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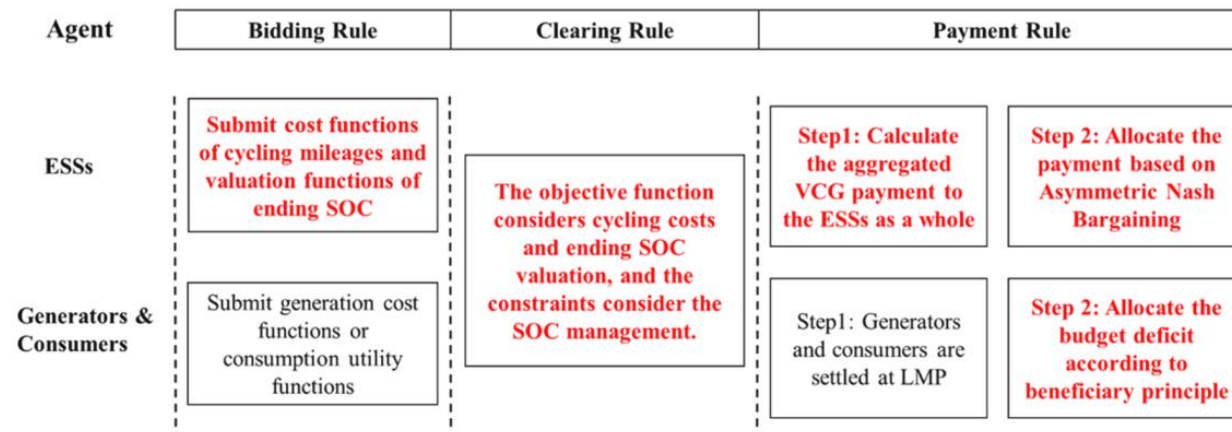
Data-driven Approximation of VPP Feasible Regions

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Background

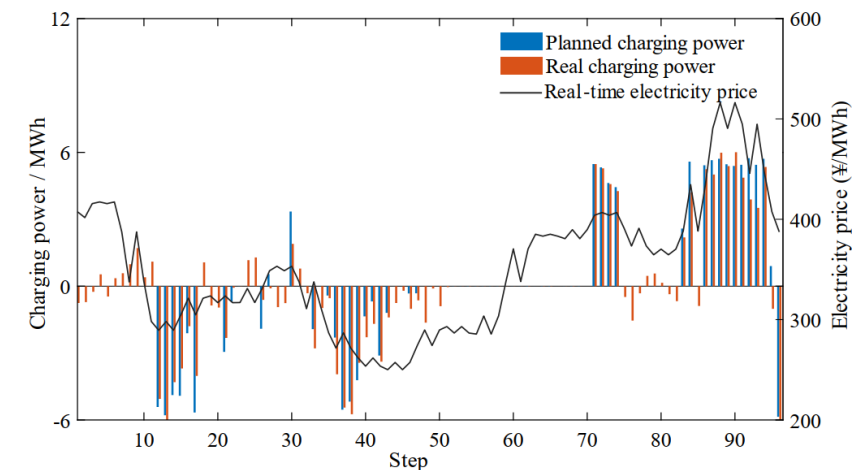
ISOs are introducing new bidding models

- to better integrate emerging distributed energy resources (DERs)
- **new bidding models** to represent DER feasible regions (FRs)
- incorporating **FR into dispatch model**, instead of self-dispatch



New bidding models designed for energy storages*

*Fang et al., 2022.



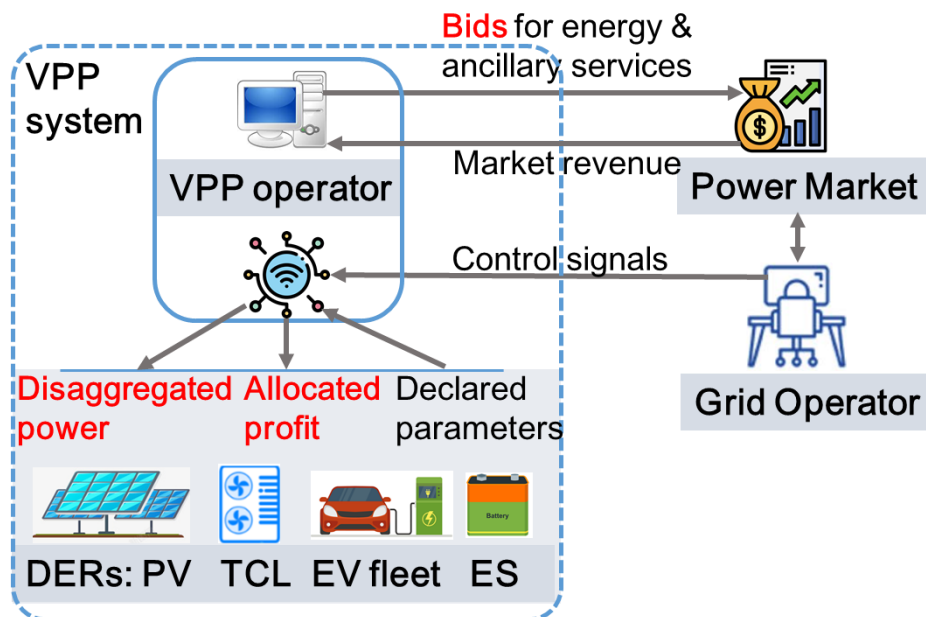
Difference between self-dispatch and optimal dispatch results #

#Wei et al., 2022

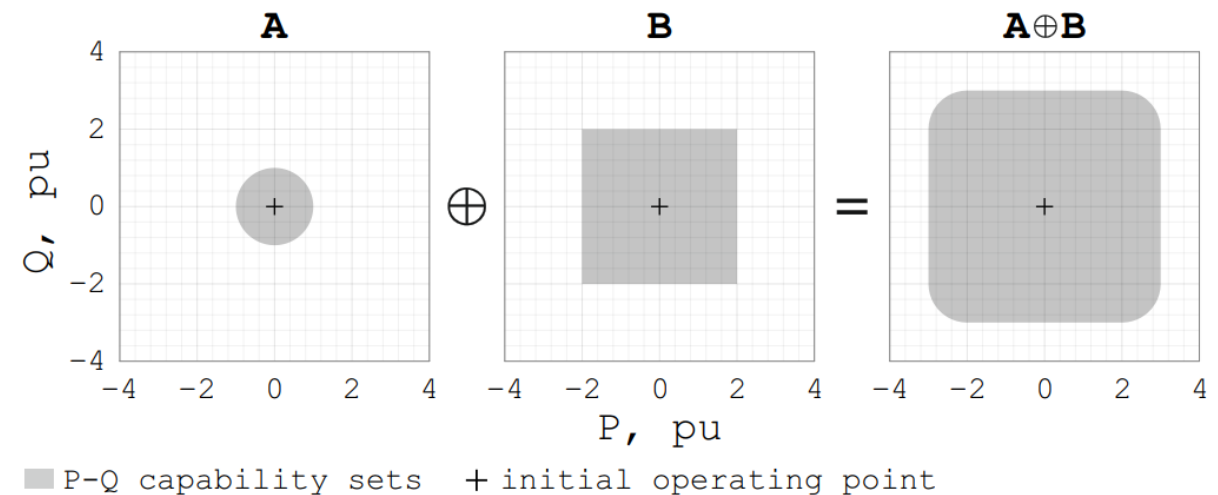
Background

Bidding of VPP: feasible region aggregation

- small-capacity DERs needs **aggregation** by Virtual Power Plants (VPPs)
- VPP submits its **FR as a whole** through the bidding model
- addition of multiple sets (**Minkowski addition**): **NP-hard**



VPP interactions with the power market

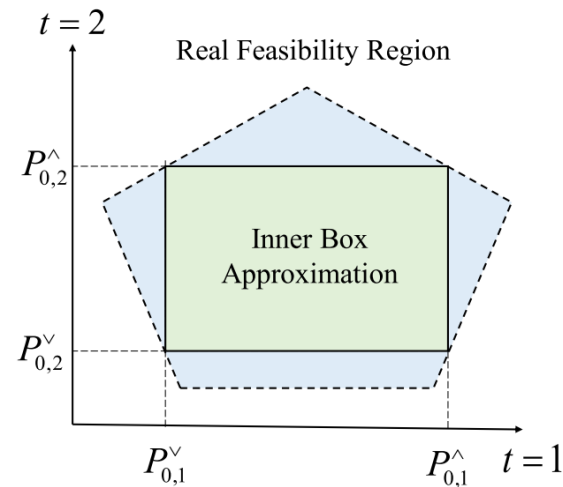


Example: Minkowski addition of P-Q capability sets of two DERs. (Churkin et al., 2023)

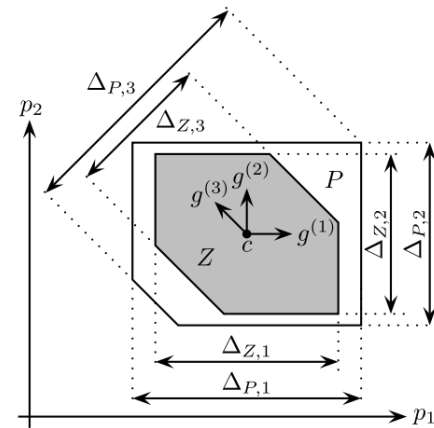
Background

Analytical approximation of aggregate FR

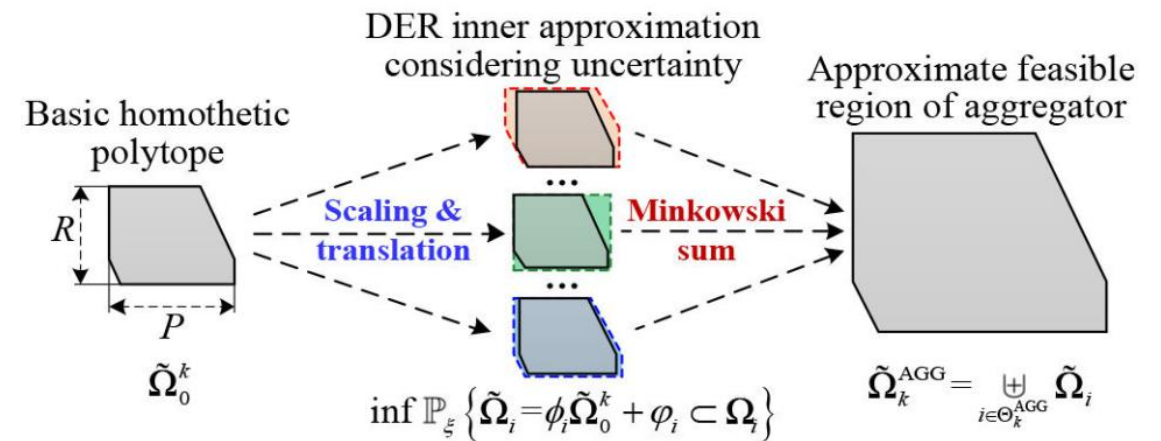
- tied with the form of individual FRs, such as **box, ellipse, zonotope**
- rely on **assumptions** on the operation of individual DERs
- cannot be adaptively applied in VPP bidding



Box form of FRs
(Chen et al., 2020)



A PE-polytope P and inscribed zonotope Z (gray)
(Muller et al., 2019)

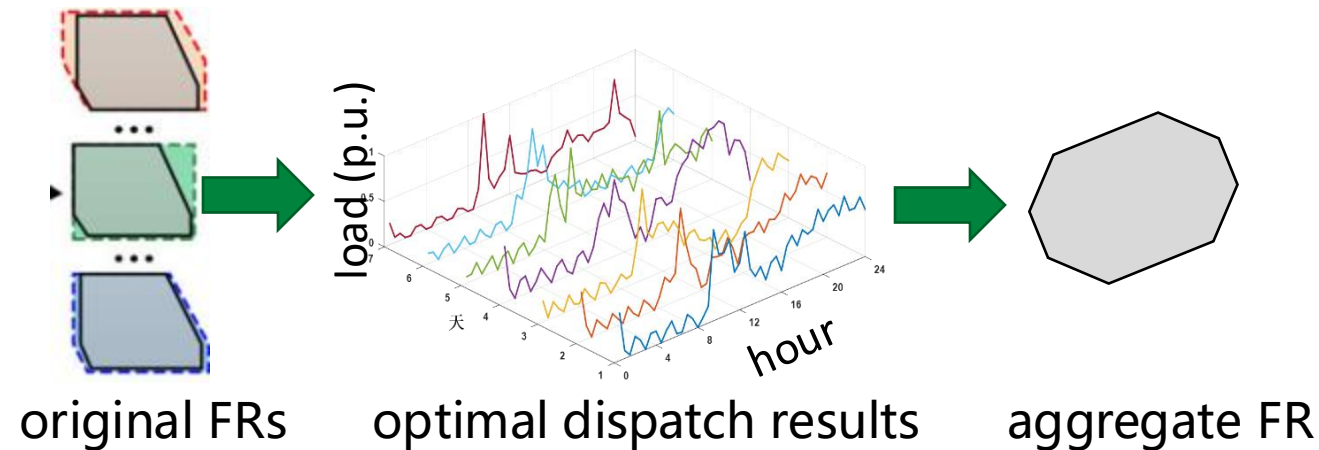


Aggregation of approximate FRs

Motivation

Approximate the FR of VPPs in a data-driven manner

- abandon the bottom-up computation of analytical methods
- use data to determine the parameters of an approximate FR
- how to measure the degree of approximation of two FRs?



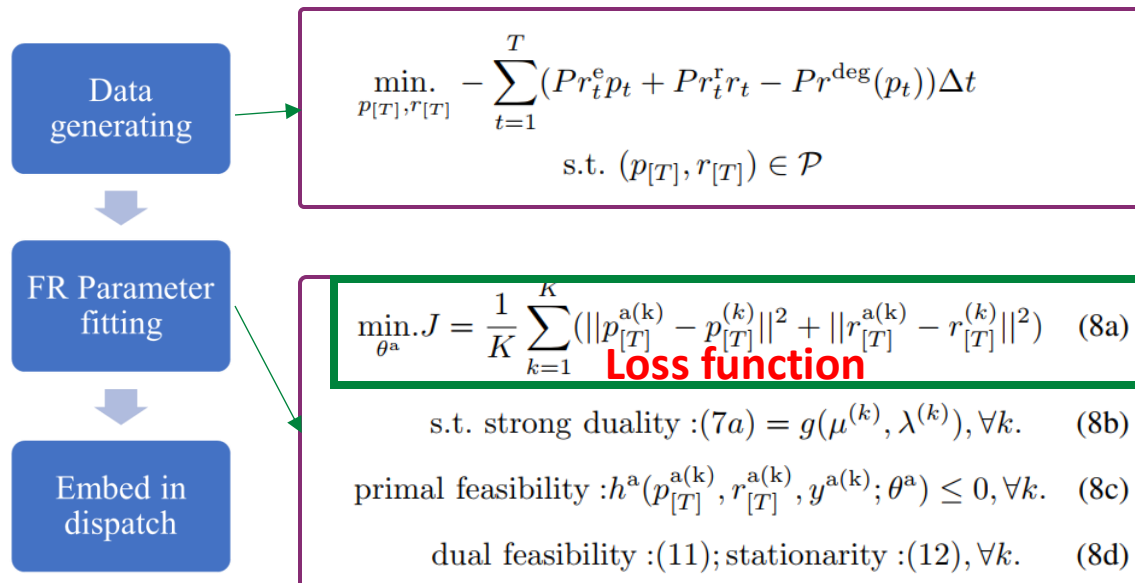
Data-driven feasible region aggregation

$P := \{ (p_{[T]}, r_{[T]}) : \exists y_{[I],[T]}, \text{ s.t. } h(p_{[T]}, r_{[T]}, y_{[I],[T]}; \theta_{[I]}) \leq 0 \}.$	P : The original FR , I is the number of resources
$P^a := \{ (p_{[T]}, r_{[T]}) : \exists y_{[I^a],[T]}^a, \text{ s.t. } h^a(p_{[T]}, r_{[T]}, y_{[I^a],[T]}^a; \theta_{[I^a]}^a) \leq 0 \}.$	P^a : approximate FR (dimension $I^a \ll I$)
$\min_{\theta^a} J(P, P^a(\theta^a))$	FR distance measurement

Methodology

Data-driven Inverse Optimization

- generate dispatch results using original constraints
- regard these data as optimal dispatch results within the approximate FR and fit the parameters of the approximate FR



- Idea: if the optimal dispatch results based on the approximate FR **under various scenarios** are close to the results based on the original FR, then the FR is considered sufficiently approximate.

Results and Conclusion

Data-driven method comparable to analytical method

- Using prices from PJM to represent dispatching scenarios
- Employing FR form of virtual battery to approximate 4000 EVs.

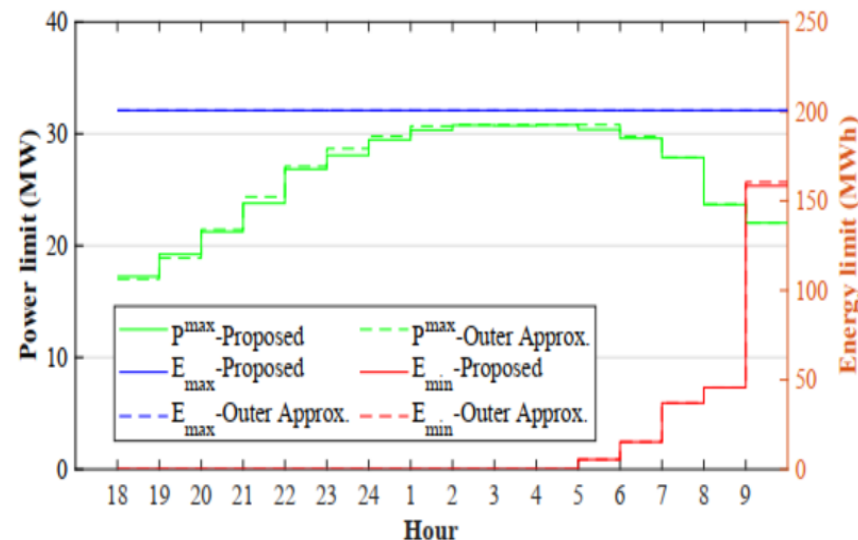


TABLE I
NORMALIZED ERROR (MAE) OF AGGREGATE FR

DER operation model	Outer Approx. [7]	Proposed (I=1)	Proposed (I=2)
Decoupled operation [19]	1.8%	1.6%	1.7%
Coupled operation [18]	13.6%	13.4%	7.5%

The aggregate FR parameters obtained from the proposed method **close to** those derived from the analytical approach.

The error in FR aggregation based on the data-driven methods is **lower than** that of analytical methods in some scenarios.

- Ruike Lyu, Hongye Guo, Qixin Chen. Approximating Energy-Regulation Feasible Region of Virtual Power Plants: A Data-driven Inverse Optimization Approach. PESGM 2024.