Distributed Optimal Coordination for Distributed Energy Resources in Power Systems

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Reference

Results in this presentation are mainly based on the paper:

Di Wu, Tao Yang, Anton A. Stoorvogel, and Jakob Stoustrup. Distributed optimal coordination for distributed energy resources in power systems. *IEEE Transactions on Automation Science and Engineering*, Volume: 14 Issue: 2, Pages: 414 - 424, 2017. DOI: 10.1109/TASE.2016.2627006 .

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In order to unleash this potential, however, new control and coordination approaches are required, which can handle the massive complexity involved.

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Employing DERs in the operation of large infrastructures bears significant promise of safer, more effective and more efficient use of those infrastructures.
In order to unleash this potential, however, new control and coordination approaches are required, which can handle the massive complexity involved.
In particular, handling distributed energy storages in a rational manner is a challenge for state-of-the-art approaches. This lecture proposes a novel approach to that end.

Approach

In the sequel, we shall propose a coordination approach based on online optimization. The approach proceeds as follows:

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2. Operational conditions are introduced as constraints
3. A (nonconvex) optimization problem is formed by cost function and constraints
4. The nonconvex optimization problem is restated as a convex optimization problem
5. An iterative algorithm is proposed based on a *consensus and gradient* approach

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Objective function

An optimal solution minimizes the following cost function:

$$\mathcal{J}(p, p^{\text{batt}}, E) = \sum_{t=1}^{T} \sum_{i=1}^{N} C_i(p_{i,t})$$

subject to a number of constraints. Here:

$C_i(p_{i,t})$ is the cost function of generator i for period t, which is dominated by fuel cost.

$p = [p_{i,t}]$ contains the power from generator or storage i during period t.

$p^{\text{batt}} = \left[p_{i,t}^{\text{batt}}\right]$ contains the rate of change of energy stored in storage device i at the end of period t, which is positive when storage device is discharged.

$E = [E_{i,t}]$ contains the energy stored in storage i at time period t.

N is number of generators, T is number of time samples.

Balancing constraints

At every time instant, the energy generated plus the energy stored must equal the current load:

$$\sum_{i=1}^{N+M} p_{i,t} - D_t = 0$$

Here:
$p_{i,t}$ is the power from generator or storage i during period t.
D_t is the total load during period t.
N is number of generators, M is number of storages.

Ramping constraints

At every time instant, the power change must satisfy ramping constraints for generators and storages:

$$\Delta \underline{p}_i \leq p_{i,t} - p_{i,t-1} \leq \Delta \overline{p}_i$$

Here:
$p_{i,t}$ is the power from generator or storage i during period t.
$\Delta \underline{p}_i$ and $\Delta \overline{p}_i$ are the lower and upper ramping constraints for generator or storage i, respectively.

Generator capacity constraints

At every time instant, the power delivered by each generator must satisfy capacity constraints:

$$p_i^{\min} \leq p_{i,t} \leq p_i^{\max}$$

Here:
$p_{i,t}$ is the power from generator i during period t.
$p_i^{\min}$ and $p_i^{\max}$ are the minimal and maximal capacity for generator i, respectively.

Storage rate change constraints

At every time instant, the change of power to storage must satisfy storage rate change constraints:

$$p_{i,t}^{\text{batt}} = \begin{cases} \frac{p_{i,t}}{\eta_i^+}, & \text{if } p_{i,t} \geq 0 \\ p_{i,t}\eta_i^-, & \text{if } p_{i,t} < 0 \end{cases}$$

Here:

$p_{i,t}$ is the power from generator i during period t.

$p_{i,t}^{\text{batt}}$ is the rate of change of energy stored in storage device i at the end of period t, which is positive when storage device is discharged.

η_i^+ and η_i^- are, respectively, the discharging and charging efficiency of storage device i, respectively, including components such as conductors, power electronics, and batteries.

Storage energy update

At each time instant, the energy $E_{i,t}$ stored in storage i at time t is updated according to:

$$E_{i,t} = E_{i,t-1} - p_{i,t}^{\mathrm{batt}} \Delta T$$

Here:
$p_{i,t}^{\mathrm{batt}}$ is the rate of change of energy stored in storage device i at the end of period t, which is positive when storage device is discharged.
ΔT is the time step size.

Storage energy constraints

At every time instant, storage capacity constraints must be satisfied:

$$0 \leq E_{i,t} \leq E_i^{\max}$$

Here:
$E_i^{\max}$ is the maximal storage capacity of storage i.

Storage end constraints

At the end of each optimization, the original charge of state for each storage much be restored:

$$E_{i,T} = E_{i,0}$$

Here:
$E_{i,T}$ and $E_{i,0}$ are the end and initial state of charge for storage i, respectively.

Multi-step optimization problem

$$
\begin{aligned}
\textbf{P:}\quad \min_{p_{i,t},p^{\text{batt}}_{i,t},E_{i,t}} \quad & \textstyle\sum_{t=1}^{T}\sum_{i=1}^{N} C_i(p_{i,t}), \\
\text{s.t.} \quad & \textstyle\sum_{i=1}^{N+M} p_{i,t} - D_t = 0 && \forall t \in \mathcal{T} \\
& \Delta\underline{p}_i \le p_{i,t} - p_{i,t-1} \le \Delta\overline{p}_i && \forall t \in \mathcal{T}, \forall i \in \mathcal{N} \\
& p_i^{\min} \le p_{i,t} \le p_i^{\max} && \forall t \in \mathcal{T}, \forall i \in \mathcal{L} \\
& p^{\text{batt}}_{i,t} = \begin{cases} \frac{p_{i,t}}{\eta_i^{+}}, & \text{if } p_{i,t} \ge 0 \\ p_{i,t}\eta_i^{-}, & \text{if } p_{i,t} < 0 \end{cases} && \forall t \in \mathcal{T}, \forall i \in \mathcal{M} \\
& E_{i,t} = E_{i,t-1} - p^{\text{batt}}_{i,t}\Delta T && \forall t \in \mathcal{T}, \forall i \in \mathcal{M} \\
& 0 \le E_{i,t} \le E_i^{\max} && \forall t \in \mathcal{T}, \forall i \in \mathcal{M} \\
& E_{i,T} = E_{i,0} && \forall i \in \mathcal{M}
\end{aligned}
$$

where $\mathcal{T} = \{1, \dots, T\}$, $\mathcal{N} = \{1, \dots, N\}$, $\mathcal{M} = \{N+1, \dots, N+M\}$, and $\mathcal{L} = \{1, \dots, N+M\}$.

Convexifying optimization problem

The posed optimization problem is *non-convex* due to the storage rate change constraint:

$$p_{i,t}^{\text{batt}} = \begin{cases} \frac{p_{i,t}}{\eta_i^+}, & \text{if } p_{i,t} \geq 0 \\ p_{i,t}\eta_i^-, & \text{if } p_{i,t} < 0 \end{cases}$$

The optimization problem, however, can be convexified by replacing the storage rate change constraint by:

$$p_{i,t}^{\text{batt}} = \frac{1}{\eta_i^+} p_{i,t}^+ - \eta_i^- p_{i,t}^-$$

and by adding two storage capacity constraints of the form:

$$0 \leq p_{i,t}^+ \leq p_i^{\max},\ 0 \leq p_{i,t}^- \leq -p_i^{\min}$$

Modified optimization problem

$$
\begin{aligned}
\mathbf{P}': \quad & \min_{p_{i,t},p^+_{i,t},p^-_{i,t},p^{\text{batt}}_{i,t},E_{i,t}} && \textstyle\sum_{t=1}^{T}\sum_{i=1}^{N} C_i(p_{i,t}), && \\
& \text{s.t.} && \textstyle\sum_{i=1}^{N+M} p_{i,t} - D_t = 0 && \forall t \in \mathcal{T} \\
& && \Delta\underline{p}_i \le p_{i,t} - p_{i,t-1} \le \Delta\overline{p}_i && \forall t \in \mathcal{T}, \forall i \in \mathcal{N} \\
& && p_i^{\min} \le p_{i,t} \le p_i^{\max} && \forall t \in \mathcal{T}, \forall i \in \mathcal{L} \\
& && p^{\text{batt}}_{i,t} = \tfrac{1}{\eta_i^+} p^+_{i,t} - \eta_i^- p^-_{i,t} && \forall t \in \mathcal{T}, \forall i \in \mathcal{M} \\
& && E_{i,t} = E_{i,t-1} - p^{\text{batt}}_{i,t}\Delta T && \forall t \in \mathcal{T}, \forall i \in \mathcal{M} \\
& && 0 \le E_{i,t} \le E_i^{\max} && \forall t \in \mathcal{T}, \forall i \in \mathcal{M} \\
& && E_{i,T} = E_{i,0} && \forall i \in \mathcal{M} \\
& && 0 \le p^+_{i,t} \le p_i^{\max},\ 0 \le p^-_{i,t} \le -p_i^{\min} && \forall t \in \mathcal{T}, \forall i \in \mathcal{M}
\end{aligned}
$$

Convexifying result

The modified optimization problem $\mathbf{P}'$ is equivalent to the original optimization problem $\mathbf{P}$ by virtue of the following result:

Theorem

Any solution with a pair of $p_{i,t}^{+}$ and $p_{i,t}^{-}$ to be nonzero cannot be an optimal solution of $\mathbf{P}'$ when $\eta_i^{+}\eta_i^{-} < 1$.

Convexifying result

The modified optimization problem $\mathbf{P}'$ is equivalent to the original optimization problem $\mathbf{P}$ by virtue of the following result:

Theorem

Any solution with a pair of $p^{+}_{i,t}$ and $p^{-}_{i,t}$ to be nonzero cannot be an optimal solution of $\mathbf{P}'$ when $\eta_i^{+}\eta_i^{-} < 1$.

The condition $\eta_i^{+}\eta_i^{-} < 1$ essentially means that a charging-discharging cycle is not lossless.

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Algorithm: Multiple storage devices - Part I

Initialize $k = 0$ and $\lambda_i(0) = 0 \in \mathbb{R}^T$ for $\forall\, i \in \mathcal{L}$.

repeat

  procedure Local optimization

    for each node $i = 1, \ldots, N$ **do**

$$p_i(k) = \underset{p_i \in \Omega_{\mathcal{N},i}}{\arg\min} \sum_{t=1}^{T} C_i(p_{i,t}) - \lambda_i(k)' p_i$$

    end for

    for each node $i = N+1, \ldots, N+M$ **do**

$$\{p_i^+(k), p_i^-(k)\} = \underset{\{p_i^+, p_i^-\} \in \tilde{\Omega}_{\mathcal{M},i}}{\arg\min} \quad \lambda_i(k)' \left(p_i^- - p_i^+\right)$$

$$p_i(k) = p_i^+(k) - p_i^-(k)$$

    end for

  end procedure

  procedure Consensus and Gradient

    for each node $i = 1, \ldots, N+M$ **do**

$$\lambda_i(k+1)$$

$$= \lambda_i(k) - \underbrace{\beta \sum_{v=1}^{N+M} \ell_{iv} \lambda_v(k)}_{\text{consensus part}} - \underbrace{\alpha_k \left(p_i(k) - D^i\right)}_{\text{gradient part}}$$

    end for

  end procedure

  $k = k + 1$

until Error small enough

for each node $i = 1, \ldots, N$ **do**

  $p_i^{\text{sol}} = p_i(k-1)$

end for

Algorithm: Multiple storage devices - Part II

Initialize $m = 0$ and $\lambda_i(0) = 0$ for $\forall i \in \mathcal{L}$.
repeat
    procedure LOCAL OPTIMIZATION
        for each node $i = 1, \ldots, N$ **do**
            $p_i(m) = p_i^{\mathrm{sol}}$
        end for
        for each node $i = N+1, \ldots, N+M$ **do**
            $\{p_i^+(m), p_i^-(m)\}$
                $= \underset{\{p_i^+, p_i^-\} \in \tilde{\Omega}_{\mathcal{M},i}}{\arg\min} \quad \|p_i^+ - p_i^-\|^2 - \lambda_i(m)' \left(p_i^+ - p_i^-\right)$
            $p_i(m) = p_i^+(m) - p_i^-(m)$
        end for
    end procedure
    procedure CONSENSUS AND GRADIENT
        for each node $i = 1, \ldots, N+M$ **do**
            $\lambda_i(m+1)$
                $= \lambda_i(m) \underbrace{- \beta \sum_{v=1}^{N+M} \ell_{iv} \lambda_v(m)}_{\text{consensus part}} - \underbrace{\alpha_m \left(p_i(m) - D^i\right)}_{\text{gradient part}}$
        end for
    end procedure
    $m = m + 1$
until Error small enough
for each node $i = N+1, \ldots, N+M$ **do**
    $p_i^{\mathrm{sol}} = p_i(m-1)$
end for

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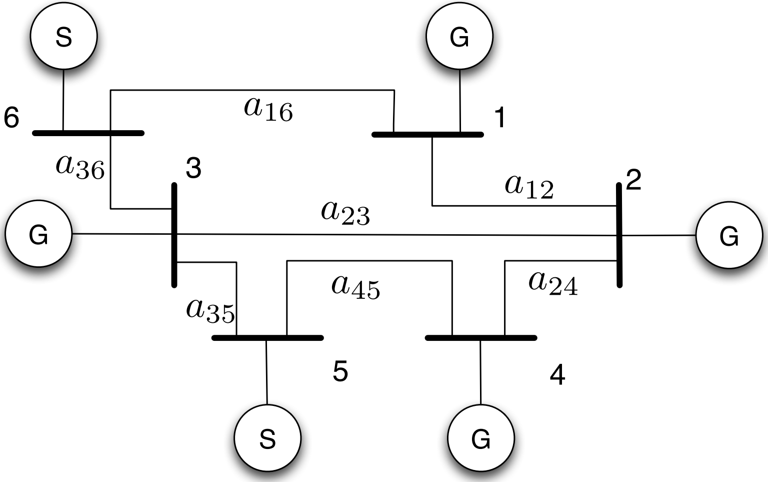
Example: IEEE six-bus power system



Parameters for example

A quadratic function is used to represent generation cost as a function of power output, which is given by

$$C_i(p_{i,t}) = a_i p_{i,t}^2 + b_i p_{i,t} + c_i,$$

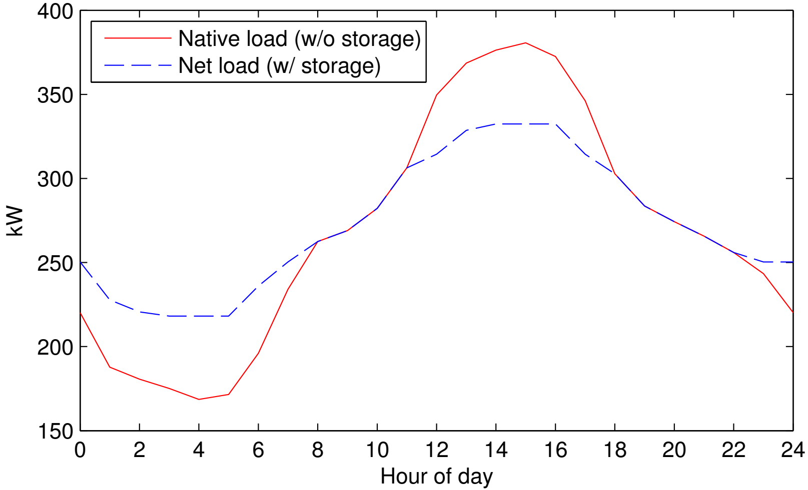
Table: Generator Parameters

Bus	a_i (\$/kW^{2}h)	b_i (\$/kWh)	c_i (\$/h)	Range (kW)
1	0.00024	0.0267	0.38	[30,60]
2	0.00052	0.0152	0.65	[20,60]
3	0.00042	0.0185	0.4	[50,200]
4	0.00031	0.0297	0.3	[20,140]

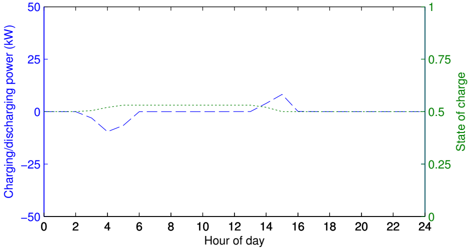
Table: Storage Parameters

Bus	E_s (kWh)	$p_{\min}$ (kW)	$p_{\max}$ (kW)	η_+	η_-
5	500	-50	50	0.8	0.8
6	400	-40	40	0.88	0.88

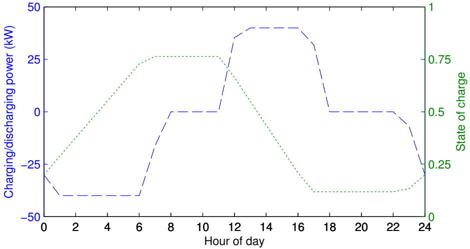
Native load vs. net load



Charging (negative) and discharging (positive) power and state of charge

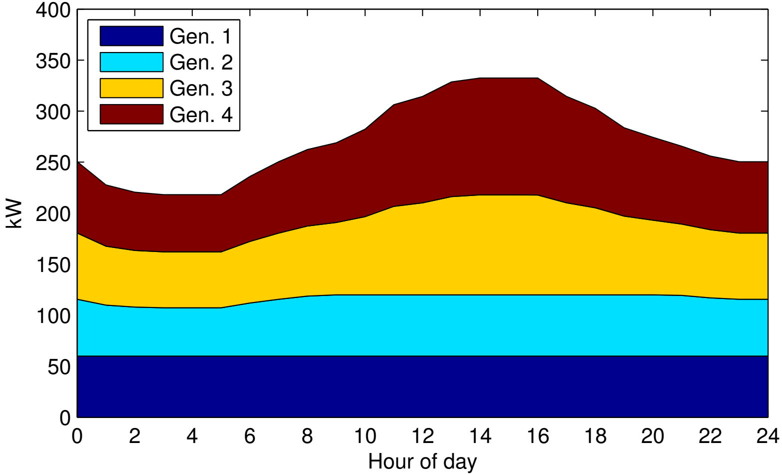


(a) Battery 1



(b) Battery 2

Generations from DGs



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- A general distributed control and coordination framework has been proposed
- The approach is applicable for operating large infrastructures with DERs, also including distributed storages
- The approach is scalable
- The approach involves two tuning parameters, which are topology dependent and for which yet no systematic analysis for guiding their choice is known