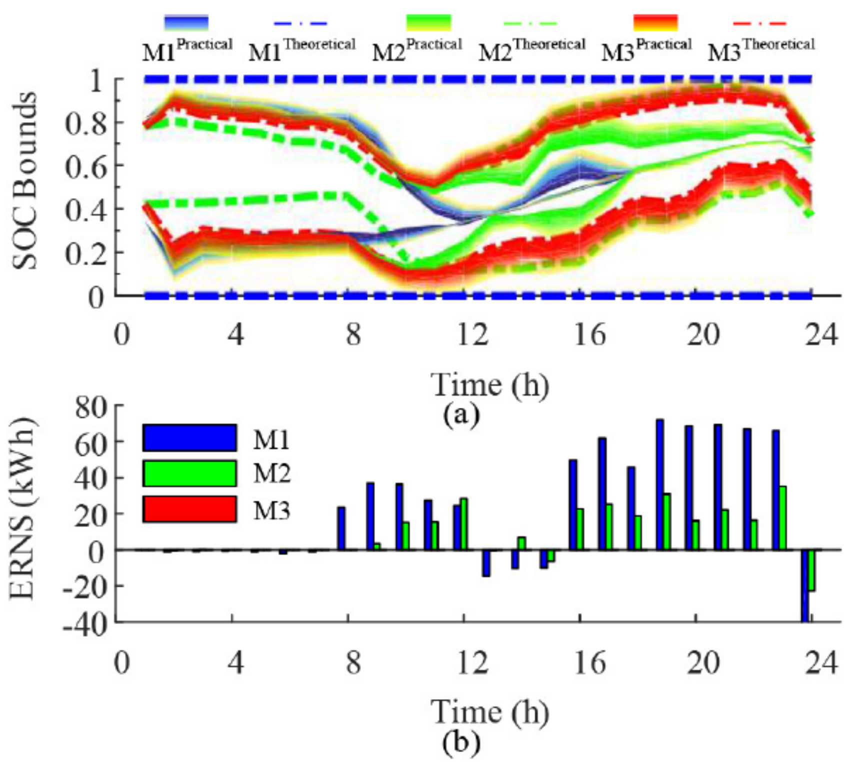


Fig. 6. Reliability performance comparison with respect to (a) practical and theoretical SoC bounds (95%) and (b) ERNS.

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

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)	$\overline{\text{EP}}$ (%)	$\underline{\text{EP}}$ (%)	$\overline{\text{CT}}$ (%)	$\underline{\text{CT}}$ (%)
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-Duration

2、Chance-Constrained GES Operations under DDU

✓ Economic Dispatch in Microgrid with GES (Case 1)

- **Convergence and Scalability Performance**

It converges quickly!

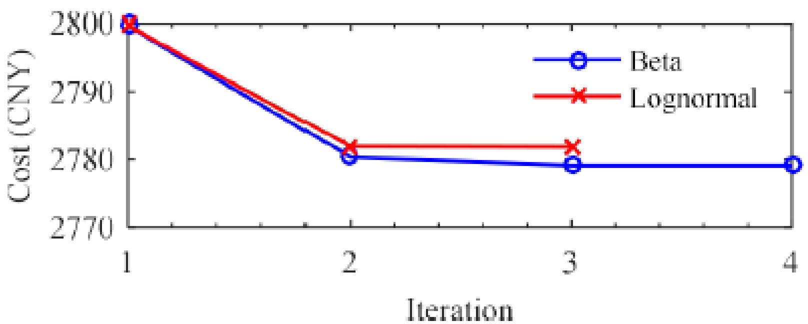


Fig. 8. Convergence performance under Beta and Lognormal distribution (95%)

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

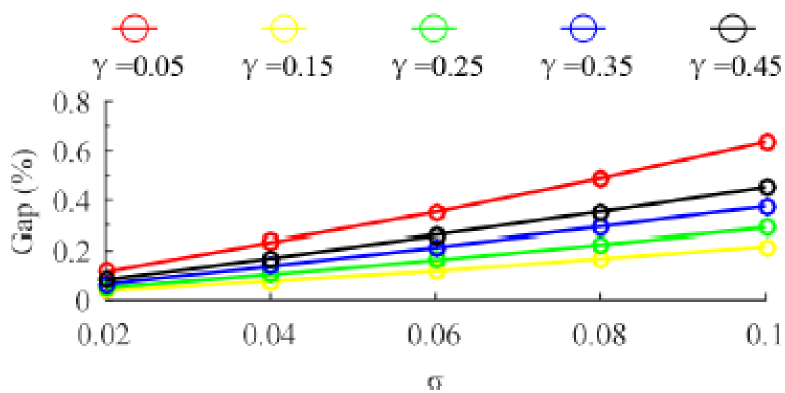


Fig. 7. Sensitivity of gap with probability level and standard deviations

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

2、Chance-Constrained GES Operations under DDU

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

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

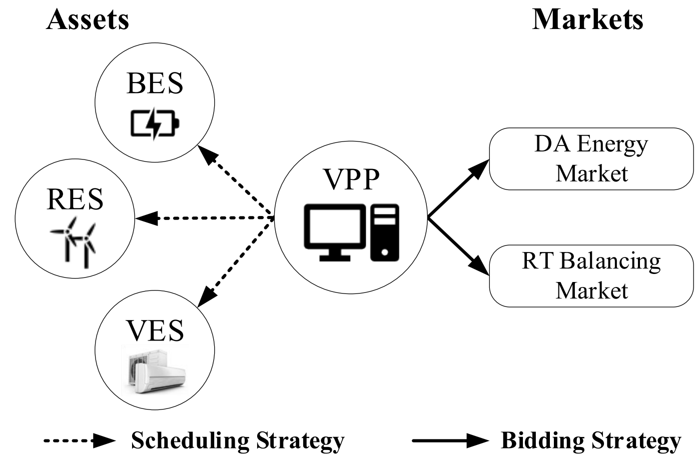
Average Profit

CVaR

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

$$S_s^{\text{net}} = \Delta t\Bigg[\sum_{\forall t\in\Omega_T}\lambda_{s,t}^{\text{DA}}P_t^{\text{DA}} + \sum_{\forall t\in\Omega_T}(\lambda_{s,t}^{\text{R+}}P_{s,t}^{\text{R+}} - \lambda_{s,t}^{\text{R-}}P_{s,t}^{\text{R-}})$$

$$-\sum_{\forall i\in\Omega_R}\sum_{\forall t\in\Omega_T}C_i^{\text{RES}}P_{s,i,t}^{\text{RES}} - \sum_{\forall i\in\Omega_G}\sum_{\forall t\in\Omega_T}C_{\text{d/c},i}^{\text{GES}}P_{\text{d/c},s,i,t}^{\text{GES}}\Bigg]$$



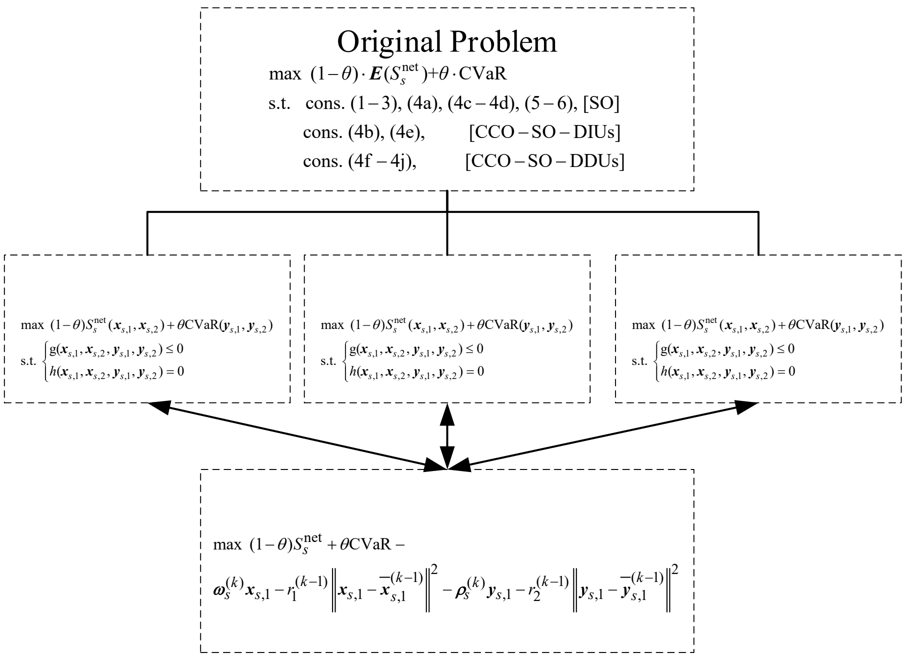
Hybrid Uncertainty Reformulations

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	$P_{s,i,t}^{\text{RES,AW}}$	DIUs	Scenarios
GES	$\overline{P}_{\text{c/d},i,t}^{\text{GES}}$, $\overline{SoC}_{i,t}^{\text{GES,DIU}}$, $\underline{SoC}_{i,t}^{\text{GES,DIU}}$, $\beta_{i,t}^{\text{GES}}$	DIUs	Explicit Quantiles
GES	$\overline{SoC}_{i,t}^{\text{GES,DDU}}$, $\underline{SoC}_{i,t}^{\text{GES,DDU}}$	DDUs	Iterative Quantiles

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

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



Asymmetric From Decomposition Method×

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** eps1> δ_1 **do**

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

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

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

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

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

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

$k\leftarrow k+1$

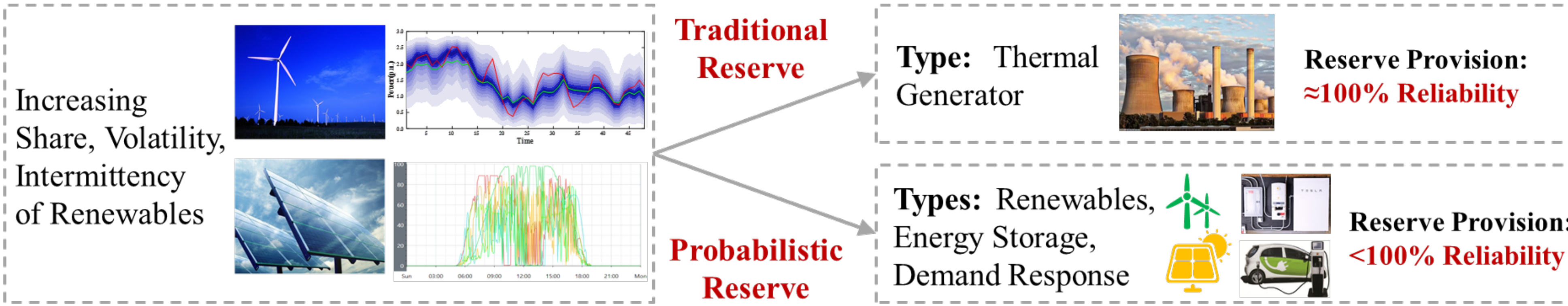
End

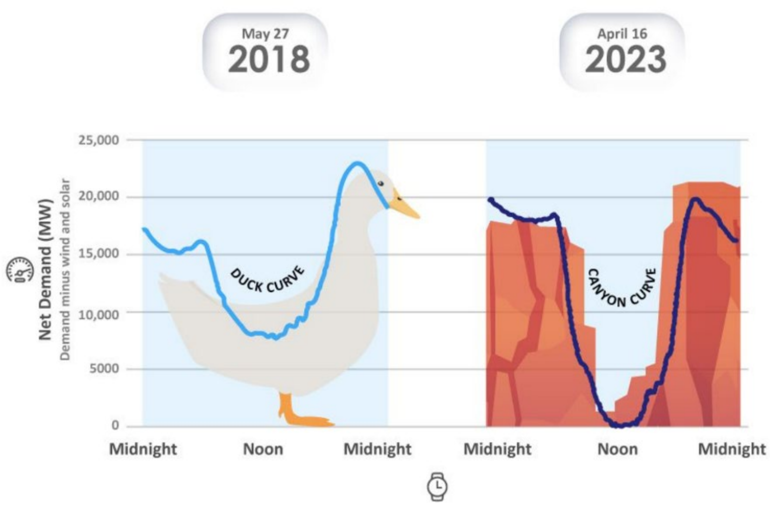
Sep 3 **Return** $x_{s,1}=x_{s,1}^{(k)}$, $y_{s,1}=y_{s,1}^{(k)}$

2、Chance-Constrained GES Operations under DDU

✓ 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**





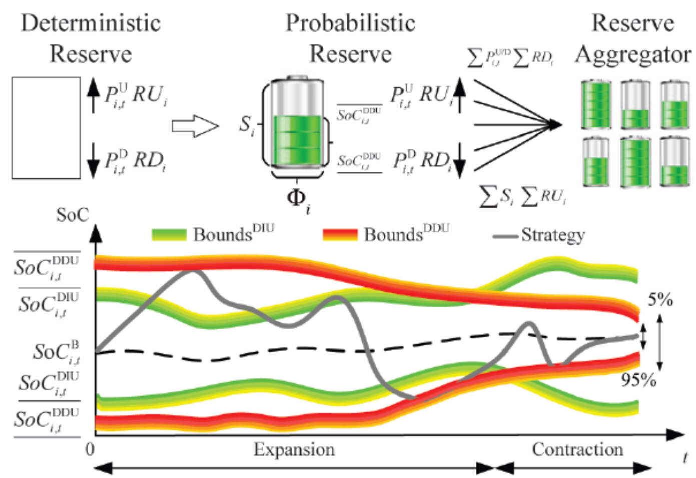


Fig. 1. Illustration of probabilistic reserve model.

Probabilistic Reserve

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

✓ Reliability-Aware Probabilistic Reserve Procurement (Case 3)

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

DA-Joint Chance-Constrained Optimization under DDU

$$\min_{P^{\mathrm{U}}_{i,t},P^{\mathrm{D}}_{i,t},SoC_{i,t}} \sum_{t\in\boldsymbol{\Omega}_{\mathrm{T}}}\sum_{i\in\boldsymbol{\Omega}_{\mathrm{A}}}(c^{\mathrm{U}}_t P^{\mathrm{U}}_{i,t}+c^{\mathrm{D}}_t P^{\mathrm{D}}_{i,t})\Delta t \tag{2a}$$

$$\text{subject to: } (1\mathrm{a})-(1\mathrm{h}) \tag{2b}$$

$$\mathbb{P}\left(\sum_{i\in\boldsymbol{\Omega}_{\mathrm{A}}}(P^{\mathrm{D}}_{i,t}-P^{\mathrm{U}}_{i,t})\ge \mathrm{P}^{\mathrm{S,DIU}}_t\right)\ge 1-\epsilon \quad \forall t\in\boldsymbol{\Omega}_{\mathrm{T}} \tag{2c}$$

$$0\le P^{\mathrm{U}}_{i,t},\ 0\le P^{\mathrm{D}}_{i,t} \tag{1a}$$

$$\mathbb{P}(P^{\mathrm{U}}_{i,t}\le \overline{P}^{\mathrm{U,DIU}}_{i,t})\ge 1-\epsilon,\ \mathbb{P}(P^{\mathrm{D}}_{i,t}\le \overline{P}^{\mathrm{D,DIU}}_{i,t})\ge 1-\epsilon \tag{1b}$$

$$P^{\mathrm{U}}_{i,t+1}-P^{\mathrm{U}}_{i,t}\le RU_i,\ P^{\mathrm{D}}_{i,t+1}-P^{\mathrm{D}}_{i,t}\le RD_i \tag{1c}$$

$$SoC_{i,t+1}=(1-\varepsilon_i)SoC_{i,t}+\eta_{\mathrm{c},i}P^{\mathrm{U}}_{i,t}\Delta t/S_i - P^{\mathrm{D}}_{i,t}\Delta t/(\eta_{\mathrm{d},i}S_i)+\alpha^{\mathrm{DIU}}_{i,t} \tag{1d}$$

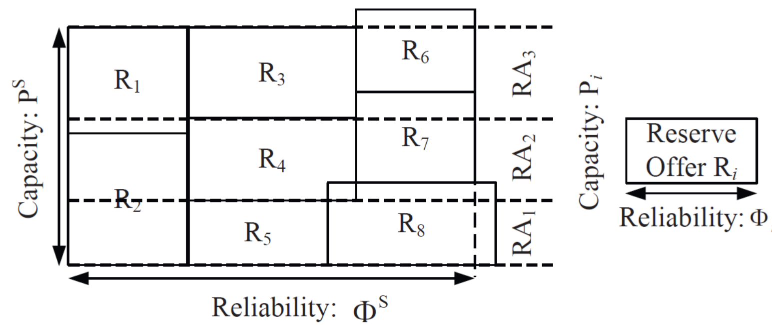
$$\mathbb{P}(\underline{SoC}^{\mathrm{DDU}}_{i,t}\le SoC_{i,t}\le \overline{SoC}^{\mathrm{DDU}}_{i,t})\ge 1-\epsilon \tag{1e}$$

$$\overline{SoC}^{\mathrm{DDU}}_{i,t}=h(g(\overline{SoC}^{\mathrm{DIU}}_{i,t},\ c^{\mathrm{U}}_t),\ \beta^{\mathrm{U}}_i RD_{i,t}) \tag{1f}$$

$$\underline{SoC}^{\mathrm{DDU}}_{i,t}=h(g(\underline{SoC}^{\mathrm{DIU}}_{i,t},\ c^{\mathrm{D}}_t),\ \beta^{\mathrm{D}}_i RD_{i,t}) \tag{1g}$$

$$RD_{i,t}=\lambda\sum_{\tau=1}^{t}\left(P^{\mathrm{U}}_{i,\tau}/\overline{P}^{\mathrm{U}}_i+P^{\mathrm{D}}_{i,\tau}/\overline{P}^{\mathrm{D}}_i\right)/T + (1-\lambda)|SoC_{i,t}-SoC^{\mathrm{B}}_{i,t}| \tag{1h}$$

RT-Reliability Commitment



$$\min_{P_i,P_{i,j},z_{i,j},\phi_i}\sum_{i\in\boldsymbol{\Omega}_{\mathrm{A}}}\sum_{j\in\boldsymbol{\Omega}_{\mathrm{R}}}\rho_j P_{i,j} \tag{3a}$$

$$\phi_i=1-\prod\nolimits_j(1-\Phi_j z_{i,j}) \quad \forall i\in\boldsymbol{\Omega}_{\mathrm{A}} \tag{3b}$$

$$P_i-P_{i,j}\le \mathrm{M}(1-z_{i,j}) \quad \forall i\in\boldsymbol{\Omega}_{\mathrm{A}},\forall j\in\boldsymbol{\Omega}_{\mathrm{R}} \tag{3c}$$

$$\Phi^{\mathrm{S}}\le\prod\nolimits_i\phi_i \tag{3d}$$

$$\mathrm{P}^{\mathrm{S}}\le\sum\nolimits_i P_i \tag{3e}$$

$$\sum\nolimits_i P_{i,j}\le \mathrm{P}_j \quad \forall j\in\boldsymbol{\Omega}_{\mathrm{R}} \tag{3f}$$

$$z_{i,j}\in\{0,1\} \quad \forall i\in\boldsymbol{\Omega}_{\mathrm{A}},\forall j\in\boldsymbol{\Omega}_{\mathrm{R}} \tag{3g}$$

$$P_{i,j}P_i\ge 0 \quad \forall i\in\boldsymbol{\Omega}_{\mathrm{A}},\forall j\in\boldsymbol{\Omega}_{\mathrm{R}} \tag{3h}$$

$$P_i\ge\underline{\mathrm{P}}^{\mathrm{A}} \quad \forall i\in\boldsymbol{\Omega}_{\mathrm{A}} \tag{3i}$$

$$\phi_i\ge\underline{\Phi}^{\mathrm{A}} \quad \forall i\in\boldsymbol{\Omega}_{\mathrm{A}} \tag{3j}$$

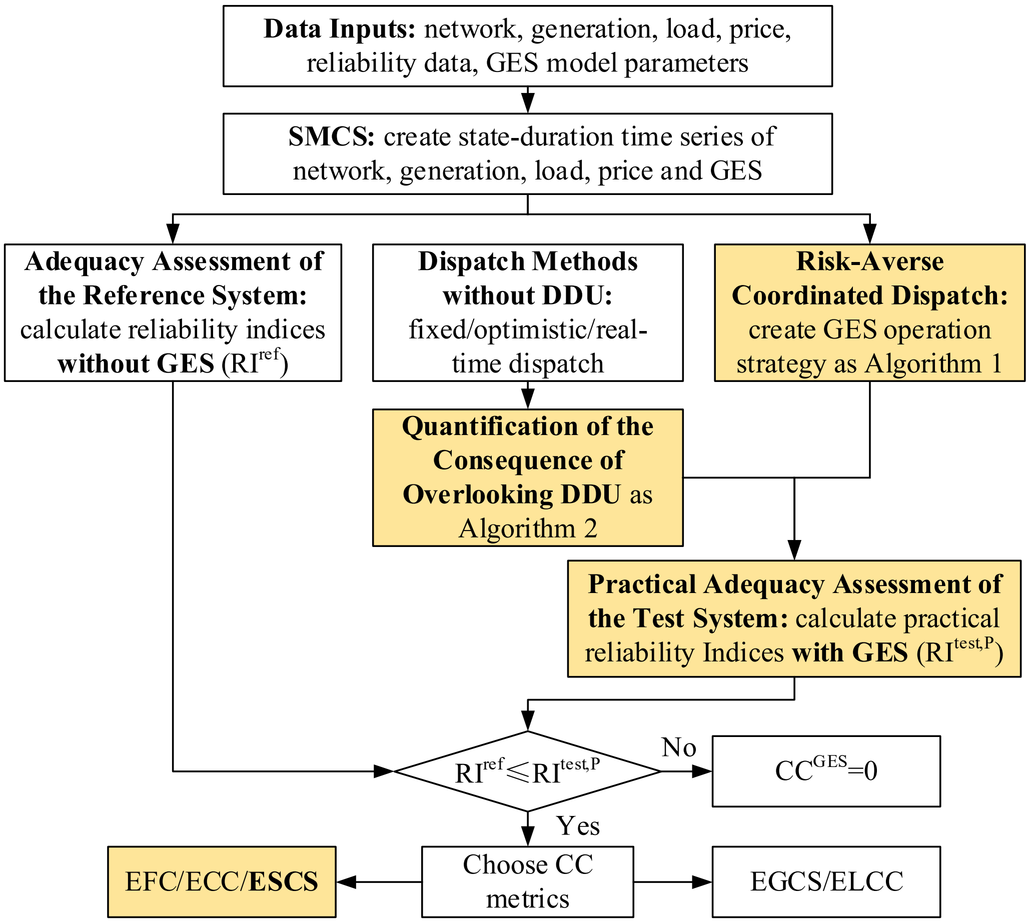
Reformulation with Log Function

Piecewise Linear Approximation

3、Capacity Credit Evaluation of GES under DDU

✓ 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**

✓ Capacity Credit Evaluation of GES (Case 4)

- **Risk-Averse Coordinated Dispatch of GES (Market Simulation)**

① Normal Status: Day-ahead Energy Arbitrage

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

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

② Emergency Status: Real-time Adequacy Support

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

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

DDU

③ Recovery Status: Real-time Capacity Recovery

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

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

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

Contents

Conclusions

- ✓ **GES Model: Better Capture the Stochasticity of Flexible Resources (DERs) by Physics-Informed Flexibility Learning and Incorporating Decision-Dependent Occupant Behavior**

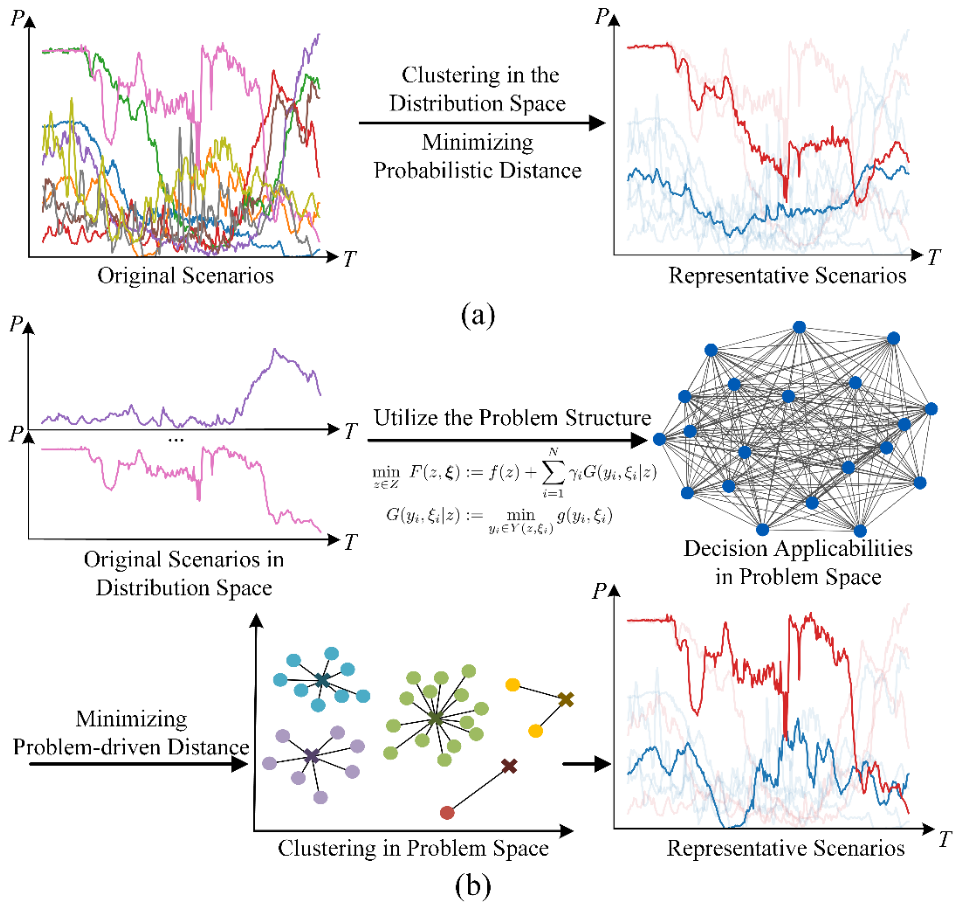
- ✓ **Chance-Constrained Optimization under DDU: Tractable & Scalable Solutions to Hedging Risk from DDU, Improve the Availability and Performance of Coordinated GES Units, Enhanced Reliability and Economic Efficiency of the Power System.**

- ✓ **Industrial Applications: Learning DDU with Real-World Data?**

✓ Problem-Driven Scenario Reduction—Stochastic Optimization

- **Focus on the Implementation Performance & Representativeness of Scenarios**

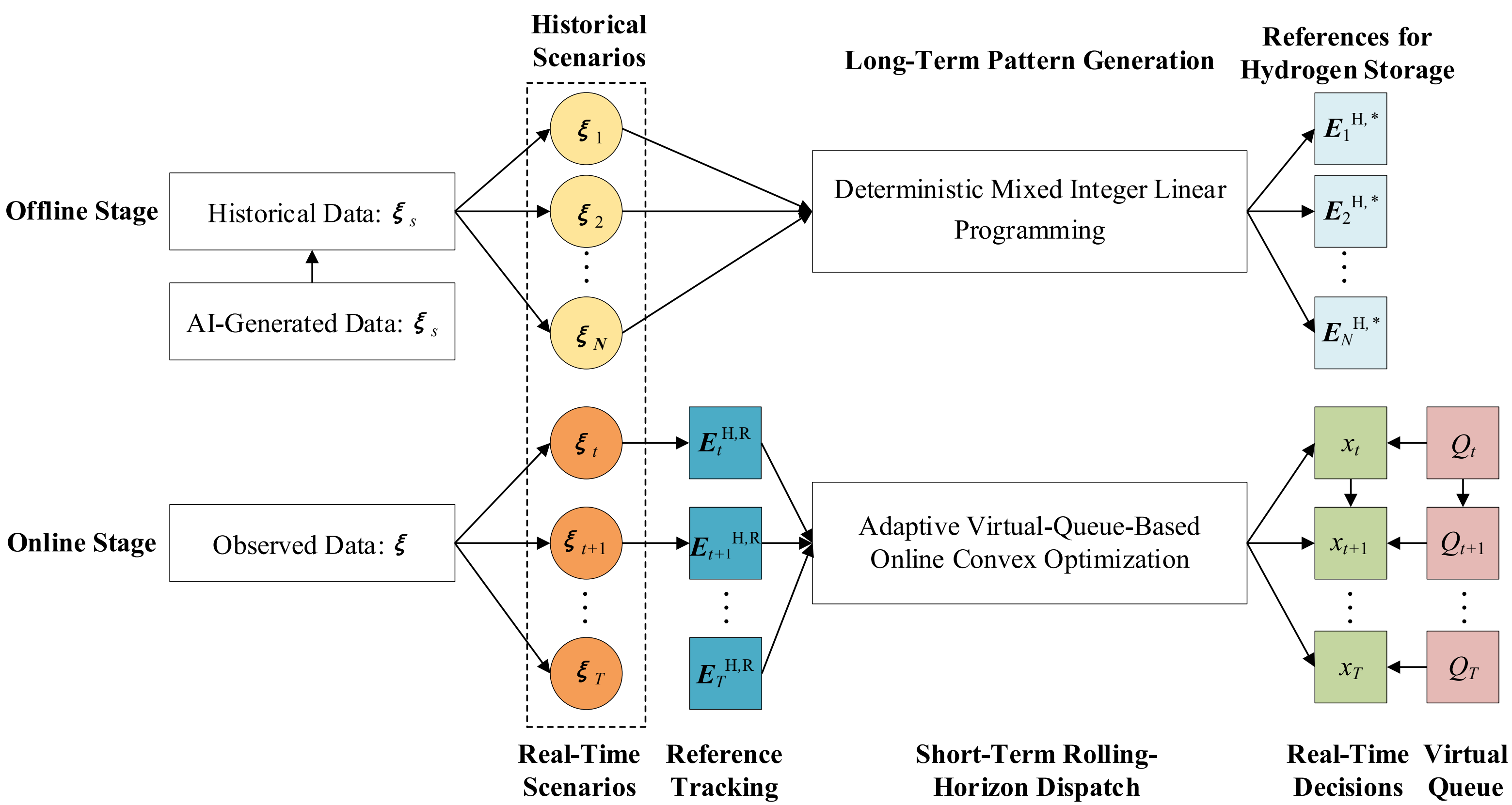
Y. Zhuang, L. Cheng, N. Qi et al, "Problem-Driven Scenario Reduction Framework for Power System Stochastic Operation," *IEEE Transactions on Power Systems, 2024.*



✓ 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.***

$$\min \mathbb{E} \sum\nolimits_t \left(G(g_t+\varphi_t \boldsymbol{d_t})+M(p_t+\psi_t \boldsymbol{d_t})\right) \quad (1a)$$

$$g_t+p_t-b_t=D_t: \boxed{\lambda_t} \quad \textbf{Electricity Price} \quad (1b)$$

$$e_{t+1}-e_t=-p_t/\eta+b_t\eta: \boxed{\theta_t} \quad \textbf{Storage Opportunity Price} \quad (1c)$$

$$\varphi_t+\psi_t=1: \boxed{\pi_t} \quad \textbf{Reserve Price} \quad (1d)$$

$$0 \le \varphi_t, \psi_t \le 1 \quad (1e)$$

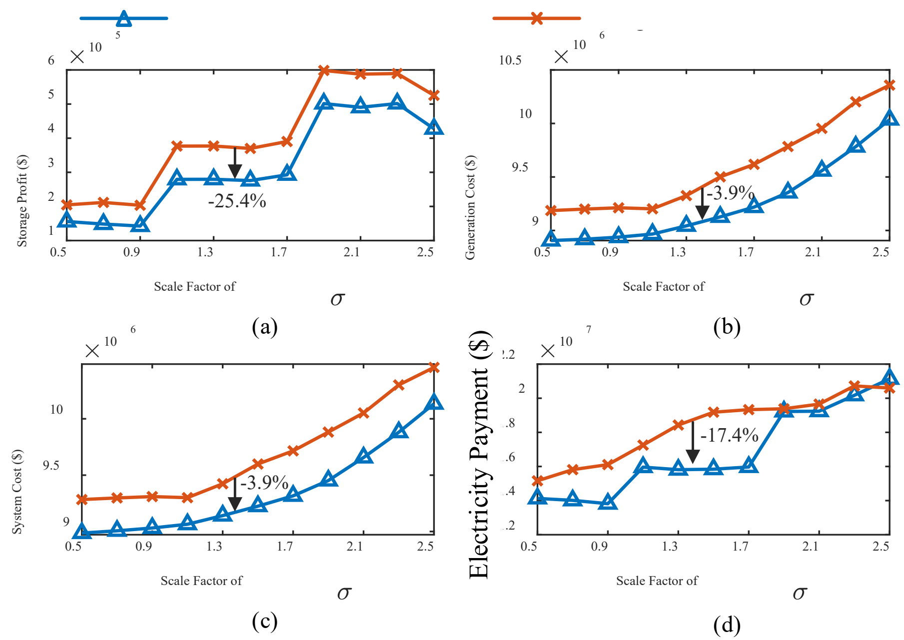
$$\mathbb{P}\left(\underline{G} \le g_t+\varphi_t \boldsymbol{d_t} \le \overline{G}\right) \ge 1-\epsilon: \ \underline{\nu}_t, \ \overline{\nu}_t \quad (1f)$$

$$b_t p_t = 0 \quad (1g)$$

$$0 \le b_t, \ \mathbb{P}\left(b_t-\psi_t \boldsymbol{d_t} \le \overline{P}\right) \ge 1-\epsilon: \ \underline{\alpha}_t, \ \overline{\alpha}_t \quad (1h)$$

$$0 \le p_t, \ \mathbb{P}\left(p_t+\psi_t \boldsymbol{d_t} \le \overline{P}\right) \ge 1-\epsilon: \ \underline{\beta}_t, \ \overline{\beta}_t \quad (1i)$$

$$\mathbb{P}\left((\psi_t \boldsymbol{d_t}+p_t)/\eta \le e_t \le \overline{E}-(b_t-\psi_t \boldsymbol{d_t})\eta\right) \ge 1-\epsilon: \ \underline{\iota}_t, \ \overline{\iota}_t \quad (1j)$$



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

Thank You!

Ning Qi

Columbia University, New York, NY
Email: nq2176@columbia.edu

Sep. 19th, 2024, Caltech