Context-Aware Stochastic Modeling of CER Aggregators in Electricity Markets

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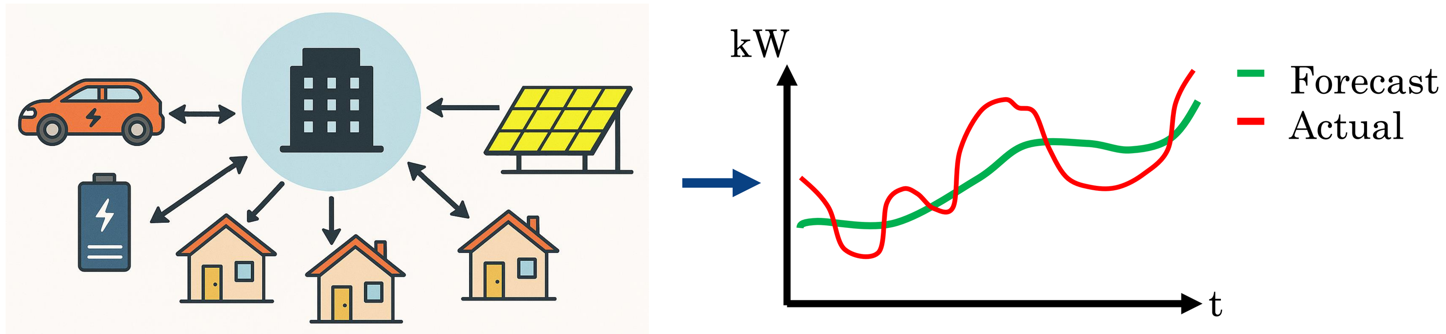
Introduction

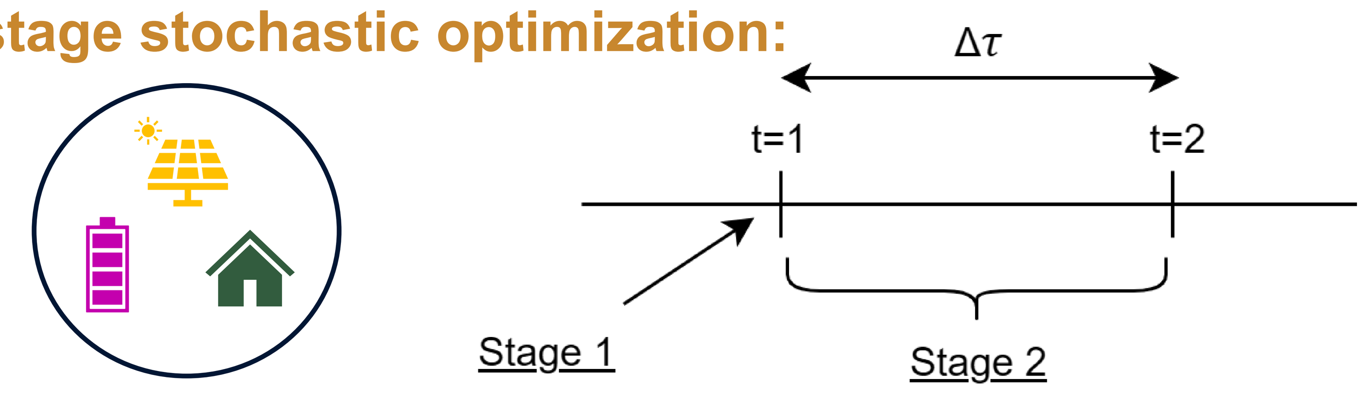
- Aggregators of consumer energy resources (CERs) face challenges due to their inherent uncertainties.



- Stochastic optimization handles such uncertainties, but can lead to infeasible problems or loss in revenues if not chosen appropriately.
- This work provides guidance for CER aggregators to select the best optimization method based on the context of the use case.

Methodology

Two-stage stochastic optimization:



Energy and FCAS bids: / BES and PV variables: x

BES and PV new operating points: y_ξ

PV and load uncertainty: ξ

BES and PV power needs to be adjusted to compensate for PV and load forecast errors

k (slack variable) denotes **aggregated dispatch conformance (ADC)** violations

- Equality constraints: Power balance at first-stage (F) and second-stage (S)
- Inequality constraints: Operational limits at first-stage (F) and second-stage (S)

Risk-neutral Optimization

$$\max_{x, y_\xi, k_\xi^-, k_\xi^+} \left(f^F(x) + \mathbb{E}_\xi[-\pi^k(k_\xi^- + k_\xi^+)]\right),$$
$$\text{s.t.} \quad h^F(x) = 0, \quad g^F(x) \le 0,$$
$$-k_\xi^- \le h^S(x, y_\xi, \xi) \le k_\xi^+, \quad \forall \xi,$$
$$k_\xi^-, k_\xi^+ \ge 0, \quad \forall \xi,$$
$$g^S(y_\xi) \le 0, \quad \forall \xi.$$

Chance-constrained Optimization

$$\max_{x, y_\xi} \min_{\Theta_\epsilon} f^F(x),$$
$$\text{s.t.} \quad h^F(x) = 0, \quad g^F(x) \le 0,$$
$$\mathbb{P}\Big(\xi \in \Theta_\epsilon \mid h^S(x, y_\xi, \xi) = 0,$$
$$g^S(y_\xi, \xi) \le 0\Big) \ge 1 - \epsilon.$$

Robust Optimization

$$\max_{x, y_\xi, k_\xi^-, k_\xi^+} \left(f^F(x) + \min_{\xi \in \Theta}[-\pi^k(k_\xi^- + k_\xi^+)]\right),$$
$$\text{s.t.} \quad h^F(x) = 0, \quad g^F(x) \le 0,$$
$$-k_\xi^- \le h^S(x, y_\xi, \xi) \le k_\xi^+, \quad \forall \xi \in \Theta,$$
$$k_\xi^-, k_\xi^+ \ge 0, \quad \forall \xi \in \Theta,$$
$$g^S(y_\xi, \xi) \le 0, \quad \forall \xi \in \Theta.$$

Quick Decisions? Recourse Policies

$$y_\xi = y + d^\top \xi$$

First-stage operating point (y); Recourse Coefficients (d)

Tractable Reformulations? Scenario Optimization

Risk-neutral: Sampling a known probability distribution

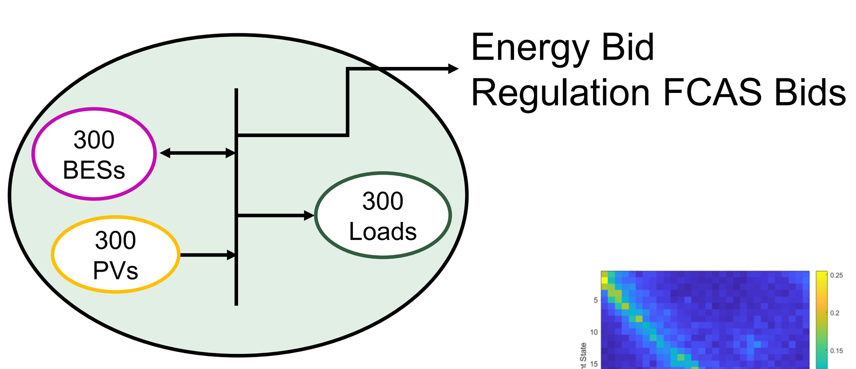
Robust: Select an uncertainty set

Chance-constrained: Using probabilistically robust design

Scalable Approaches? Linear relaxations for BES complementarity

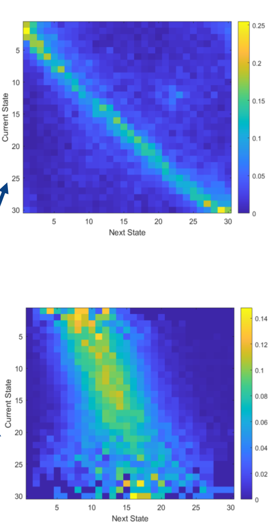
Reducing the dimensionality by integrating correlated CERs

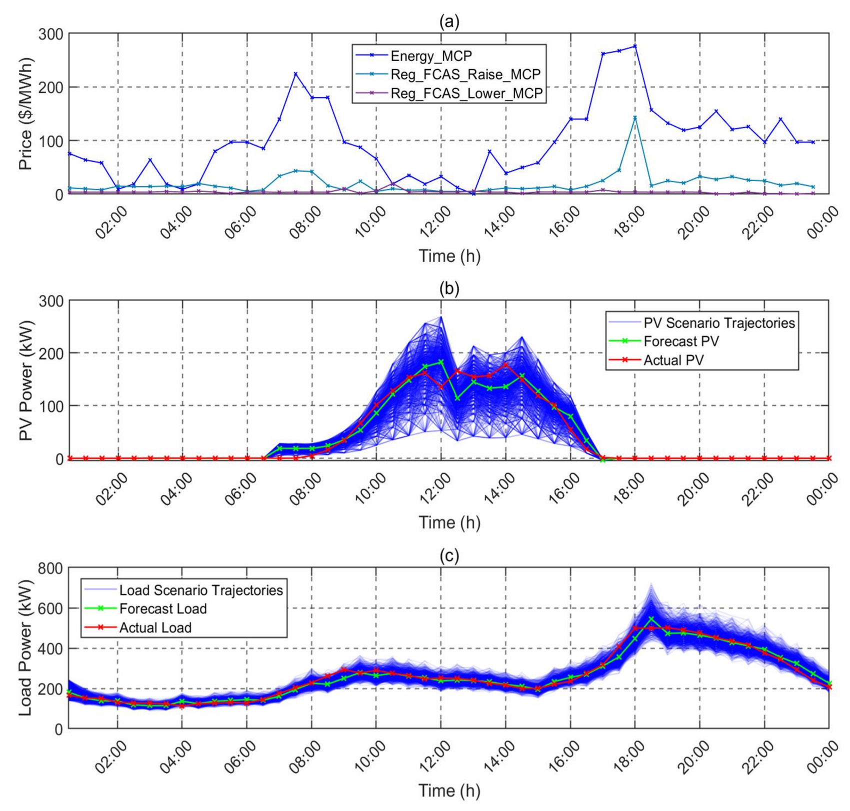
Case Study



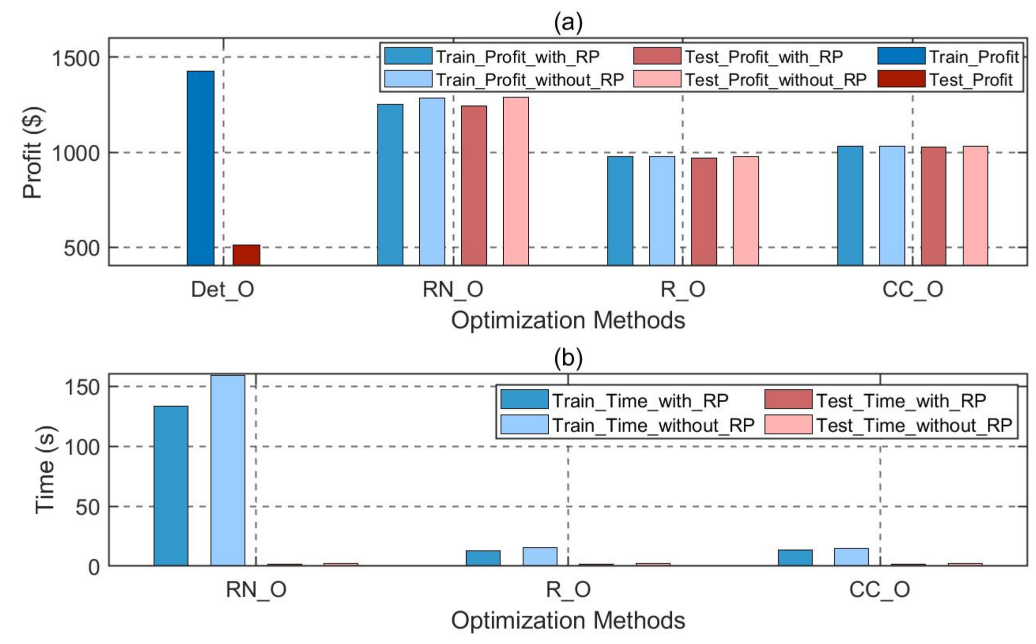
PV and load data from 300 houses in Ausgrid Network for 3 years

MCMC method for Scenario Generation





Results



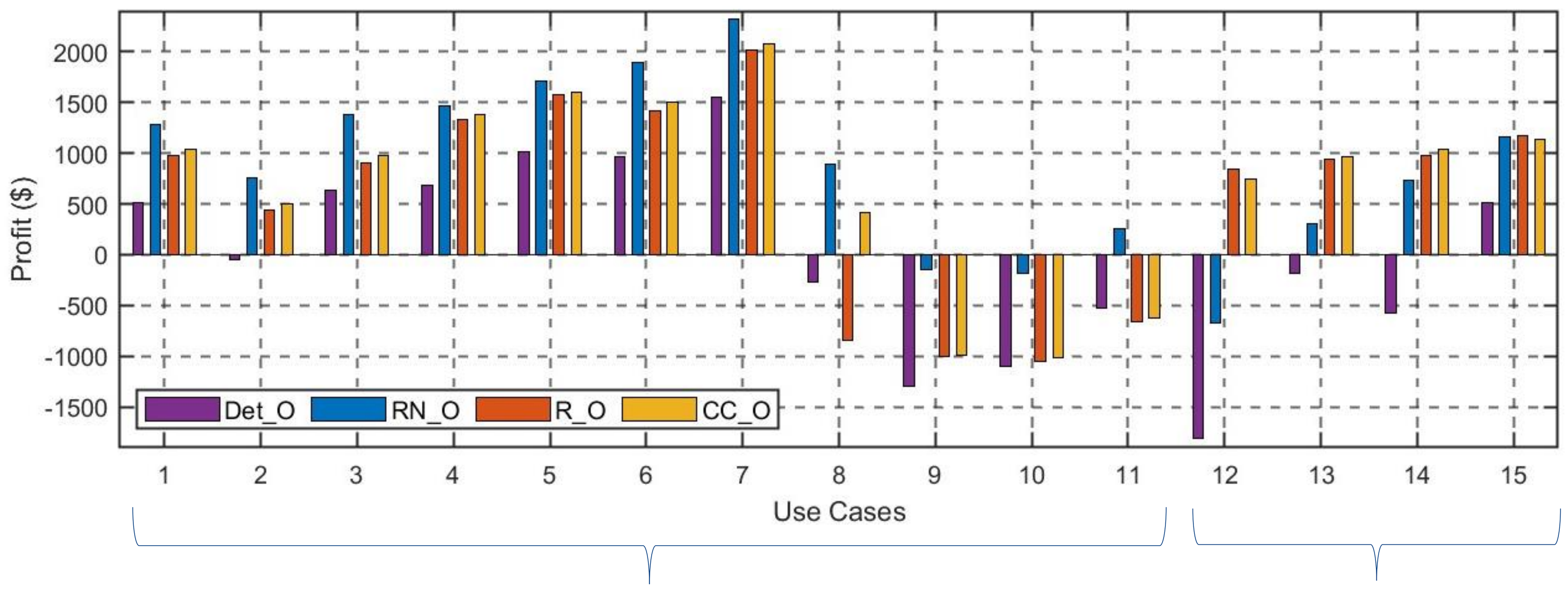
Baseline Case

Significant profit increase with stochastic methods.

Low actual power mismatches. RN_O > CC_O > R_O (profits)

Linear recourse policy reduces computational time.

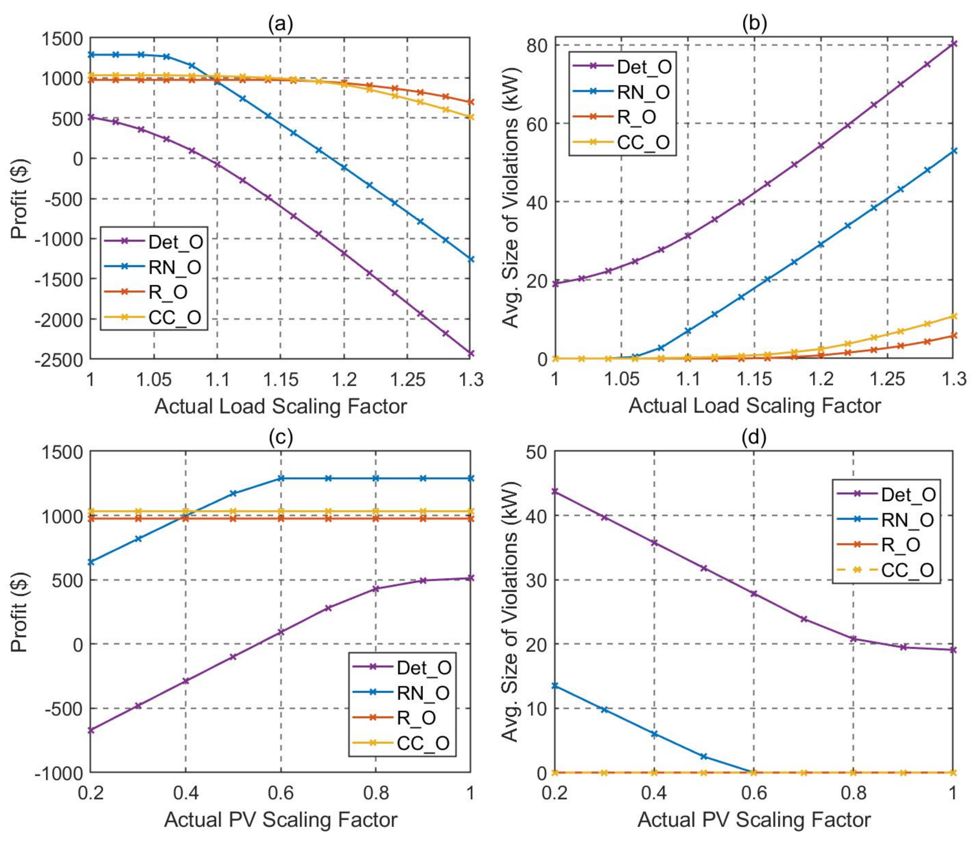
Performance under Use Cases of Different Contexts



Different operational and market settings (Use Cases 1–11)

Different uncertainty characteristics (Use Cases 12–15)

Case	Forecast PV	Forecast Load	Uncertainty PV	Uncertainty Load	BES Capacity	Energy Price	FCAS Prices	Penalty Cost	Actual PV	Actual Load	Market Preference
1	Mod	Mod	Mod	Mod	Mod	Mod	Mod	Mod	Mod	Mod	Energy + FCAS
2	Mod	Mod	Mod	Mod	Mod	Mod	Mod	Mod	Mod	Mod	Energy
3	Mod	Mod	Mod	Mod	Mod	High	Low	Mod	Mod	Mod	Energy + FCAS
4	Mod	Mod	Mod	Mod	Mod	Low	High	Mod	Mod	Mod	Energy + FCAS
5	High	Low	High	Low	Mod	Mod	Mod	Mod	High	Low	Energy + FCAS
6	Low	High	Low	High	High	Mod	Mod	Mod	Low	High	Energy + FCAS
7	Mod	Mod	Mod	Mod	High	Mod	Mod	Mod	Mod	Mod	Energy + FCAS
8	High	High	High	High	Mod	Mod	Mod	Mod	High	High	Energy + FCAS
9	High	High	High	High	Low	Mod	Mod	Mod	High	High	Energy + FCAS
10	Low	High	Low	High	Low	Mod	Mod	Mod	Low	High	Energy + FCAS
11	Mod	Mod	Mod	Mod	Low	Mod	Mod	Mod	Mod	Mod	Energy + FCAS
12	Mod	Mod	Mod	Mod	Mod	Mod	Mod	Mod	Mod	1.25×Mod	Energy + FCAS
13	Mod	Mod	Mod	Mod	Mod	Mod	Mod	Low	Mod	1.25×Mod	Energy + FCAS
14	Mod	Mod	Mod	Mod	Mod	Mod	Mod	Mod	0.5×Low	Mod	Energy + FCAS
15	Mod	Mod	0.5×Low	0.5×Low	Mod	Mod	Mod	Mod	Mod	Mod	Energy + FCAS

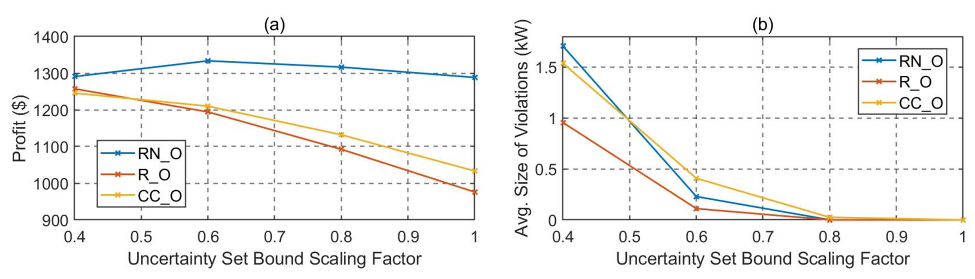


When actual power mismatch is higher (Extended Cases 12 & 14):

- Significant rise in ADC violations.
- Robust and chance-constrained methods excel as their ADC violations are low due to conservativeness.

When actual power mismatch is lower (Extended Cases 12 & 14):

- Risk-neutral method excels with low conformance violations.



When uncertainty set is contracted (Extended Case 15):

- Profits move closer to each other.
- ADC violations increase.

Conclusions

- Risk-neutral methods are recommended when uncertainty is low (correctly captured) under typical operational and market conditions.
- Robust methods are more suitable under high uncertainty, particularly when large power mismatches arise from inaccurately modeled uncertainty.
- Chance-constrained methods are preferred when seeking a balance between profitability and controlled risk of constraint violations.

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