含储能新型电力系统的现货市场出清模型研究

Clearing Model for Energy Markets of Renewable Power Systems with Energy Storage

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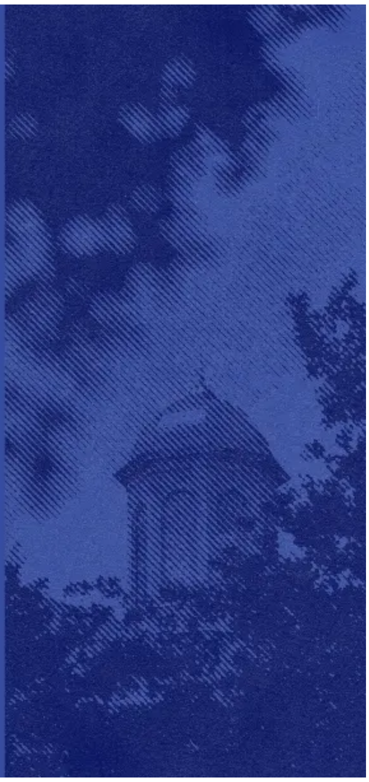
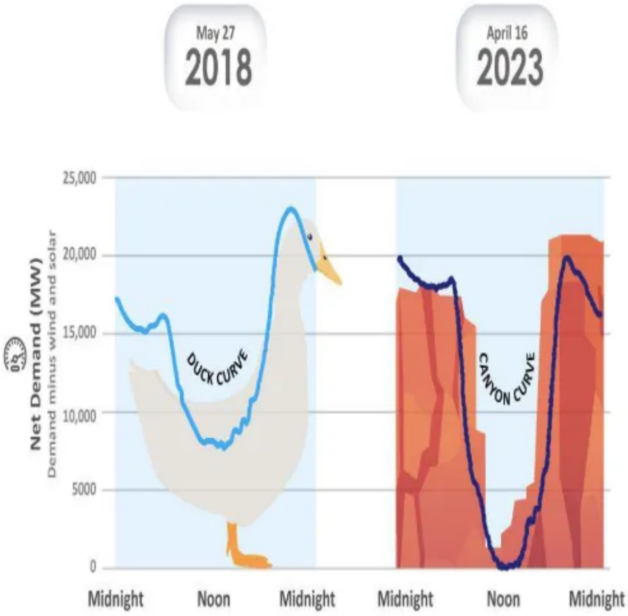


储能在新型电力系统中的角色



Arshad Mansoor

储能在新型电力系统中的重要性

- The duck curve
  - Net demand is reduced during the day (the duck's belly)
  - Net demand sharply increases at sunset (the duck's neck)
  - The need for flexibility significantly increases
- The canyon curve
  - Recently, CAISO's net load has reached zero or gone negative
  - Dispatchable resources are sharply reduced during the daytime
  - The need for flexibility conversely increases as the sun sets
  - Solutions:
    - **Charging/discharging of batteries**
    - **Additional forms of energy storage**
    - …

新型电力系统中的储能技术

Electro-
Chemical

Mechanical

Bulk
Mechanical

Hydrogen

Thermal

Bulk
Gravitational

Mobile

California Energy Storage Alliance (CESA)

国内的大规模储能项目（电化学储能）

山东东营津辉795兆瓦/1600兆瓦时集中式储能项目

 https://m.thepaper.cn/newsDetail_forward_27942810

国内的大规模储能项目（抽水蓄能）

河北丰宁3600兆瓦抽水蓄能电站

 http://he.people.com.cn/n2/2022/0124/c192235-35109507.html

我国储能参与电力现货市场的现状

» 电力现货市场建设情况

» 第一批电力现货试点区域（南方(从广东起步)、蒙西、浙江、山西、山东、福建、四川、甘肃8个地区）中，山西、广东的电力现货市场已分别于2023年12月22日、2023年12月28日转入正式运行

» 第二批6个试点地区，江苏、安徽、辽宁、湖北、河南这5个地区全年共完成9次结算试运行

» 相关政策

» 2023年9月，国家发改委、国家能源局印发《电力现货市场基本规则(试行)》(发改能源规[2023]1217号)，明确提出推动分布式发电、负荷聚合商、储能和虚拟电厂等新型经营主体参与交易。

» 储能如何参与电力现货市场？

» 独立储能参与电力现货市场的报价方式主要有报量报价、报量不报价两种方式

» 山东、山西、甘肃、青海、广东等省份明确了独立储能参与现货市场的规则

» 广东省独立储能（电网侧储能）作为独立主体参与现货市场，充放电价格均采用所在节点的分时电价；电源侧储能联合发电机组，在现货市场以报量报价的方式参与交易

» 山西省独立储能按月自主选择以"报量报价"或"报量不报价"的方式参与现货市场，向新能源企业租赁的容量不影响独立储能作为整体参与现货市场

» 山东省独立储能在现货市场电能量交易中按照报量不报价原则出清，上网电量价格按照市场出清价格结算，并享受容量补偿费

» ……

储能参与电力现货市场"快进"

美国ISOs/RTOs如何管理电力现货市场中的储能？

» NYISO and MISO

» Energy storage must offer in as a generator or load **separately** in the day-ahead market

» But may allow different offers in the real-time market

» PJM and NYISO (Phase 2)

» The ISO/RTO software will **optimize the operational mode** of PSH (pumped storage hydro) based on production cost minimization

» ISO-NE

» Includes features to more realistically capture the parameters of PSH in **pumping modes**, like minimum pumping levels, minimum run and down times, etc.

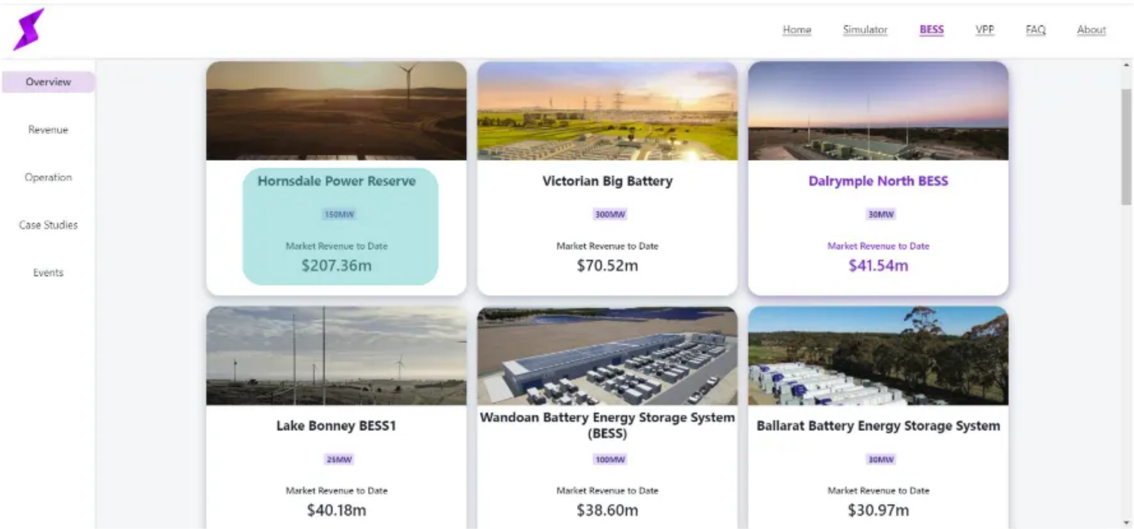
» CAISO

» Has plans for its storage resources to provide **cost offers** from withdrawal mode to injection/generation mode if the resources have a continuous operation between maximum withdrawal and maximum injection (thus excluding PSH)

» …

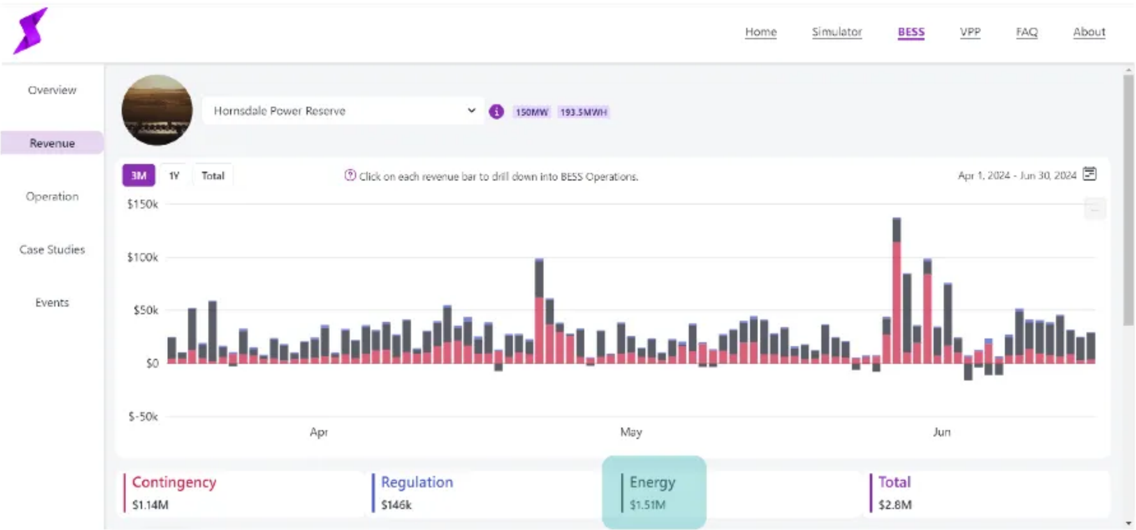
Independent System Operator and Regional Transmission Organization Energy Storage Market Modeling Working Group White Paper

澳洲电力市场中的电化学储能



 NEM BESS

Hornsdale Power Reserve近期盈利情况



 NEM BESS

储能参与电力市场与电力调度的挑战

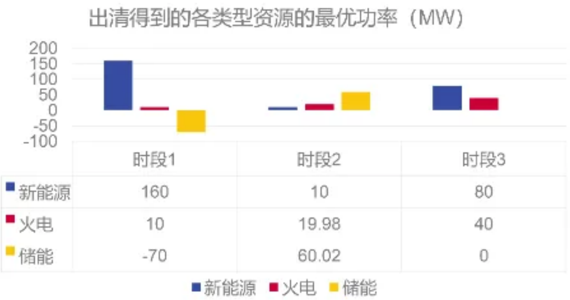
储能在现货市场中的成本回收问题

系统参数及市场申报情况

	负荷（MW）	新能源发电出力（MW）	火力发电机组报价（￥/MWh）	储能充电 / 放电报价（￥/MWh）
时段1	100	160	300	200 / 400
时段2	90	10	300	100 / 200
时段3	120	80	300	200 / 400

- ❑ 火力发电机组出力上下限：10MW~100MW
- ❑ 储能充、放电功率上限：100MW
- ❑ 储能充、放电效率：95%
- ❑ 储能SOC初始值、最大值：100MWh、200MWh
- ❑ 储能约束：末时段SOC与初始值一致

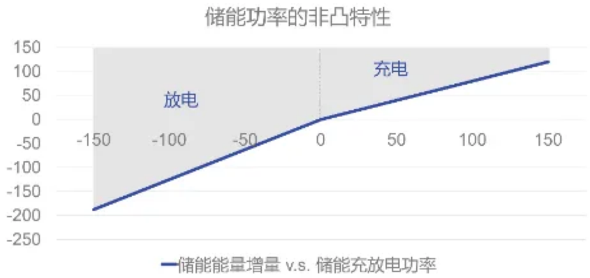
出清及结算结果



- ❑ 以社会福利最大化为目标，使用混合整数规划进行出清计算
- ❑ 基于拉格朗日乘子得到每个时段的边际出清价格：￥276.71、￥300.00、￥300.00
- ❑ 根据电价和储能各时段的充放电功率进行结算，可知储能的收益为**￥-1,365.00**

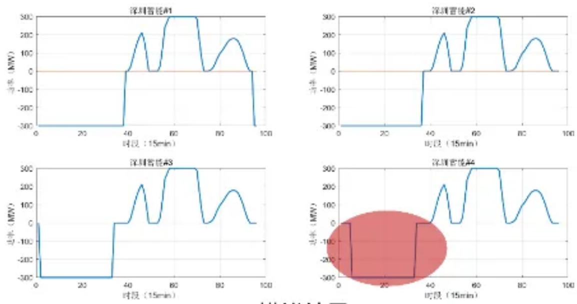
储能在现货市场中的模型非凸性

储能一般模型的非凸性



- ❑ 充放电工况下的能量-功率特性不同
- ❑ 储能的充放电工况互斥，不允许能量往下松弛
- ❑ 储能的能量—功率可行域是非凸的
- ❑ 在电力现货市场出清模型中需引入二进制决策变量（0-1）来刻画非凸性
- ❑ 非凸优化问题求解的算法复杂是指数级别的

非可变抽蓄的功率特性

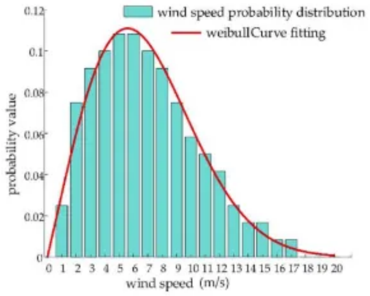


模拟结果

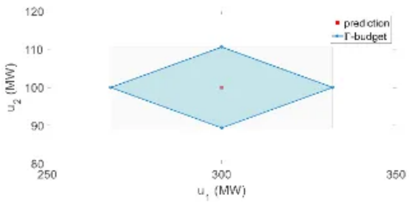
- ❑ 抽水蓄能机组（变速抽水蓄能机组除外）从发电工况转变为抽水（泵）工况后，必须满功率运行
- ❑ 向电网注入的功率从零骤然变成一个较大的、固定的负功率，功率无法光滑调节
- ❑ 功率特性存在显著的离散性

新能源随机性?

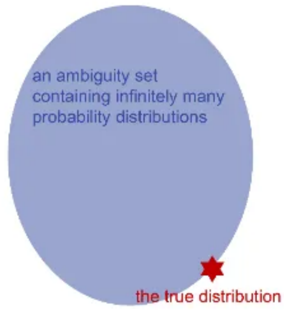
随机性



不确定性



模糊性



- ❑ 随 机 性：具备概率特性。例如，用伯努利分布刻画抛硬币实验
- ❑ 不确定性：一般意义上的结果不明确。例如，鲁棒优化中的不确定集（所有可能的结果均会落在集合之内）
- ❑ 模 糊 性：模型不明确。例如，不知道新能源发电出力的具体概率分布，使用模糊集刻画新能源发电出力

考虑新能源发电不确定性的出清模型

随机规划（随机性）

$$\min_{x\in\{x|Fx\geq f\}} c_1^\top x + \mathbb{E}_{\xi\sim\mathbb{P}}[Q(x,\xi)]$$

$$\text{with } Q(x,\xi) = \min_{y\in\{y|Ax+By+C\xi=d\}} c_2^\top y$$

鲁棒优化（不确定性）

$$\min_{x\in\{x|Fx\geq f\}} c_1^\top x + Q(x,\bar{\xi})$$

$$\text{with } Q(x,\bar{\xi}) = \min_{y\in\{y|Ax+By+C\bar{\xi}=d\}} c_2^\top y$$

$$\text{and } \{y \mid Ax+By+C\xi=d\} \text{ unempty } \forall \xi\in\Xi$$

分布鲁棒优化（模糊性）

$$\min_{x\in\{x|Fx\geq f\}} c_1^\top x + \max_{\mathbb{P}\in\mathcal{P}} \mathbb{E}_{\xi\sim\mathbb{P}}[Q(x,\xi)]$$

$$\text{with } Q(x,\xi) = \min_{y\in\{y|Ax+By+C\xi=d\}} c_2^\top y$$

$$\text{and } \mathcal{P} \text{ being an ambiguity set}$$

- x 日前决策变量，如开机计划；$Q(x,\xi)$ 日内最优成本函数；ξ 不确定量或随机向量，如新能源发电出力；$\mathbb{P}$ 随机向量的概率分布

样本平均估计+Benders分解

$$\min_{x\in\{x|Fx\geq f\}} c_1^\top x + \sum_{s\in S}\omega_s Q(x,\xi_s)$$

$$\text{s.t.}\begin{cases} Q(x,\xi_1) = \min\limits_{y_1\in\{y|Ax+By+C\xi_1=d\}} c_2^\top y_1 \\ \ldots \\ Q(x,\xi_{|S|}) = \min\limits_{y_{|S|}\in\{y|Ax+By+C\xi_{|S|}=d\}} c_2^\top y_{|S|} \end{cases}$$

对偶转化、极限场景辨识+迭代

$$\min_{x\in\{x|Fx\geq f\}} c_1^\top x + Q(x,\bar{\xi})$$

$$\text{s.t.}\begin{cases} Ax+By_1+C\xi_1^{\text{Extreme}}=d \\ \ldots \\ Ax+By_V+C\xi_V^{\text{Extreme}}=d \end{cases}$$

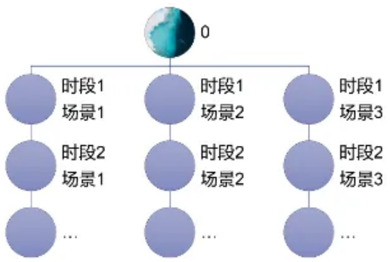
对偶转化、极限分布辨识+迭代

$$\min_{x\in\{x|Fx\geq f\}} c_1^\top x + \eta$$

$$\text{s.t.}\begin{cases} \eta \geq \sum\limits_{s_1\in S_1}\omega_{s_1} Q(x,\xi_{s_1}^{\text{Extremal}}) \\ \ldots \\ \eta \geq \sum\limits_{s_V\in S_V}\omega_{s_V} Q(x,\xi_{s_V}^{\text{Extremal}}) \end{cases}$$

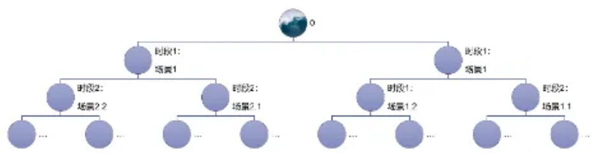
非确定型决策模型中的非预期性（non-anticipativity）约束

并行的场景（忽略了非预期性）



- ❑ 求解非确定型决策问题需要对未来场景进行采样（样本平均估计、极限场景、极端概率分布等），基于采样进行模拟决策，制定最优策略
- ❑ 如果不确定量的样本是并行的时序轨迹，并基于这些轨迹进行模拟决策，则相当于利用未来的观测值来制定当前策略，是偏乐观的

场景树（考虑了非预期性）



- ❑ 以场景树的形式采样并构建确定型的决策模型，可以满足非预期性约束
  - ❑ 保证任意时刻的决策仅依赖于该时刻以前的观测值
  - ❑ 保证在同样的历史轨迹之下决策方案是一致的
- ❑ 场景数量呈指数增长
  - ❑ $2^{24} = 16777216$
  - ❑ $3^{24} = 2.82429536481 \times 10^{11}$

A recourse function is non-anticipative if the decision depends only on the past observations but not on the future. By R. T. Rockafellar

非预期性的实例

A multistage game investors play with the uncertainty of price:

One owes a stock, and now he/she is in 05/2022. In determining whether to sell the stock, he/she needs to account for the uncertainty of the future price. Depending on his/her uncertainty model and profit maximization model, he/she **may or may not** sell the stock in 05/2022.

非预期性的实例（2）

A multistage game investors play with the uncertainty of price:

The here-and-now decision in 05/2022: selling or holding?

If his/she model does not respect the nonanticipativity, i.e., assuming that the investment decision can be made with all future price signals (in a scenario), then the optimal here-and-now decision is to **sell the stock right now**, since he/she can profit from any short-term growth in the future.

考虑不确定性和非预期性的多阶段优化模型与算法

考虑非预期性的非确定型优化模型

Optimization models

» Single-stage optimization model

» Determines beforehand how the resources linearly react temporally independently to the deviation of power output of variable renewable generation (VRE)

» **Two-stage optimization model**

» Determines beforehand the operational range of temporally coupled resources (e.g., energy-limited, ramping-limited) so that they will be dispatched temporally independently

» Multistage optimization model

» Precisely model the sequential decision making forward through time

How does it work?

Find a robust linear reaction function via *static* robust optimization. Then dispatch following the simple rule

Restrict the decision space + Temporally decomposition

Find a robust operational boundaries via *adjustable* robust optimization. Then implement the here-and-now decision

The multistage optimization model works simply because it is precise

用于电力系统优化调度的储能一般模型

$0 \leq p_t^{\mathrm{DC}} \leq P^{\mathrm{DC,max}}$	Lower/upper limit of discharging power
$0 \leq p_t^{\mathrm{CH}} \leq P^{\mathrm{CH,max}}$	Lower/upper limit of charging power
$0 \leq e_{t-1} - (p_t^{\mathrm{DC}}/\eta^{\mathrm{DC}})\Delta$	Upper limit of the state of energy (SOE)
$e_{t-1} + \eta^{\mathrm{CH}} p_t^{\mathrm{CH}} \Delta \leq E^{\max}$	Lower limit of the SOE
$p_t^{\mathrm{DC}} p_t^{\mathrm{CH}} = 0$	Cannot discharge and charge simultaneously

The operation of energy storage are temporally *coupled* due to the SOE constraints

The discharging/charging power deployed at time *t* steers the SOE to a new state, which will become the initial state of the next period and limit the usability of the storage at time *t*+1.

When working on a temporally coupled system, the two-stage uncertainty-aware optimization model does not respect the nonanticipativity.

基于储能最优鲁棒能量边界的多阶段优化模型

$$E_s^{\min} \le \underline{e}_{s,t}^{\mathrm{S}} \le \overline{e}_{s,t}^{\mathrm{S}} \le E_s^{\max} \quad \forall s \in \mathcal{S}, t \in \mathcal{T}$$

$$\overline{e}_{s,t}^{\mathrm{S}} - \underline{e}_{s,t-1}^{\mathrm{S}} \le \eta_s^{\mathrm{Ch}} P_s^{\mathrm{Ch,max}} \Delta t \quad \forall s \in \mathcal{S}, t \in \mathcal{T}$$

$$\underline{e}_{s,t}^{\mathrm{S}} - \overline{e}_{s,t-1}^{\mathrm{S}} \ge -\frac{1}{\eta_s^{\mathrm{Dis}}} P_s^{\mathrm{Dis,max}} \Delta t \quad \forall s \in \mathcal{S}, t \in \mathcal{T}$$

$$\underline{e}_{s,t}^{\mathrm{S}} \le e_{s,t}^{\mathrm{S}} \le \overline{e}_{s,t}^{\mathrm{S}} \quad \forall s \in \mathcal{S}, t \in \mathcal{T}$$

$$0 \le p_{s,t}^{\mathrm{Ch}} \le x_{s,t}^{\mathrm{S}} P_s^{\mathrm{Ch,max}} \quad \forall s \in \mathcal{S}, t \in \mathcal{T}$$

$$0 \le p_{s,t}^{\mathrm{Dis}} \le \left(1 - x_{s,t}^{\mathrm{S}}\right) P_s^{\mathrm{Dis,max}} \quad \forall s \in \mathcal{S}, t \in \mathcal{T}$$

$$x_{s,t}^{\mathrm{S}} \in \{0,1\} \quad \forall s \in \mathcal{S}, t \in \mathcal{T}$$

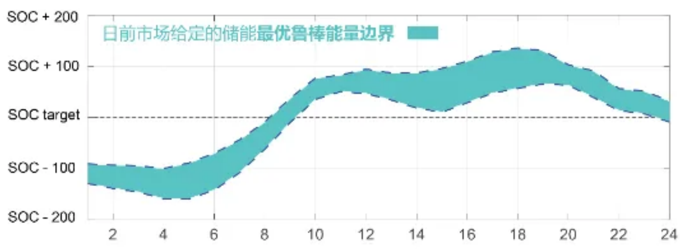
$$e_{s,t}^{\mathrm{S}} = e_{s,t-1}^{\mathrm{S}} + \eta_s^{\mathrm{Ch}} p_{s,t}^{\mathrm{Ch}} \Delta t - \frac{1}{\eta_s^{\mathrm{Dis}}} p_{s,t}^{\mathrm{Dis}} \Delta t \ \forall s \in \mathcal{S}, t \in \mathcal{T}$$

$$\underline{e}_{s,t}^{\mathrm{S}} = \overline{e}_{s,t}^{\mathrm{S}} = e_{s,0}^{\mathrm{S}} \quad \forall s \in \mathcal{S}, t = |\mathcal{T}|$$

将储能SOE决策变量转化成不确定量，实现时序解耦！

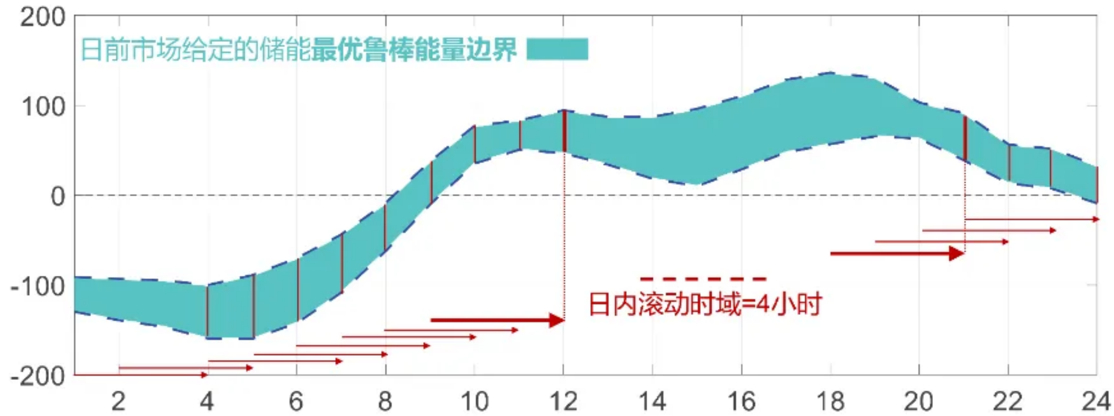
$$e_{s,t}^{\mathrm{S}} = u_{s,t}^{\mathrm{S}} + \eta_s^{\mathrm{Ch}} p_{s,t}^{\mathrm{Ch}} \Delta t - \frac{1}{\eta_s^{\mathrm{Dis}}} p_{s,t}^{\mathrm{Dis}} \Delta t \quad \forall s \in \mathcal{S}, t \in \mathcal{T}$$

- ❑ 基于鲁棒优化原理，在日前优化调度中确定储能在日内各时段的能量边界
- ❑ 日内、实时运行时，储能只需要保证每个时段的能量水平在边界之内
- ❑ 可以使用两阶段（分布）鲁棒优化的成熟算法求解含储能的非确定型多阶段优化调度问题



示意图

储能调度在日前、日内优化中的衔接



- ❑ 日内电力现货市场采取前瞻（look-ahead）调度模式，基于模型预测控制原理进行滚动出清
- ❑ 日前电力现货市场确定的储能最优鲁棒能量边界**仅在每个滚动时域的最后一个时间窗口**对储能能量边界进行限定
- ❑ **既能发挥储能在日内电力现货市场的灵活性，又能兼顾日前较长周期市场的最优决策，避免短视问题**

储能调度在日前、日内优化中的衔接（2）

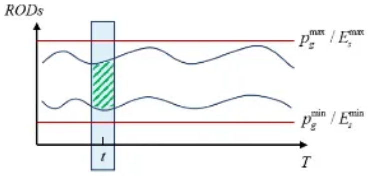
- 在日前得到的**储能最优鲁棒能量边界**（以及其他可调资源的鲁棒运行域）的基础上，采用改进的日前-日内衔接方法进行前瞻调度，更加充分地发挥其灵活资源的调节和互济能力
- **日内前瞻调度基于日前确定的完整时域上的鲁棒运行域来开展**，能够克服能量受限型灵活资源在日内调度中的**短视问题**，保证全天调度运行的安全性

日内静态优化策略

考虑单个时段的能量边界约束，独立决策

$$\underline{p}_{g,t}^{\mathrm{G}*} \le p_{g,t}^{\mathrm{G}} \le \overline{p}_{g,t}^{\mathrm{G}*} \quad \forall g \in \mathcal{G}$$

$$\underline{e}_{s,t}^{\mathrm{S}*} \le e_{s,t}^{\mathrm{S}} \le \overline{e}_{s,t}^{\mathrm{S}*} \quad \forall s \in \mathcal{S}$$



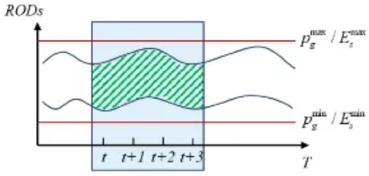
实时经济调度可行域示意图

日内动态优化策略#1

考虑滚动时域内的多时段的能量边界约束

$$\underline{p}_{g,\tau}^{\mathrm{G}*} \le p_{g,\tau}^{\mathrm{G}} \le \overline{p}_{g,\tau}^{\mathrm{G}*} \quad \forall g \in \mathcal{G}, \tau \in \mathcal{T}_t$$

$$\underline{e}_{s,\tau}^{\mathrm{S}*} \le e_{s,\tau}^{\mathrm{S}} \le \overline{e}_{s,\tau}^{\mathrm{S}*} \quad \forall s \in \mathcal{S}, \tau \in \mathcal{T}_t$$



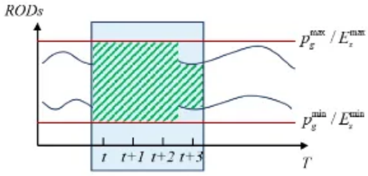
前瞻调度策略 1 可行域示意图

动态优化策略#2（√）

仅在滚动时域最后一个时段约束能量边界

$$\underline{e}_{s,\tau}^{\mathrm{S}*} \le e_{s,\tau}^{\mathrm{S}} \le \overline{e}_{s,\tau}^{\mathrm{S}*} \quad \forall s \in \mathcal{S}, \tau = |\mathcal{T}_t|$$

$$E_s^{\min} \le e_{s,\tau}^{\mathrm{S}} \le E_s^{\max} \quad \forall s \in \mathcal{S}, \tau = \mathcal{T}_t \setminus |\mathcal{T}_t|$$



前瞻调度策略 2 可行域示意图

处理新能源不确定性的分布鲁棒优化方法

Why distributionally robust optimization (DRO) is good?

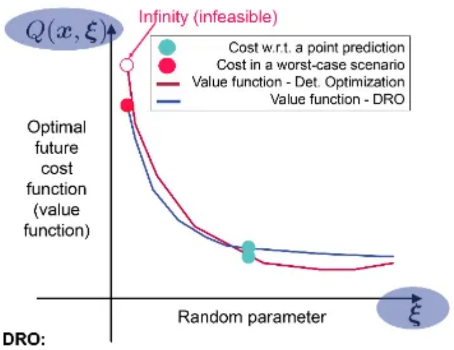
$$\min_{x \in \mathcal{X}} \max_{\mathbb{P} \in \mathcal{P}} f(x) + \mathbb{E}_{\mathbb{P}}[Q(x, \xi)]$$

where

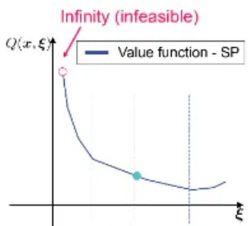
x is the first-stage decision

$\mathcal{P}$ is the ambiguity set of distributions of the random vector ξ

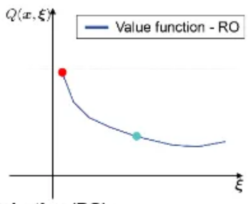
$f(x), Q(x, \xi)$ are the here-and-now cost, second-stage cost, respectively



DRO:
1) The value function is bounded **(robustness)**
2) The worst-case cost expectation is minimized **(out-of-sample performance guaranteed)**



Stochastic programming (SP):
1) The value function may be unbounded **(no robustness)**
2) The cost expectation w.r.t. an empirical dist. is minimized



Robust optimization (RO):
1) The value function is bounded **(robustness)**
2) The cost w.r.t. a scenario (typically the worst-case one) is minimized

基于值函数估计的高效求解算法

Optimization models	The second-stage problems	Benders' decomposition/ Benders' type algorithm	Column-and-constraint generation method (C&CG)	Extremal-distribution-based algorithm (extended C&CG)
» Two-stage SP	Evaluate the cost expectation on a finitely discrete set of scenarios	☺		
» Two-stage RO	Evaluate the worst-case cost on an infinite uncertainty set	☹ (cutting planes in the x domain do not suffice*)	☺	
» Tow-stage DRO	Evaluate the worst-case cost expectation on an infinite support	☹ (cutting planes in the x domain do not suffice**)	☹ (dozens of supporting points in the ξ domain do not suffice***)	☺

Solve the master problem

- Solve a mixed-integer linear program (MILP)
- Obtain a first-stage decision

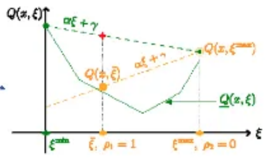
Solve the sub-problem

(evaluate the worst-case cost expectation on an infinite support)

- Relax the second-stage MILP recourse to a linear program (LP)
- Refine the **value function** of the relaxed recourse problem
- Recover a discrete distribution
- Refine the discrete distribution to get an extremal distribution

Update the master problem

- Augment the scenarios in the extremal distribution to the master problem



[*] Bertsimas, Dimitris, et al. "Adaptive robust optimization for the security constrained unit commitment problem." *IEEE Transactions on Power Systems* 28.1 (2012): 52-63.
[**] Zhang, Xiaodong, and Haoyong Chen. "Data-driven distributionally robust unit commitment with Wasserstein metric: Tractable formulation and efficient solution method." *IEEE Transactions on Power Systems* 35.6 (2020): 4940-4943.
[***] Velloso, Alexandre, David Pozo, and Alexandre Street. "Distributionally robust transmission expansion planning: A multi-scale uncertainty approach." *IEEE Transactions on Power Systems* 35.5 (2020): 3353-3365.

结果与讨论

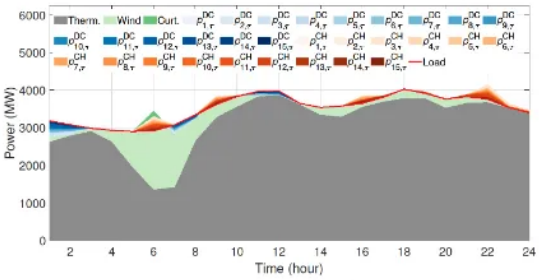
各类型资源的优化结果

A modified IEEE 118-bus system with 38% renewable generation capacity

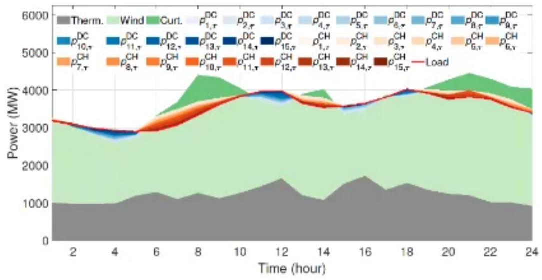
Resources	Thermal generators	ESS	Wind farms
» Number	39	15	4
» Total capacity	5540 MW	424 MW, 1463 MWh	3395 MW

» Simulation of chronological operations of intraday markets are performed on 7 typical days. (The day-ahead market clearing model that models the optimal robust energy bounds of energy storage as decision-dependent uncertainty is being studied, and will be presented in the near future!)

» ESS function well to hedge against the variability and uncertainty of VRE



Dispatch results on a day with lower VRE output (Day 2)



Dispatch results on a day with higher VRE output (Day 6)

经济性对比和分析

» **Model 2**, a distributionally robust intraday market clearing model that does not respect nonanticipativity, induces a slightly higher (0.22%) average cost. The costs of Model 2 can be slower, but the cost on Day 6 is significantly higher.

» **Model 3**, a deterministic-optimization-based model, incurs load shedding of amount 107.27 MWh and 485.64 MWh on Day 1 and Day 2, respectively.

Comparison of dispatch costs

Day	Model 1 (ours)	Model 2		Model 3	
	Cost ($)	Cost ($)	Difference (%)	Cost ($)	Difference (%)
» Day 1	1,108,205	1,111,460	0.29%	1,163,699	5.01%
» Day 2	878,541	878,265	-0.03%	1,179,757	34.29%
» Day 3	761,912	760,541	-0.18%	760,459	-0.19%
» Day 4	677,320	676,143	-0.17%	675,594	-0.25%
» Day 5	499,806	503,264	0.69%	494,861	-0.99%
» Day 6	350,460	356,771	1.77%	346,120	-1.24%
» Day 7	303,198	303,167	-0.01%	304,041	0.28%

所提算法的效率

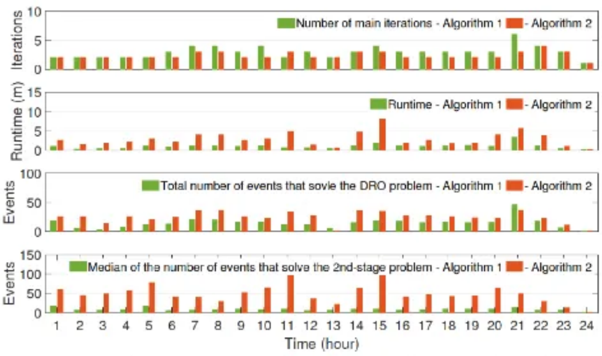
» **Algorithm 1:** our algorithm, which makes use of the value function of the relaxed (convex) ESS model

» **Algorithm 2:** another algorithm that uses the nested column-and-constraint generation method to refine a discrete set of scenarios

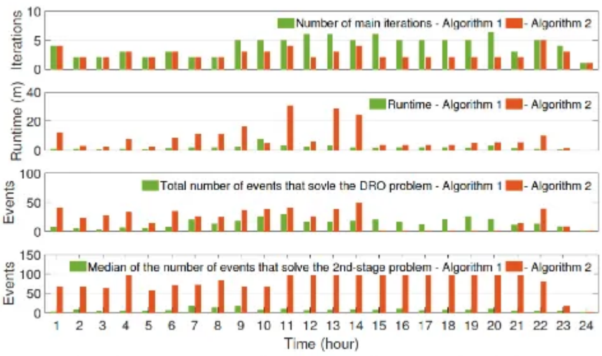
» **Improvements:**

  » less runtime (49.39s vs. 153.03s on Day 2; 112.46s vs. 525.55s on Day 6)

  » less scenarios/events (13 vs. 22 on Day 2; 15 vs. 22 on Day 6)



Performance of two algorithms (Day 2)



Performance of two algorithms (Day 6)

Thanks!

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Read more: X. Zheng, M. E. Khodayar, J. Wang, M. Yue and A. Zhou, "Distributionally Robust Multistage Dispatch With Discrete Recourse of Energy Storage Systems," in IEEE Transactions on Power Systems, doi: 10.1109/TPWRS.2024.3369664.