

Network-Cognizant Time-Coupled Aggregate Flexibility of Distribution Systems Under Uncertainties

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Outline

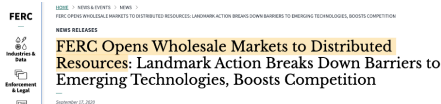
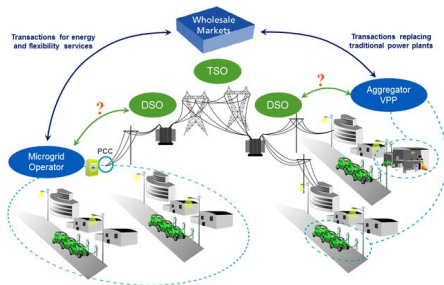
- 1 Background
- 2 Device and system model
- 3 Formulation of the aggregate flexibility region characterization problem
- 4 Adaptive robust optimization formulation and tractable safe approximation
- 5 Simulation results
- 6 Conclusion

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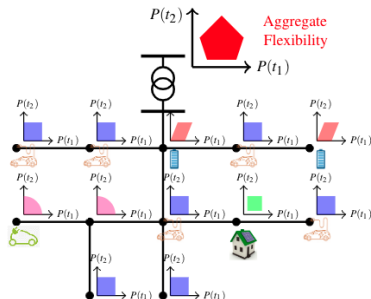
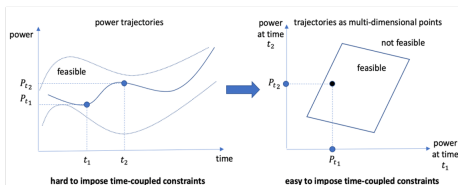
Background

- Distribution systems are transitioning from passive grid elements to active virtual power plants (VPPs).
- With FERC Order 2222, regulatory barrier preventing DERs from participating in grid service is lifted.
- **Question:** As a VPP, what is the “generation capability” of a distribution system? In other words, what is the power potential of a distribution system in providing grid service?



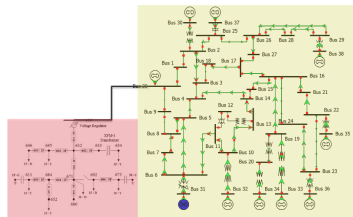
Background

Aggregate flexibility: the *power generation shaping capability* of a collection of heterogeneous DERs located on a feeder, or geographically distributed across multiple feeders over several hours to a day.

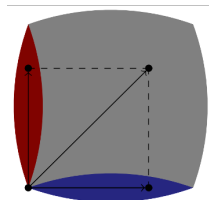


Background: Existing Approaches

- T&D co-simulation/co-optimization
 - ▶ High computational complexity
 - ▶ Requires continuous comm. between T&D
- Device-level aggregation
 - ▶ System agnostic
 - ▶ Requires homogeneity of DERs



- We need a new approach that:
 - ▶ is network-cognizant
 - ▶ is DER heterogeneity-compatible
 - ▶ is scalable
 - ▶ captures temporal correlations



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DER Models with Time Coupling

Energy storage

$$\begin{cases} \underline{P}_{k,\phi}^{(e)} \leq p_{k,\phi}^{(e)}(t) \leq \bar{P}_{k,\phi}^{(e)}, \\ e_{k,\phi}(t) = \kappa_k e_{k,\phi}(t-1) - \tau p_{k,\phi}^{(e)}(t), \\ \underline{e}_{k,\phi} \leq e_{k,\phi}(t) \leq E_{k,\phi}, \end{cases}$$

HVAC system

$$\begin{cases} 0 \leq p_{k,\phi}^{(h)}(t) \leq \bar{P}_{k,\phi}^{(h)}(t), \\ \underline{H}_k \leq H_k^{\text{in}}(t) \leq \bar{H}_k, \\ H_k^{\text{in}}(t) = H_k^{\text{in}}(t-1) + \alpha_k (H_k^{\text{out}}(t) - H_k^{\text{in}}(t-1)) + \tau \beta_k p_k(t)^{(h)}(t), \end{cases}$$

PV inverter

$$0 \leq p_{k,\phi}^{(pv)}(t) \leq \bar{P}_{k,\phi}^{(pv)}(t).$$

Aggregate Flexibility: Model

Devices

Energy storage units, PV inverters, HVAC systems

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Network Model

$$\mathbf{v} = \mathbf{M}_{\Delta}^{(p)} \mathbf{p}_{\Delta} + \mathbf{M}_{\Delta}^{(q)} \mathbf{q}_{\Delta} + \mathbf{M}_Y^{(p)} \mathbf{p}_Y + \mathbf{M}_Y^{(q)} \mathbf{q}_Y + \tilde{\mathbf{v}}$$

$$\underline{\mathbf{v}} \leq \mathbf{v} \leq \bar{\mathbf{v}}$$

$$\mathbf{p}_0 = \mathbf{G}_{\Delta}^{(p)} \mathbf{p}_{\Delta} + \mathbf{G}_{\Delta}^{(q)} \mathbf{q}_{\Delta} + \mathbf{G}_Y^{(p)} \mathbf{p}_Y + \mathbf{G}_Y^{(q)} \mathbf{q}_Y + \mathbf{c}$$

Aggregate Flexibility: Model

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Compact Model with Uncertainty

$$\begin{aligned} \mathbf{Wp} &\leq \mathbf{z}(\zeta) \\ \mathbf{p}_0 &= \mathbf{Dp} + \mathbf{b}(\zeta) \end{aligned} \quad (*)$$

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Motivation for Ellipsoidal Inner Approximation

$$\begin{aligned}\mathbf{W}\mathbf{p} &\leq \mathbf{z}(\zeta) \\ \mathbf{p}_0 &= \mathbf{D}\mathbf{p} + \mathbf{b}(\zeta)\end{aligned}\tag{*}$$

Goal

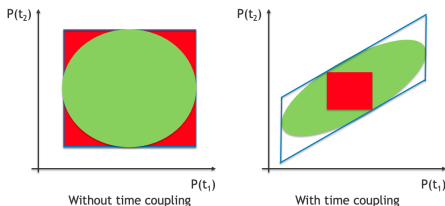
With full controllability of DERs downstream, derive the aggregate power flexibility at the feeder level ($\mathcal{F} = \{p_0 : \exists(p_0, p(p_0)) \text{ that satisfies } (*) \text{ for all } \zeta\}$).

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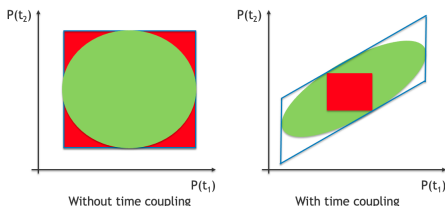


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Challenge

Finding the maximum volume inscribed ellipsoidal in a polytopic projection is nontrivial computationally.

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Ellipsoidal Inner Approximation: Adaptive Robust Optimization

We want to identify the maximum volume inscribing ellipsoid (MVE)

$$\mathcal{E} = \{\mathbf{p}_0 : \mathbf{p}_0 = \mathbf{E}\boldsymbol{\xi} + \mathbf{e}, \|\boldsymbol{\xi}\| \leq 1\} \subset \mathbb{R}^T$$

parameterized by $\mathbf{E} \succeq 0$ and $\mathbf{e} \in \mathbb{R}^T$ such that for any $\mathbf{p}_0 \in \mathcal{E}$ and any $\|\boldsymbol{\zeta}_t\| \leq 1, \forall t$, there exists $\mathbf{p}(\mathbf{p}_0, \boldsymbol{\zeta})$ such that system constraints are satisfied.

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Initial Formulation

$$\max_{\mathbf{e}, \mathbf{E} \succeq 0} \left\{ \log \det \mathbf{E} : \forall \|\boldsymbol{\xi}\| \leq 1, \forall \|\boldsymbol{\zeta}_t\| \leq 1, \exists \mathbf{p} \text{ s.t. } \mathbf{E}\boldsymbol{\xi} + \mathbf{e} = \mathbf{D}\mathbf{p} + \mathbf{b}(\boldsymbol{\zeta}), \mathbf{W}\mathbf{p} \leq \mathbf{z}(\boldsymbol{\zeta}) \right\},$$

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Proposition

The problem can be equivalently formulated as

$$\max_{\mathbf{e}, \mathbf{E} \succeq 0} \left\{ \log \det \mathbf{E} : \forall \|\boldsymbol{\xi}\| \leq 1, \forall \mathbf{u} \in \mathcal{U}, \exists \mathbf{y} \text{ s.t. } \mathbf{W}_1 \tilde{\mathbf{D}}^{-1}(\mathbf{E}\boldsymbol{\xi} + \mathbf{e}) + \mathbf{W}_2 \mathbf{y} \leq \mathbf{u} \right\},$$

where the vector of individual DER control variables \mathbf{p} can be recovered as $\mathbf{p} = \mathbf{B}_1 \tilde{\mathbf{D}}^{-1}(\mathbf{p}_0 - \mathbf{b}(\boldsymbol{\zeta})) + \mathbf{B}_2 \mathbf{y}$ given \mathbf{p}_0 , \mathbf{y} , and $\boldsymbol{\zeta}$.

Quadratic and affine policies

Quadratic policy:

$$\mathbf{y} = \left\{ \begin{array}{c} \vdots \\ \boldsymbol{\eta}^\top \mathbf{Q}_i \boldsymbol{\eta} \\ \vdots \end{array} \right\} + \mathbf{L}\boldsymbol{\eta} + \mathbf{c},$$

where $\boldsymbol{\eta} := \begin{bmatrix} \xi \\ \zeta \end{bmatrix}$. Affine policy:

$$\mathbf{y} = \mathbf{K}\boldsymbol{\xi} + \sum_{t=1}^T \mathbf{L}_t \boldsymbol{\zeta}_t + \boldsymbol{\gamma},$$

Policy-Based Formulations

- Quadratic policy: SDP inner approximation with tightness factor at most $9.19\sqrt{\ln(T+1)}$.
- Affine policy: exact SOCP reformulation.

Policy-Based Safe Approximations

Quadratic policy-based approximation

Let $\rho^i := ([\mathbf{w}_{1,i}\tilde{\mathbf{D}}^{-1}\mathbf{E}, -\boldsymbol{\theta}_i] + \mathbf{w}_{2,i}\mathbf{L})/2$ and:

$$\mathbf{J}_i := \begin{bmatrix} \lambda_{1,i}\mathbf{I}_T & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \lambda_{2,i}\mathbf{I}_{N_U} & & \vdots \\ \vdots & & \ddots & \mathbf{0} \\ \mathbf{0} & \cdots & & \lambda_{T+1,i}\mathbf{I}_{N_U} \end{bmatrix}$$

for $i = 1, \dots, m$, then the problem can be approximated by

$$\begin{aligned} & \max_{\substack{\mathbf{E} \succeq \mathbf{0}, \mathbf{e}, \mathbf{c}, \mathbf{L}, \\ \{\mathbf{Q}_i\}_{i=1}^m, \{\lambda_{k,i}\}_{k=0,i=1}^{T+1,m}}} \log \det \mathbf{E} \\ & \text{s.t. } (\forall i = 1, \dots, m) \\ & \sum_{k=0}^{T+1} \lambda_{k,i} + \mathbf{w}_{1,i}\tilde{\mathbf{D}}^{-1}\mathbf{e} + \mathbf{w}_{2,i}\mathbf{c} - \nu_i \leq 0, \\ & \begin{bmatrix} \lambda_{0,i} & \mathbf{0} \\ \mathbf{0} & \mathbf{J}_i \end{bmatrix} \succeq \begin{bmatrix} 0 & \sum_{j=1}^{(n-1)T} \rho^j \\ (\rho^i)^\top & \sum_{j=1}^{(n-1)T} \mathbf{w}_{2,i,j}\mathbf{Q}_j \end{bmatrix}, \\ & \lambda_{k,i} \geq 0, \quad k = 0, \dots, T+1 \end{aligned}$$

Affine policy-based approximation

$$\begin{aligned} & \max_{\substack{\mathbf{E} \succeq \mathbf{0}, \mathbf{e}, \mathbf{K}, \{\mathbf{L}_t\}_{t=1}^T, \boldsymbol{\gamma}, \{\alpha_i\}_{i=1}^m}} \log \det \mathbf{E} \\ & \text{s.t. } (\forall i = 1, \dots, m) \\ & \|\mathbf{w}_{1,i}\tilde{\mathbf{D}}^{-1}\mathbf{E} + \mathbf{w}_{2,i}\mathbf{K}\| + \sum_{k=1}^T \|\mathbf{w}_{2,i}\mathbf{L}_k - \boldsymbol{\theta}_{k,i}\| \leq \alpha_i, \\ & \alpha_i + \mathbf{w}_{1,i}\tilde{\mathbf{D}}^{-1}\mathbf{e} + \mathbf{w}_{2,i}\boldsymbol{\gamma} - \nu_i \leq 0, \end{aligned}$$

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Affine policy-based approximation

$$\begin{aligned} & \max_{\mathbf{E} \succeq \mathbf{0}, \mathbf{e}, \mathbf{K}, \{\mathbf{L}_t\}_{t=1}^T, \boldsymbol{\gamma}, \{\alpha_i\}_{i=1}^m} \log \det \mathbf{E} \\ & \text{s.t. } (\forall i = 1, \dots, m) \\ & \|\mathbf{w}_{1,i}\tilde{\mathbf{D}}^{-1}\mathbf{E} + \mathbf{w}_{2,i}\mathbf{K}\| + \sum_{k=1}^T \|\mathbf{w}_{2,i}\mathbf{L}_k - \boldsymbol{\theta}_{k,i}\| \leq \alpha_i, \\ & \alpha_i + \mathbf{w}_{1,i}\tilde{\mathbf{D}}^{-1}\mathbf{e} + \mathbf{w}_{2,i}\boldsymbol{\gamma} - \nu_i \leq 0, \end{aligned}$$

The two safe approximations are **incomparable**.

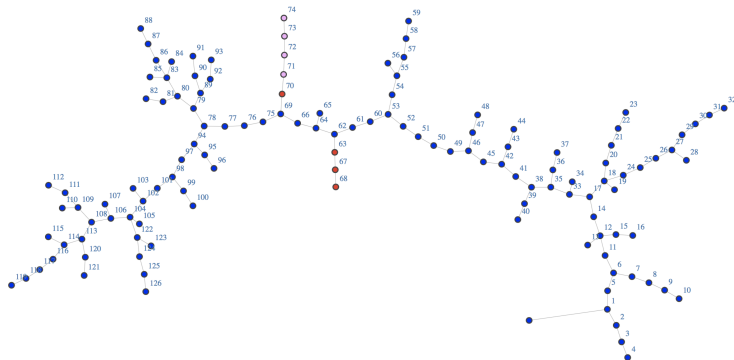
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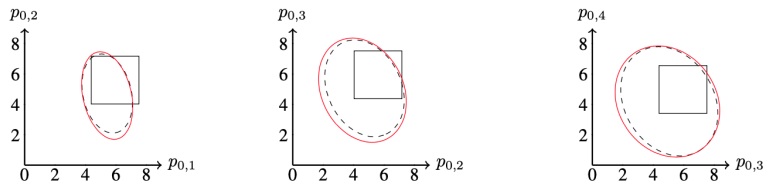
Simulation: Test System

Southern California Edison (SCE) 126-node three-phase distribution feeder.

- 27 energy storage units;
- 33 PV inverters;
- 5 HVAC systems.



Simulation Results



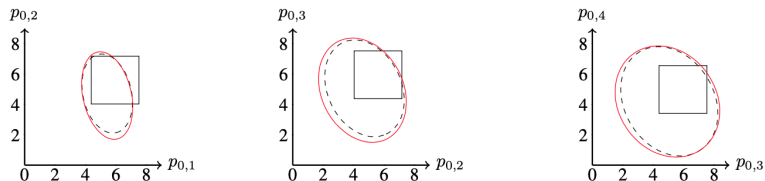
(a) Projected flexibility: 9:00–11:00. (b) Projected flexibility: 10:00–12:00. (c) Projected flexibility: 11:00–13:00.

Fig. 1: Projection of flexibility region approximations. (hyperbox: black solid line; affine policy: black dashed line; quadratic policy: red solid line.)

Table: Volumes of Flexibility Region Approximation

Method	Volume
Ellipsoid by quadratic policy	271.55
Ellipsoid by affine policy	217.57
Hyperbox approximation	96.88

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Numerical simulations suggest the ellipsoidal approximations capture 75-80% of the true flexibility region.

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Summary

- Encapsulation of distribution system generation shaping capability by aggregate flexibility region.
- Ellipsoidal characterization of aggregate flexibility region to capture time-coupling DER flexibility.
- Tractable safe approximations of resulting ARO formulation based on quadratic and affine second-stage policies.

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Future directions

- Rigorous guarantees on constraint satisfaction
- Strategies for DER disaggregation

Thank you!
Questions?