Towards Net-Zero: The Role of Generalized Energy Storage Systems

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Bio

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Research Interest: Flexibility Modeling, Optimization under Uncertainty and Market Design for Generalized Energy Storage System

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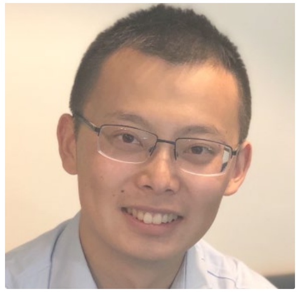
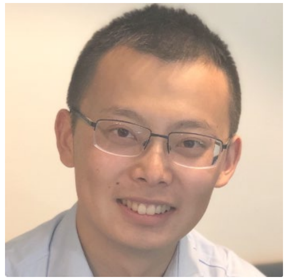


Group

PI



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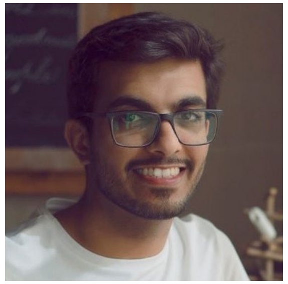

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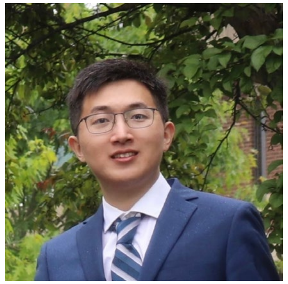

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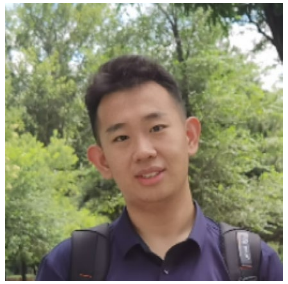

Ning Qi

Master Students

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Research Interests

- Energy Storage Market Design & Energy Economics (Bidding, Market Power)
- Long-Duration Storage (Hydro, Hydrogen)
- Decarbonization Technology (CO_2 Electrolyzer, Direct Air Capture)
- Demand-Side Management
- Decision-Focus Learning & Conformal Prediction
- ……

1. Background

2. Battery Energy Storage

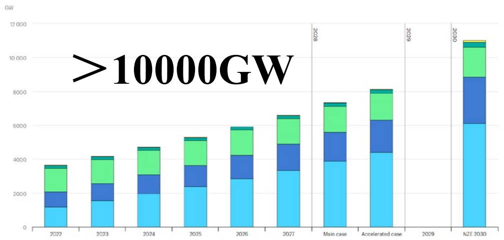
3. Long-Duration Energy Storage

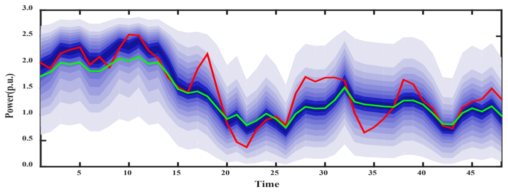
4. Virtual Energy Storage

5. Conclusion and Future Work

Background—Role of Generalized Energy Storage

Renewables

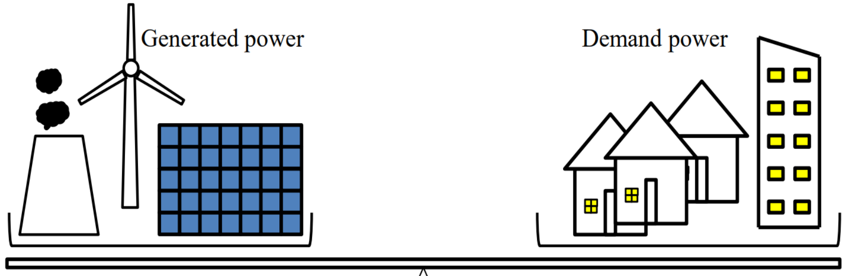



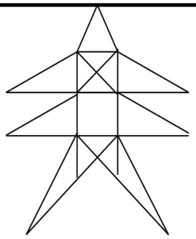


Capacity

Uncertainty

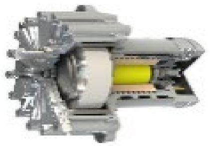
Power Supply-Demand Balance






PSH

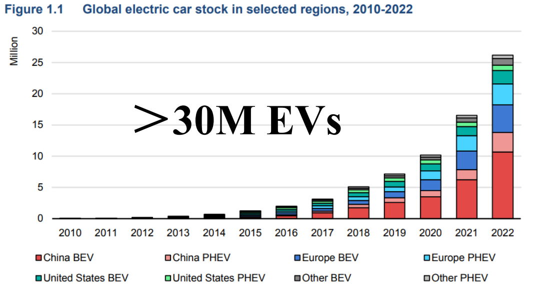

Battery

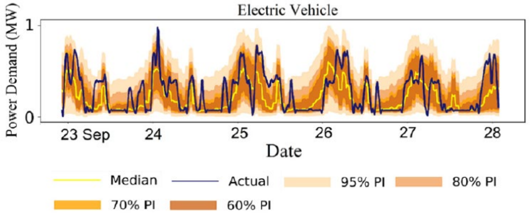

Flywheel

Flexible Loads


Capacity

Uncertainty





Flexibility for Multiple Services

Energy Storage

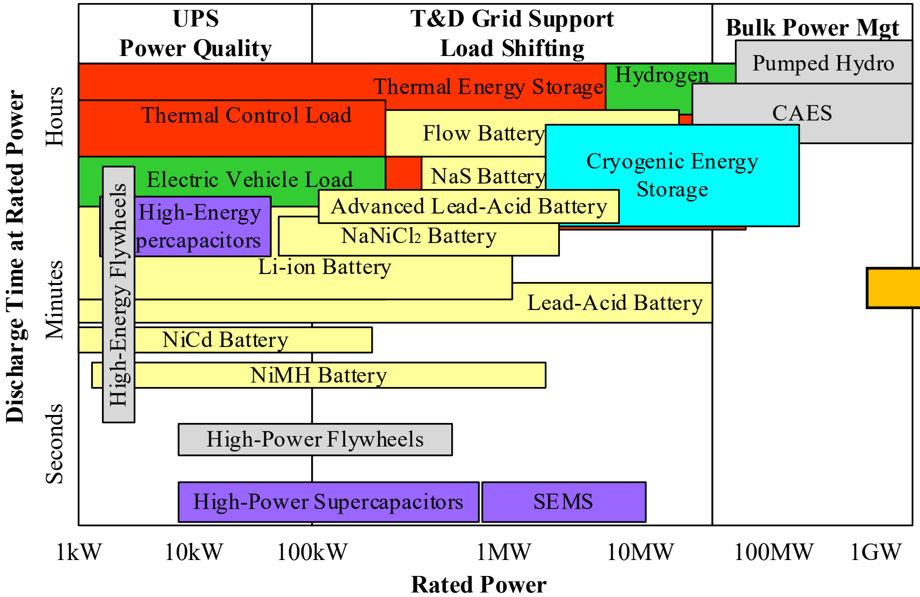
Virtual Energy Storage

- Energy Shifting (Peak Shaving)
- Frequency/Voltage Regulation
- Capacity Market…

Generalized Energy Storage (GES)

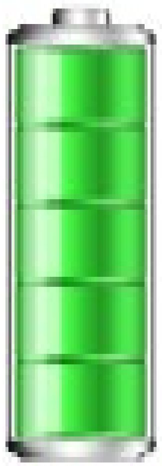
Background—Role of Generalized Energy Storage

- GES: an individual unit or a portfolio of heterogeneous quasi-storage units uniformly
- "1"+"1">"2": Long/short-duration GES; Physical/virtual GES



Classification

Power



SoC/SoE

Diverse exogenous and endogenous uncertainties

- Fault/off-state
- SoC estimation error
- Degradation
- Baseline behavior
- Response willingness
- Bidding
- ……

It is impossible to view everything from a purely deterministic perspective—Pierre Pinson

Flexibility + Uncertainty=Credible Flexibility

Background—Pricing of Energy Storage

Background—Pricing of Energy Storage

Cost Recovery

Conventional Generator

Market Design

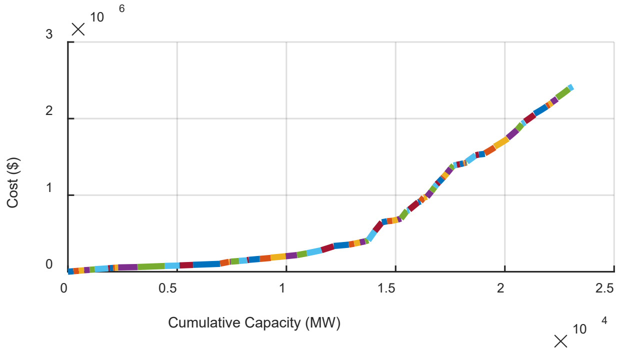
VS

Energy Storage

Small Storage

Lose Money Without Intelligence

	Conventional Generator	Energy Storage
Bid:	**Marginal Cost**	**Opportunity Cost**
Bid Generation:	**Fuel Cost Curve**	**Price Prediction based on Private Model**
Market Clearing:	**Marginal Energy Price**	**No Default Bid or Price**



$$Q_{t-1}(e_{t-1}|\hat{\lambda}_t) := \max_{p_t, b_t} \hat{\lambda}_t (p_t - b_t) - c p_t + V_t(e_t)$$

$$V_{t-1}(e_{t-1}) := \mathbb{E}_{\hat{\lambda}_t}\left[Q_{t-1}(e_{t-1}|\hat{\lambda}_t)\right]$$

Profit Maximization

Background—Pricing of Energy Storage

☺

Cost Recovery

Conventional Generator

Market Design

VS

Energy Storage

☹

Small Storage

Lose Money Without Intelligence

	Conventional Generator	Energy Storage
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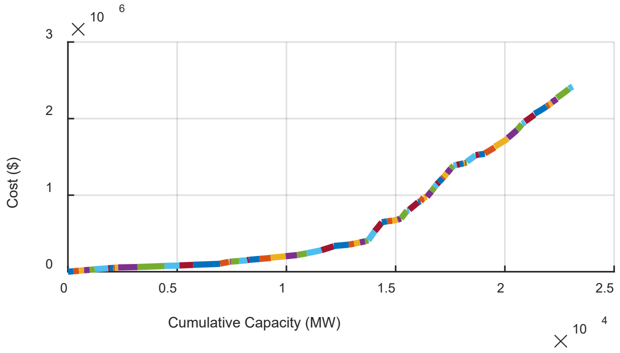


$$Q_{t-1}(e_{t-1}|\hat{\lambda}_t) := \max_{p_t, b_t} \hat{\lambda}_t (p_t - b_t) - c p_t + V_t(e_t)$$

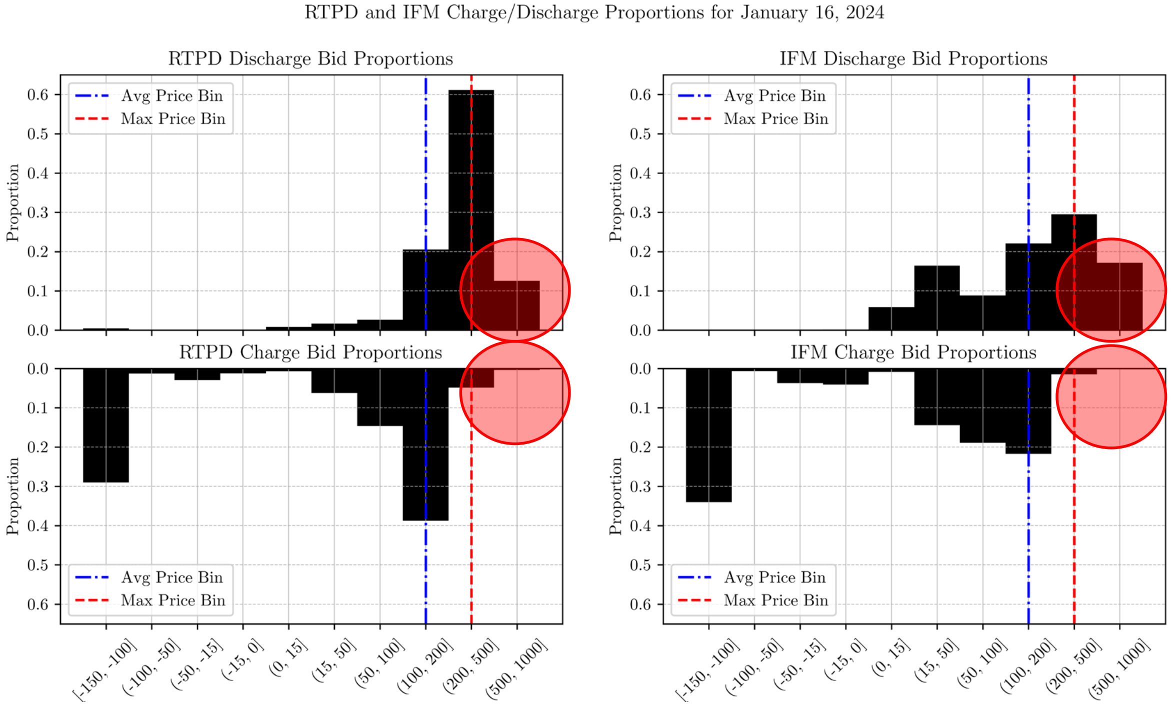
$$V_{t-1}(e_{t-1}) := \mathbb{E}_{\hat{\lambda}_t} \left[Q_{t-1}(e_{t-1}|\hat{\lambda}_t) \right]$$

Profit Maximization

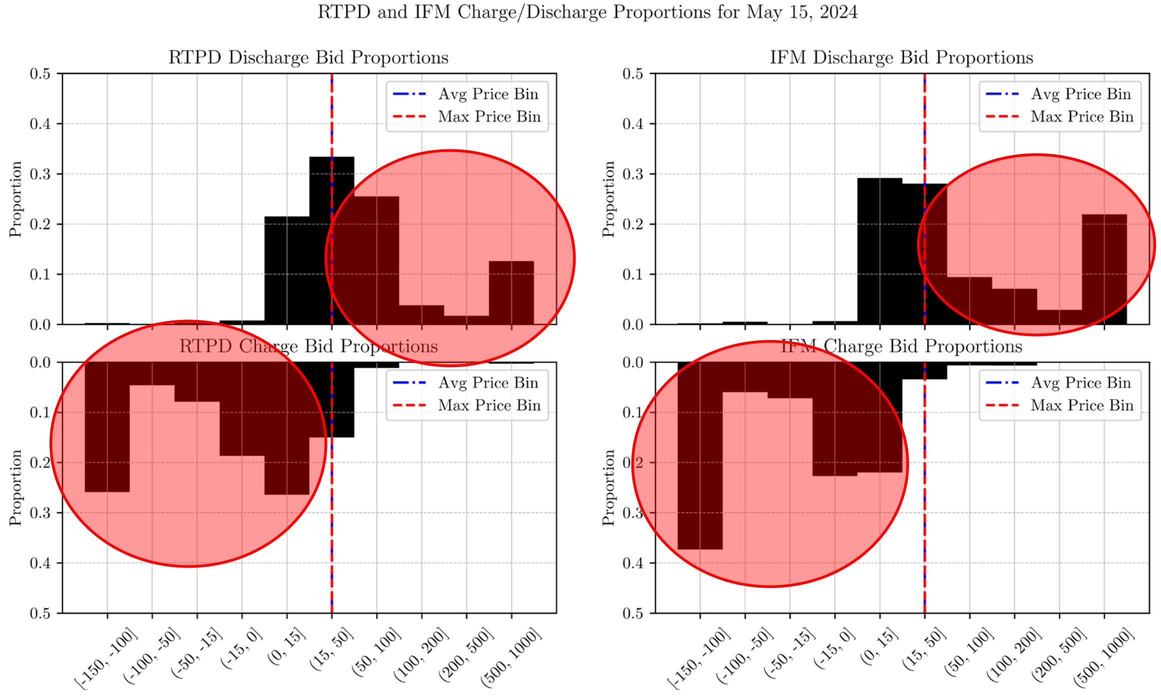
Market Clearing:	Marginal Energy Price	No Default Bid or Price

Background—Pricing of Energy Storage

Large Storage: Capacity Withholding (Extreme High Bid: $500-1000/MWh！)



Normal Price Day



Default Bid?

Price Spike Day

https://www.caiso.com/library/daily-energy-storage-reports

Background—Pricing of Uncertainty

Deterministic Formulation

$$\min \sum_t [\sum_i G_i(g_{i,t}) + \sum_s M_s(p_{s,t})] \quad (1a)$$

$$[\lambda_t]: \sum_i g_{i,t} + \sum_s p_{s,t} - \sum_s b_{s,t} = D_t, \forall t \in \mathcal{T} \quad (1b)$$

Energy Price

$$[\theta_{s,t}]: e_{s,t+1} - e_{s,t} = -p_{s,t}/\eta_s + b_{s,t}\eta_s, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \quad (1c)$$

$$[\pi_t]: \sum_i \varphi_{i,t} + \sum_s \psi_{s,t} \geq d_t, \forall t \in \mathcal{T} \quad (1d)$$

Reserve Price

$$[\underline{\nu}_{i,t}, \overline{\nu}_{i,t}]: \underline{G}_i \leq g_{i,t} \leq \overline{G}_i - \varphi_{i,t}, \forall t \in \mathcal{T}, \forall i \in \mathcal{G} \quad (1e)$$

$$[\underline{\kappa}_{i,t}, \overline{\kappa}_{i,t}]: -RD_i \leq g_{i,t} - g_{i,t-1} \leq RU_i, \forall t \in \mathcal{T}, \forall i \in \mathcal{G} \quad (1f)$$

$$[\underline{\alpha}_{s,t}, \overline{\alpha}_{s,t}]: 0 \leq b_{s,t} \leq \overline{P}_s, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \quad (1g)$$

$$[\underline{\beta}_{s,t}, \overline{\beta}_{s,t}]: 0 \leq p_{s,t} \leq \overline{P}_s - \psi_{s,t}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \quad (1h)$$

$$[\underline{\iota}_{s,t}, \overline{\iota}_{s,t}]: (\psi_{s,t} + p_{s,t})/\eta_s + \underline{E}_s \leq e_{s,t}, \quad (1i)$$
$$e_{s,t} \leq \overline{E}_s - b_{s,t}\eta_s, \forall t \in \mathcal{T}, \forall s \in \mathcal{S}$$

- **Price and Dispatch Decoupled with Uncertainty**
- **Reserve Price≈0，Lose Profit for Reserve Provision**
- ✓ **Incorporate Uncertainty into Pricing and Dispatch**

Probabilistic Formulation

☐ Stochastic Optimization

× Revenue adequacy and cost recovery for each scenario
× Scenario-Based Price, No Default Price
✓ Market Analysis × Market Clearning

☐ Robust Optimization

✓ Conservative

☐ Chance-Constrained Optimization

✓ Tractable
✓ Scalable
✓ Control the Risk

Chance-Constrained Storage Pricing for Social-Welfare Maximization!

[1] J. Kazempour, P. Pinson, and B. F. Hobbs, "A stochastic market design with revenue adequacy and cost recovery by scenario: Benefits and costs," *IEEE Transactions on Power Systems*, vol. 33, no. 4, pp.3531–3545, 2018.
[2] Y. Dvorkin, "A chance-constrained stochastic electricity market," *IEEE Transactions on Power Systems*, vol. 35, no. 4, pp. 2993–3003, 2019.

Problem Formulation & Preliminary

Two-Stage Chance-Constrained Economic Dispatch

$$\min \mathbb{E}\sum_t [\sum_i G_i(g_{i,t}+\varphi_{i,t}\boldsymbol{d_t})+\sum_s M_s(p_{s,t}+\psi_{s,t}\boldsymbol{d_t})] \quad (1a)$$

Expectation

$$[\lambda_t]: \sum_i g_{i,t}+\sum_s p_{s,t}-\sum_s b_{s,t}=D_t, \forall t \quad (1b)$$

Energy Price

$$[\theta_{s,t}]: e_{s,t+1}-e_{s,t}=-p_{s,t}/\eta_s+b_{s,t}\eta_s, \forall t, \forall s \quad (1c)$$

Storage Price

$$[\pi_t]: \sum_i \varphi_{i,t}+\sum_s \psi_{s,t}=1, \forall t \quad (1d)$$

Reserve Cost

$$0\leq \varphi_{i,t},\psi_{s,t}\leq 1, \forall t, \forall i, \forall s \quad (1e)$$

$$[\underline{\nu}_{i,t}, \overline{\nu}_{i,t}]: \mathbb{P}\big(\underline{G}_i\leq g_{i,t}+\varphi_{i,t}\boldsymbol{d_t}\leq \overline{G}_i\big)\geq 1-\epsilon, \forall t, \forall i \quad (1f)$$

$$[\underline{\kappa}_{i,t}, \overline{\kappa}_{i,t}]: -RD_i\leq g_{i,t}-g_{i,t-1}\leq RU_i, \forall t, \forall i \quad (1g)$$

$$[\underline{\alpha}_{s,t}, \overline{\alpha}_{s,t}]: 0\leq b_{s,t}, \mathbb{P}\big(b_{s,t}-\psi_{s,t}\boldsymbol{d_t}\leq \overline{P}_s\big)\geq 1-\epsilon, \forall t, \forall s \quad (1h)$$

$$[\underline{\beta}_{s,t}, \overline{\beta}_{s,t}]: 0\leq p_{s,t}, \mathbb{P}\big(p_{s,t}+\psi_{s,t}\boldsymbol{d_t}\leq \overline{P}_s\big)\geq 1-\epsilon, \forall t, \forall s \quad (1i)$$

$$[\underline{\iota}_{s,t}, \overline{\iota}_{s,t}]: \mathbb{P}\Big((\psi_{s,t}\boldsymbol{d_t}+p_t)/\eta_s\leq e_{s,t} \leq \overline{E}_s-(b_{s,t}-\psi_{s,t}\boldsymbol{d_t})\eta_s\Big)\geq 1-\epsilon, \forall t, \forall s \quad (1j)$$

Chance-Constraints

$$b_{s,t}p_{s,t}=0, \forall t, \forall s \quad (1k)$$

Complementary Constraints

- First-Stage: Pre-dispatch $g_{i,t}\ p_{s,t}, b_{s,t}, e_s, \varphi_{i,t}, \psi_{s,t}$
- Second-Stage: Re-dispatch $\varphi_{i,t}\boldsymbol{d_t}\ \ \psi_{s,t}\boldsymbol{d_t}$

✓ Opportunity Pricing for Storage
✓ Default Bid and Benchmark the Market Power

Deterministic Reformulation

$$\mathbb{E}\big(G_i(g_{i,t}+\varphi_{i,t}\boldsymbol{d_t})\big)=\sum_{j=0}^{n}C_j\sum_{k=0}^{j}\binom{j}{k}g_{i,t}^{j-k}\varphi_{i,t}^{k}\mathbb{E}(\boldsymbol{d}_t)^k$$

$$\mathbb{E}\big(M_s(p_{s,t}+\psi_{s,t}\boldsymbol{d_t})\big)=M_s(p_{s,t}+\psi_{s,t}\mu_t)$$

$$\mathbb{E}(\boldsymbol{d}_t)^k=\sum_{0\leq j\leq k}^{j\ even}\binom{k}{j}\mu_t^{k-j}\sigma_t^j(j-1)!!$$

$$\underline{G}_i\leq g_{i,t}+\varphi_{i,t}\widehat{d}_t,\ g_{i,t}+\varphi_{i,t}\widetilde{d}_t\leq \overline{G}_i$$

$$b_{s,t}-\psi_{s,t}\widehat{d}_t\leq \overline{P}_s,\ p_{s,t}+\psi_{s,t}\widetilde{d}_t\leq \overline{P}_s$$

$$(\psi_{s,t}\widetilde{d}_t+p_{s,t})/\eta_s\leq e_{s,t},\ e_{s,t}\leq \overline{E}_s-(b_{s,t}-\psi_{s,t}\widehat{d}_t)\eta_s$$

$$\widehat{d}t=\mu_t-F^{-1}(1-\epsilon)\sigma_t,\ \widetilde{d}t=\mu_t+F^{-1}(1-\epsilon)\sigma_t$$

- Solve MILP with Binary Variables
- Substitute Binary Variables with Solution
- Resolve LP

Robust Competitive Equilibrium !

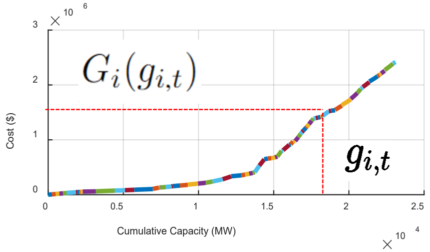
Theoretical Analysis

- **Proposition 1: Physical Cost Origins: (1) Marginal Cost of Cleared Generator & Storage (2) Storage Efficiency**

$$\theta_{s,t} = H_i(g_{i,t} + \varphi_{i,t}\boldsymbol{d_t})/\eta_s$$ **Charging**

$$\theta_{s,t} = \eta_s(H_i(g_{i,t} + \varphi_{i,t}\boldsymbol{d_t}) - M_s)$$ **Discharging**

$$\partial \mathbb{E} G_i(g_{i,t} + \varphi_{,t}\boldsymbol{d_t})/\partial g_{,t} = H_i(g_{i,t} + \varphi_{i,t}\boldsymbol{d_t})$$

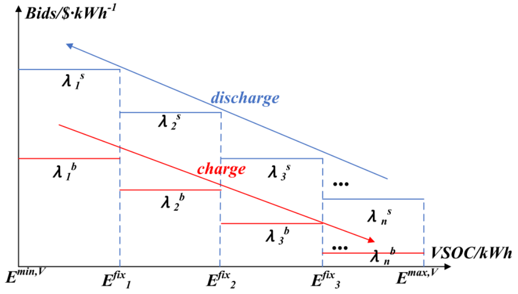


- **Proposition 2: Convex Opportunity Price: Monotonically Decreases with Storage SoC**

$$\partial\theta_{s,t}/\partial e_{s,t} \leq 0$$

Quadratic/Super-Quadratic Generation Cost Function

SoC-Dependent Bid[1]



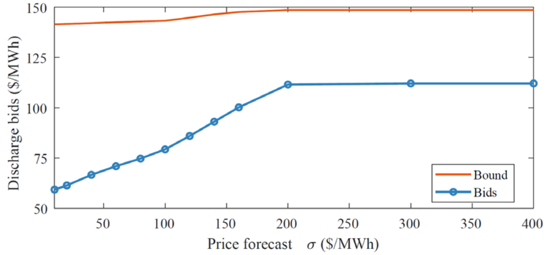
- **Proposition 3: Uncertainty-aware Price: Monotonically Increases with Uncertainty**

$$\partial\theta_{s,t}/\partial\sigma_t \geq 0$$

Quadratic/Super-Quadratic Generation Cost Function

$$\mathbb{E}(\theta_{s,t}(\boldsymbol{d_t})) > \theta_{s,t}(\mathbb{E}(\boldsymbol{d_t}))$$

Uncertainty-Aware and Bounded Bid[2]



- **Theorem: Constrained and Bounded Price**

$$\theta_{s,t-1} = \frac{\eta_s}{\widetilde{d}_t}\left(\theta_{s,t}\eta_s\widehat{d}_t + \lambda_t\left(\frac{\widetilde{d}_t}{\eta_s^2} - \widehat{d}_t\right) + \pi_t - M_s\mu_t\right)$$ **Charging**

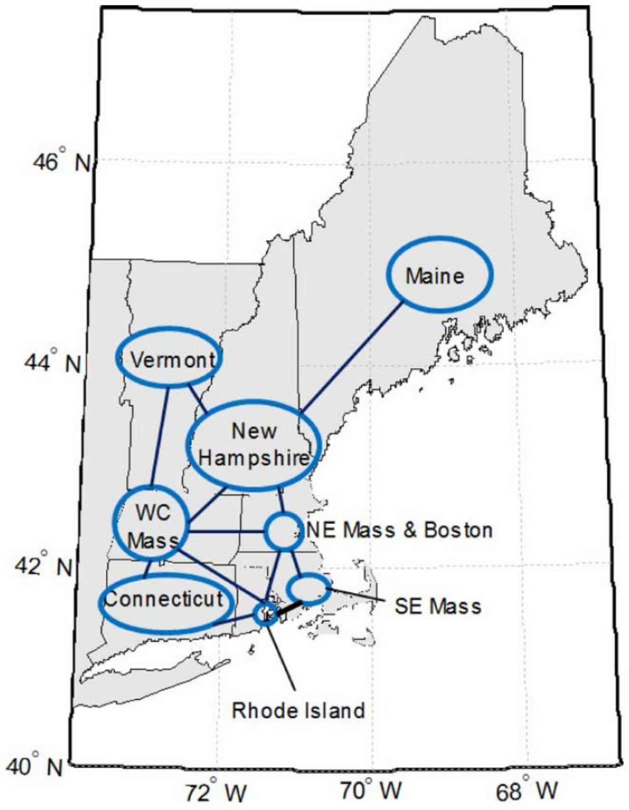
$$\theta_{s,t-1} = \frac{1}{\eta_s\widehat{d}_t}\left(\frac{\theta_{s,t}\widetilde{d}_t}{\eta_s} + \lambda_t(\eta_s^2\widehat{d}_t - \widetilde{d}_t) + \pi_t + M_s(\widetilde{d}_t - \eta_s^2\widehat{d}_t - \mu_t)\right)$$ **Discharging**

Linear Relationship with Energy and Reserve Price

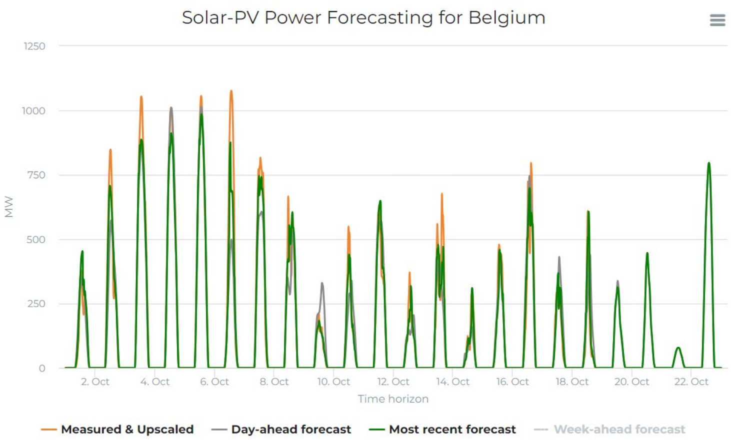
[1] N. Zheng, X. Qin, D. Wu, G. Murtaugh and B. Xu, "Energy Storage State-of-Charge Market Model," *IEEE Transactions on Energy Markets, Policy and Regulation*, vol. 1, no. 1, pp. 11-22, March 2023.
[2] Q., Xin, I. Lestas, and B. Xu. "Economic Capacity Withholding Bounds of Competitive Energy Storage Bidders." *arXiv preprint* arXiv:2403.05705 (2024).

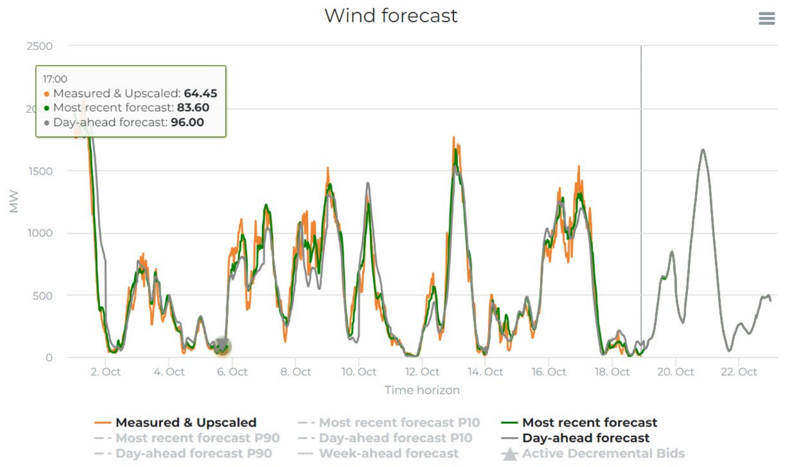
Case Study—Test System

- **ISO-NE 8-Zone Test System**



- **76 Generators: 23.1 GW**
- **Load: 13 GW**
- **Renewables: Wind and Solar[1]+, 10%-90% of Total Generation Capacity**
- **Uncertainty: Elia Historical Data[2]**
- **Multiple Storages: 10%-60% of Total Generation Capacity; 4-8-12 hr duration; 0.8, 0.85, 0.9, 0.95 One-Way Efficiency**
- **Coding[3]: MatLab and solved by Gurobi 11.0 solver, Intel Corei9-13900HX @ 2.30GHz with RAM 16 GB.**

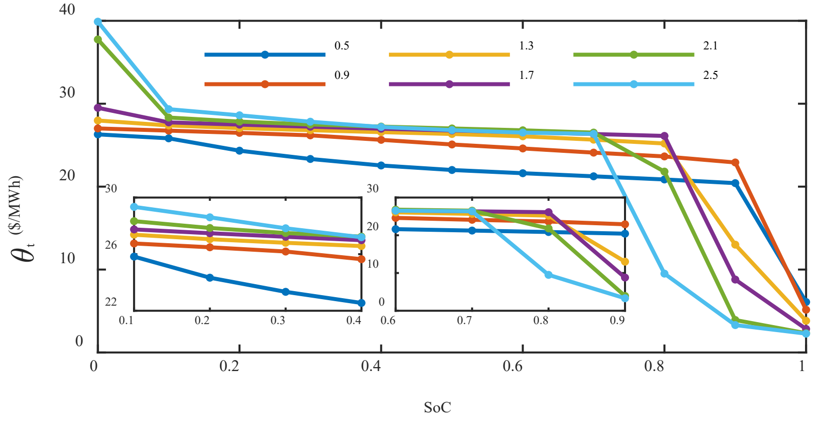




[1] D. Krishnamurthy, W. Li, and L. Tesfatsion, "An 8-zone test systembased on iso new england data: Development and application," *IEEE Transactions on Power Systems*, vol. 31, no. 1, pp. 234–246, 2015
[2] Elia, "Forecast error data from elia," 2024. [Online]. Available:https://www.elia.be/en/grid-data.
[3] Code and Data: https://github.com/thuqining/Storage_Pricing_for_Social_Welfare_Maximization

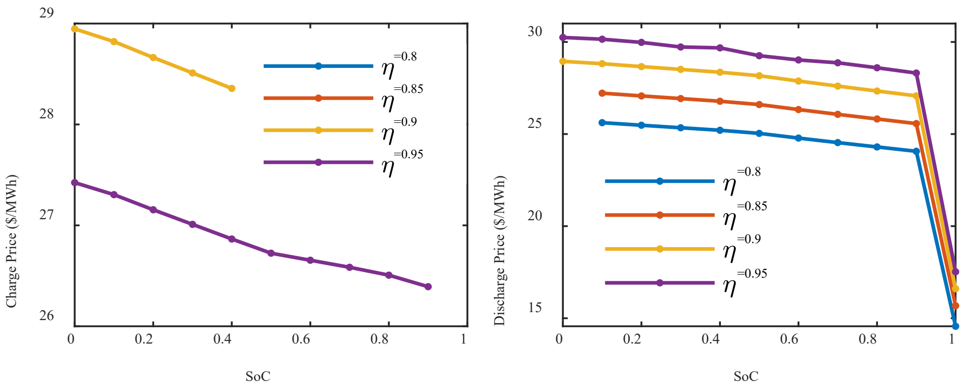
Case Study—Simulation Results

- **Convex Opportunity Price Function θ(SoC)**
- **Monotonically Decreasing**



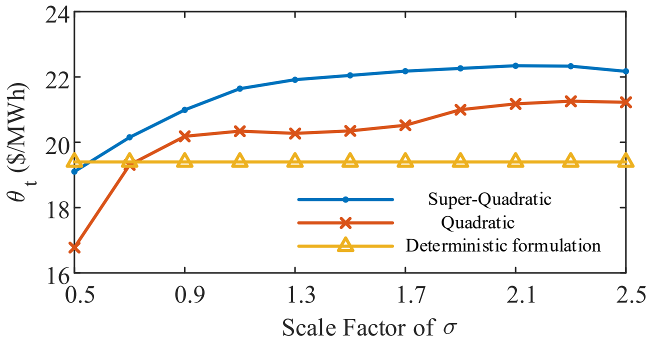
- **Higher Efficiency: Higher Discharge Price**

Lower Charge Price

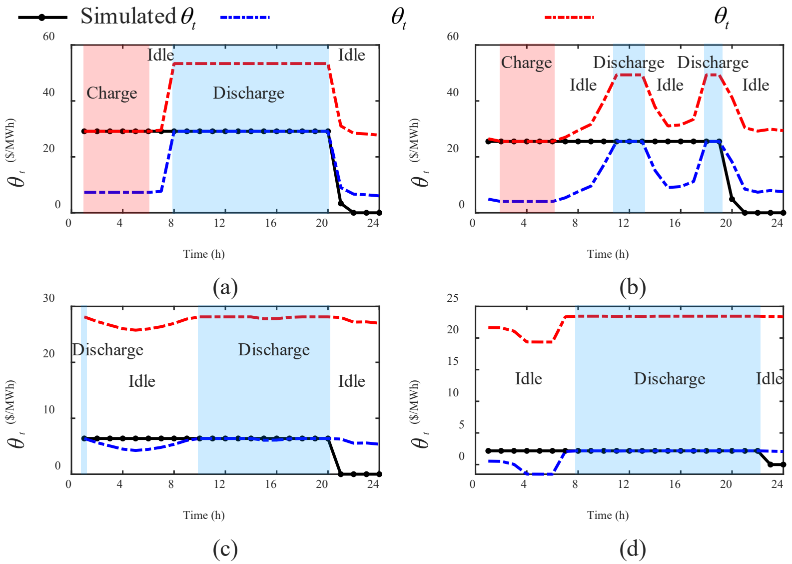


(a) (b)

- **Uncertainty-Aware Price Function θ(σ)**
- **Proposed Formulation: Monotonically Increasing**
- **Deterministic Formulation: Fixed**



- **Constrained and bounded Price; Anticipated Default Bid**



Case Study—Comparative Results

- **Benchmark Comparison**
- **Storage Profit Maximization[1,2]**

$$V_{t-1}(e_{t-1}) = \max_{p_t,\, b_t} \lambda_t(p_t - b_t) - Mp_t + V_t(e_t)$$
$$e_{t+1} - e_t = -p_t/\eta + b_t\eta$$
$$0 \le b_t \le \overline{P},\ 0 \le p_t \le \overline{P}$$
$$0 \le e_t \le \overline{E}$$
$$p_t = 0,\ \lambda_t < 0$$

Opportunity Value Function

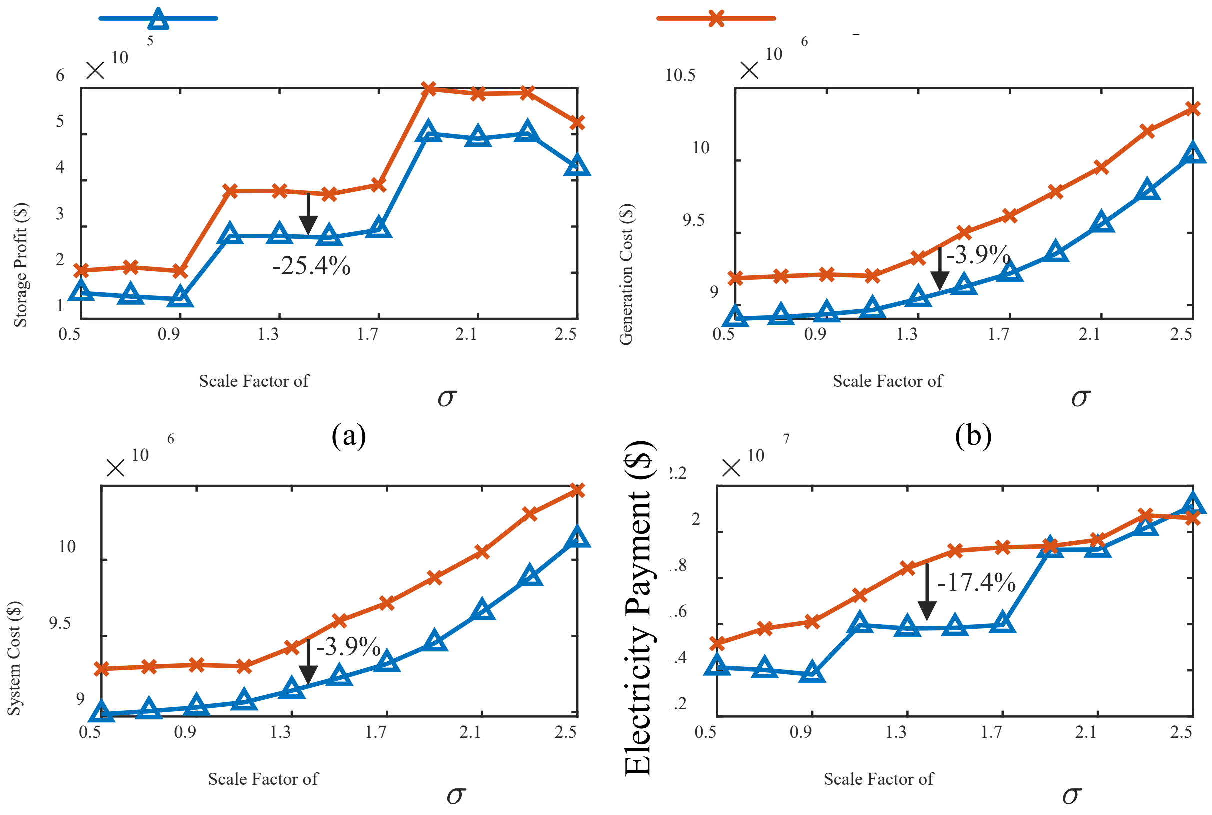
$$O_t(p_t) = \frac{\partial(Mp_t + V_t(e_t))}{\partial p_t} = M + \frac{1}{\eta} v_t(e_{t-1} - p_t/\eta)$$
$$B_t(b_t) = \frac{\partial(V_t(e_t))}{\partial b_t} = \eta v_t(e_{t-1} + b_t\eta)$$

Storage Bid

$$\min \sum_i \sum_t G(g_{i,t}) + O_t(p_t) - B_t(b_t)$$

Market Clearing

- **Enhance social welfare, reduce conventional generator production and consumer payment; Sacrifice storage margins**
- **Electricity Payment Increase by 17%**
- **Storage Profit Reduces by 0.5% (based on Electricity Payment)**



(a) (b) (c) (d)

[1] X. Qin, I. Lestas, and B. Xu, "Economic capacity withholding bounds of competitive energy storage bidders," arXiv preprint arXiv:2403.05705,2024

[2] N. Zheng, X. Qin, D. Wu, G. Murtaugh and B. Xu, "Energy Storage State-of-Charge Market Model," IEEE Transactions on Energy Markets, Policy and Regulation, vol. 1, no. 1, pp. 11-22, March 2023.

Case Study—Comparative Results

- **Benefit scales up with increased renewable and storage integration**

Sensitivity Analysis of Renewable capacity

Storage Duration	Storage Capacity	Storage Profit (10^5\$)	Generation Cost (10^6\$)	System Cost (10^6\$)	Electricity Payment (10^7\$)
4-hr	20%	1.41(-40%)	8.95(-2.5%)	9.05(-2.5%)	1.38(-18%)
	40%	3.37(-15%)	8.69(-9.4%)	8.81(-10%)	1.35(-26%)
	60%	5.12(-23%)	8.43(-13%)	8.59(-14%)	1.33(-27%)
8-hr	20%	3.37(-26%)	8.69(-2.6%)	8.81(-3.2%)	1.35(-12%)
	40%	6.78(-23%)	8.17(-12%)	8.37(-13%)	1.31(-18%)
	60%	6.84(-31%)	7.71(-10%)	8.00(-10%)	1.11(-28%)
12-hr	20%	5.12(-23%)	8.43(-2.4%)	8.59(-2.6%)	1.33(-9.1%)
	40%	6.87(-30%)	7.70(-6.9%)	8.00(-6.7%)	1.11(-22%)
	60%	9.08(-33%)	7.09(-11%)	7.53(-10%)	1.05(-25%)

Sensitivity Analysis of Storage Capacity

Renewable Capacity	Storage Profit (10^5\$)	Generation Cost (10^6\$)	System Cost (10^6\$)	Electricity Payment (10^7\$)
10%	1.47(-30%)	9.18(-4.2%)	9.28(-4.1%)	1.47(-22%)
30%	1.41(-39%)	8.95(-2.5%)	9.05(-2.5%)	1.38(-18%)
50%	1.45(-28%)	8.75(-2.9%)	8.84(-3.0%)	1.31(-21%)
70%	1.44(-29%)	8.58(-3.3%)	8.66(-3.4%)	1.24(-22%)
90%	1.36(-41%)	8.43(-2.5%)	8.52(-2.3%)	1.20(-20%)

Case Study—Comparative Results

● Uncertainty Realization & Risk-Aversion

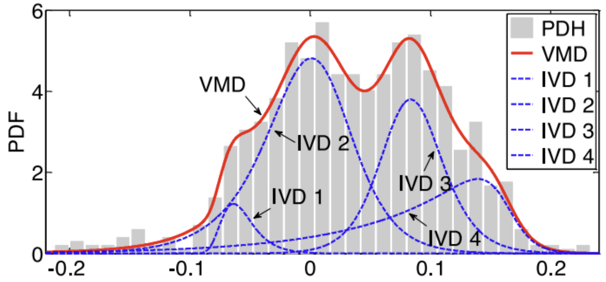
(1) Gaussion Distribution

$$F^{-1}(1-\epsilon) = \Phi^{-1}(1-\epsilon)$$

(2) Ambiguous Distribution

Type & Shape	$F^{-1}(1-\epsilon)$	ϵ
No Distribution Assumption (NA)	$\sqrt{(1-\epsilon)/\epsilon}$	$0<\epsilon\leq 1$
Symmetric Distribution (S)	$\sqrt{1/2\epsilon}$	$0<\epsilon\leq 1/2$
	0	$1/2<\epsilon\leq 1$
Unimodal Distribution (U)	$\sqrt{(4-9\epsilon)/9\epsilon}$	$0<\epsilon\leq 1/6$
	$\sqrt{(3-3\epsilon)/(1+3\epsilon)}$	$1/6<\epsilon\leq 1$

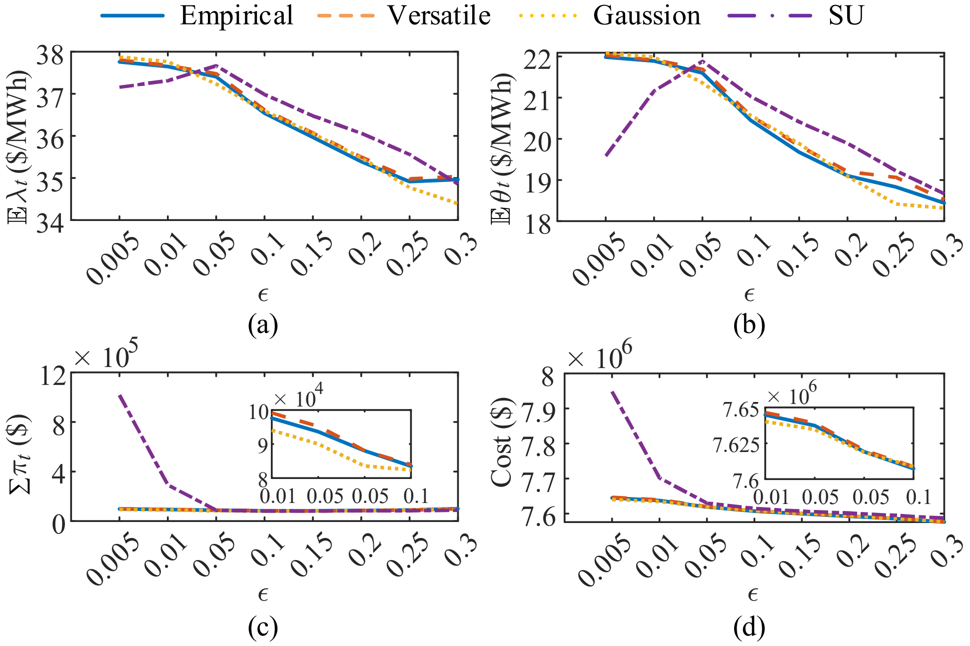
(3) Versatile Distribution[1]



$$F^{-1}(1-\epsilon \mid a,b,c) = c - \ln\Big((1-\epsilon)^{-1/b} - 1\Big)/a$$

[1] Z.-S. Zhang, Y.-Z. Sun, D. W. Gao et al., "A versatile probabilitydistribution model for wind power forecast errors and its applicationin economic dispatch," IEEE Transactions on Power Systems, vol. 28,no. 3, pp. 3114–3125, 2013.

- **More** Risk-Aversion→**Higher** Cost & Prices
- **Versatile Distribution** Best Fits the Netload Forecast Error



Distributions	Energy Price	Storage Price
Versatile	0.08	0.12
Gaussion	0.23	0.20
SU	0.48	1.00

Compared with Empirical Result Lower RMSE: Better Fitting

Case Study—Comparative Results

- **Computational Efficiency**

Generator Number	1	76	76	76	76	76	76	76	76	76
Storage Number	1	1	5	10	50	100	500	1000	5000	10000
Time1 (s)	0.08	0.42	0.57	0.78	5.63	11.86	370.00	424.45	>3000	>3000
Time2 (s)	0.04	0.35	0.46	0.59	0.74	1.16	2.85	5.32	33.34	72.60

Scalable!

Time1: Complementary Constraints to Prevent Storage from Simultaneous Charging and Discharging

Time2: Relaxation of Complementary Constraints[1]

$$\mathbf{E}^r\left(\mathbf{P}_c^r, \mathbf{P}_d^r\right) = \mathbf{1}_T E_0 + \eta_c \mathbf{A}\mathbf{P}_c^r - \frac{1}{\eta_d}\mathbf{A}\mathbf{P}_d^r$$

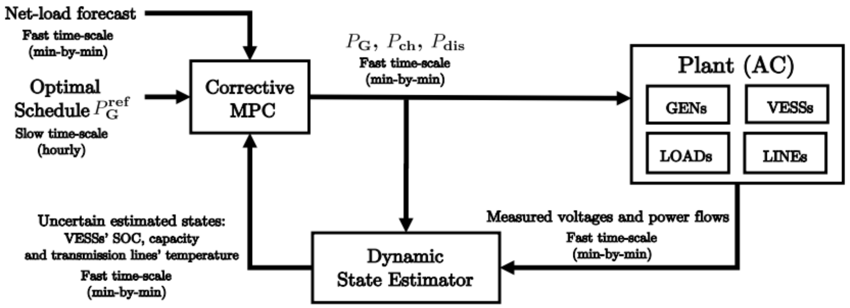
$$\begin{aligned}
&\mathbf{0} \leq \mathbf{1}_T E_0 + \eta_c \mathbf{A}\mathbf{P}_c - \frac{1}{\eta_d}\mathbf{A}\mathbf{P}_d \\
&\mathbf{E}_{\max} \geq \mathbf{1}_T E_0 + \eta \mathbf{A}(\mathbf{P}_c - \mathbf{P}_d) \\
&0 \leq \mathbf{P}_c \leq \mathbf{1}_T P_{\max} \\
&0 \leq \mathbf{P}_d \leq \mathbf{1}_T P_{\max} \\
&\mathbf{P}_c + \mathbf{P}_d \leq \mathbf{1}_T P_{\max}
\end{aligned}$$

[1] N. Nazir and M. Almassalkhi, "Guaranteeing a physically realizable battery dispatch without charge-discharge complementarity constraints," *IEEE Transactions on Smart Grid*, vol. 14, no. 3, pp. 2473–2476, 2021.

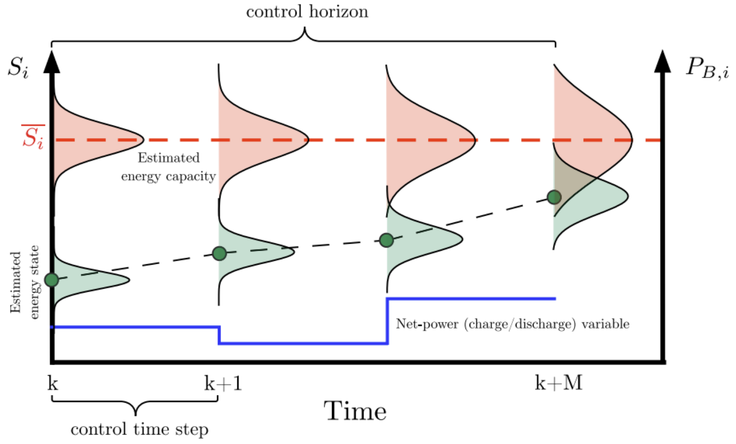
目录

可信灵活性量测——荷电状态估计

- 荷电状态(SoC)是电动汽车负荷核心**调控参考**。
- 荷电状态(SoC)量测误差不可避免→**误差矫正、误差概率分布**。

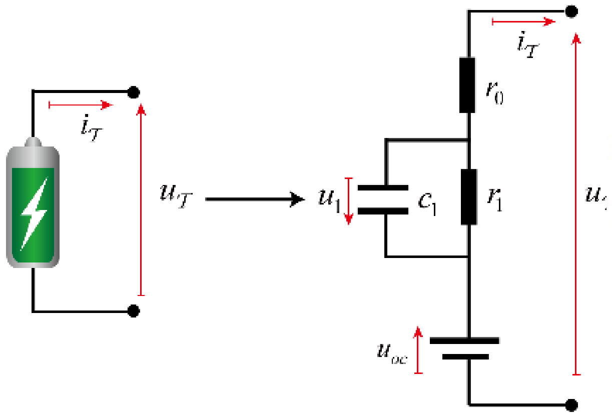


基于SoC的模型预测控制(MPC)

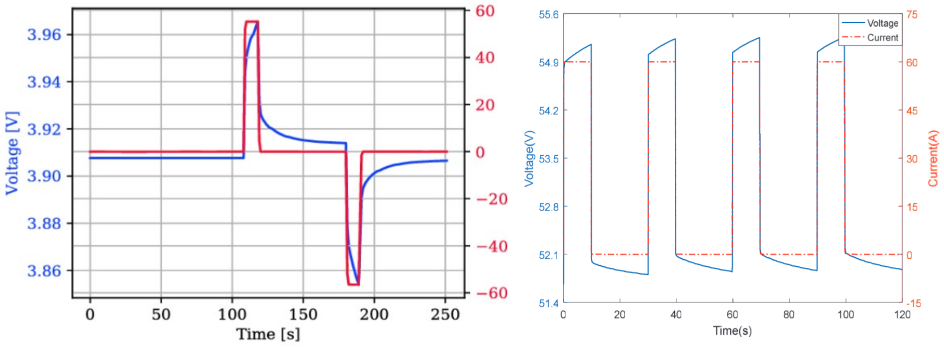


SoC误差矫正

等效电路模型



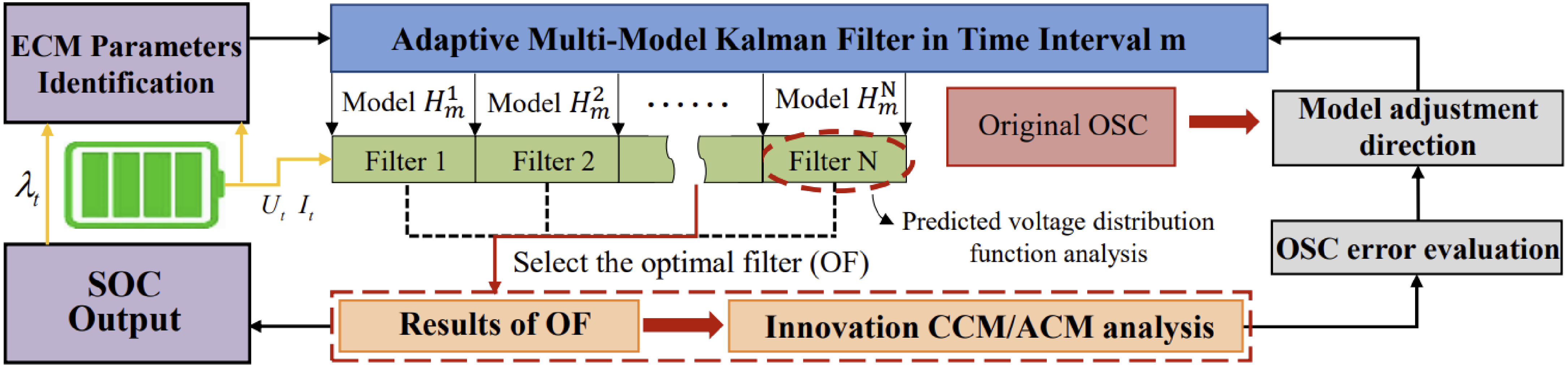
电池量测数据



荷电状态估计

- ☐ 直接测量：安时积分法和开路电压法→累积误差
- ☐ 数据驱动：通过量测数据和机器学习算法学习电池的特性和行为→大量数据、耗时
- ☐ 模型驱动：利用电池模型和测量数据来估计电池的SOC，过程中引入**滤波算法**处理噪声和模型的不确定性。

◆ 构建了自适应多模型卡尔曼滤波方法实现电动汽车电池SoC**快速估计**，实现变工况运行下电池SoC**估计偏差矫正**，为运行调控提供SoC**可信分布**。



1. 等效电路模型参数辨识
2. 多模型卡尔曼滤波器模型构建与参数更新
3. 预测电压概率分布，选择最优滤波器输出

D. Paizulamu*, L. Cheng, Y. Zhuang, H. Xu, **N. Qi**, S. Ci. LiFePO4 Battery SOC Estimation under OCV-SOC Curve Error Based onAdaptive Multi-Model Kalman Filter. IEEE Transactions on Transportation Electrification. 2024.

可信灵活性量测——荷电状态估计

◆ **提出自适应最小二乘法(AFRLS)，实现复杂工况下电池参数(电阻、电容)的快速在线辨识，为SoC估计提供模型支撑。**

– **综合考虑温度、容量、SOC、充放电状态对端电压影响**

$$\frac{dU_{oc}}{dt}=\frac{\partial U_{oc}}{\partial SOC}\frac{\partial SOC}{\partial t}+\frac{\partial U_{oc}}{\partial T}\frac{\partial T}{\partial t}+\frac{\partial U_{oc}}{\partial Q}\frac{\partial Q}{\partial t}+\frac{\partial U_{oc}}{\partial CD}\frac{\partial CD}{\partial t}$$

- [20%,80%],[80%,100%]内主导
- 短时间影响较大
- 短时间影响较小

– **AFRLS参数估计** $[R_0,R_p,C_p]=[-\theta_2,\frac{\theta_1\theta_2+\theta_3}{\theta_1-1},\frac{(1-\theta_1)\Delta t}{\ln\theta_1\times(\theta_1\theta_2+\theta_3)}]$

量测方程

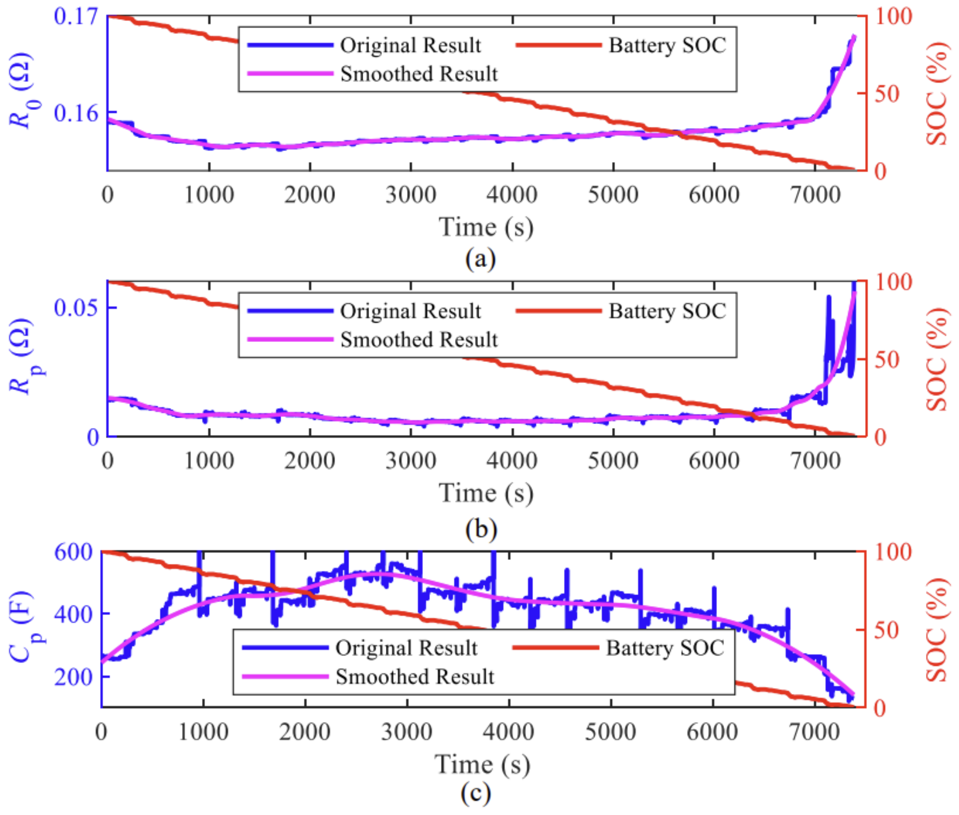
$$y_k=H_k\theta+v_k$$
$$\theta=\text{constant}$$
$$E(v_k)=0$$
$$E(v_k v_i^{\mathrm{T}})=R_k\delta_{k-i}$$

更新模型增益

$$\hat{\theta}_0=E(\theta)$$
$$P_0=E[(\theta-\hat{\theta}_0)(\theta-\hat{\theta}_0)^{\mathrm{T}}]$$
$$K_k=P_{k-1}H_k^{\mathrm{T}}(\lambda_k+H_kP_{k-1}H_k^{\mathrm{T}})^{-1}$$

回归系数与协方差更新

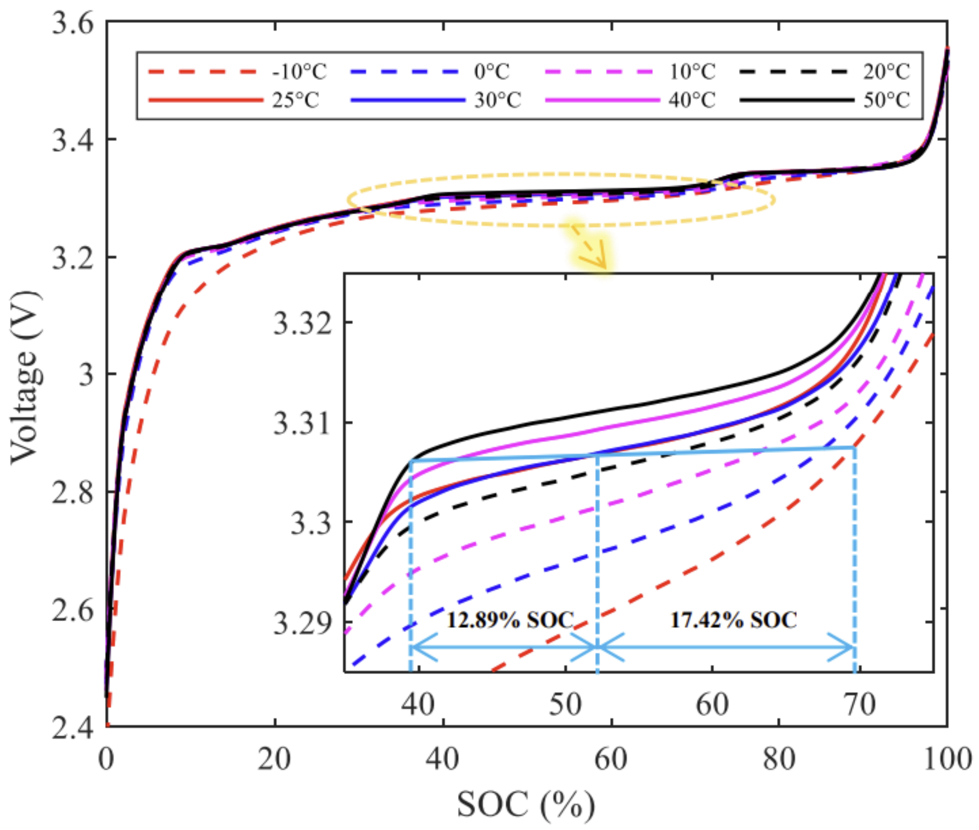
$$\theta_k=\theta_{k-1}+K_k(y_k-H_k\theta_{k-1})$$
$$P_k=\frac{1}{\lambda_k}(I-K_kH_k)P_{k-1}$$



电池阻抗随放电过程先变小后增大
放电末期传递阻抗和极化效应明显加剧

可信灵活性量测——荷电状态估计

- ◆ 传统滤波器模型依赖于固定工况下**精确OCV-SoC曲线**。
- ◆ LiFePO4具有**宽平台区**，不同工况(温度、老化、SoC)下特性**差异巨大**。

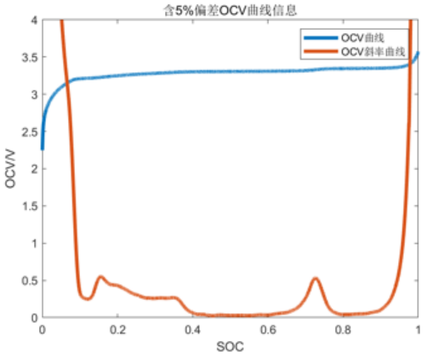


滤波器模型建立

$$x_k = F_{k-1}x_{k-1} + G_{k-1}u_{k-1} + w_{k-1}$$
$$y_k = h_k(x_k) + D_k u_k + v_k$$

求解

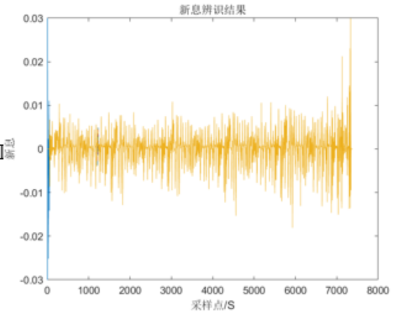
$$\hat{x}_k^+ = \hat{x}_k^- + K_k(y_k - h_k(\hat{x}_k^-) - D_k u_k)$$
$$P_k^+ = (I - K_k H_k)P_k^-$$



OCV曲线误差对滤波器性能影响定量分析

新息是唯一观测可分析量

$$\tilde{r}_k = \tilde{H}_k \varepsilon_k + v_k + g_k(x_k)$$
$$E(\tilde{r}_k \tilde{r}_i^{\mathrm{T}}) = \tilde{H}_k E(\varepsilon_k) g_i(x_i)^{\mathrm{T}} + g_k(x_k) E(\varepsilon_i^{\mathrm{T}}) \tilde{H}_i^{\mathrm{T}} + g_k(x_k) g_i(x_i)^{\mathrm{T}}$$
$$E(\tilde{r}_k \tilde{r}_k^{\mathrm{T}}) = \tilde{H}_k P_k^- \tilde{H}_k^{\mathrm{T}} + \tilde{H}_k E(\varepsilon_k) g_k(x_k)^{\mathrm{T}} + g_k(x_k) E(\varepsilon_k^{\mathrm{T}}) \tilde{H}_k^{\mathrm{T}} + R_k$$



- 新息的互相关矩阵与自相关矩阵联合表征当前量测模型与真实量测方程的误差g(x)。当参考曲线与当前工况下OCV-SOC曲线误差为零时，滤波器的先验/后验估计值都应是无偏的，并且新息应当是零均值的白噪声。

可信灵活性量测——荷电状态估计

◆ **根据参考OCV-SoC曲线和量测电压设置多个梯度方向的卡尔曼滤波器，根据滤波器新息变化更新各滤波器模型的后验概率，通过贝叶斯估计确定最优（概率最大）滤波器。**

各滤波器设定下的端电压的理论输出值

$$\hat{y}_{kj} = H_m^j \hat{x}_{kj}^- + [h_k^j(\hat{x}_0^+) - H_m^j \hat{x}_0^+] + D_k u_k + v_k$$

理论输出值对应的概率密度

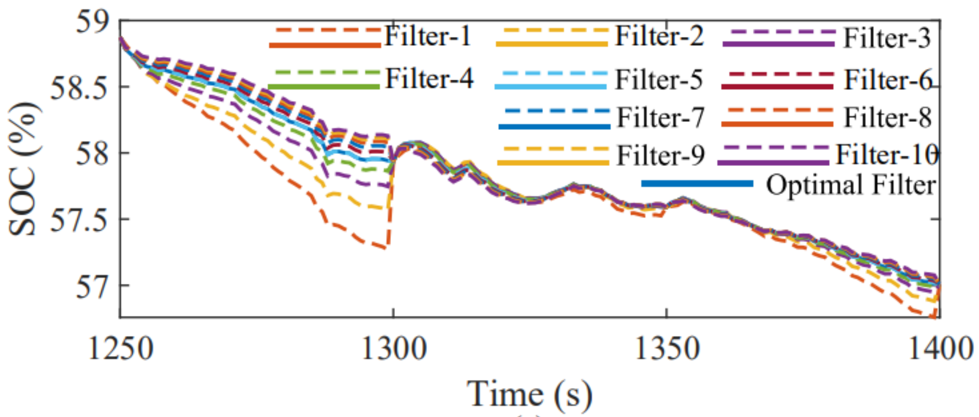
$$\mathrm{pdf}(\hat{y}_{kj} = y_k | H_m^j) = \frac{1}{\sqrt{2\pi} S_k^{1/2}} \exp\left(-\frac{(y_k - E(\hat{y}_{kj}))^2}{2S_k}\right)$$

各滤波器真实概率更新

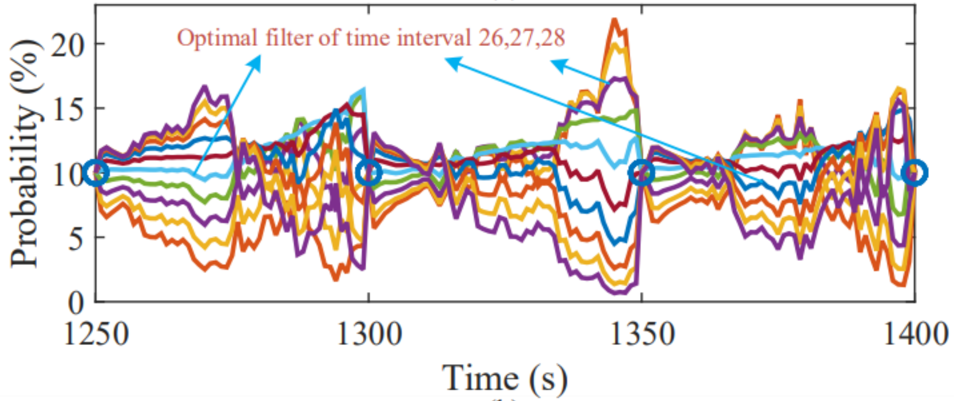
$$\Pr(H_m^j | y_k) = \frac{\mathrm{pdf}(\hat{y}_{kj} = y_k | H_m^j)\Pr(H_m^j | y_{k-1})}{\sum_{i=1}^{n} \mathrm{pdf}(\hat{y}_{ki} = y_k | H_m^i)\Pr(H_m^i | y_{k-1})}$$

$$H_m = \operatorname{argmax}_{H_m^j} \Pr(H_m^j | y_k)$$

- □ 计算量较小，计算效率高，适用于**在线估计**。
- □ 动态调整参考OCV-SoC以及SoC量测误差，适用于**变工况运行**。
- □ 提供可信SoC参考，适用于**SoC可信灵活性评估**。
- □ 提供了SoC置信区间，适用于**鲁棒调度控制**。



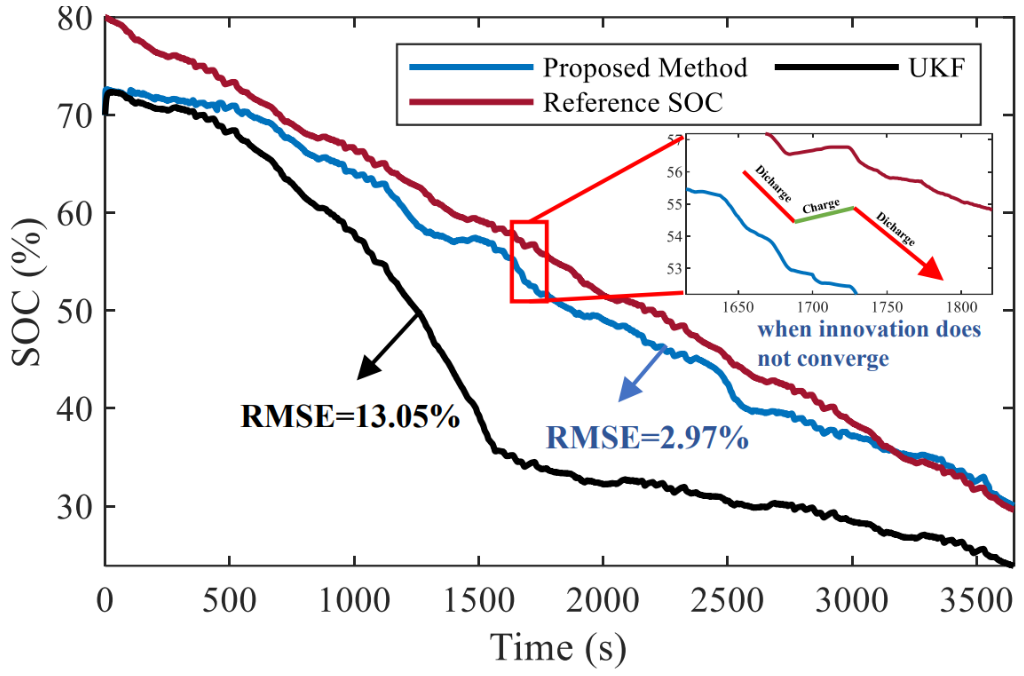
(a)

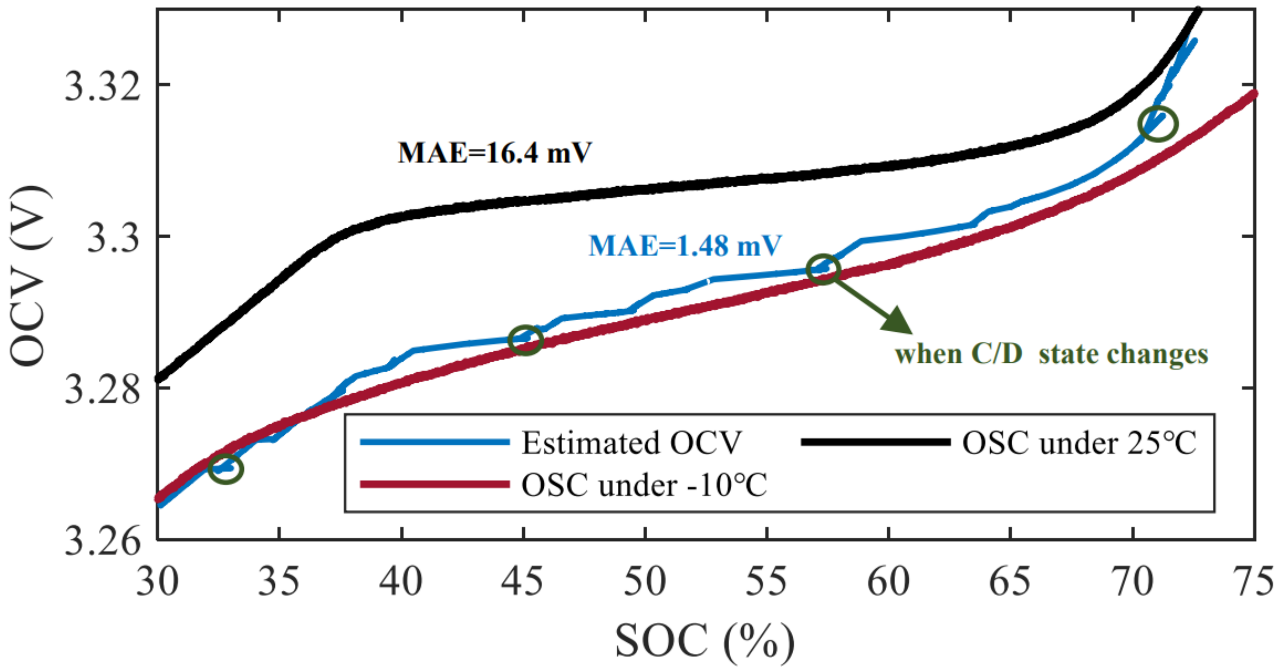


(b)

可信灵活性量测——荷电状态估计

◆ **对比实验：初始SOC偏差-10%；US06，-10℃工况；参考25℃曲线。**





- ◻ 算法精度：曲线带有误差时，所提方法全放电区间**RMSE 2.97%**，**无迹卡尔曼滤波(UKF)为13.05%。**
- ◻ OCV-SOC曲线矫正效果：25°C初始曲线**MAE=16.4mV**，矫正曲线偏差**MAE=1.48mV。**

可信灵活性量测——荷电状态估计

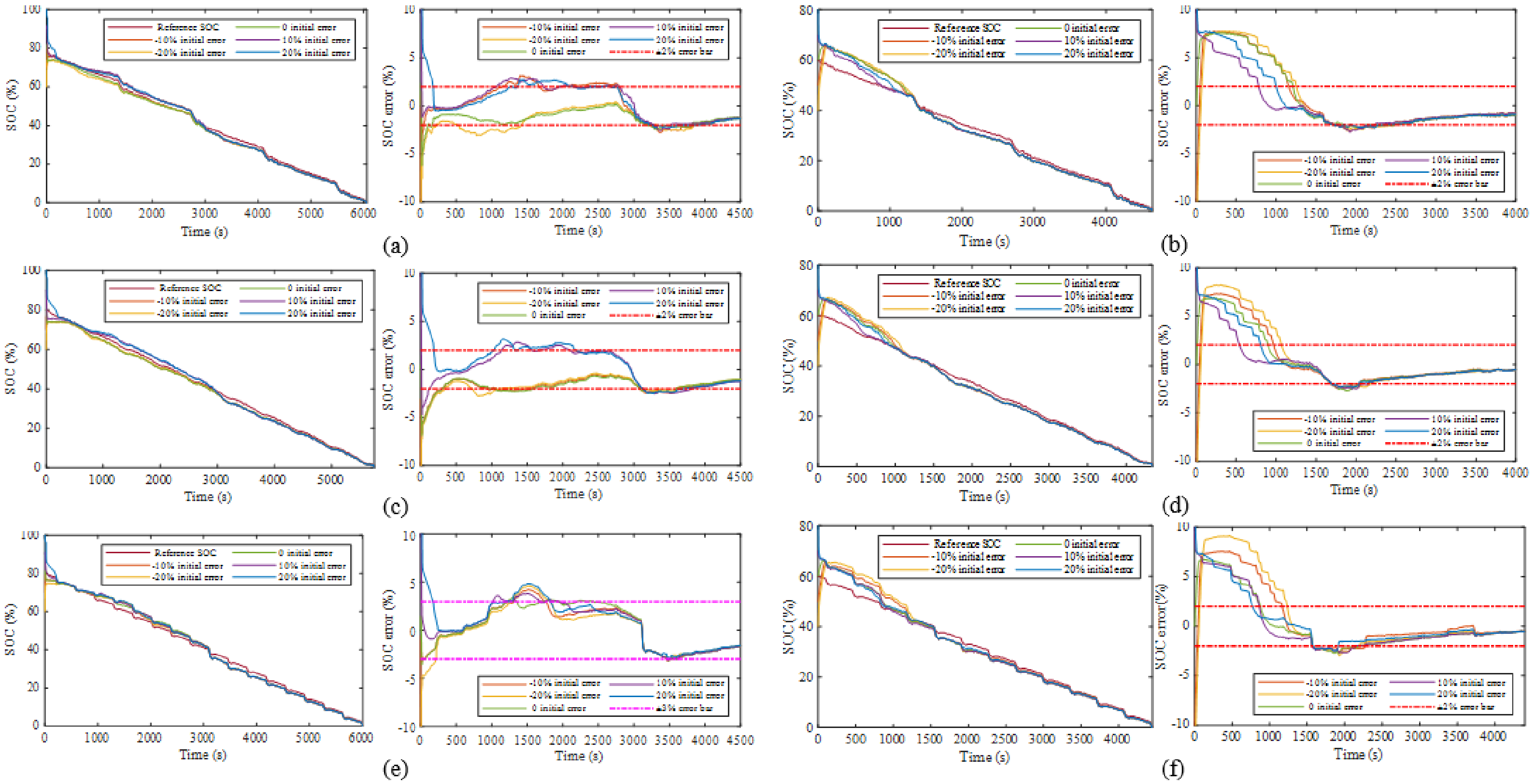
- **高温工况**算法精度/鲁棒性/收敛速度性能测试，US06/FUDS/DST工况，不同初始估计偏差。
- 初始SOC偏差-20%~20%，极化电压误差-100%。

平台区外启动　　平台区内启动

FUDS

US06

DST



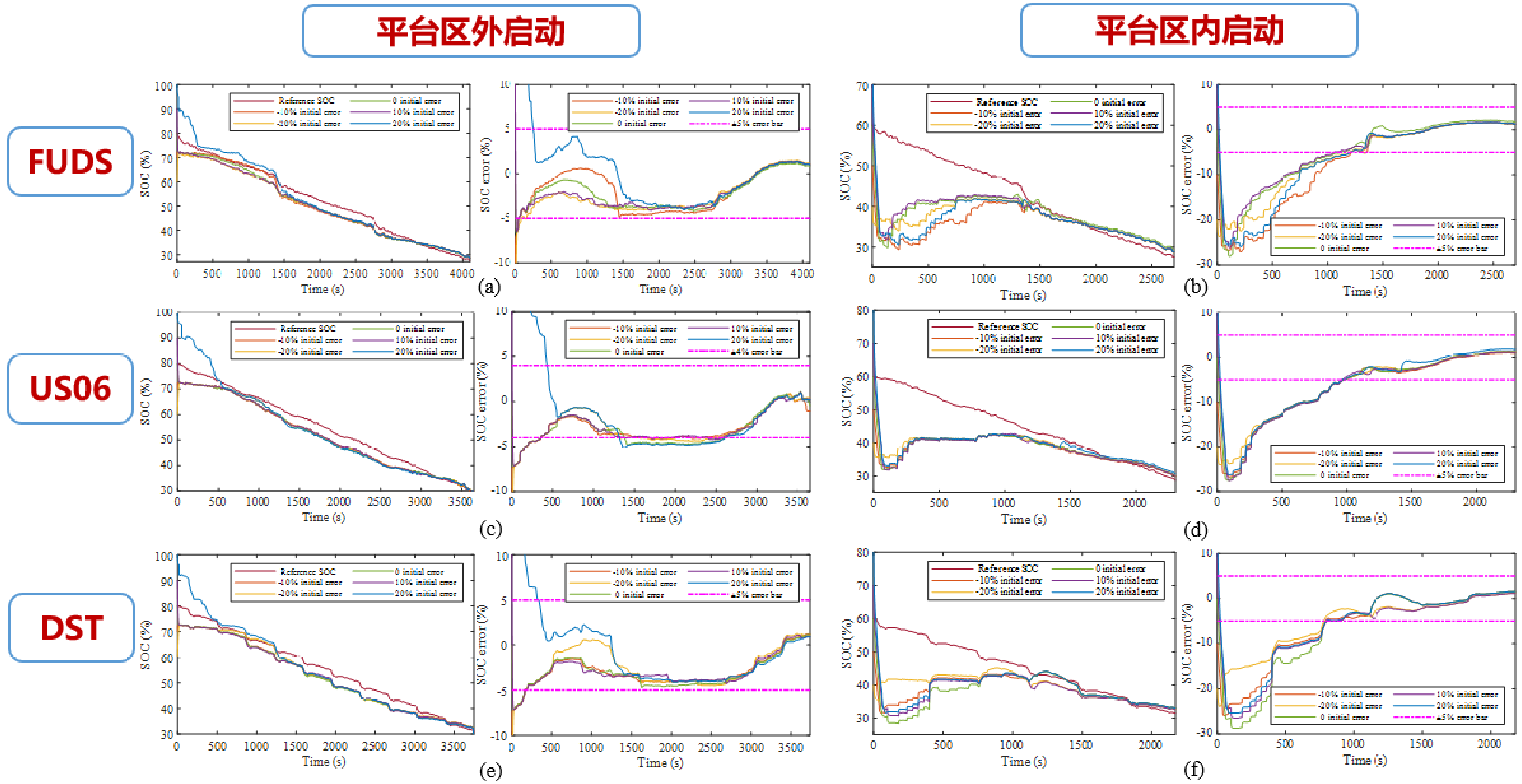
DST(Dynamic Stress Test)
FUDS(Federal Urban Driving Schedule)
US06(Supplemental Federal Test Procedure)

- **算法收敛性与泛化能力：**三种工况以及不同初始SOC误差下均能较快矫正到5%误差以内。
- **后期矫正效果：**经过平台区后SOC估计误差减小并收敛到2%以内。
- **平台区性能：**60%初始SOC条件下，需要更长时间才能实现SOC误差收敛。

可信灵活性量测——荷电状态估计

◆ 低温工况算法精度/鲁棒性/收敛速度性能测试，US06/FUDS/DST工况，不同初始估计偏差。

◆ 初始SOC偏差-20%~20%，极化电压误差-100%。



DST(Dynamic Stress Test)
FUDS(Federal Urban Driving Schedule)
US06(Supplemental Federal Test Procedure)

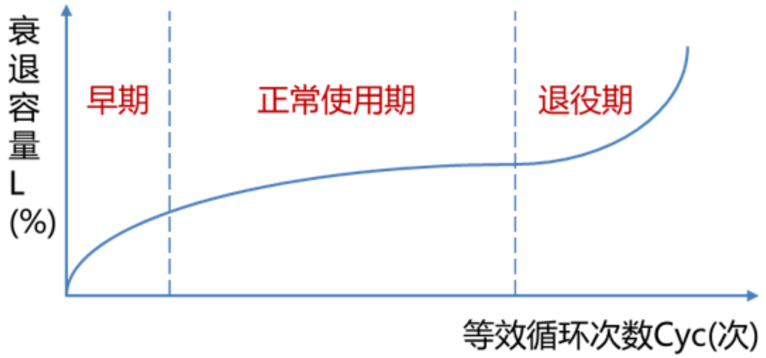
- **算法收敛性与泛化能力：**对初始SOC偏差有较强的鲁棒性，但SOC估计结果需要更长时间收敛。
- **后期矫正效果：**经过平台区后SOC估计误差减小并收敛到2%以内。
- **平台区性能：**60%初始SOC条件下，需要较长时间才能实现SOC误差收敛。

可信灵活性量测——健康状态估计

- ◆ 电动汽车调控需要考虑**电池老化过程**。
- ◆ 电池老化过程受SoC影响较大，精确的SoC估计有利于提升**健康状态(SoH)估计**。
- ◆ SoC/SoH估计隶属于BMS系统，亟需实现**BMS和EMS耦合协同**。

– 状态相依的全寿命周期电池单体SOH模型

$$\begin{cases} L_{c} = 1-\alpha_{sei}e^{-d_{sei}} - \alpha_{sds}e^{-d_{sds}} - \left(1-\alpha_{sei}-\alpha_{sds}\right)\left(1-\kappa e^{d_{cps}}\right) \\ SOH = 1-L_{c} \end{cases}$$

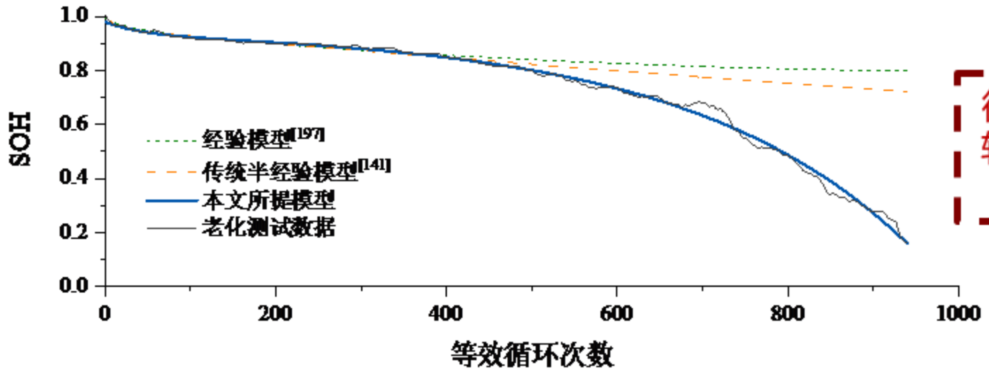


– 分析不同工况对稳态衰退率影响

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

日历老化：电池随时间推移的内在退化，与**放置时间、电池单体温度、平均SOC**

循环老化：充放电循环造成的寿命衰减，与**循环的放电深度、平均SOC、平均温度**



循环老化数据：较好拟合出80%后的衰退状况

目录

可信灵活性预测——电动汽车负荷预测

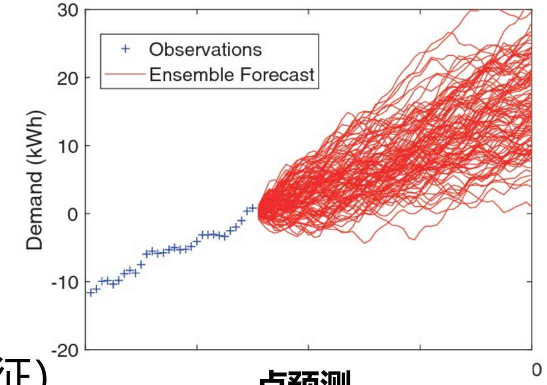
◆ 经典方法并不适用于**小规模、强波动**的电动汽车负荷预测。

◆ 现有方法对**复杂时空耦合**特征提取不足。

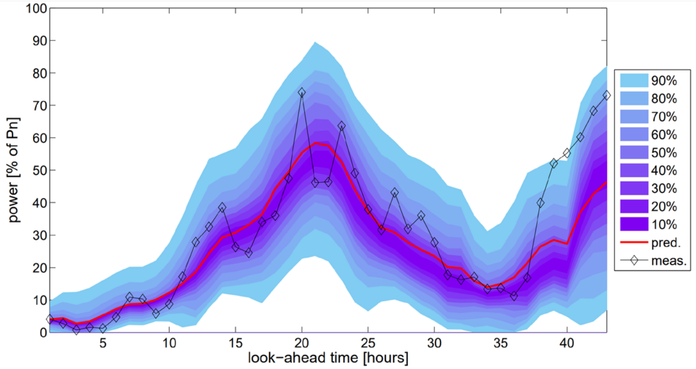
预测形式

- ➢ 超短期预测
- ➢ 短期预测
- ➢ 长期预测

- 直接预测
- 间接预测（先预测其重要特征）

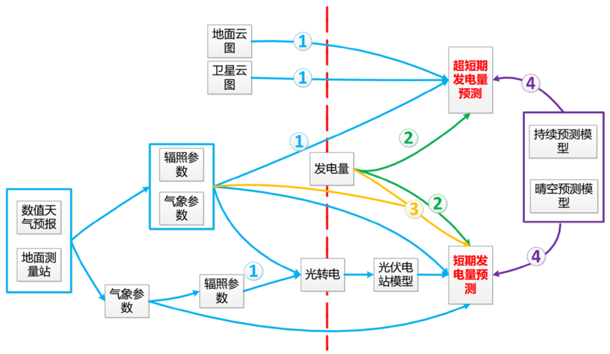


点预测

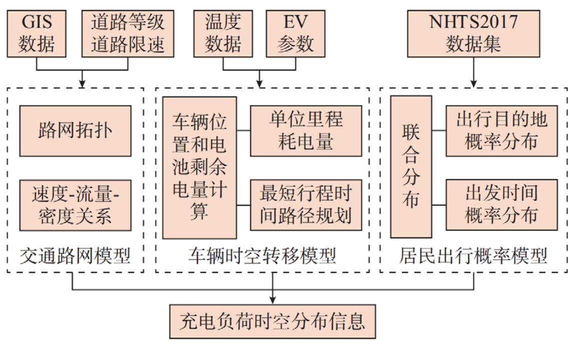


概率预测

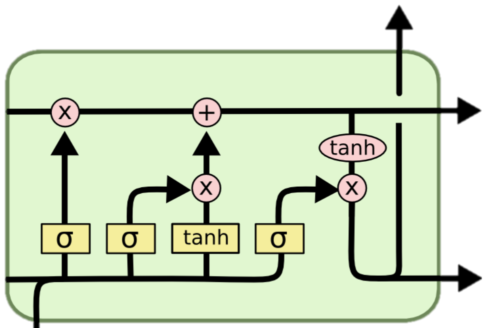
预测方法



物理模型（基于气象数据的光伏功率预测）



物理模型（基于出行模型的EV充电功率预测）

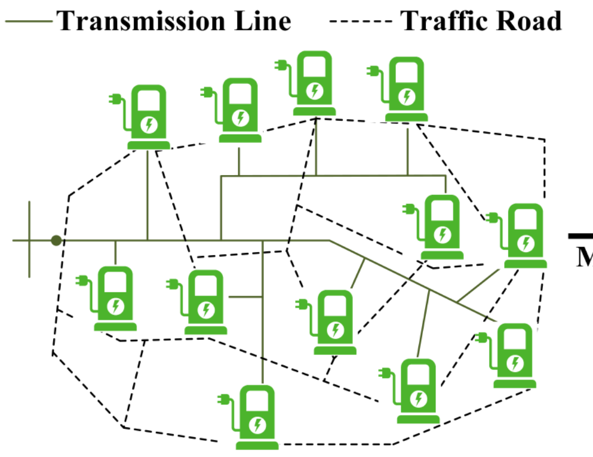


机器学习模型（LSTM网络）

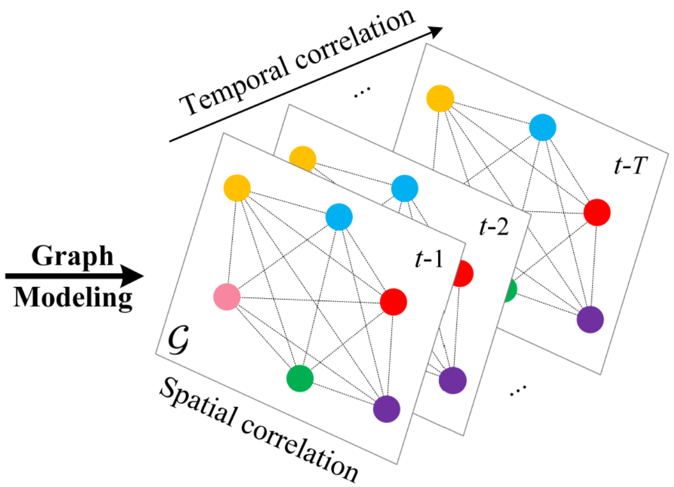
◆ 提出基于**自适应时空图卷积神经网络**的电动汽车负荷概率预测方法。

□ 分析交通-电力网络间、电动汽车负荷的**时空耦合特性**，构建**时空图结构(输入层)**。

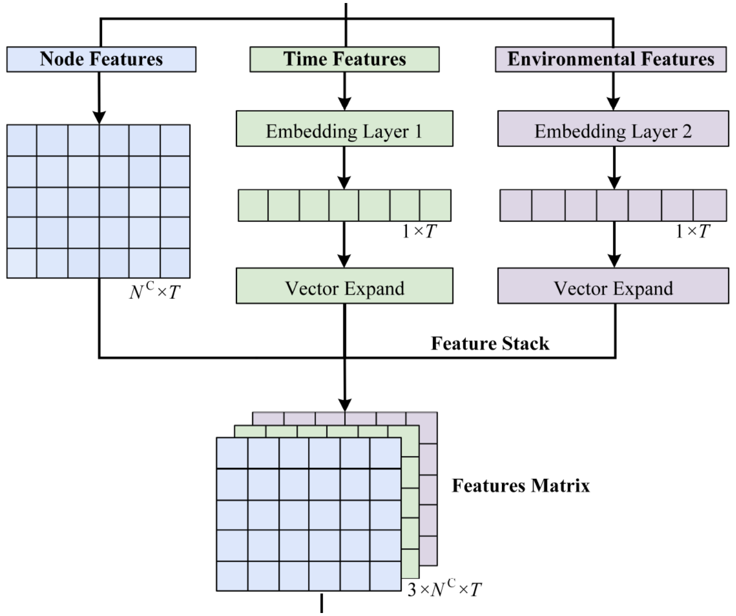
✓ 提供物理知识指导，提升机器学习模型的准确性、可解释性和泛化能力。



Multiple Charging Stations in Coupled Power and Transportation Network



Spatio-Temporal Graph Structure



节点特征：功率值、拓扑链接
时间特征：时段和星期几
环境特征：天气条件（温度、降水）

Y. Zhuang*, L. Cheng, **N. Qi**, X. Wang, Y. Chen. Real-time Hosting Capacity Assessment for Electric Vehicles: A Sequential Forecast-then-Optimize Method. *Applied Energy*. 2024.

可信灵活性预测——电动汽车负荷预测

◆ 提出基于**自适应时空图卷积神经网络**的电动汽车负荷概率预测方法。

自适应空间耦合特征挖掘：

- **时不变因素：**充电站的地理位置、交通网络的拓扑结构、充电设施的固有

$$\boldsymbol{W}^{\mathrm{TI}} = Relu(Softmax((\boldsymbol{E}\boldsymbol{E}^{T})))$$

- **时变因素：**实时交通流量、天气条件、电动汽车运行状态、充电设施在任何给定时刻的即时可用性

$$d^{\mathrm{M}}(\boldsymbol{P}_i,\boldsymbol{P}_j)=\sqrt{(\boldsymbol{P}_i-\boldsymbol{P}_j)\boldsymbol{M}\boldsymbol{M}^{\mathrm{T}}(\boldsymbol{P}_i-\boldsymbol{P}_j)^{\mathrm{T}}} \quad \boldsymbol{W}^{\mathrm{TV}}=\left\{W_{ij}^{\mathrm{TV}} \,\middle|\, W_{ij}^{\mathrm{TV}}=\frac{\exp\left(-d^{\mathrm{M}}(\boldsymbol{P}_i,\boldsymbol{P}_j)/(2\sigma^2)\right)}{\sum_{k\in\mathcal{V}}\exp\left(-d^{\mathrm{M}}(\boldsymbol{P}_i,\boldsymbol{P}_k)/(2\sigma^2)\right)}, i,j\in\mathcal{V}\right\}$$

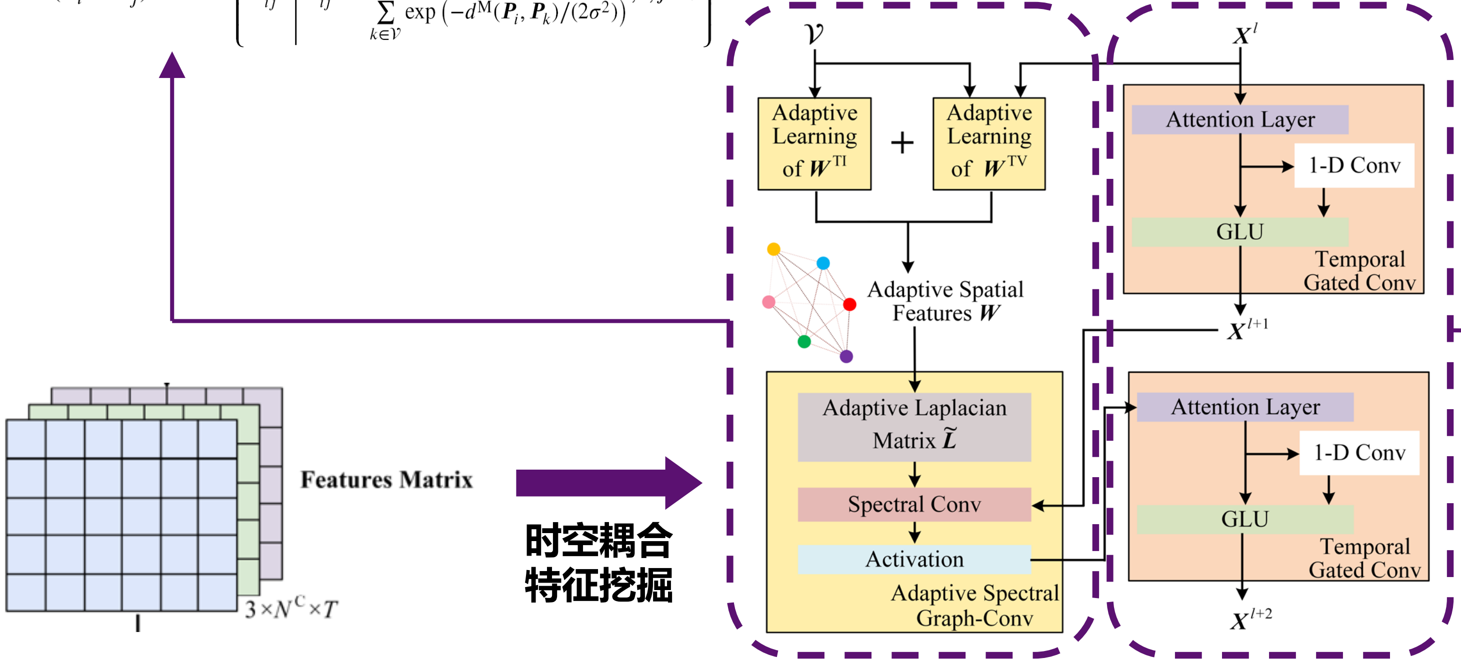
带注意力机制的时间耦合特征挖掘：

- **时间注意力机制：**通过分配权重来捕捉时间段的不同重要性，确保模型专注于最能说明未来趋势的时期

$$\boldsymbol{A}_{\mathrm{tt}}=\mathrm{softmax}\left(\frac{\boldsymbol{Q}\boldsymbol{K}^{T}}{\sqrt{d_k}}\right)\boldsymbol{V}$$

- **门控卷积神经网络：**保持计算精度，同时降低复杂度

$$\boldsymbol{X}^{\mathrm{out}}=(\boldsymbol{X}^{\mathrm{in}}*\boldsymbol{B}+\boldsymbol{b})\odot\psi(\boldsymbol{X}^{\mathrm{in}}*\boldsymbol{C}+\boldsymbol{c})$$

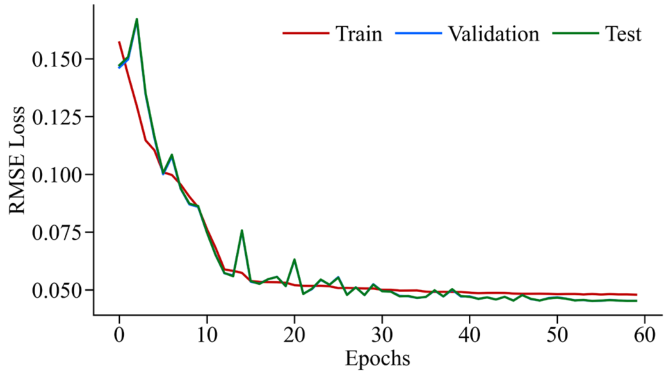


Y. Zhuang*, L. Cheng, **N. Qi**, X. Wang, Y. Chen. Real-time Hosting Capacity Assessment for Electric Vehicles: A Sequential Forecast-then-Optimize Method. *Applied Energy*. 2024.

可信灵活性预测——电动汽车负荷预测

◆ 确定性预测结果：**收敛性强、预测精度高、鲁棒性强。**

◆ **自适应图模块、时间注意力机制、二阶池化层**有效提升模型预测精度。

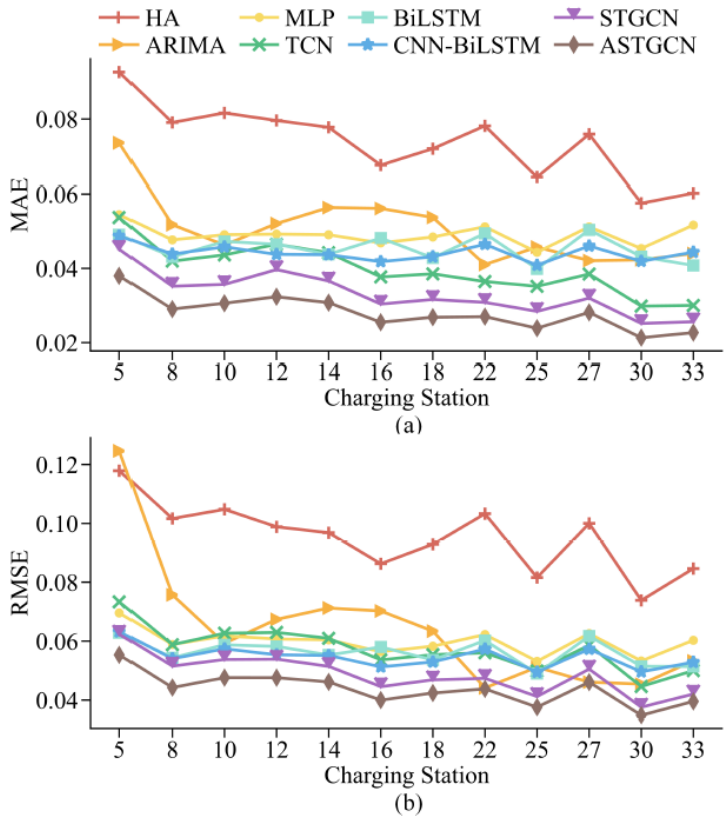


训练过程的loss损失

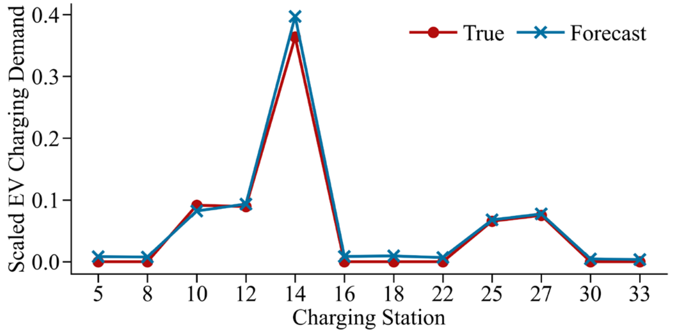
Performance comparison of deterministic forecasting models.

Type	Model	MAE	WAPE (%)	RMSE
Statistical Models	HA	0.0739	62.57	0.0959
	ARIMA	0.0647	110.73	0.0783
Deep Learning Models	MLP	0.0491	42.05	0.0600
	TCN	0.0397	34.02	0.0577
	BiLSTM	0.0454	38.89	0.0564
	CNN-BiLSTM	0.0442	37.90	0.0548
	STGCN	0.0330	28.69	0.0486
	ASTGCN	0.0285	24.45	0.0442

已有方法对比



不同充电站预测误差



不同充电站预测结果

Performance comparison of ASTGCN variants.

Model	MAE	WAPE (%)	RMSE
ASTGCNnoWA	0.0338	28.96	0.0477
ASTGCNnoTA	0.0302	25.85	0.0458
ASTGCNfc	0.0290	24.90	0.0449
ASTGCN	0.0285	24.45	0.0442

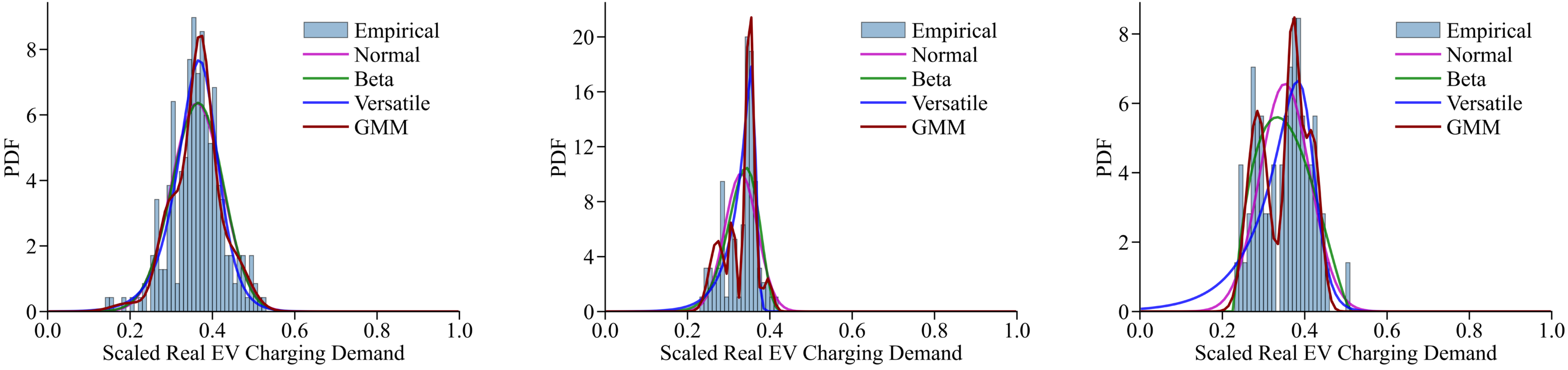
本方法变体对比

可信灵活性预测——电动汽车负荷预测

- **概率预测**=确定性预测+**预测误差概率分布。**
- 高斯混合模型捕捉**多峰、偏斜度**等特征，具有最好拟合结果，适用于**不确定性优化**调度。

高斯混合模型(GMM)：

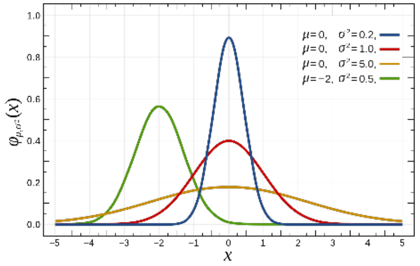
$$\Delta x_i \sim \mathcal{X}_i = \sum_{\mathbf{k}} \left(\left(\prod_{s=1}^{|S|} \pi_{sk_s}^{(j_s)} \right) \mathcal{N}\left(\sum_{s=1}^{|S|} S_{is}\mu_{sk_s}^{(j_s)}, \sqrt{\sum_{s=1}^{|S|} S_{is}^2 (\sigma_{sk_s}^{(j_s)})^2} \right) \right)$$



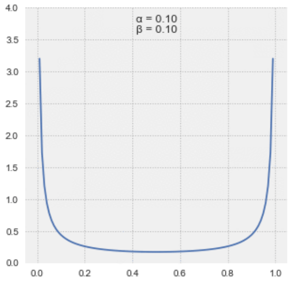
(a) Station 5 (b) Station 14 (c) Station 27

可信灵活性预测——电动汽车负荷预测

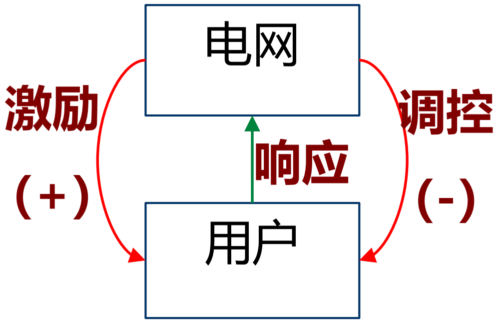
◆ 非决策依赖不确定性(DIU)预测→决策依赖不确定性(DDU)预测。



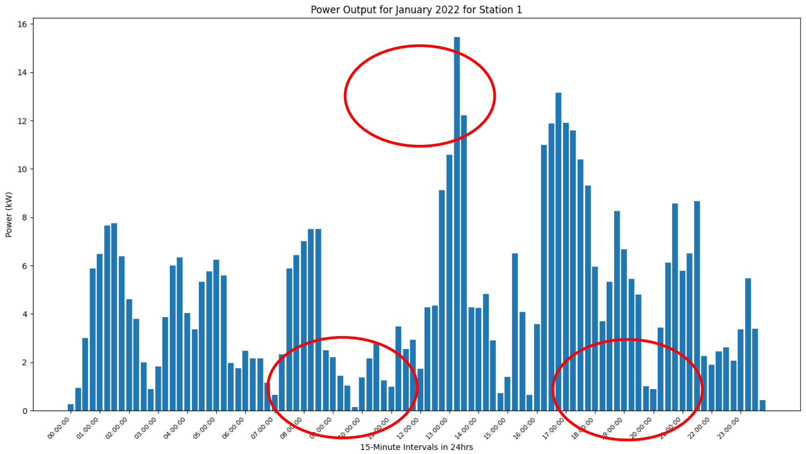
DIU (静态)



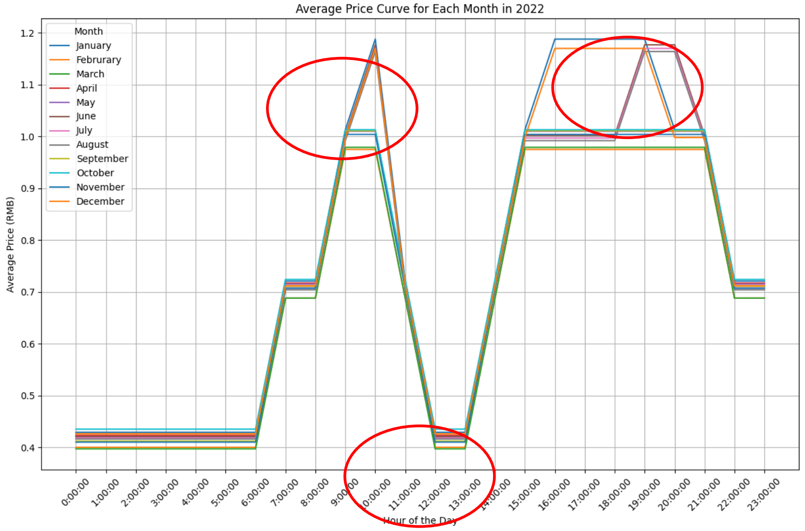
DDU (动态)



需求响应意愿



电动汽车负荷
(不确定性)



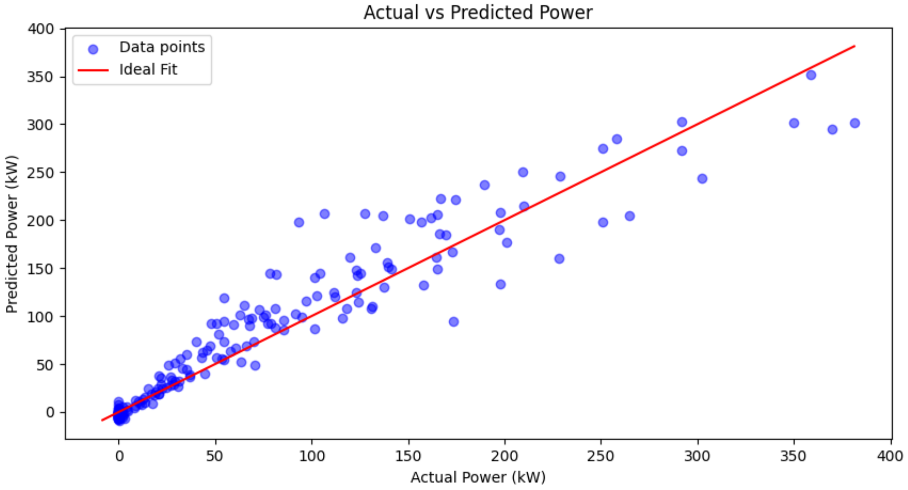
电价
(需求响应决策)

可信灵活性预测——电动汽车负荷预测

- ◆ 构建决策变量与不确定性之间的**显式关系**，而不是仅仅将决策变量作为预测输入信息。
- ◆ 构建未来功率与历史功率、历史电价与未来电价的**线性DDU模型**，通过LASSO实现回归预测。
- ◆ 通过**价格激励**调整电动汽车充电行为，进一步通过不确定性优化确定**最优电价**。

DDU模型

$$P[t]=a_0+a_1t+a_2t^2+a_3t^3+b_0Y[t]+b_1(Y[t+1]-Y[t])+b_2(Y[t+2]-Y[t])+b_3(Y[t+3]-Y[t])+b_4(Y[t+4]-Y[t])+b_5(Y[t]-Y[t-1])+b_6(Y[t]-Y[t-2])+b_7(Y[t]-Y[t-3])+b_8(Y[t]-Y[t-4])+c_1(P[t+1]-P[t])+c_2(P[t+2]-P[t])+c_3(P[t+3]-P[t])+c_4(P[t+4]-P[t])+d_1\sin(2\pi t/24)+d_2\sin(4\pi t/24)+d_3\cos(2\pi t/24)+d_4\cos(4\pi t/24)$$



Feature	Coefficient
Y[t] - Y[t-1]	4.158214
Y[t+3] - Y[t]	1.715470
Y[t] - Y[t-3]	0.507904
Y[t+2] - Y[t]	-0.526777
P[t+2] - P[t]	-15.137127
P[t+3] - P[t]	-18.805607
P[t+1] - P[t]	-19.591318
P[t+4] - P[t]	-21.454651

LASSO回归预测

$$\min_{\beta_0,\beta}\left\{\sum_{i=1}^{N}\left(y_i-\beta_0-x_i^T\beta\right)^2\right\} \text{ subject to } \sum_{j=1}^{p}|\beta_j|\le t.$$

RMSE: 26.58
R-squared: 0.90

目录

可信灵活性调控——可信灵活性模型

◆ 考虑**用户用能需求**与**运行控制策略**的影响，提出考虑决策依赖不确定性的广义储能模型，统一刻画储能、温控负荷和电动汽车的**可信灵活性**。

模型

广义储能运行约束

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

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

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

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

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

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

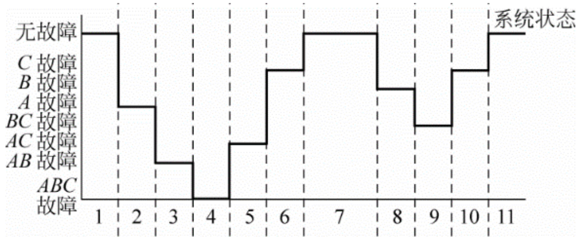
特点：

（1）动态时变

（2）基线用能

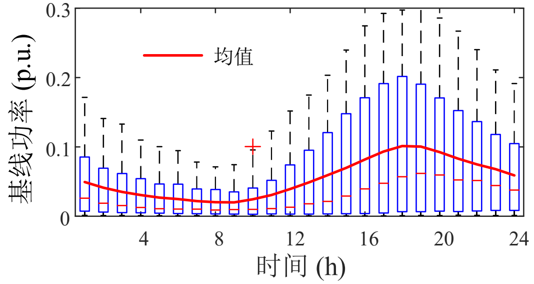
非决策依赖不确定性

运行状态 $f(\omega_t^{VES}) = \begin{cases} p_t^{VES} & \omega_t = 1 \\ 1 - p_t^{VES} & \omega_t = 0 \end{cases}$



基线用能： $P_t^{base} \sim \mathcal{LN}(\mu_{P_t^{base}}, \sigma_{P_t^{base}})$

$SoC_t^{base} \sim \mathcal{LN}(\mu_{SoC_t^{base}}, \sigma_{SoC_t^{base}})$



决策依赖不确定性

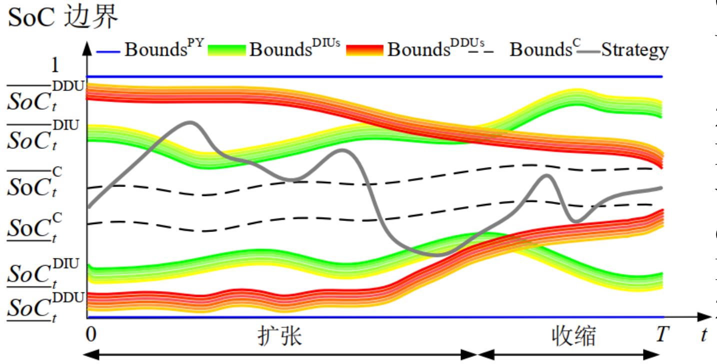
价格激励+　　不舒适度−

可用容量边界： $\overline{SoC}_{i,t}^{DDU} = h\left(g\left(\overline{SoC}_{i,t}^{DIU}, c_{c,i,t}^{S}\right), \beta_i^{U} RD_{i,t}\right)$

不舒适度建模：

$$RD_{i,t} = \begin{cases} \sum_{t}^{\tau=1}\left(P_{c,i,\tau}^{GES}/\overline{P}_{c,i} + P_{d,i,\tau}^{GES}/\overline{P}_{d,i}\right)/T, & i \in EV \\ \lambda\sum_{t}^{\tau=1}\left(P_{c,i,\tau}^{GES}/\overline{P}_{c,i} + P_{d,i,\tau}^{GES}/\overline{P}_{d,i}\right)/T + (1-\lambda)\left|SoC_{i,t}^{GES} - SoC_{i,t}^{B,av}\right|, & i \in TCL \\ \lambda\sum_{t}^{\tau=1}\left(P_{c,i,\tau}^{GES}/\overline{P}_{c,i} + P_{d,i,\tau}^{GES}/\overline{P}_{d,i}\right)/T + (1-\lambda)(SoC_{i,t}^{GES} - SoC_{i,t}^{B,av}), & i \in EV \end{cases}$$

可用容量的动态变化（“+/−”）



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.

可信灵活性调控——机会约束优化

◆ 基于DDU实现方式，提出了三种**机会约束**下模型重述与求解方法：**分布鲁棒优化、数据驱动在线优化和迭代优化**，解决了不确定性与决策变量**耦合**求解难题，实现资源**可信调度响应**。

含DDU的机会约束

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

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

不可预知

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

求解困难

?

不确定性 ξ

模糊信息　　观测数据　　完全分布

分布鲁棒

TABLE I

ROBUST APPROXIMATION OF NORMALIZED INVERSE CUMULATIVE DISTRIBUTION WITH INCOMPLETE INFORMATION

Type & Shape	$F^{-1}(1-\epsilon)$	ϵ
No Distribution Assumption (NA)	$\sqrt{(1-\epsilon)/\epsilon}$	$0<\epsilon\le1$
Symmetric Distribution (S)	$\sqrt{1/2\epsilon}$	$0<\epsilon\le1/2$
	0	$1/2<\epsilon\le1$
Unimodal Distribution (U)	$\sqrt{(4-9\epsilon)/9\epsilon}$	$0<\epsilon\le1/6$
	$\sqrt{(3-3\epsilon)/(1+3\epsilon)}$	$1/6<\epsilon\le1$
Symmetric & Unimodal Distribution (SU)	$\sqrt{2/9\epsilon}$	$0<\epsilon\le1/6$
	$\sqrt{3}(1-2\epsilon)$	$1/6<\epsilon\le1/2$
	0	$1/2<\epsilon\le1$

数据驱动在线优化

$$a_i(\boldsymbol{x})^{\mathrm{T}}\boldsymbol{\mu}(\boldsymbol{x})+\psi_K\boldsymbol{r}(\boldsymbol{x})+\pi_K\overline{F}_{\boldsymbol{x}}^{-1}(1-\epsilon)\|\boldsymbol{y}\|_2\le b_i(\boldsymbol{x})$$

$$\sqrt{a_i(\boldsymbol{x})^{\mathrm{T}}\boldsymbol{\Sigma}a_i(\boldsymbol{x})}\le y_1,\sqrt{2\psi_K\boldsymbol{r}(\boldsymbol{x})}\le y_2$$

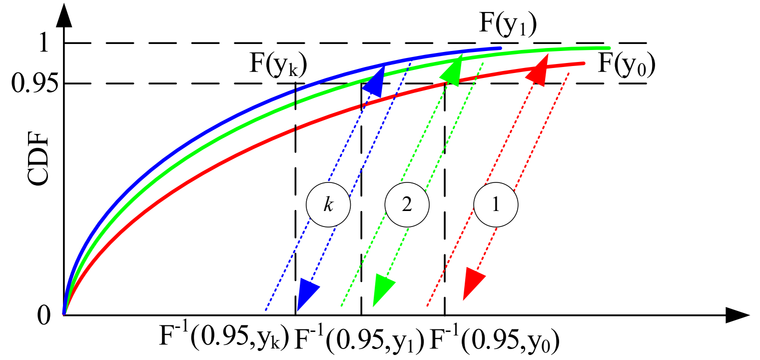
$$\psi_K=K^{(1/p-1/2)}$$

$$\pi_K=\left(1-\frac{4}{\epsilon}\exp\left(-\left(K^{1/p}-2\right)^2/2\right)\right)^{-1/2}$$

K: 观测数据数量

$r(x)$: DDU半径

迭代优化



$$\overline{F}_{\boldsymbol{x}}^{-1}(1-\epsilon)\to\boldsymbol{x}^{(0)}\to\boldsymbol{\xi}\left(\boldsymbol{x}^{(0)}\right)\to F_{\boldsymbol{x}^{(0)}}^{-1}(1-\epsilon)\to\boldsymbol{x}^{(1)}\to\cdots\boldsymbol{x}^{(k)}$$

可信灵活性调控——承载能力评估

- 根据概率预测结果，建立了基于**机会约束优化**的配电网**实时**承载能力评估方法(**运行**)。
- **长期**承载能力评估(**规划**)在配电网末端节点**高估**，在配电网中间节点**低估**。

$$\max \sum_{i\in\Omega^{C}} \int_{0}^{\overline{P}_{i,t}} p_{i,t}\hat{\mathcal{P}}_{i,t}(p_{i,t})\,dp_{i,t}$$

$$V_{j,t}^2 = V_{i,t}^2 - 2(r_{ij}P_{ij,t}^{\mathrm{Ln}} + x_{ij}Q_{ij,t}^{\mathrm{Ln}}) + (r_{ij}^2 + x_{ij}^2)I_{ij,t}^2$$

$$p_{j,t} = P_{ij,t}^{\mathrm{Ln}} - r_{ij}I_{ij,t}^2 - \sum_{l:j\to l} P_{jl,t}^{\mathrm{Ln}}$$

$$q_{j,t} = Q_{ij,t}^{\mathrm{Ln}} - x_{ij}I_{ij,t}^2 - \sum_{l:j\to l} Q_{jl,t}^{\mathrm{Ln}}$$

$$V_{i,t}^2 I_{ij,t}^2 = (P_{ij,t}^{\mathrm{Ln}})^2 + (Q_{ij,t}^{\mathrm{Ln}})^2$$

$$\underline{V} \le V_{i,t} \le \overline{V}$$

$$|I_{ij,t}| \le \overline{I}_{ij}$$

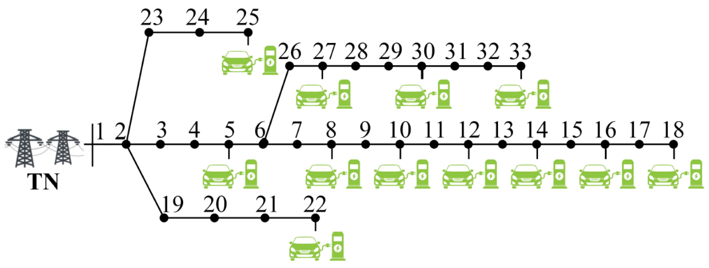
$$p_{i,t} = P_{i,t}^{\mathrm{L}} + \overline{P}_{i,t}, \forall i \in \Omega^{\mathrm{C}}$$

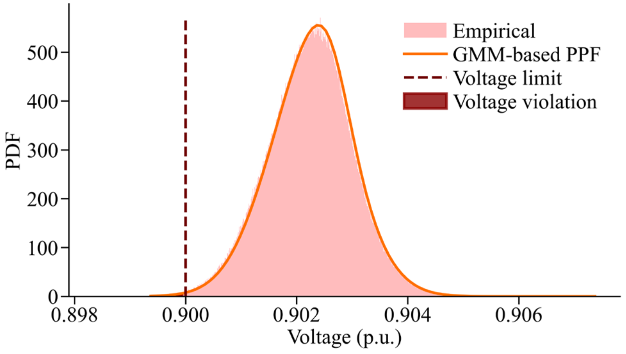
$$p_{i,t} = P_{i,t}^{\mathrm{L}}, \forall i \in \Omega^{\mathrm{L}}/\Omega^{\mathrm{C}}$$

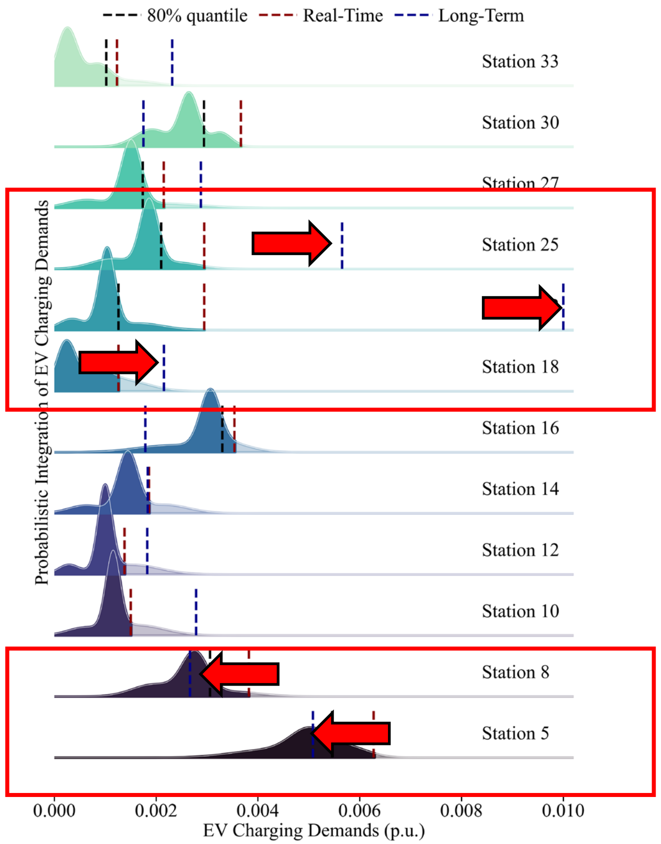
$$q_{i,t} = Q_{i,t}^{\mathrm{L}}$$

$$\hat{\mathcal{P}}_{i,t}(p_{i,t} \le \overline{P}_{i,t}) \ge 1 - \epsilon_i, \forall i \in \Omega^{\mathrm{C}}$$

电动汽车负荷接入期望值







末端节点

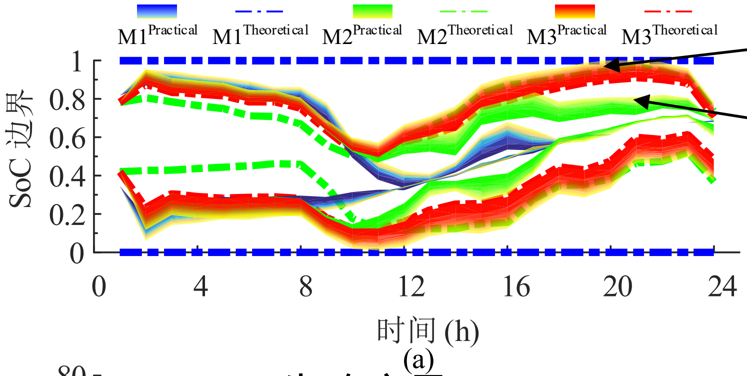
中间节点

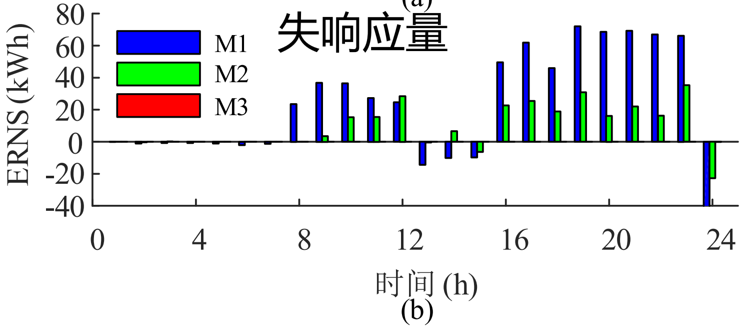
Y. Zhuang*, L. Cheng, **N. Qi**, X. Wang, Y. Chen. Real-time Hosting Capacity Assessment for Electric Vehicles: A Sequential Forecast-then-Optimize Method. *Applied Energy*. 2024.

可信灵活性调控——微电网经济调度

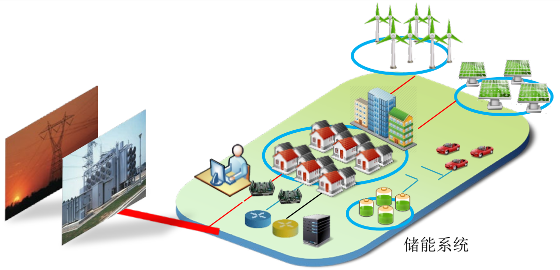
◆ **建立了考虑DDU的微电网机会约束经济调度方法，准确刻画灵活性资源失响应风险，保障灵活性资源可信响应，降低微电网实时运行成本(实时购电、备用、停电)。**

M1：确定性优化；M2：计及DIU优化；M3：计及DDU优化





M1边界收缩严重→完全不响应
M2边界部分收缩→日内失响应
M3边界鲁棒→无失响应



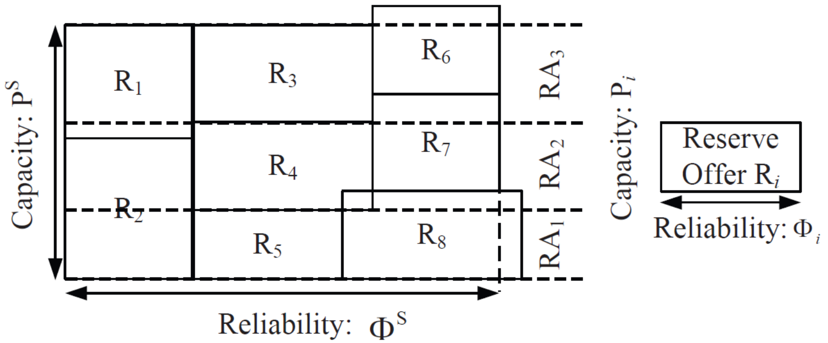
γ	指标	M1	M2	M3
0.05	LORP/ERNS		0.3/12.0	0.0/0.0
	$\text{Cost}^{PC}\text{Cost}^{RT}$	LORP: 0.6	429.2/3156.8	0.0/2799.7
0.25	LORP/ERNS	ERNS: 30.8	0.4/14.0	0.1/3.0
	$\text{Cost}^{PC}\text{Cost}^{RT}$	Cost^{PC}: 1057.9	440.0/2909.0	0.0/2541.9
0.45	LORP/ERNS	Cost^{RT}: 3088.3	0.4/15.2	0.2/3.6
	$\text{Cost}^{PC}\text{Cost}^{RT}$		487.4/2810.4	0.0/2407.7

- 实际SoC边界：M1高估最多，M3差异最小
- 失响应风险：M1最多，M3最少
- 惩罚成本：M1最多，M3几乎为0

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.

可信灵活性调控——概率备用

- 建立**可靠性感知**的概率备用两阶段调度模型，提出**可靠性组合约束**近似方法，保证计算效率。
- **“不确定性”**转化为**“确定性”**，提高系统备用容量，降低系统运行成本。



概率备用

日前：考虑DDU的概率备用调度

协同

日内：考虑可靠性约束的概率备用组合优化

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

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

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

$$\boxed{\Phi^S \le \prod_i \phi_i} \quad (3d)$$

$$\mathrm{P}^S \le \sum_i P_i \quad (3e)$$

$$\sum_i P_{i,j} \le \mathrm{P}_j \quad \forall j\in\Omega_R \quad (3f)$$

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

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

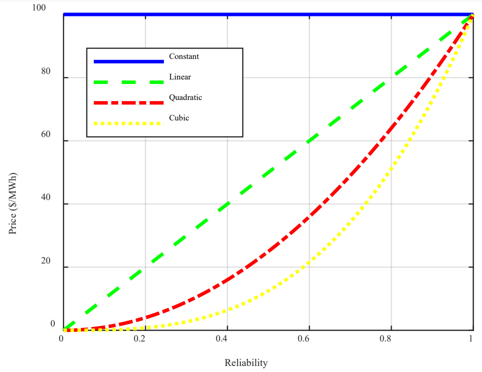
$$P_i \ge \underline{\mathrm{P}}^A \quad \forall i\in\Omega_A \quad (3i)$$

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

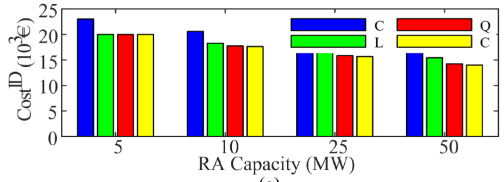
近似方法

$$\ln(1-\phi_i) = \sum_j \ln(1-\Phi_j) z_{i,j}$$

$$\ln(\Phi^S) \le \sum_i \ln(\phi_i) \quad f(x) = \sum_i w_i f(b_i), \quad x = \sum_i w_i b_i$$

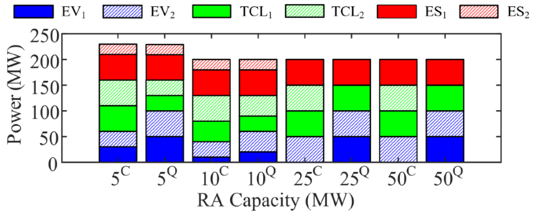


概率备用价格



(a)

系统成本



(b)

备用组合

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

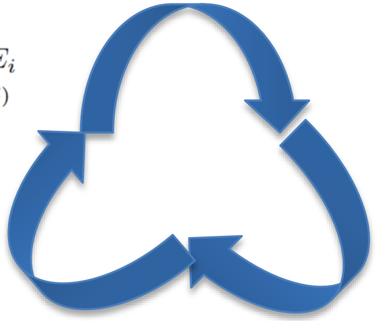
可信灵活性调控——可信容量评估

◆ **提出市场驱动、风险厌恶的再调度方法，刻画灵活性资源能量市场与容量市场交互行为，通过考虑DDU机会约束优化保障灵活性资源的可信响应，提高可信容量评估的准确性。**

① 正常状态：能量市场电价套利

$$\max \sum_{t\in\mathcal{T}_{\mathrm{N}}^{(\delta)}} c_t^{\mathrm{EM}}(P_{\mathrm{d},i,t}^{\mathrm{PD}}-P_{\mathrm{c},i,t}^{\mathrm{PD}})$$

$$\begin{aligned}
\text{s.t.}\quad & \underline{SoC}^{\mathrm{CW}}\le SoC_{i,t}^{\mathrm{PD}},\ \forall t\in\mathcal{T}_{\mathrm{N}}^{(\delta)}\\
& SoC_{i,t+1}^{\mathrm{PD}}=(\eta_{\mathrm{c},i}P_{\mathrm{c},i,t}^{\mathrm{PD}}-P_{\mathrm{d},i,t}^{\mathrm{PD}}/\eta_{\mathrm{d},i})\Delta t/E_i\\
&\qquad +(1-\varepsilon_i\Delta t)SoC_{i,t}^{\mathrm{PD}},\ \forall t\in\mathcal{T}_{\mathrm{N}}^{(\delta)}\\
& \underline{SoC}_{i,t}\le SoC_{i,t}^{\mathrm{PD}}\le\overline{SoC}_{i,t},\ \forall t\in\mathcal{T}_{\mathrm{N}}^{(\delta)}\\
& SoC_{i,T}^{\mathrm{PD}}=SoC_{i,0}^{\mathrm{PD}},\ \forall t\in\mathcal{T}_{\mathrm{N}}^{(\delta)}\\
& 0\le P_{\mathrm{c},i,t}^{\mathrm{PD}}\le S_{\mathrm{c},i,t}\overline{P}_{\mathrm{c},i,t},\ \forall t\in\mathcal{T}_{\mathrm{N}}^{(\delta)}\\
& 0\le P_{\mathrm{d},i,t}^{\mathrm{PD}}\le S_{\mathrm{d},i,t}\overline{P}_{\mathrm{d},i,t},\ \forall t\in\mathcal{T}_{\mathrm{N}}^{(\delta)}\\
& 0\le S_{\mathrm{c},i,t}^{\mathrm{PD}}+S_{\mathrm{d},i,t}^{\mathrm{PD}}\le 1,\ \forall t\in\mathcal{T}_{\mathrm{N}}^{(\delta)}
\end{aligned}$$



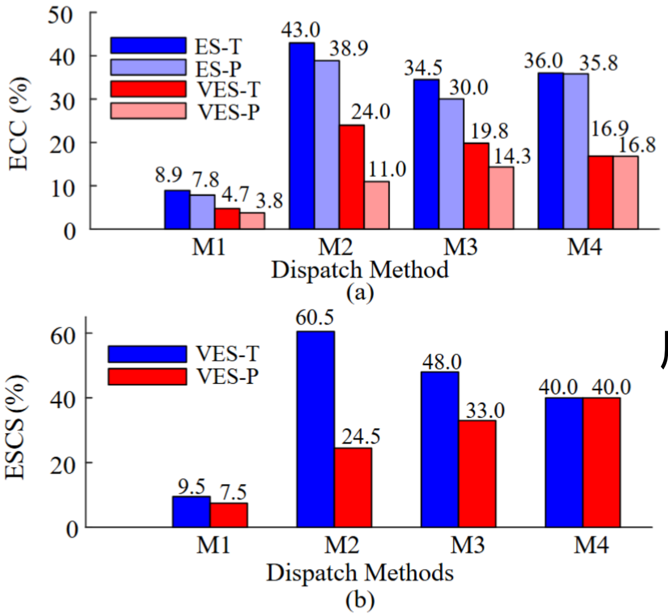
② 紧急状态：容量市场充裕支撑

$$\min \sum_{t\in\mathcal{T}_{\mathrm{E}}^{(k)}}\sum_{i\in\mathcal{B}} P_{i,t}^{\mathrm{LC}}$$

$$\begin{aligned}
\text{s.t.}\ & NC_{i,t}+P_{i,t}^{\mathrm{LC}}+P_{\mathrm{d},i,t}^{\mathrm{RD}}-P_{\mathrm{c},i,t}^{\mathrm{RD}}=0,\ \forall t\in\mathcal{T}_{\mathrm{E}}^{(k)},\ \forall i\in\mathcal{B}\\
& 0\le P_{i,t}^{\mathrm{LC}}\le P_{i,t}^{\mathrm{LD}},\ \forall t\in\mathcal{T}_{\mathrm{E}}^{(k)},\ \forall i\in\mathcal{B}\\
& 0\le P_{\mathrm{c},i,t}^{\mathrm{RD}}\le S_{\mathrm{c},i,t}^{\mathrm{RD}}\overline{P}_{\mathrm{c},i,t},\ \forall t\in\mathcal{T}_{\mathrm{E}}^{(k)},\ \forall i\in\mathcal{B}\\
& 0\le P_{\mathrm{d},i,t}^{\mathrm{RD}}\le S_{\mathrm{d},i,t}^{\mathrm{RD}}\overline{P}_{\mathrm{d},i,t},\ \forall t\in\mathcal{T}_{\mathrm{E}}^{(k)},\ \forall i\in\mathcal{B}\\
& 0\le S_{\mathrm{c},i,t}^{\mathrm{RD}}+S_{\mathrm{d},i,t}^{\mathrm{RD}}\le 1,\ \forall t\in\mathcal{T}_{\mathrm{E}}^{(k)},\ \forall i\in\mathcal{B}\\
& SoC_{i,t+1}^{\mathrm{RD}}=(\eta_{\mathrm{c},i}P_{\mathrm{c},i,t}^{\mathrm{RD}}-P_{\mathrm{d},i,t}^{\mathrm{RD}}/\eta_{\mathrm{d},i})\Delta t/E_i\\
&\qquad +(1-\varepsilon_i\Delta t)SoC_{i,t}^{\mathrm{RD}},\ \forall t\in\mathcal{T}_{\mathrm{E}}^{(k)},\ \forall i\in\mathcal{B}\\
& SoC_{i,t}^{\mathrm{RD}}=SoC_{i,t}^{\mathrm{PD}},\ t=t_0^{(k)},\ \forall i\in\mathcal{B}\\
& \mathbb{P}(\underline{SoC}_{i,t}^{\mathrm{DDU}}\le SoC_{i,t}^{\mathrm{RD}}\le\overline{SoC}_{i,t}^{\mathrm{DIU}})\ge 1-\epsilon,\ \forall t\in\mathcal{T}_{\mathrm{E}}^{(k)},\ \forall i\in\mathcal{B}\\
& \underline{SoC}_{i,t}^{\mathrm{DDU}}=h(g(\underline{SoC}_{i,t}^{\mathrm{DIU}},c^{\mathrm{CM}}),D_{i,t}),\ \forall t\in\mathcal{T}_{\mathrm{E}}^{(k)},\ \forall i\in\mathcal{B}\\
& g=\underline{SoC}_{i,t}^{\mathrm{DIU}}(1-\mathcal{G}(\mu_g,\sigma_g)),\ \forall t\in\mathcal{T}_{\mathrm{E}}^{(k)},\ \forall i\in\mathcal{B}\\
& h=(\underline{SoC}_{i,t}^{\mathrm{B}}-Q_g)\mathcal{H}(\mu_h,\sigma_h)+Q_g,\ \forall t\in\mathcal{T}_{\mathrm{E}}^{(k)},\ \forall i\in\mathcal{B}\\
& \mu_g=\alpha_i c_t^{\mathrm{CM}},\ \mu_h=\beta_i D_{i,t},\ \forall t\in\mathcal{T}_{\mathrm{E}}^{(k)},\ \forall i\in\mathcal{B}\\
& D_{i,t}=\frac{\rho\sum_{\kappa=1}^{k-1}D_{i,t_{\mathrm{e}}^{(\kappa)}}}{k-1}+(1-\rho)\times\{\lambda\sum_{\tau=t_{\mathrm{s}}^{(k)}}^{t}\frac{P_{\mathrm{d},i,\tau}^{\mathrm{RD}}}{\overline{P}_{\mathrm{d},i,\tau}T}\\
&\qquad +(1-\lambda)|SoC_{i,t}^{\mathrm{RD}}-SoC_{i,t}^{\mathrm{B}}|\},\ \forall t\in\mathcal{T}_{\mathrm{E}}^{(k)},\ \forall i\in\mathcal{B}
\end{aligned}$$

③ 恢复状态: 容量恢复继续套利

$$\begin{aligned}
P_{\mathrm{c},i,t}^{\mathrm{RD}}=&\min\{[SoC_{i,t}^{\mathrm{PD}}-(1-\varepsilon_i\Delta t)SoC_{i,t-1}^{\mathrm{RD}}]E_i/(\eta_{\mathrm{c},i}\Delta t)\\
&\overline{P}_{\mathrm{c},i,t},\ \varphi_{i,t}NC_t\},\ \forall t\in\mathcal{T}_{\mathrm{R}}^{(k)},\ \forall i\in\mathcal{B}\\
P_{\mathrm{d},i,t}^{\mathrm{RD}}=&\min\{[(1-\varepsilon_i\Delta t)SoC_{i,t-1}^{\mathrm{RD}}-SoC_{i,t}^{\mathrm{PD}}]E_i\eta_{\mathrm{d},i}/\Delta t\\
&\overline{P}_{\mathrm{d},i,t}\},\ \forall t\in\mathcal{T}_{\mathrm{R}}^{(k)},\ \forall i\in\mathcal{B}
\end{aligned}$$



M1：固定调度
M2：贪婪调度
M3：市场驱动再调度
M4：市场驱动风险厌恶再调度

M4：理论与实际可信容量**差距最小**
实际可信容量最高、获利最大

N. Qi, P. Pinson, M. R. Almassalkhi, Y. Zhuang, Y. Su, F. Liu*, "Capacity Credit Evaluation of Generalized Energy Storage under Decision-dependent Uncertainty," *IEEE Transactions on Power Systems*, 2024.

目录

总结与展望

- **可信量测与可信预测是实现可信调控的关键与前提：可信灵活性模型。**
- **需要增强量测、预测与调控之间的耦合：BMS&EMS，Decision-Focus Learning。**
- **可信调控不仅需要考虑不确定性，更考虑不确定性与决策的耦合关系(DDU)。**
- **未来需要关注电动汽车等灵活性资源在备用与容量市场的应用。**

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[1] D. Paizulamu*, L. Cheng, Y. Zhuang, H. Xu, **N. Qi**, S. Ci. LiFePO4 Battery SOC Estimation under OCV-SOC Curve Error Based onAdaptive Multi-Model Kalman Filter. *IEEE Transactions on Transportation Electrification*. 2024.

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[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, 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.

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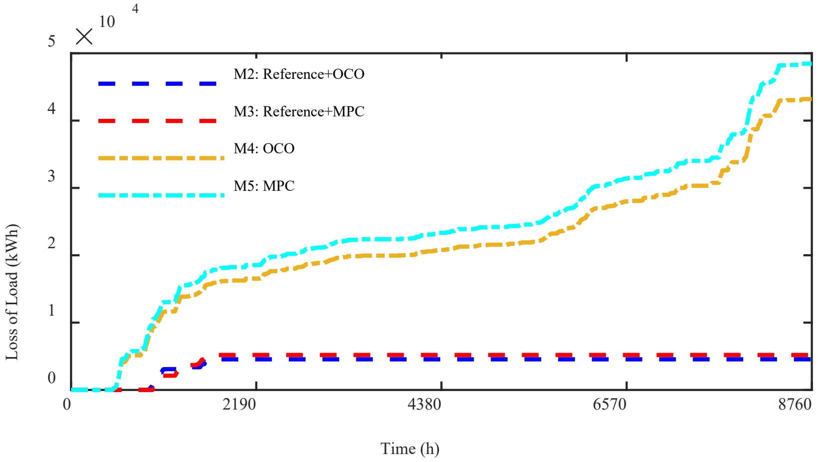
[6] **N. Qi**, L. Cheng, Kaidi Huang, Asad Mujeeb, Feng Liu*, Pierre Pinson, "Reliability-Aware Probabilistic Reserve Procurement under Decision-Dependent Uncertainty," *2024 IEEE PES General Meeting (PESGM),* IEEE, 2024, pp. 1–5. (Best Paper).

总结与展望



×10^4
5
4
3
2
1
0
Loss of Load (kWh)
M2: Reference+OCO
M3: Reference+MPC
M4: OCO
M5: MPC
0
2190
4380
6570
8760
Time (h)

Thank You!

齐宁
哥伦比亚大学
2024年12月15日