Energy Exchange in a Network of Microgrids

Final presentation

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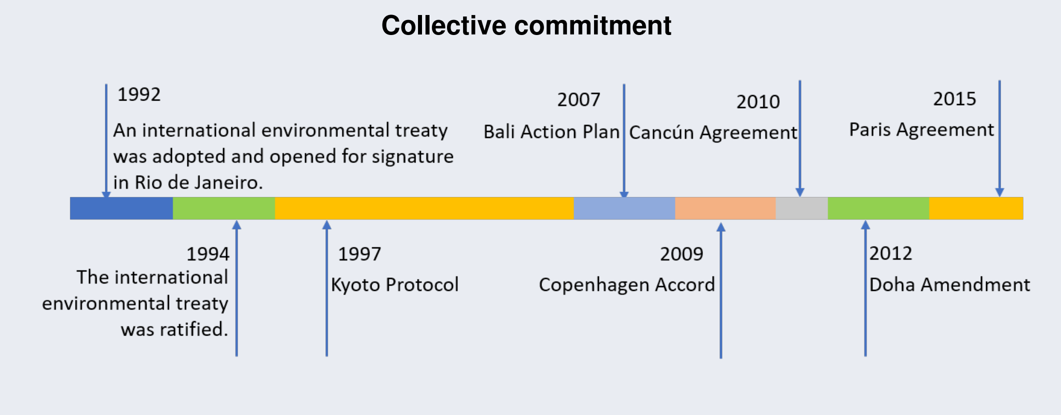
Outline

Section 1

Background and Motivations

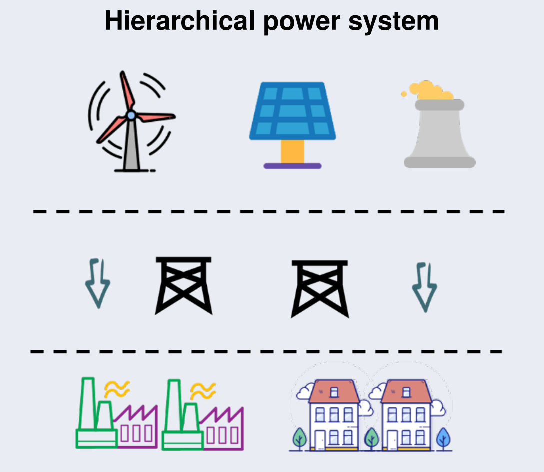
- Changes in Distribution Systems
- From Centralized to Peer-to-Peer (P2P) Markets
- Motivations and Contributions

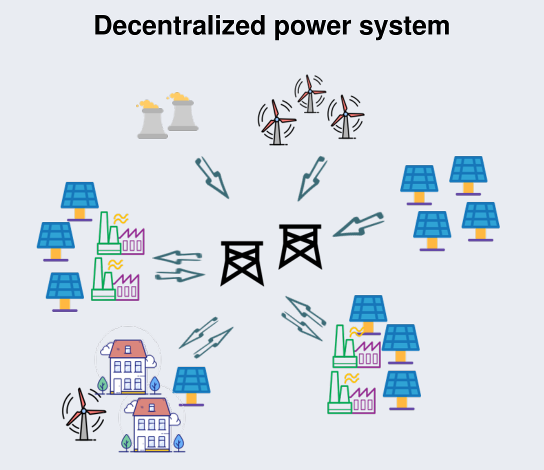
Changes in Distribution Systems



Greenhouse gas reduction $\longrightarrow$ Decarbonization $\longrightarrow$ Renewable energy

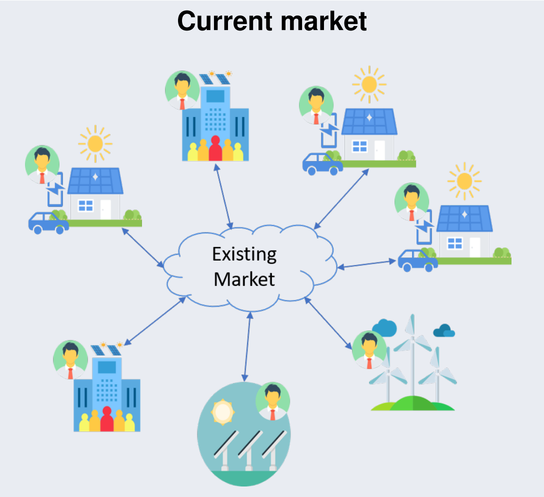
Changes in Distribution Systems





Decentralized power system $\longrightarrow$ Deregulated electricity market

From Centralized to Peer-to-Peer (P2P) Markets



From Centralized to Peer-to-Peer (P2P) Markets

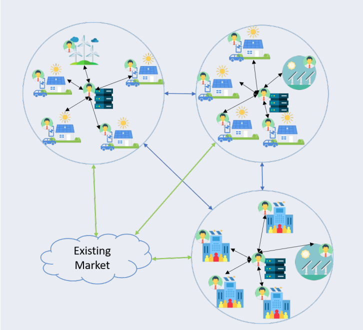
A P2P market[1]

A P2P market, characterized by the lack of a supervisory agent, consists of a simultaneous negotiation over the price and energy of multi-bilateral trades along a predefined trading scheme.

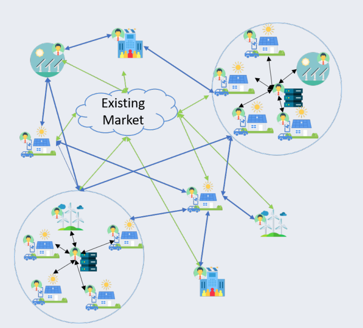
[1] E. Sorin, L. Bobo and P. Pinson, March 2019

Full P2P markets

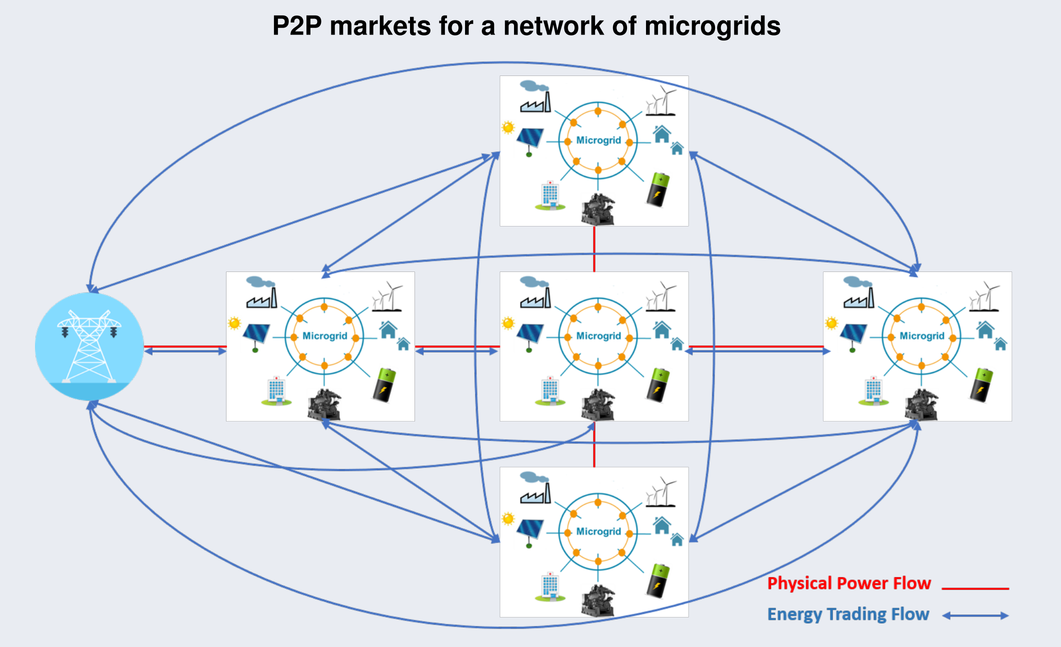
Community P2P markets



Hybrid P2P markets

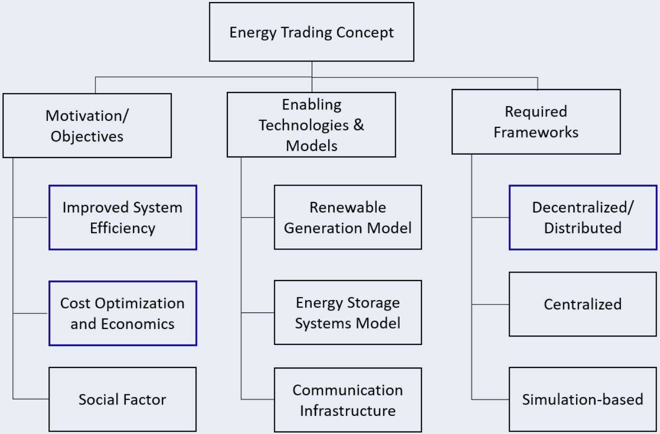


From Centralized to Peer-to-Peer (P2P) Markets



Motivations and Contributions

Energy trading concept overview



Our works

- P2P energy trading

Motivations and Contributions

Motivations: P2P energy trading

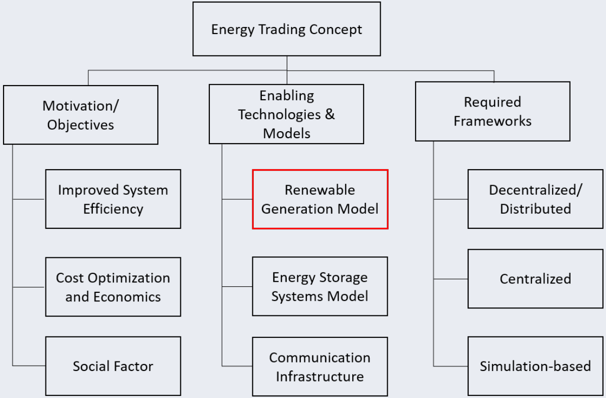
- Conflict exists between an efficient market and a feasible solution for power flow in the physical network
- Power trades determined at a virtual layer might face a re-dispatching problem
- A microgrid can be a possible unit for efficient energy management in the future electricity market.

Contributions: P2P energy trading

- A preference mechanism is adapted into P2P energy trading for a network of microgrids
- All the physical constraints regarding power flow are included in the model
- The effect of preference mechanism on the resulting power flow is analyzed for achieving the desired power flow or a predefined network configuration.
- A distributed algorithm is developed to realize such a P2P energy trading market model.

Motivations and Contributions

Energy trading concept overview



Our works

- P2P energy trading
- Wind power forecasting

Motivations and Contributions

Motivations: wind power forecasting

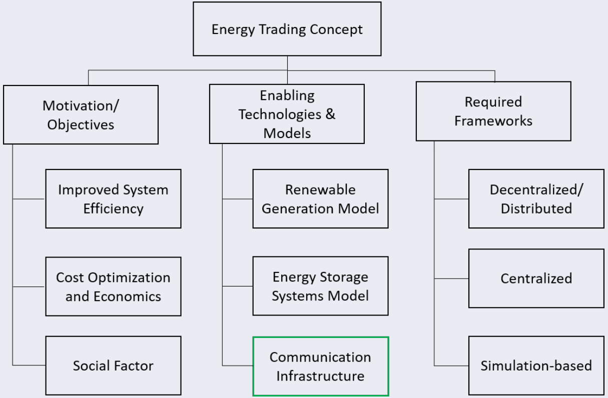
- Wind power is highly required and indispensable in the energy trading market
- Wind power forecasts at different levels (at a single wind farm, at a regional scale)

Contributions: wind power forecasting

- Wind power forecast for a wind turbine:
  how to estimate wind turbine power curve?
- Wind power forecast for a single wind farm:
  how to deal with large data of wind speeds and wind power outputs?
- Wind power forecast in a region:
  how to reconcile the forecast at a region level with the forecasts at a wind farm level with data privacy preserving?

Motivations and Contributions

Energy trading concept overview



Our works

- P2P energy trading
- Wind power forecasting
- Communication techniques

Motivations and Contributions

Motivations: communication techniques

- Power line Communication (PLC) is a candidate communication solution among the information and communication techniques for accomplishing P2P energy trading.
- Power line channels are disturbed by strong impulsive noise (IN).

Contributions: communication techniques

- IN modeling is investigated in narrowband power line communication
- An algorithm for IN mitigation is proposed to improve the data transmission performance.

Section 2

Problem Setup

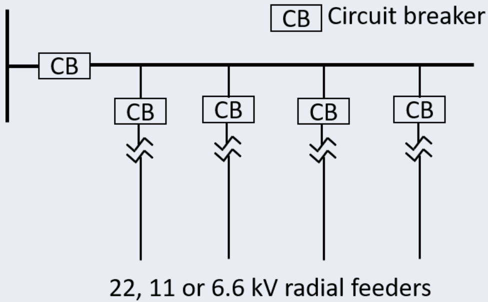
- Model of a Network of Microgrids
- Model of a Microgrid
- Optimization Objectives

Model of a Network of Microgrids

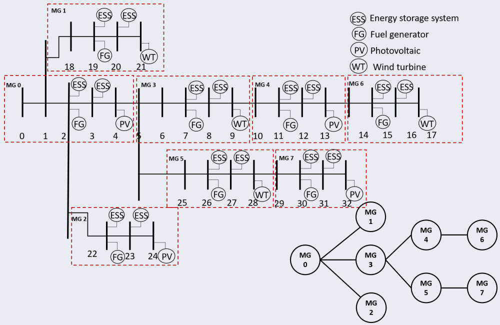
Radial distribution network

In such systems, different feeders radiate from a substation or a generating station and feed the distributors at one end. The main characteristic of a radial distribution system is that the power flow is in only one direction.

Radial distribution system



IEEE 33-bus distribution system



Model of a Microgrid

A microgrid

A microgrid is a localized group of electricity sources and loads that normally operates in grid-connected mode and in islanding mode as well. The distributed energy resources in a microgrid include:

- Fuel generator (FG)
- Energy storage system (ESS)
- Load
- Renewable energy sources (PV and wind energy)
- Distribution lines

Model of a Microgrid

Notations

- Ω the set of all microgrids in a network
- ω_n the set of the trading microgrid partners for MG n
- $\mathcal{G}_n$ the set of fuel generators in MG n
- $\mathcal{S}_n$ the set of ESSs in MG n
- $\mathcal{B}_n$ the set of the buses in MG n
- $\mathcal{T}_n$ the set of the distribution lines in MG n
- $\mathcal{E}$ the set of the connecting edges in the network of microgrids

Model of a Microgrid

Fuel generator model

The generation cost for the k-th FG, $k \in \mathcal{G}_n$ for every generic MG n is expressed as

$$
\begin{aligned}
& f_{G,k}(p_{G,k}) = \frac{1}{2} a_k^2 p_{G,k}^2 + b_k p_{G,k} + c_k, && \text{(1a)} \\
& \underline{p}_{G,k} \leq p_{G,k} \leq \overline{p}_{G,k} && \text{(1b)} \\
& \underline{q}_{G,k} \leq q_{G,k} \leq \overline{q}_{G,k} && \text{(1c)} \\
& -\gamma_{G,k} \leq p_{G,k}^{t+1} - p_{G,k}^{t} \leq \gamma_{G,k}. && \text{(1d)}
\end{aligned}
$$

- $p_{G,k}$ and $q_{G,k}$ are the generated active and reactive power;
- a_k, b_k and c_k are the cost coefficients and are nonnegative;
- $\underline{p}_{G,k}$ and $\overline{p}_{G,k}$ are the lower and upper bounds of the active power output;
- $\underline{q}_{G,k}$ and $\overline{q}_{G,k}$ are the counterparts for the reactive power;
- $\gamma_{G,k}$ represents the ramp rate bound.

Model of a Microgrid

Energy storage system model

The model of the k-th ESS, $k \in \mathcal{S}_n$ for every generic MG n is expressed as

$$x_k^{t+1} = x_k^t + \beta_{\text{char},k} p_{\text{char},k}^t - \beta_{\text{disc},k} p_{\text{disc},k}^t \tag{2a}$$

$$\underline{x}_k \leq x_k^t \leq \overline{x}_k \tag{2b}$$

$$0 \leq p_{\text{char},k}^t \leq \overline{p}_{\text{char},k} \tag{2c}$$

$$0 \leq p_{\text{disc},k}^t \leq \overline{p}_{\text{disc},k}. \tag{2d}$$

- x_k^t denotes the state of charge of MG n at time t;
- $\beta_{\text{char},k}$ and $\beta_{\text{disc},k}$ denote the charging and discharging efficiency;
- $\underline{x}_k$ and $\overline{x}_k$ are the lower and upper bounds of the state of charge x_k^t;
- r $\overline{p}_{\text{char},k}$ is upper bound of the charging power $p_{\text{char},k}^t$;
- $\overline{p}_{\text{disc},k}$ is upper bound of the discharging power $p_{\text{disc},k}^t$

Load and RESs models

Loads and RESs are considered as non-dispatchable units.

Model of a Microgrid

Distribution line models

The *DistFlow* model can be described for any two neighboring buses i and j as

$$P_i' - P_j' - R_{ij}\frac{P_i'^2 + Q_i'^2}{V_i^2} - P_j = 0, \tag{3a}$$

$$Q_i' - Q_j' - X_{ij}\frac{P_i'^2 + Q_i'^2}{V_i^2} - Q_j = 0, \tag{3b}$$

$$V_i^2 - 2(R_{ij}P_i' + X_{ij}Q_i') + (R_{ij}^2 + X_{ij}^2)\frac{P_i'^2 + Q_i'^2}{V_i^2} - V_j^2 = 0, \tag{3c}$$

$$P_i = P_i^D - P_i^G, \quad Q_j = Q_i^D - Q_i^G \tag{3d}$$

$$P_j = P_j^D - P_j^G, \quad Q_j = Q_i^D - Q_i^G, \tag{3e}$$

$$\underline{P}' \leq P_i', P_j' \leq \overline{P}' \quad \underline{Q}' \leq Q_i', Q_j' \leq \overline{Q}'$$

$$\underline{V} \leq V_i, V_j \leq \overline{V} \tag{3f}$$

Branch line

- P_i', Q_i' and V_i: active outlet power, reactive outlet power and voltage at bus i;
- P_j, Q_j: equivalent loads at bus j;
- P_j^D: local demand at bus j ;
- P_j^G: local generation at bus j;
- R_{ij} and X_{ij} are resistance and reactance.

Model of a Microgrid

Distribution line models

The *DistFlow* models can be described for any two neighboring buses i and j as

Linearized DistFlow Model

$$P_i^{'} - P_j^{'} - P_j = 0, \tag{4a}$$

$$Q_i^{'} - Q_j^{'} - Q_j = 0, \tag{4b}$$

$$V_i - \frac{R_{ij}P_i^{'} + X_{ij}Q_i^{'}}{V_0} - V_j = 0, \tag{4c}$$

$$\underline{P}^{'} \leq P_i^{'}, P_j^{'} \leq \overline{P}^{'}, \quad \underline{Q}^{'} \leq Q_i^{'}, Q_j^{'} \leq \overline{Q}^{'} \tag{4d}$$

$$\underline{V} \leq V_i, V_j \leq \overline{V}. \tag{4e}$$

Relaxed DistFlow Model

$$v_i = V_i^2 \quad v_j = V_j^2, \tag{5a}$$

$$l_{ij} \leq \frac{P_i^{'2} + Q_i^{'2}}{v_i}, \tag{5b}$$

$$P_i^{'} - P_j^{'} - R_{ij}l_{ij} - P_j = 0, \tag{5c}$$

$$Q_i^{'} - Q_j^{'} - X_{ij}l_{ij} - Q_j = 0, \tag{5d}$$

$$v_i - 2(R_{ij}P_i^{'} + X_{ij}Q_i^{'}) + (R_{ij}^2 + X_{ij}^2)l_{ij} - v_j = 0, \tag{5e}$$

$$\underline{P}^{'} \leq P_i^{'}, P_j^{'} \leq \overline{P}^{'} \quad \underline{Q}^{'} \leq Q_i^{'}, Q_j^{'} \leq \overline{Q}^{'}, \tag{5f}$$

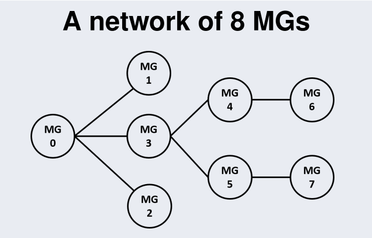
$$\underline{V} \leq V_i, V_j \leq \overline{V}. \tag{5g}$$

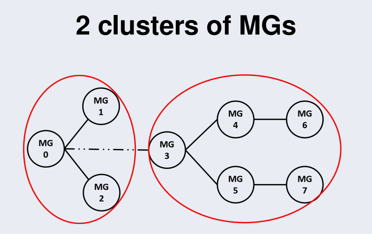
Optimization Objectives

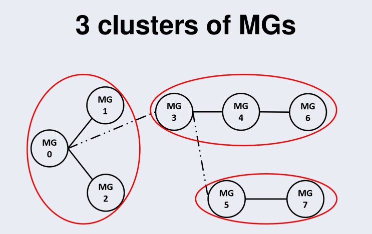
A preference mechanism

A preference mechanism is introduced to optimize the energy exchange between interconnected microgrids and customize the optimal power flow on the physical network topology. Preferences can be

- decided by single microgrids in a customized way
- enforced by the distribution system operator (DSO) to achieve a predetermined configuration.







Optimization Objectives

A preference mechanism

The preference on the energy trading p_{nm} for MG n with MG m, $m \in \omega_n$ is given as λ_{nm}, and it adds a penalty term

$$g(p_{nm}) = \lambda_{nm}|p_{nm}| \tag{6}$$

to the objective function, where λ_{nm} is nonnegative.

To well evaluate different preference values for different traders of each microgrid, κ is introduced with such constraints

$$\lambda_{nm} = \kappa\lambda_{nm}^{'}, \qquad \sum_{m\in\omega_n} \lambda_{nm}^{'} = 1, \qquad \lambda_{nm}^{'} \geq 0. \tag{7}$$

- $\lambda_{nm}^{'}$: normalized preference of power trade with MG m
- $\lambda_{nn}^{'}$: normalized preference of local energy exchange
- κ: scale parameter to scale $\lambda_{nm}^{'}$ to the price parameter λ_{nm}; it can be constant or time-varying as the electricity price.

Optimization Objectives

Objective of a MG

- Maximize the renewable energy usage;
- Prioritize a self-sufficient operation mode through a preference mechanism;
- Minimize the operational costs;
- Minimize the cost of power losses on the distribution lines with the relaxed *DistFlow* model.

Objective function of a MG

The objective function with the linearized *DistFlow* model can be expressed as

$$L_n = \sum_{t=1}^{T_s} L_n^t = \sum_{t=1}^{T_s} \Big(c_{\text{grid}}^t p_{n\text{grid}}^t + \sum_{k \in \mathcal{G}_n} f_{G,k}(p_{G,k}^t) + g_n^t\Big)$$

$$g_n^t = \kappa \lambda'_{n\text{grid}} \left| p_{n\text{grid}}^t \right| + \kappa \lambda'_{nn} \sum_{k \in \mathcal{S}_n} (p_{\text{char},k}^t + p_{\text{disc},k}^t) + \sum_{m \in \omega_n} \kappa \lambda'_{nm} \left| p_{nm}^t \right|$$

Optimization Objectives

Objective function of a MG

Linearized DistFlow Model	**Relaxed DistFlow Model**
$L_n = \sum_{t=1}^{T_s} (c_{\text{grid}}^t p_{n\text{grid}}^t + \sum_{k \in \mathcal{G}_n} f_{G,k}(p_{G,k}^t) + g_n^t)$ s.t. $(1a)-(1d), (2a)-(2d), (4a)-(4e)$	$L_n = \sum_{t=1}^{T_s} (c_{\text{grid}}^t p_{n\text{grid}}^t + \sum_{k \in \mathcal{G}_n} f_{G,k}(p_{G,k}^t) + g_n^t + c_{\text{loss}}^t \sum_{(i,j) \in \mathcal{T}_n} R_{ij} l_{ij}^t)$ s.t. $(1a)-(1d), (2a)-(2d), (5b)-(5g)$.

$$g_n^t = \kappa \lambda'_{n\text{grid}} \left| p_{n\text{grid}}^t \right| + \kappa \lambda'_{nn} \sum_{k \in \mathcal{S}_n} (p_{\text{char},k}^t + p_{\text{disc},k}^t) + \sum_{m \in \omega_n} \kappa \lambda'_{nm} \left| p_{nm}^t \right|$$

$$\sum_{k \in \mathcal{S}_n} (\beta_{\text{char},k} p_{\text{char},k}^t - \beta_{\text{disc},k} p_{\text{disc},k}^t) - \sum_{k \in \mathcal{G}_n} p_{G,k}^t + \sum_{k \in \mathcal{B}_n} p_{\text{net},k}^t = \sum_{m \in \omega_n} p_{nm}^t + p_{n\text{grid}}^t, \quad \forall t = 1, \ldots, T_s$$

$$-\sum_{k \in \mathcal{G}_n} q_{G,k}^t + \sum_{k \in \mathcal{B}_n} q_{\text{net},k}^t = \sum_{m \in \omega_n} q_{nm}^t + q_{n\text{grid}}^t, \quad \forall t = 1, \ldots, T_s$$

Price related parameters: c_{grid}^t, c_{loss}^t, κ, assuming $c_{\text{grid}}^t = c_{\text{loss}}^t = \kappa$.

Optimization Objectives

Objective function of a MG

General Preference-based P2P energy trading model

$$L_n = \sum_{t=1}^{T_s} \left(c_{\text{grid}}^t p_{\text{ngrid}}^t + \sum_{k \in \mathcal{G}_n} f_{G,k}(p_{G,k}^t) + g_n^t \right)$$

$$\text{s.t. } (1a) - (1d) \text{ (FG model)}$$

$$(2a) - (2d) \text{ (ESS model)}$$

$$g_n^t = \kappa \lambda_{\text{ngrid}}' \left| p_{\text{ngrid}}^t \right| + \kappa \lambda_{nn}' \sum_{k \in \mathcal{S}_n} (p_{\text{char},k}^t + p_{\text{disc},k}^t) + \sum_{m \in \omega_n} \kappa \lambda_{nm}' \left| p_{nm}^t \right| \text{ (Preference mechanism)}$$

$$\sum_{k \in \mathcal{S}_n} \left(\beta_{\text{char},k} p_{\text{char},k}^t - \beta_{\text{disc},k} p_{\text{disc},k}^t \right) - \sum_{k \in \mathcal{G}_n} p_{G,k}^t + \sum_{k \in \mathcal{B}_n} p_{\text{net},k}^t = \sum_{m \in \omega_n} p_{nm}^t + p_{\text{ngrid}}^t, \quad \forall t = 1, \ldots, T_s \text{ (Active power)}$$

$$- \sum_{k \in \mathcal{G}_n} q_{G,k}^t + \sum_{k \in \mathcal{B}_n} q_{\text{net},k}^t = \sum_{m \in \omega_n} q_{nm}^t + q_{\text{ngrid}}^t, \ \forall t = 1, \ldots, T_s \text{ (Reactive power, not considered)}$$

Optimization Objectives

Objective function of a MG

Our Preference-based P2P energy trading model with linearized *DistFlow* model

$$L_n = \sum_{t=1}^{T_s} \left(c_{\text{grid}}^t p_{n\text{grid}}^t + \sum_{k \in \mathcal{G}_n} f_{G,k}(p_{G,k}^t) + g_n^t \right)$$

s.t. $(1a) - (1d)$ (FG model)

$(2a) - (2d)$ (ESS model)

$(4a) - (4e)$ (linearized *DistFlow* model)

$$g_n^t = \kappa \lambda'_{n\text{grid}} \left| p_{n\text{grid}}^t \right| + \kappa \lambda'_{nn} \sum_{k \in \mathcal{S}_n} (p_{\text{char},k}^t + p_{\text{disc},k}^t) + \sum_{m \in \omega_n} \kappa \lambda'_{nm} \left| p_{nm}^t \right| \quad \text{(Preference mechanism)}$$

$$\sum_{k \in \mathcal{S}_n} (\beta_{\text{char},k} p_{\text{char},k}^t - \beta_{\text{disc},k} p_{\text{disc},k}^t) - \sum_{k \in \mathcal{G}_n} p_{G,k}^t + \sum_{k \in \mathcal{B}_n} p_{\text{net},k}^t = \sum_{m \in \omega_n} p_{nm}^t + p_{n\text{grid}}^t, \quad \forall t = 1, \ldots, T_s \text{ (Active power)}$$

$$- \sum_{k \in \mathcal{G}_n} q_{G,k}^t + \sum_{k \in \mathcal{B}_n} q_{\text{net},k}^t = \sum_{m \in \omega_n} q_{nm}^t + q_{n\text{grid}}^t, \ \forall t = 1, \ldots, T_s \text{ (Reactive power)}$$

Optimization Objectives

Objective function of a MG

Our Preference-based P2P energy trading model with relaxed *DistFlow* model

$$L_n = \sum_{t=1}^{T_s} \left(c^t_{\text{grid}} p^t_{n\text{grid}} + \sum_{k \in \mathcal{G}_n} f_{G,k}(p^t_{G,k}) + g^t_n + c^t_{\text{loss}} \sum_{(i,j) \in \mathcal{T}_n} R_{ij} l^t_{ij}\right)$$

s.t. $(1a) - (1d)$ (FG model)

$(2a) - (2d)$ (ESS model)

$(5b) - (5g)$ (relaxed *DistFlow* model)

$$g^t_n = \kappa \lambda'_{n\text{grid}} \left| p^t_{n\text{grid}} \right| + \kappa \lambda'_{nn} \sum_{k \in \mathcal{S}_n} (p^t_{\text{char},k} + p^t_{\text{disc},k}) + \sum_{m \in \omega_n} \kappa \lambda'_{nm} \left| p^t_{nm} \right| \quad \text{(Preference mechanism)}$$

$$\sum_{k \in \mathcal{S}_n} (\beta_{\text{char},k} p^t_{\text{char},k} - \beta_{\text{disc},k} p^t_{\text{disc},k}) - \sum_{k \in \mathcal{G}_n} p^t_{G,k} + \sum_{k \in \mathcal{B}_n} p^t_{\text{net},k} = \sum_{m \in \omega_n} p^t_{nm} + p^t_{n\text{grid}}, \quad \forall t = 1, \ldots, T_s \text{ (Active power)}$$

$$-\sum_{k \in \mathcal{G}_n} q^t_{G,k} + \sum_{k \in \mathcal{B}_n} q^t_{\text{net},k} = \sum_{m \in \omega_n} q^t_{nm} + q^t_{n\text{grid}}, \; \forall t = 1, \ldots, T_s \text{ (Reactive power)}$$

Optimization Objectives

Generic form of objective function of a MG

$$\min_{X_n} L_n, \quad X_n \in \mathrm{Dom}_n.$$

- X_n: all local variables to be optimized
- Dom_n: the domain of definition determined by all local constraints

Section 3

Problem Statement and Methodologies

- Full Optimization Problem Description
- Generic Form of ADMM
- ADMM-based Distribution Algorithm

Full Optimization Problem Description

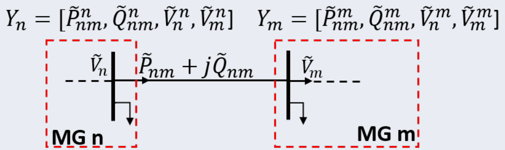
Overall objective of a network of microgrids

$$L = \sum_{n \in \Omega} L_n$$

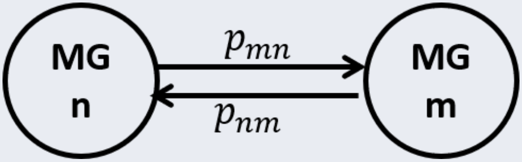
$X = [X_0, \ldots, X_{N_\Omega - 1}]$ is the vector of all the variables to be optimized in the whole optimization problem, and N_Ω is the size of Ω.

Coupling constraints

physical constraint $Y_n = Y_m$



virtual constraint $p_{nm} + p_{mn} = 0$



Full Optimization Problem Description

Generic form

$$
\begin{aligned}
&\min_{X} \sum_{n \in \Omega} L_n, \\
\text{s.t. } & p_{nm} + p_{mn} = 0 \ \ \forall n, m \in \Omega, \\
& Y_n - Y_m = 0 \ \ \forall (n, m) \in \mathcal{E}, \\
& X_n \in \mathrm{Dom}_n.
\end{aligned}
$$

Generic Form of ADMM

Generic form of the problem

$$\min\ f(x) + g(z)$$
$$\text{s.t. } Ax + Bz = c,$$

Augmented Lagrangian

$$L_\rho(x, z, y) = f(x) + g(z) + y^\top (Ax + Bz - c) + \rho/2\|Ax + Bz - c\|_2^2\,.$$

ADMM iterations

$$\begin{aligned}
x^{k+1} &= \arg\min L_\rho(x, z^k, y^k),\\
z^{k+1} &= \arg\min L_\rho(x^{k+1}, z, y^k),\\
y^{k+1} &= y^k + \rho(Ax^{k+1} + Bz^{k+1} - c),
\end{aligned}$$

Convergence criterion

primal residual: $r^{k+1} = Ax^{k+1} + Bz^{k+1} - c$ dual residual $s^{k+1} = \rho A^\top B(z^{k+1} - z^k)$

$$\left\| r^{k+1} \right\|_2 \leq \epsilon^{\text{pri}}, \quad \left\| s^{k+1} \right\|_2 \leq \epsilon^{\text{dual}}.$$

ADMM-based Distribution Algorithm

Generic form of the problem

$$
\begin{aligned}
&\min_{X} \sum_{n \in \Omega} L_n, \\
&\text{s.t. } p_{nm} + p_{mn} = 0 \;\; \forall n, m \in \Omega, \\
&Y_n - Y_m = 0 \;\; \forall (n, m) \in \mathcal{E}, \\
&X_n \in \mathrm{Dom}_n.
\end{aligned}
$$

Augmented Lagrangian

$$
(\mathbf{C} - \mathbf{C}^\top)/2 = \mathbf{P}, \qquad Y_n = Y_m = Y_{(n,m)}
$$

P is related to the bilateral trades among a network of microgrids.

$$
\mathbf{P} = \begin{pmatrix} p_{00} & \cdots & p_{0N_\Omega - 1} \\ \vdots & \ddots & \vdots \\ p_{N_\Omega - 10} & \cdots & p_{N_\Omega - 1 N_\Omega - 1} \end{pmatrix}
$$

ADMM-based Distribution Algorithm

Generic form of the problem

$$\min_{X} \sum_{n\in\Omega} L_n,$$
$$\text{s.t. } p_{nm} + p_{mn} = 0 \;\; \forall n, m \in \Omega,$$
$$Y_n - Y_m = 0 \;\; \forall (n, m) \in \mathcal{E},$$
$$X_n \in \text{Dom}_n.$$

Augmented Lagrangian

$$L'_\Omega = \sum_{n\in\Omega} L'_n$$
$$\text{s.t. } L'_n = L_n + \sum_{m\in\omega_n} \mu_{nm}\left(\frac{c_{nm} - c_{mn}}{2} - p_{nm}\right) + \rho_1\left(\frac{c_{nm} - c_{mn}}{2} - p_{nm}\right)^2$$
$$+ \sum_{(n,m)\in\mathcal{E}} \nu^{\top}_{(n,m)}\left(Y_n - Y_{(n,m)}\right) + \rho_2 \left\| Y_n - Y_{(n,m)} \right\|_2^2,$$

ADMM-based Distribution Algorithm

ADMM iterations

step i

ADMM-based Distribution Algorithm

step i

ADMM-based Distribution Algorithm

step i

MG n

$$\{\mu_{nm}^{i+1}, \boldsymbol{\nu}_{(n,m)}^{i+1}, p_{nm}^{i+1}, Y_n^{i+1}\} = \arg\min L'_n(\mu_{nm}^i, \boldsymbol{\nu}_{(n,m)}^i, c'^{\,i}_{nm}, Y_n^i, Y_{(n,m)}^i)$$

ADMM-based Distribution Algorithm

step i

MG n

$$\{\mu_{nm}^{i+1}, \boldsymbol{\nu}_{(n,m)}^{i+1}, p_{nm}^{i+1}, Y_n^{i+1}\} = \arg\min L_n'(\mu_{nm}^{i}, \boldsymbol{\nu}_{(n,m)}^{i}, c_{nm}^{\prime\, i}, Y_n^i, Y_{(n,m)}^i)$$

DSO-update intermediary variables

$$c_{nm}^{\prime\, i+1} = \frac{c_{nm}^{i+1} - c_{mn}^{i+1}}{2} = \frac{p_{nm}^{i+1} - p_{mn}^{i+1}}{2}, \forall m \in \omega_n, n \in \Omega, \quad Y_{(n,m)}^{i+1} = \frac{Y_n^{i+1} + Y_m^{i+1}}{2}, \forall (n,m) \in \mathcal{E}$$

ADMM-based Distribution Algorithm

step i

MG n

$$\{\mu_{nm}^{i+1}, \boldsymbol{\nu}_{(n,m)}^{i+1}, p_{nm}^{i+1}, Y_n^{i+1}\} = \arg\min L_n'(\mu_{nm}^{i}, \boldsymbol{\nu}_{(n,m)}^{i}, c_{nm}^{\prime\, i}, Y_n^i, Y_{(n,m)}^i)$$

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DSO-update dual variables

$$\mu_{nm}^{i+1} = \mu_{nm}^{i} + \rho_1 (c_{nm}^{\prime\, i+1} - p_{nm}^{i+1}), \quad \forall m \in \omega_n, n \in \Omega$$

$$\boldsymbol{\nu}_{(n,m)}^{i+1} = \boldsymbol{\nu}_{(n,m)}^{i} + \rho_2 \frac{(Y_n^{i+1} - Y_{(n,m)}^{i+1})}{2}, \quad \forall (n,m) \in \mathcal{E}$$

ADMM-based Distribution Algorithm

step i

MG n

$$\{\mu_{nm}^{i+1}, \boldsymbol{\nu}_{(n,m)}^{i+1}, p_{nm}^{i+1}, Y_n^{i+1}\} = \arg\min L_n'(\mu_{nm}^i, \boldsymbol{\nu}_{(n,m)}^i, c_{nm}'^{\,i}, Y_n^i, Y_{(n,m)}^i)$$

DSO-update intermediary variables

$$c_{nm}'^{\,i+1} = \frac{c_{nm}^{i+1} - c_{mn}^{i+1}}{2} = \frac{p_{nm}^{i+1} - p_{mn}^{i+1}}{2}, \forall m \in \omega_n, n \in \Omega, \quad Y_{(n,m)}^{i+1} = \frac{Y_n^{i+1} + Y_m^{i+1}}{2}, \forall (n,m) \in \mathcal{E}$$

DSO-update dual variables

$$\mu_{nm}^{i+1} = \mu_{nm}^i + \rho_1 (c_{nm}'^{\,i+1} - p_{nm}^{i+1}), \quad \forall m \in \omega_n, n \in \Omega$$
$$\boldsymbol{\nu}_{(n,m)}^{i+1} = \boldsymbol{\nu}_{(n,m)}^i + \rho_2 \frac{(Y_n^{i+1} - Y_{(n,m)}^{i+1})}{2}, \quad \forall (n,m) \in \mathcal{E}$$

DSO-Convergence

$$r^{i+1} \leq \epsilon^{\mathrm{pri}} \qquad s^{i+1} \leq \epsilon^{\mathrm{dual}}$$

ADMM-based Distribution Algorithm

step i

MG n

$$\{\mu_{nm}^{i+1}, \boldsymbol{\nu}_{(n,m)}^{i+1}, p_{nm}^{i+1}, Y_n^{i+1}\} = \arg\min L_n'(\mu_{nm}^i, \boldsymbol{\nu}_{(n,m)}^i, c_{nm}'^{\,i}, Y_n^i, Y_{(n,m)}^i)$$

DSO-update intermediary variables

$$c_{nm}'^{\,i+1} = \frac{c_{nm}^{i+1} - c_{mn}^{i+1}}{2} = \frac{p_{nm}^{i+1} - p_{mn}^{i+1}}{2}, \forall m \in \omega_n, n \in \Omega, \quad Y_{(n,m)}^{i+1} = \frac{Y_n^{i+1} + Y_m^{i+1}}{2}, \forall (n,m) \in \mathcal{E}$$

DSO-update dual variables

$$\mu_{nm}^{i+1} = \mu_{nm}^i + \rho_1 (c_{nm}'^{\,i+1} - p_{nm}^{i+1}), \quad \forall m \in \omega_n, n \in \Omega$$

$$\boldsymbol{\nu}_{(n,m)}^{i+1} = \boldsymbol{\nu}_{(n,m)}^i + \rho_2 \frac{(Y_n^{i+1} - Y_{(n,m)}^{i+1})}{2}, \quad \forall (n,m) \in \mathcal{E}$$

DSO-Convergence

$$r^{i+1} \le \epsilon^{\text{pri}} \qquad s^{i+1} \le \epsilon^{\text{dual}}$$

No

ADMM-based Distribution Algorithm

Convergence criterion

primal residuals:

$$r_{vir}^{i+1} = \sqrt{\frac{1}{N_\Omega}\sum_{n\in\Omega}\left(\sum_{m\in\omega_n}(c'^{i+1}_{nm} - p^{i+1}_{nm})^2\right)}$$

$$r_{phy}^{i+1} = \sqrt{\frac{1}{N_\Omega}\sum_{n\in\Omega}\left(\sum_{(n,m)\in\mathcal{E}}\left\| Y_n^{i+1} - Y_{(n,m)}^{i+1}\right\|_2^2\right)}$$

dual residuals:

$$s_{vir}^{i+1} = \rho_1\sqrt{\frac{1}{N_\Omega}\sum_{n\in\Omega}\left(\sum_{m\in\omega_n}(\mu^{i+1}_{nm} - \mu^{i}_{nm})^2\right)}$$

$$s_{phy}^{i+1} = \rho_2\sqrt{\frac{1}{N_\Omega}\sum_{n\in\Omega}\left(\sum_{(n,m)\in\mathcal{E}}\left\| \boldsymbol{\nu}_{(n,m)}^{i+1} - \boldsymbol{\nu}_{(n,m)}^{i}\right\|_2^2\right)}$$

residuals:

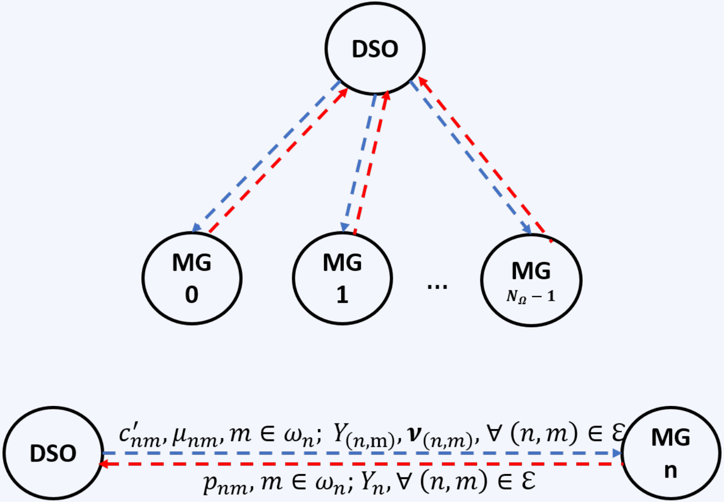
$$r^{i+1} = r_{vir}^{i+1} + r_{phy}^{i+1} \qquad s^{i+1} = s_{vir}^{i+1} + s_{phy}^{i+1}$$

convergence criterion:

$$r^{i+1} \le \epsilon^{\text{pri}}, \qquad s^{i+1} \le \epsilon^{\text{dual}}$$

ADMM-based Distribution Algorithm

Information communication design



Section 4

Simulation Results

- IEEE 33-bus Distribution System: Effect of Preference Mechanism
- IEEE 123-bus Distribution System: Convergence Performance

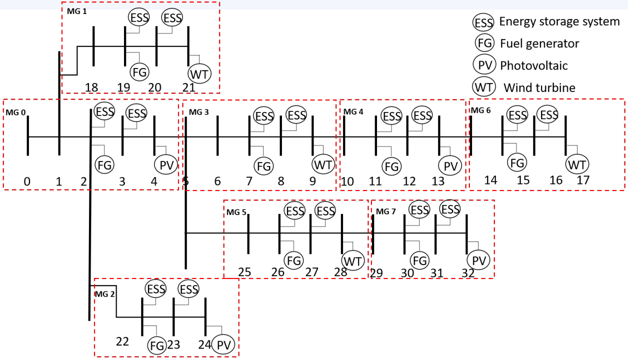
IEEE 33-bus Distribution System: Effect of Preference Mechanism

Simulation tool

- Python

Simulation conditions

- Operational mode (grid-connected or islanding mode)
- Distribution line model (linearized or relaxed *DistFlow* model)
- Preference matrix



IEEE 33-bus Distribution System: Effect of Preference Mechanism

Simulation conditions

- Operational mode (grid-connected or islanding mode)
- Distribution line model (linearized or relaxed *DistFlow* model)
- Preference matrix

In general, assume that price related parameters $c^t_{\text{grid}} = c^t_{\text{loss}} = \kappa$.

- In grid-connected mode, $c^t_{\text{grid}} = c^t_{\text{loss}} = \kappa$.
- In islanding mode, $c^t_{\text{loss}} = \kappa$, where κ is uniform for all agents, and it can be constant or time-varying in the whole time horizon. In the case studies, three scenarios of constant κ are considered as 20, 60, 100 ($/MW) and one time-varying κ scenario is considered as a uniform distribution $[20, 100]$ ($/MW).

IEEE 33-bus Distribution System: Effect of Preference Mechanism

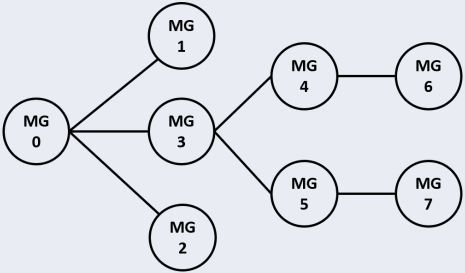
Simulation conditions

- Operational mode (grid-connected or islanding mode)
- Distribution line model (linearized or relaxed *DistFlow* model)
- Preference matrix

Case 1: Equal Preferences

MG	0	1	2	3	4	5	6	7
0	0.02	0.14	0.14	0.14	0.14	0.14	0.14	0.14
1	0.14	0.02	0.14	0.14	0.14	0.14	0.14	0.14
2	0.14	0.14	0.02	0.14	0.14	0.14	0.14	0.14
3	0.14	0.14	0.14	0.02	0.14	0.14	0.14	0.14
4	0.14	0.14	0.14	0.14	0.02	0.14	0.14	0.14
5	0.14	0.14	0.14	0.14	0.14	0.02	0.14	0.14
6	0.14	0.14	0.14	0.14	0.14	0.14	0.02	0.14
7	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.02

A network of MGs



IEEE 33-bus Distribution System: Effect of Preference Mechanism

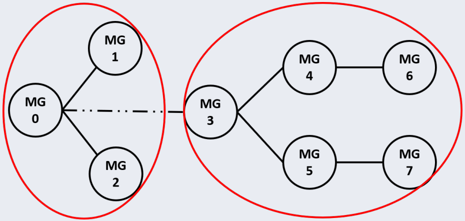
Simulation conditions

- Operational mode (grid-connected or islanding mode)
- Distribution line model (linearized or relaxed *DistFlow* model)
- Preference matrix

Case 2: 2 clusters of MGs

MG	0	1	2	3	4	5	6	7
0	0.02	0.04	0.04	0.18	0.18	0.18	0.18	0.18
1	0.04	0.02	0.04	0.18	0.18	0.18	0.18	0.18
2	0.04	0.04	0.02	0.18	0.18	0.18	0.18	0.18
3	0.30	0.30	0.30	0.02	0.02	0.01	0.03	0.02
4	0.30	0.30	0.30	0.02	0.01	0.03	0.02	0.02
5	0.30	0.30	0.30	0.01	0.02	0.02	0.02	0.03
6	0.30	0.30	0.30	0.01	0.02	0.03	0.02	0.02
7	0.30	0.30	0.30	0.02	0.02	0.02	0.02	0.02

2 clusters of MGs



IEEE 33-bus Distribution System: Effect of Preference Mechanism

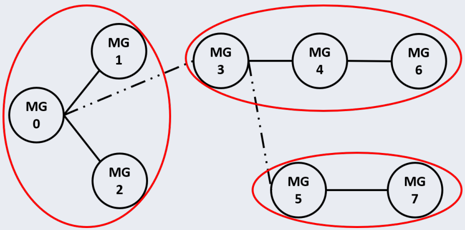
Simulation conditions

- Operational mode (grid-connected or islanding mode)
- Distribution line model (linearized or relaxed *DistFlow* model)
- Preference matrix

Case 3: 3 clusters of MGs

MG	0	1	2	3	4	5	6	7
0	0.03	0.03	0.04	0.18	0.18	0.18	0.18	0.18
1	0.04	0.02	0.04	0.18	0.18	0.18	0.18	0.18
2	0.03	0.05	0.02	0.18	0.18	0.18	0.18	0.18
3	0.18	0.18	0.18	0.03	0.03	0.18	0.04	0.18
4	0.18	0.18	0.18	0.05	0.02	0.18	0.03	0.18
5	0.15	0.15	0.15	0.15	0.15	0.03	0.15	0.07
6	0.18	0.18	0.18	0.04	0.04	0.18	0.02	0.18
7	0.15	0.15	0.15	0.15	0.15	0.05	0.15	0.05

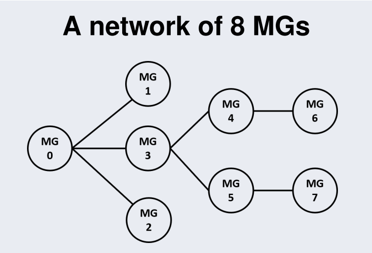
3 clusters of MGs

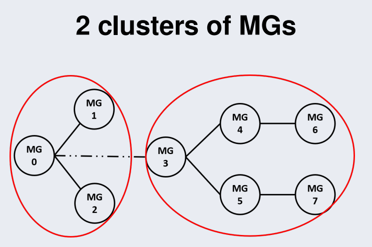


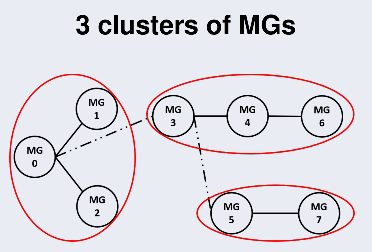
IEEE 33-bus Distribution System: Effect of Preference Mechanism

Simulation conditions

- Operational mode (grid-connected or islanding mode)
- Distribution line model (linearized or relaxed *DistFlow* model)
- Preference matrix

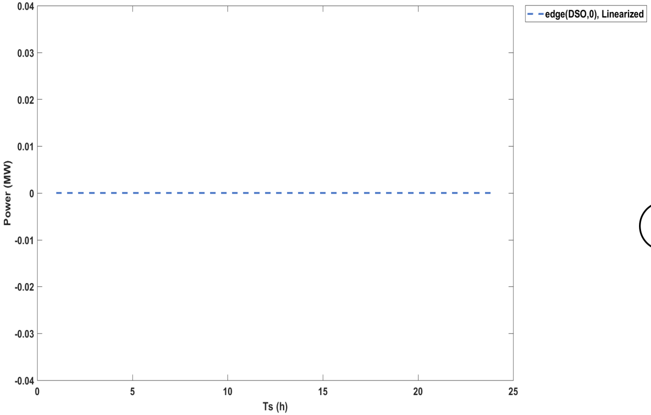


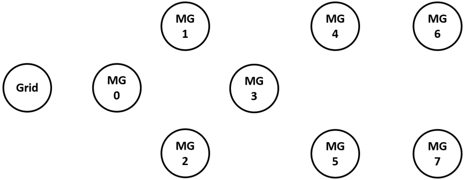




IEEE 33-bus Distribution System: Effect of Preference Mechanism

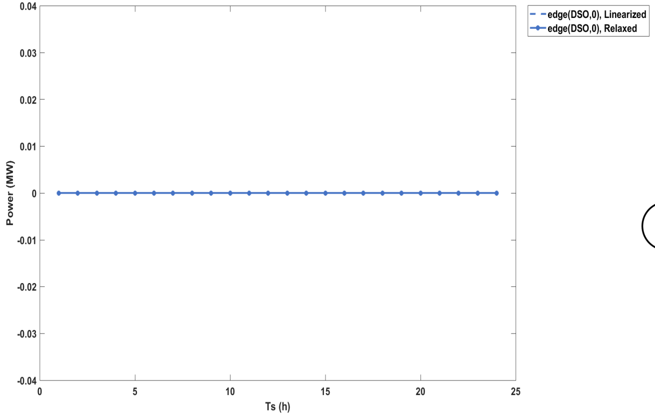
Case 1: grid-connected mode (**linearized** versus **relaxed** *DistFlow* model)

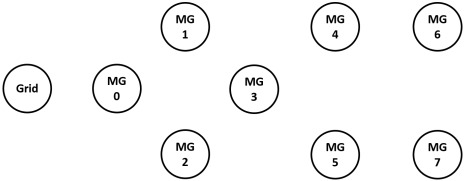




IEEE 33-bus Distribution System: Effect of Preference Mechanism

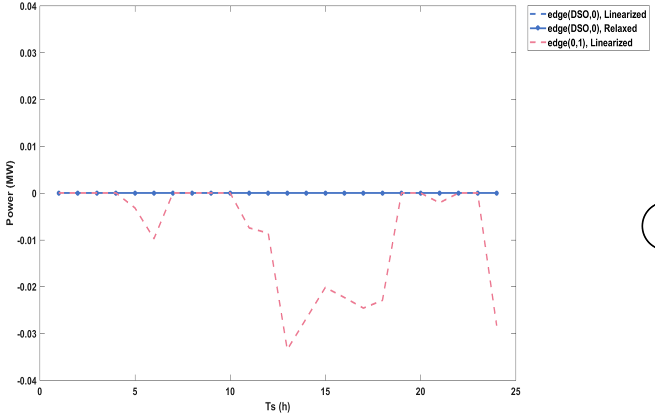
Case 1: grid-connected mode (**linearized** versus **relaxed** *DistFlow* model)

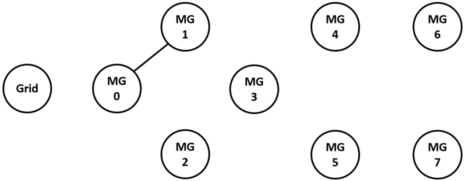




IEEE 33-bus Distribution System: Effect of Preference Mechanism

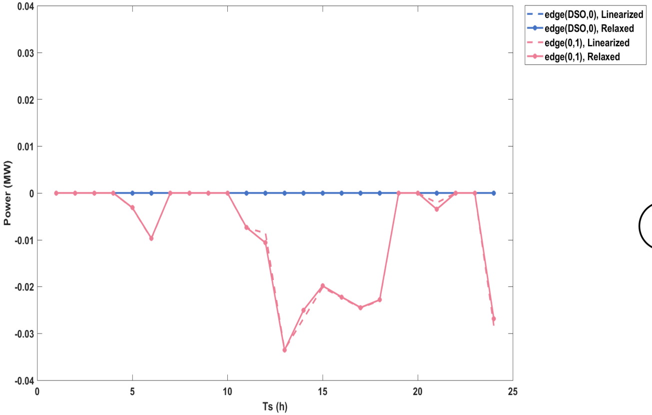
Case 1: grid-connected mode (**linearized** versus **relaxed** *DistFlow* model)

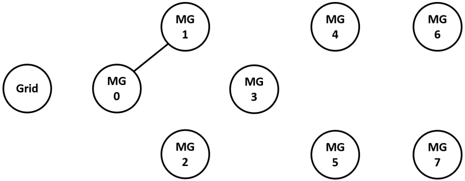




IEEE 33-bus Distribution System: Effect of Preference Mechanism

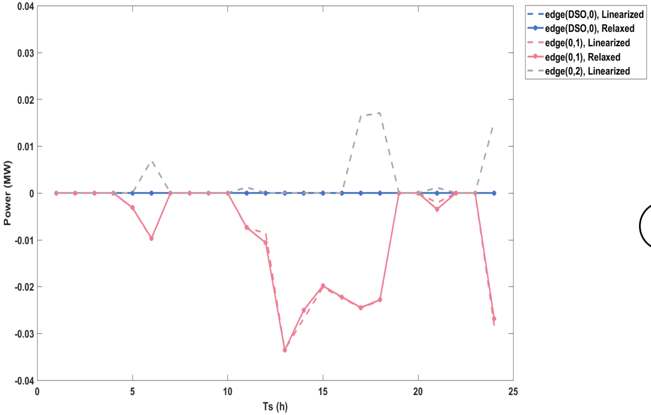
Case 1: grid-connected mode (**linearized** versus **relaxed** *DistFlow* model)

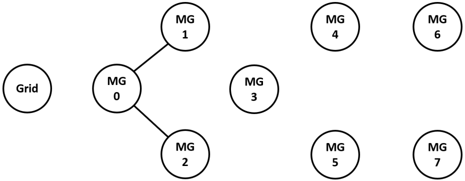




IEEE 33-bus Distribution System: Effect of Preference Mechanism

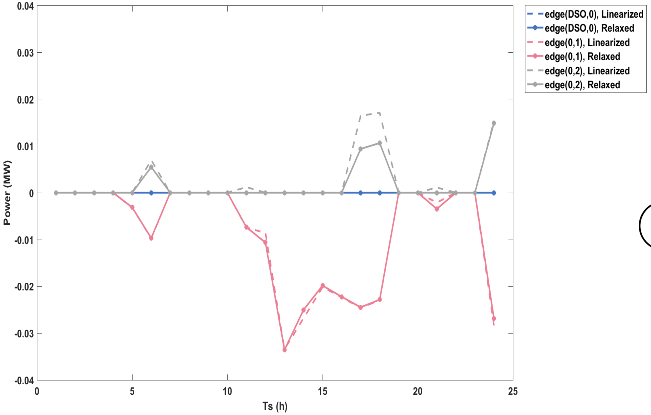
Case 1: grid-connected mode (**linearized** versus **relaxed** *DistFlow* model)

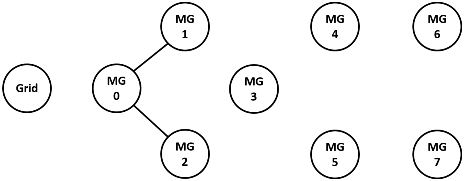




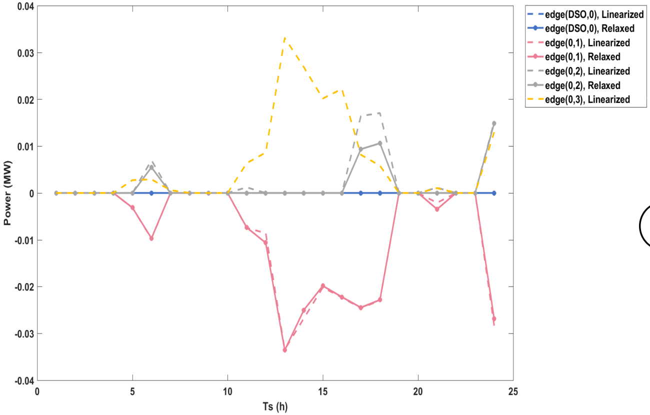
IEEE 33-bus Distribution System: Effect of Preference Mechanism

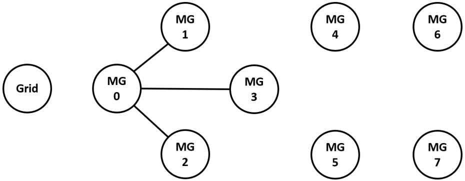
Case 1: grid-connected mode (**linearized** versus **relaxed** *DistFlow* model)





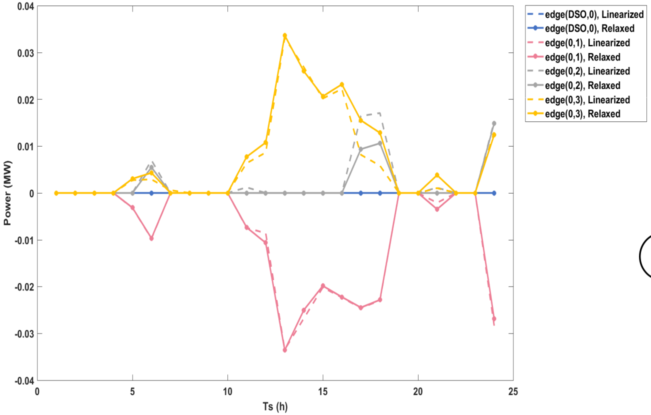
Case 1: grid-connected mode (**linearized** versus **relaxed** *DistFlow* model)

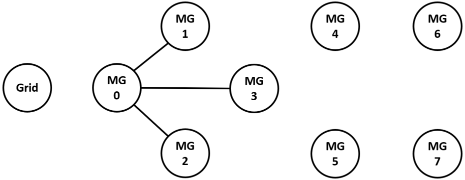




IEEE 33-bus Distribution System: Effect of Preference Mechanism

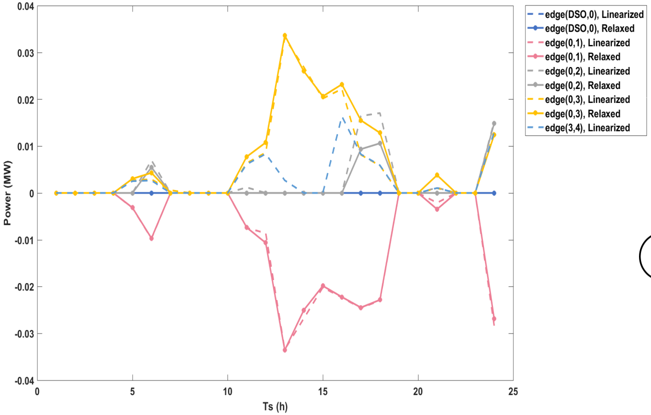
Case 1: grid-connected mode (**linearized** versus **relaxed** *DistFlow* model)

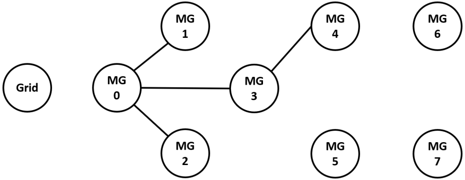




IEEE 33-bus Distribution System: Effect of Preference Mechanism

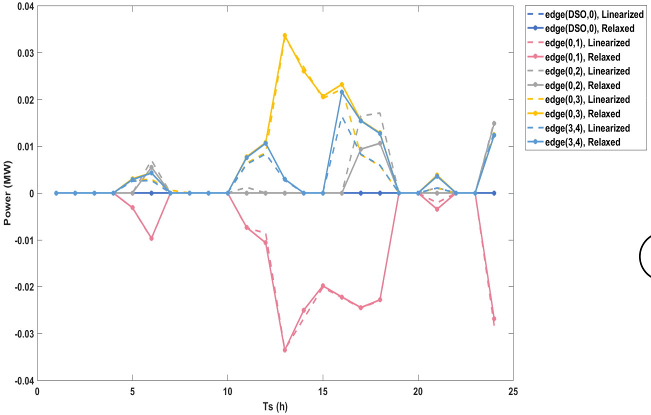
Case 1: grid-connected mode (**linearized** versus **relaxed** *DistFlow* model)

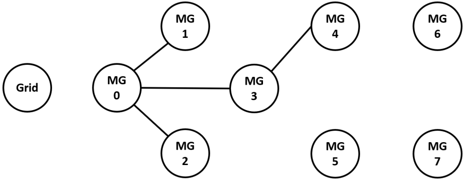




IEEE 33-bus Distribution System: Effect of Preference Mechanism

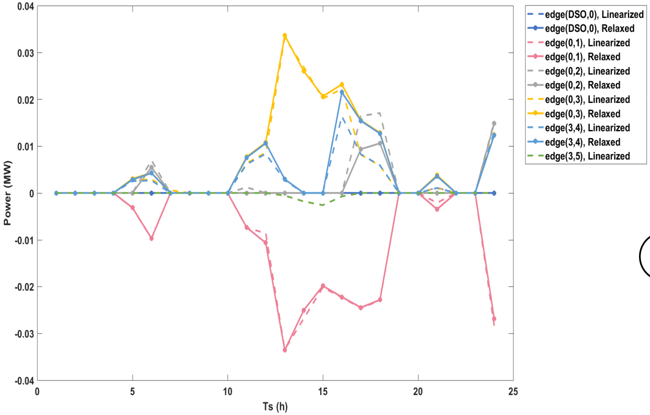
Case 1: grid-connected mode (**linearized** versus **relaxed** *DistFlow* model)

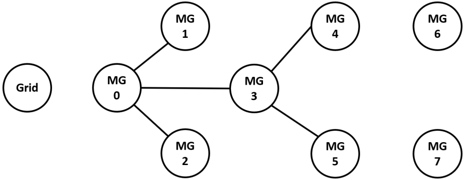




IEEE 33-bus Distribution System: Effect of Preference Mechanism

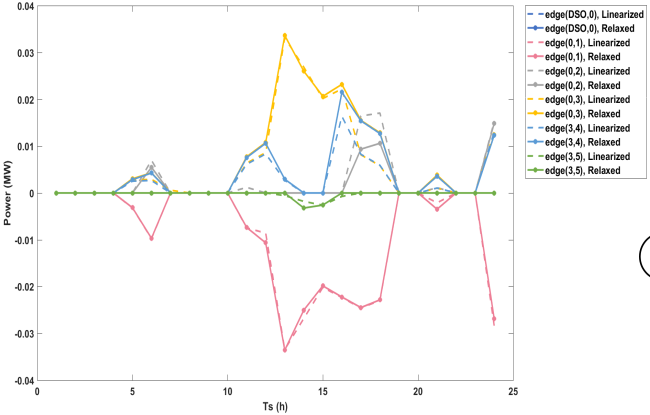
Case 1: grid-connected mode (**linearized** versus **relaxed** *DistFlow* model)

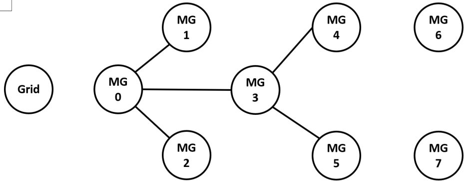




IEEE 33-bus Distribution System: Effect of Preference Mechanism

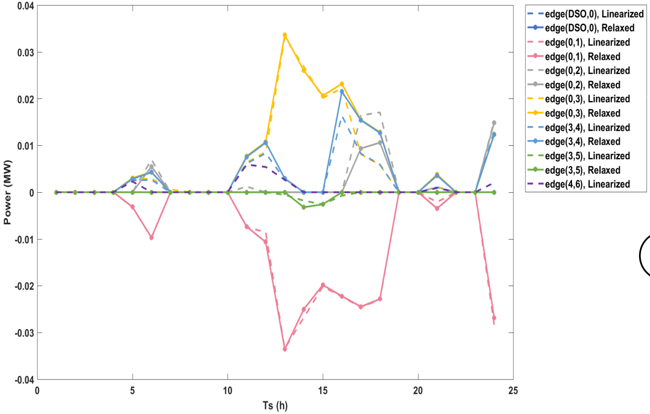
Case 1: grid-connected mode (**linearized** versus **relaxed** *DistFlow* model)

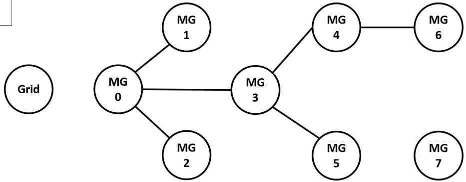




IEEE 33-bus Distribution System: Effect of Preference Mechanism

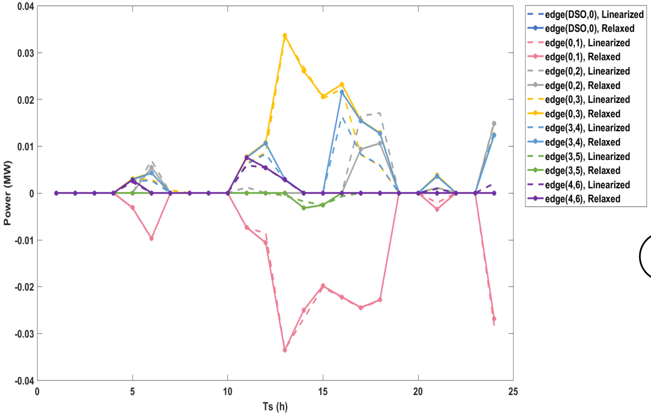
Case 1: grid-connected mode (**linearized** versus **relaxed** *DistFlow* model)

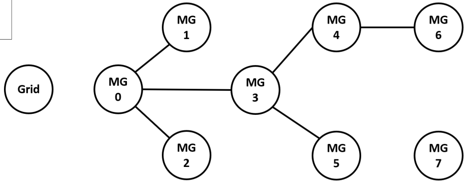




IEEE 33-bus Distribution System: Effect of Preference Mechanism

Case 1: grid-connected mode (**linearized** versus **relaxed** *DistFlow* model)





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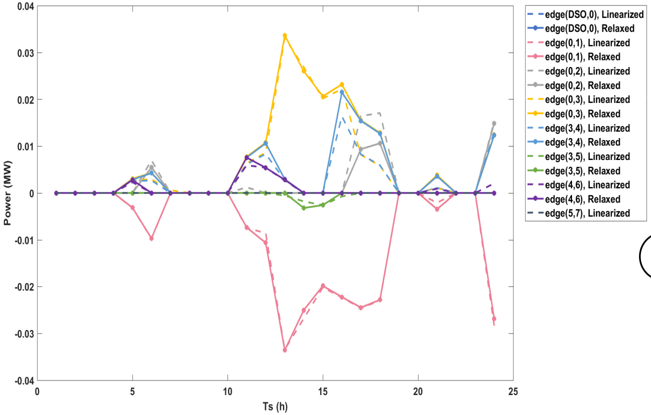
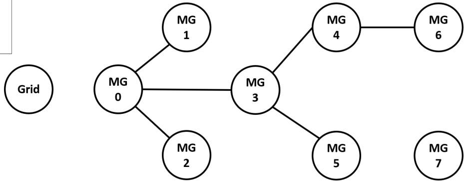
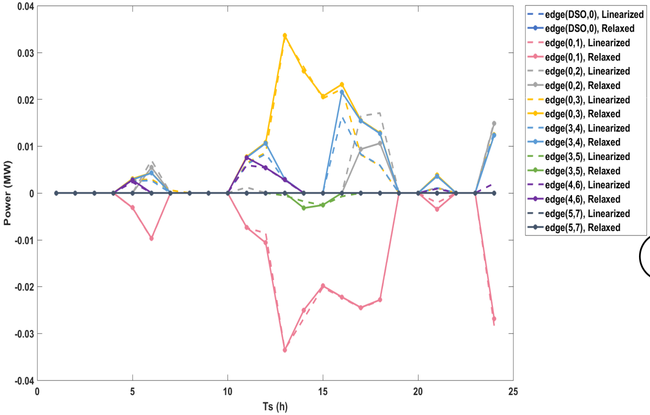
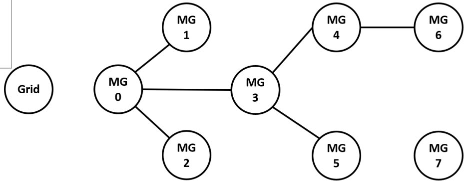




IEEE 33-bus Distribution System: Effect of Preference Mechanism

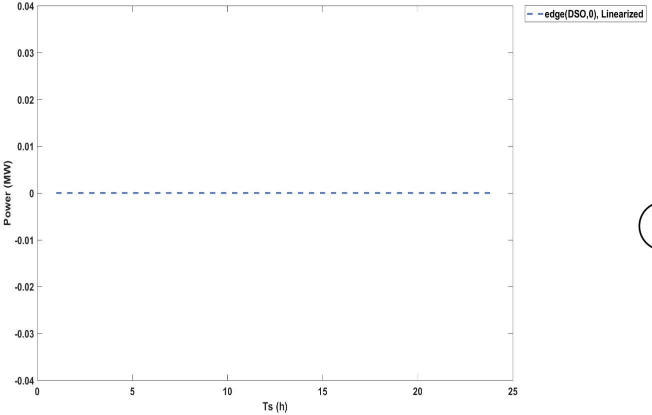
Case 1: grid-connected mode (**linearized** versus **relaxed** *DistFlow* model)

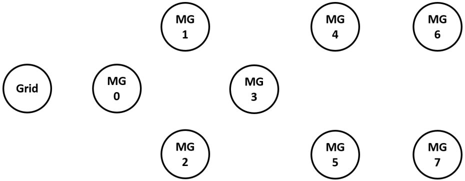




IEEE 33-bus Distribution System: Effect of Preference Mechanism

Case 1: islanding mode ($\kappa = 60$) (**linearized** versus **relaxed** *DistFlow* model)





IEEE 33-bus Distribution System: Effect of Preference Mechanism

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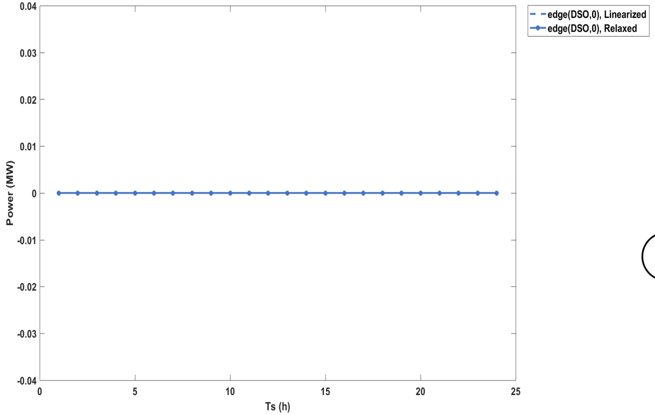

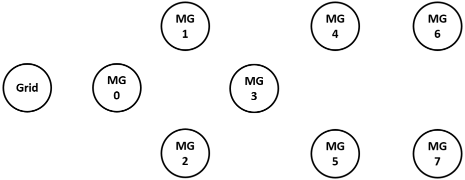

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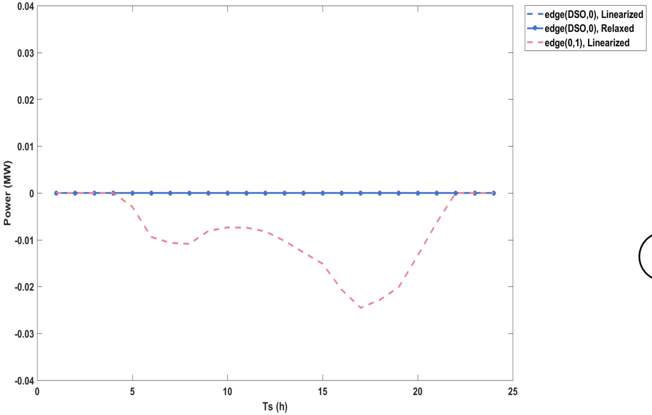

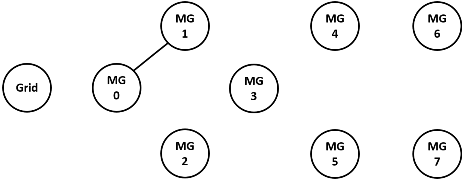

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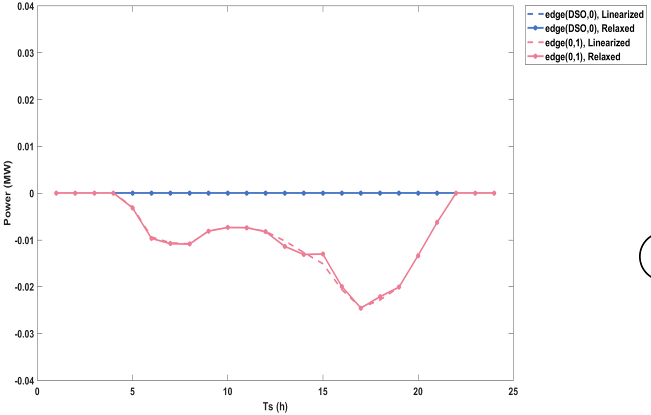

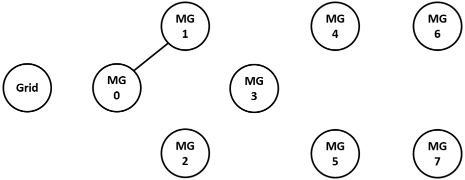

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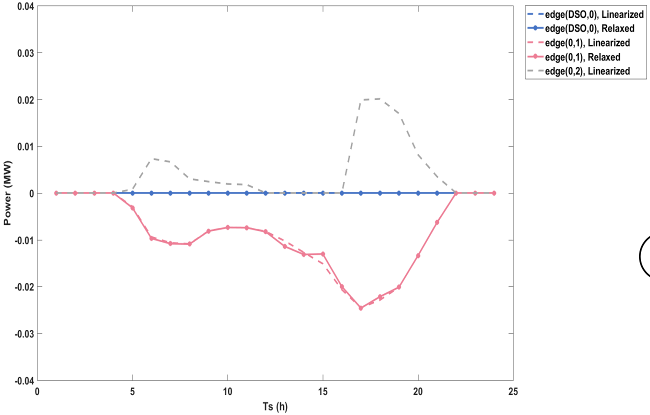

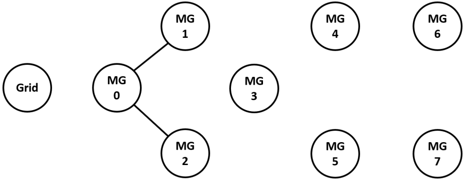

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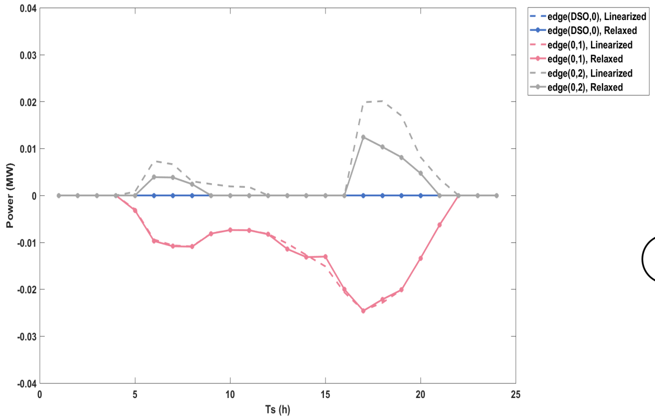

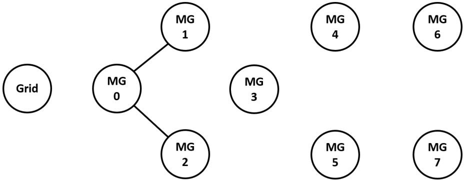

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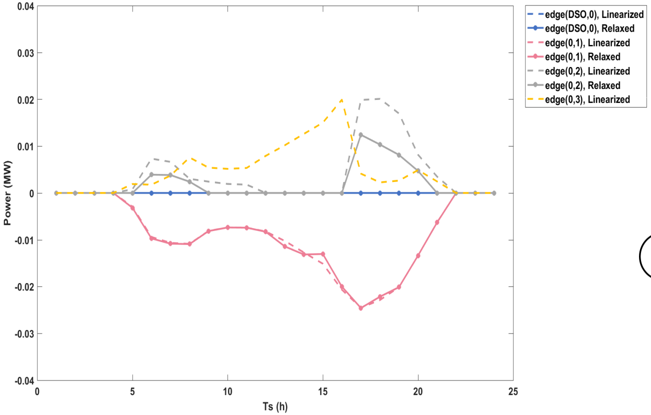

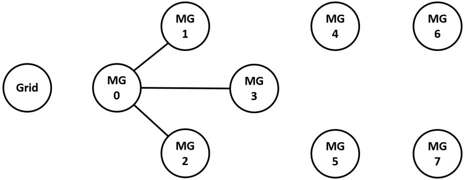

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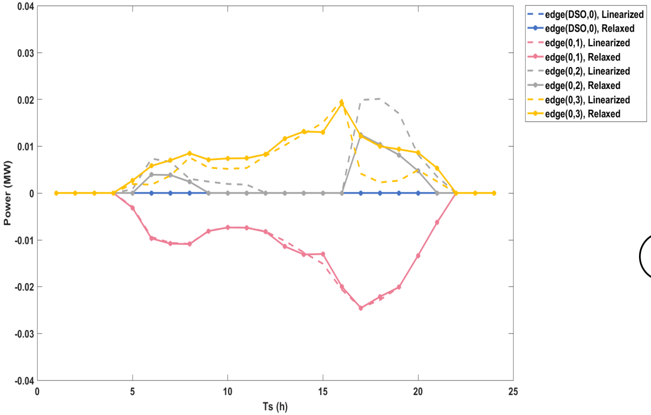

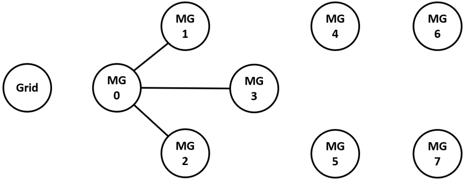

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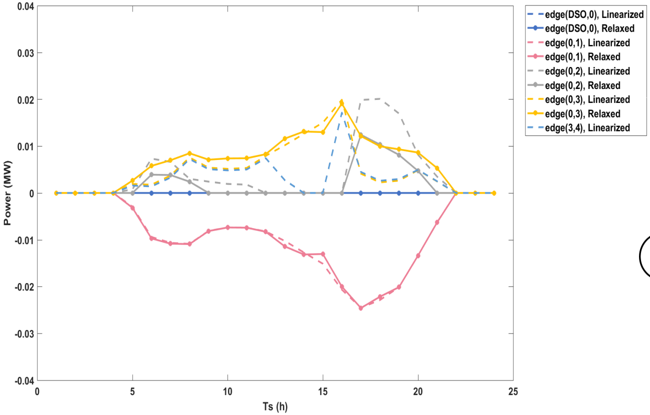

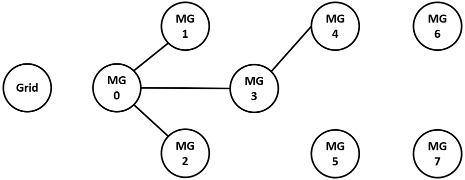

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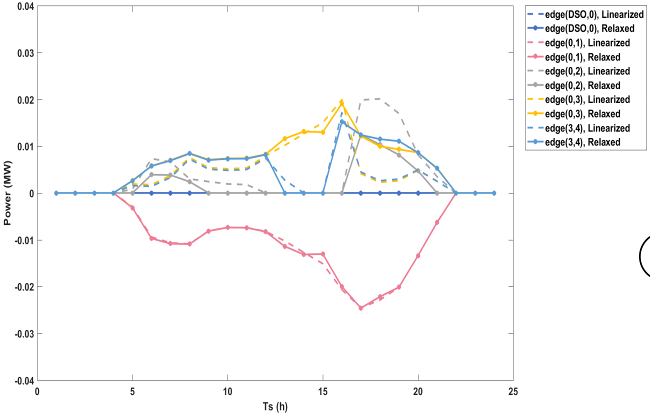

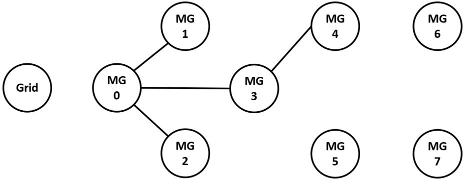

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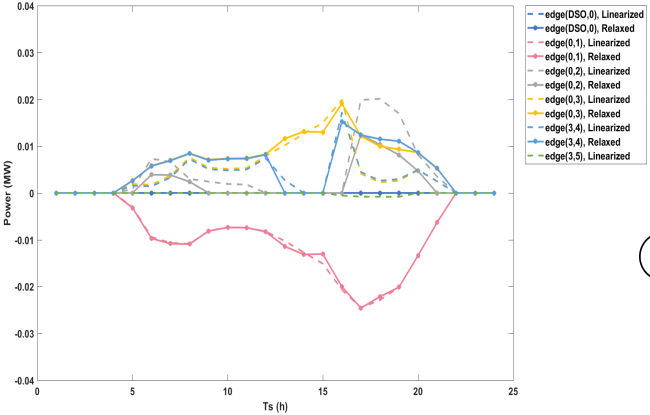

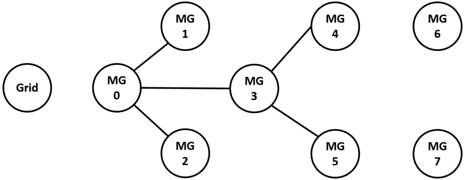

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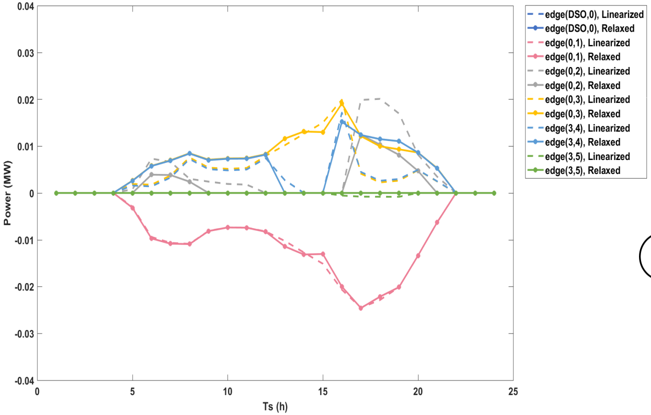

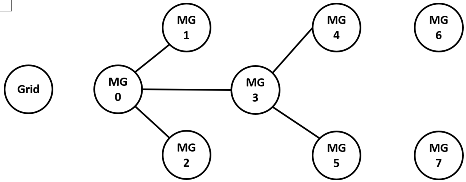

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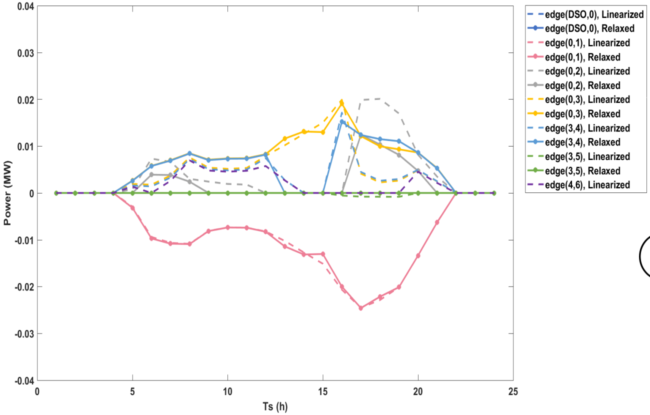

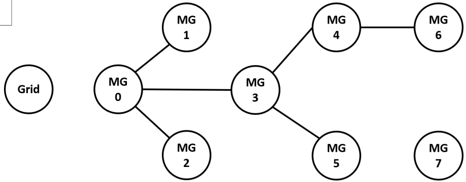

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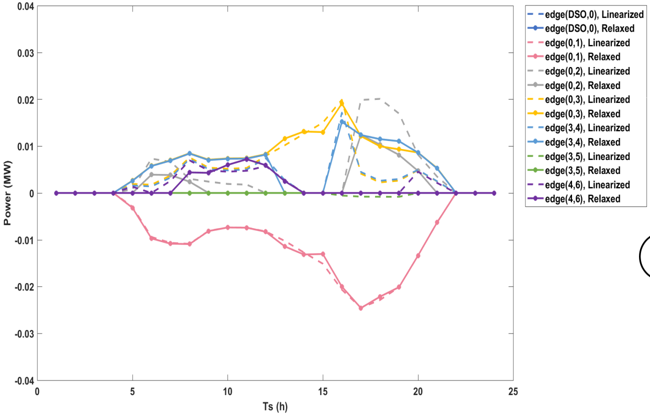

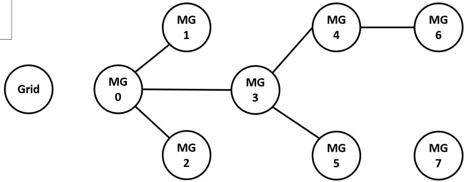

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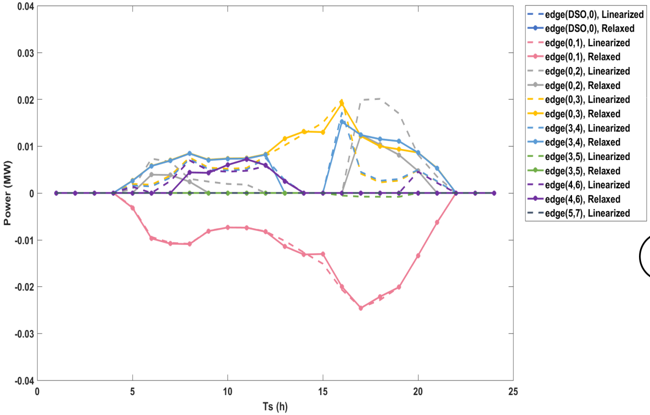

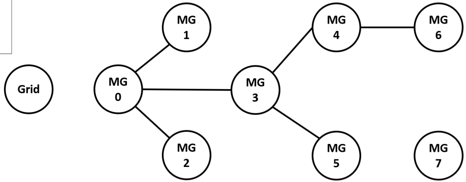

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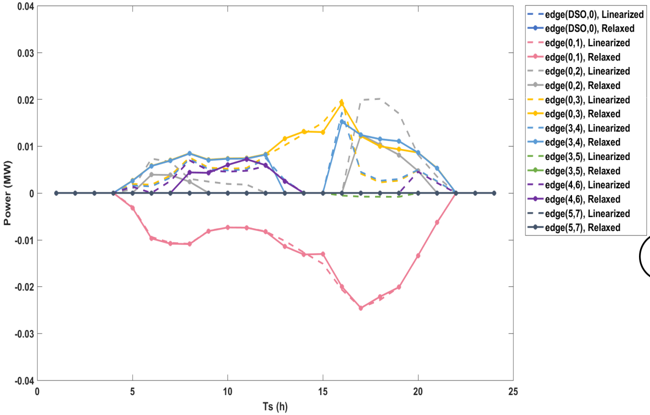
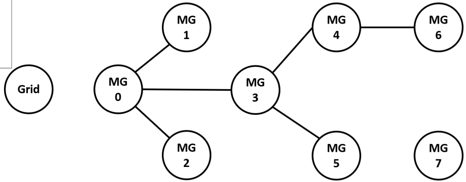




IEEE 33-bus Distribution System: Effect of Preference Mechanism

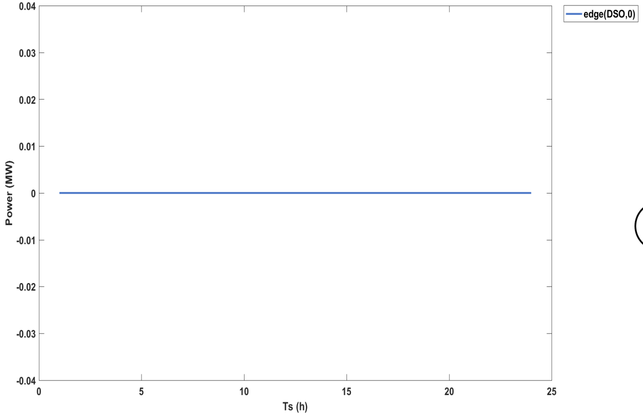
Case 1 related simulations :

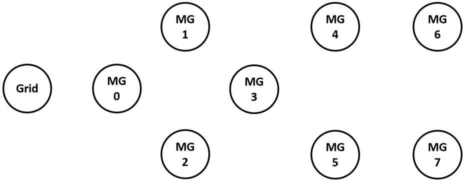
- Grid-connected mode in case 1
- Islanding mode $\kappa = 60$ in case 1

Conclusion: The results of the solutions (power flowing on the edges) are similar with two different *DistFlow* models. Therefore, we only display the results regarding the Linearized *DistFlow* model in the following to study the effect of the preference mechanism.

IEEE 33-bus Distribution System: Effect of Preference Mechanism

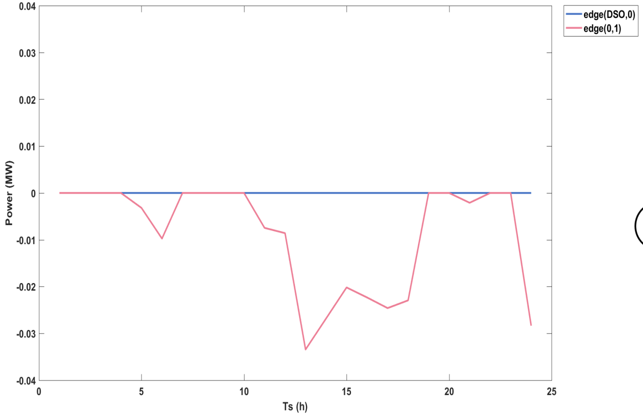
Case 1: grid-connected mode

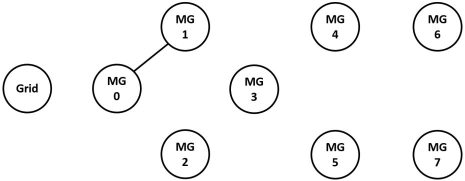




IEEE 33-bus Distribution System: Effect of Preference Mechanism

Case 1: grid-connected mode





IEEE 33-bus Distribution System: Effect of Preference Mechanism

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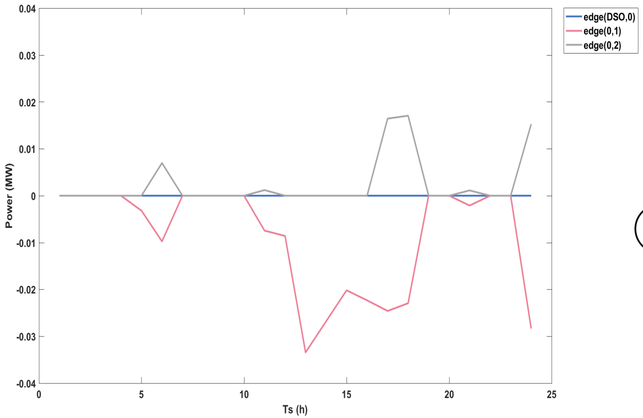

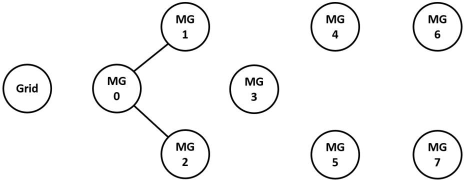

IEEE 33-bus Distribution System: Effect of Preference Mechanism

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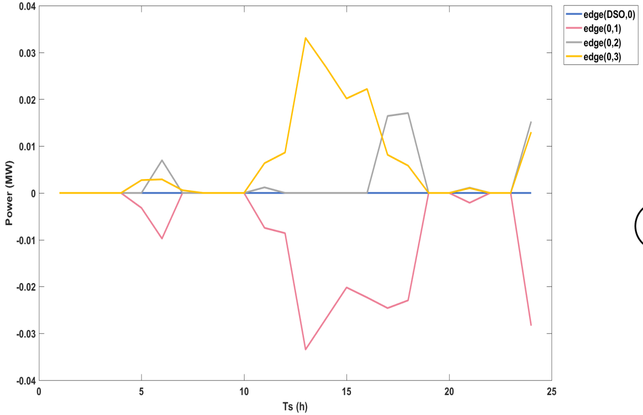

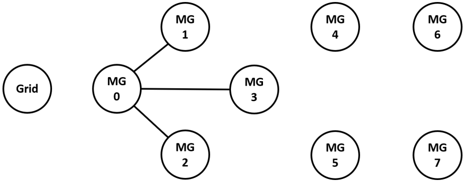

IEEE 33-bus Distribution System: Effect of Preference Mechanism

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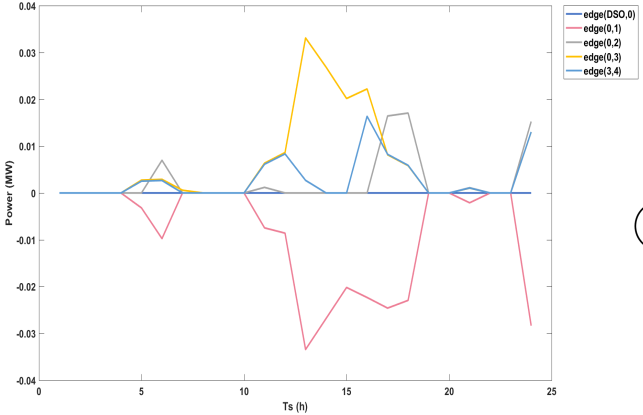

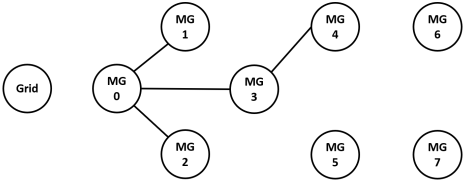

IEEE 33-bus Distribution System: Effect of Preference Mechanism

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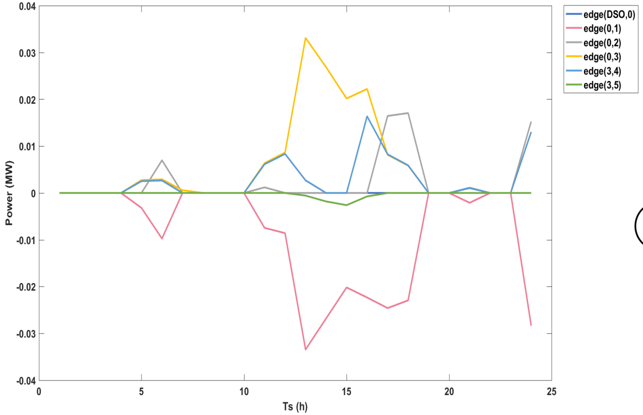

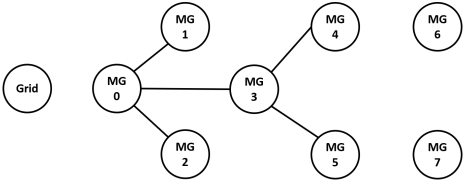

IEEE 33-bus Distribution System: Effect of Preference Mechanism

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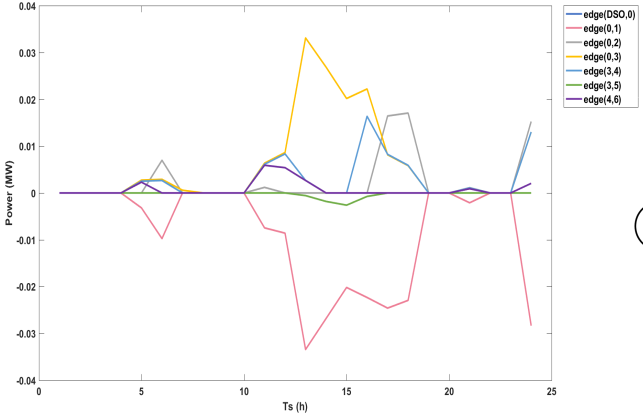

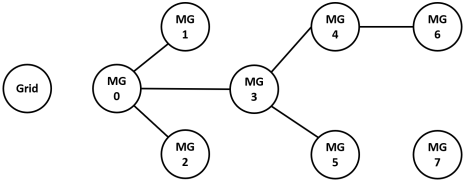

IEEE 33-bus Distribution System: Effect of Preference Mechanism

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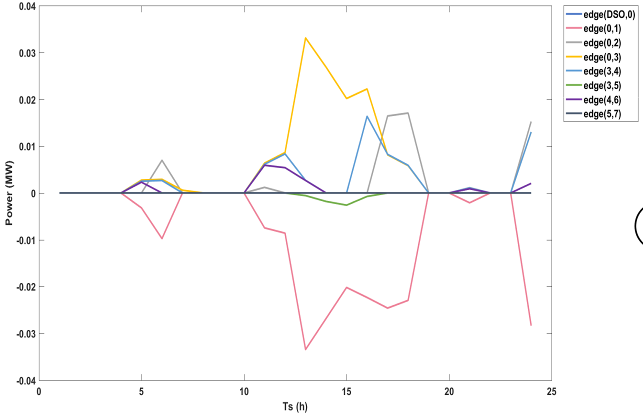
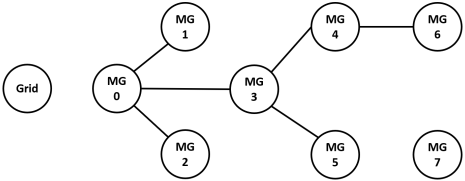
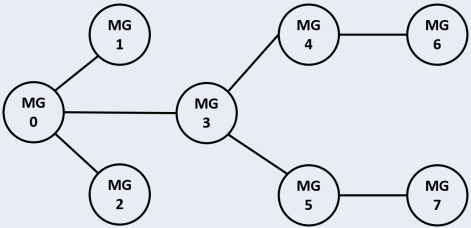




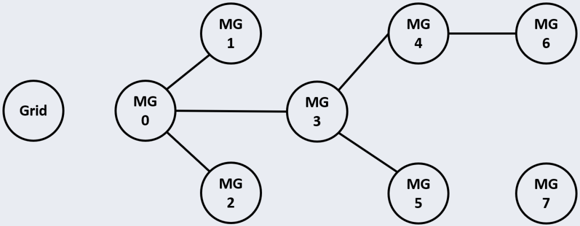
IEEE 33-bus Distribution System: Effect of Preference Mechanism

Case 1: grid-connected mode

Case 1: Equal Preferences

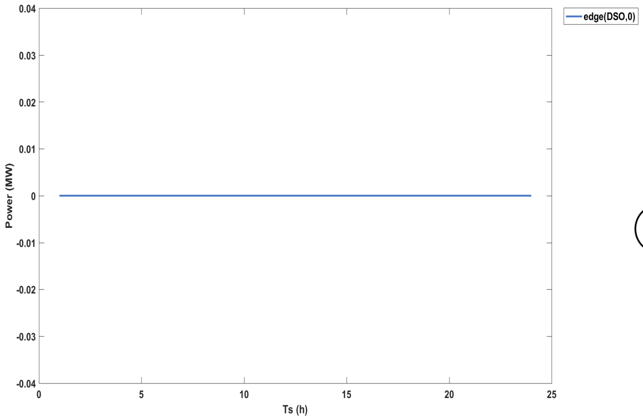


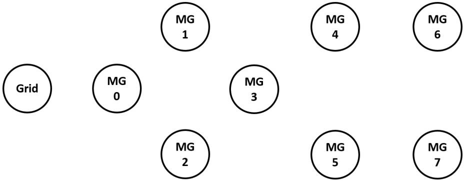
Case 1: Results



IEEE 33-bus Distribution System: Effect of Preference Mechanism

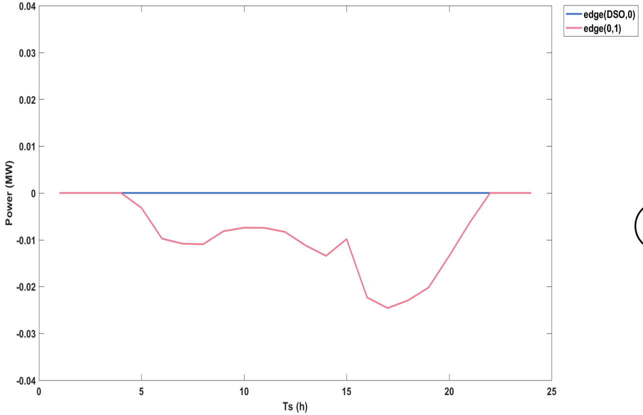
Case 2: grid-connected mode

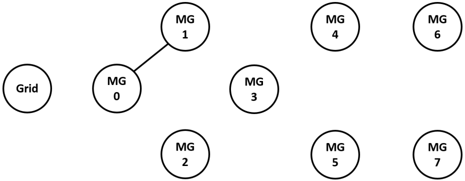




IEEE 33-bus Distribution System: Effect of Preference Mechanism

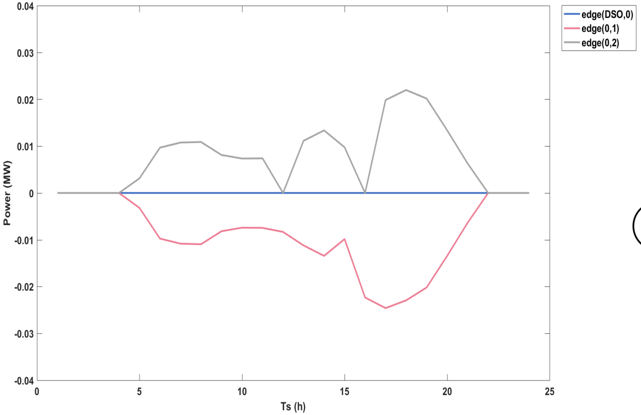
Case 2: grid-connected mode

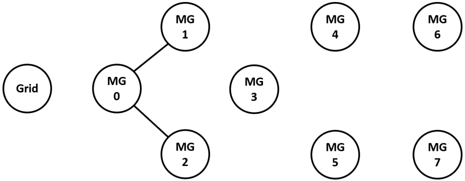




IEEE 33-bus Distribution System: Effect of Preference Mechanism

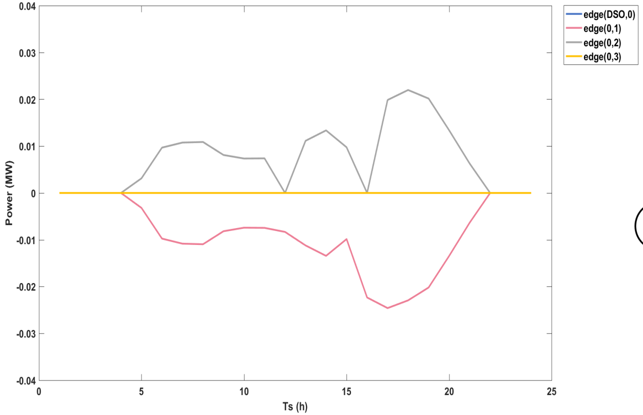
Case 2: grid-connected mode

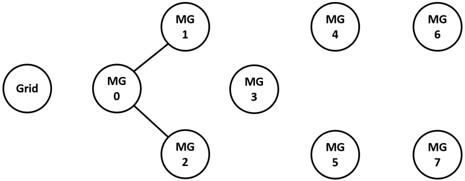




IEEE 33-bus Distribution System: Effect of Preference Mechanism

Case 2: grid-connected mode





IEEE 33-bus Distribution System: Effect of Preference Mechanism

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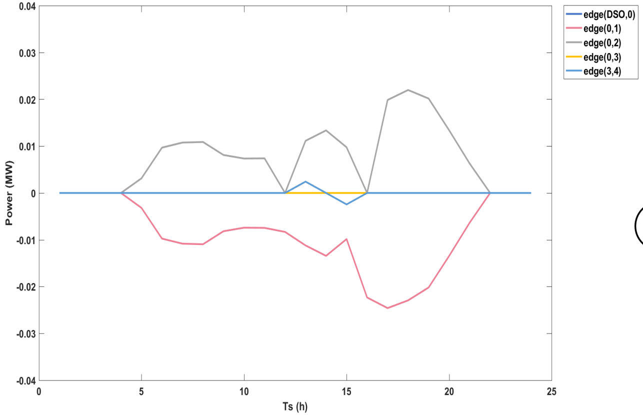
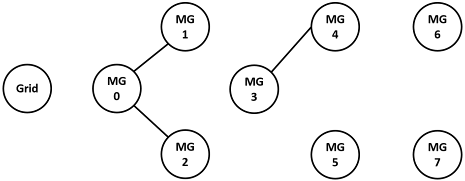
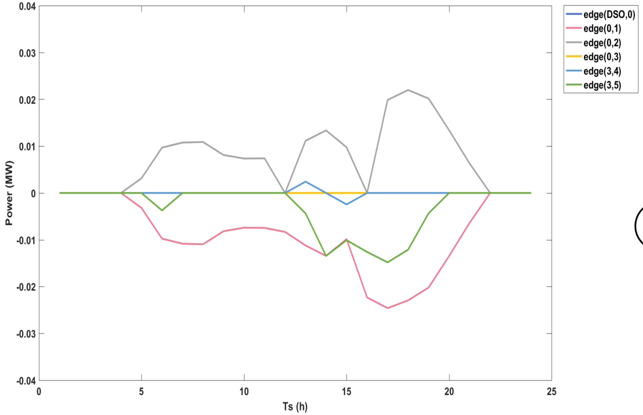
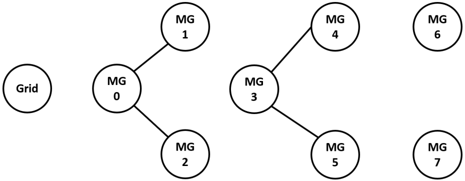




IEEE 33-bus Distribution System: Effect of Preference Mechanism

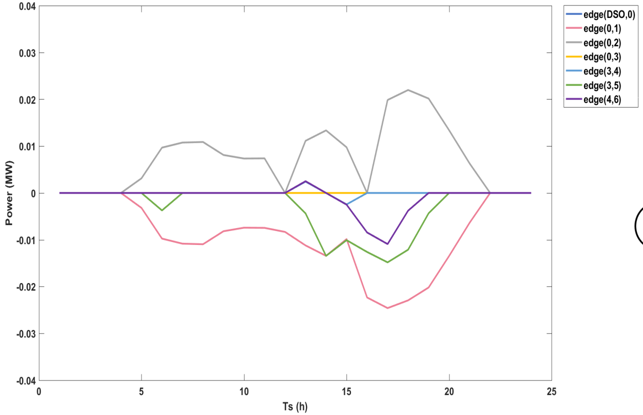
Case 2: grid-connected mode

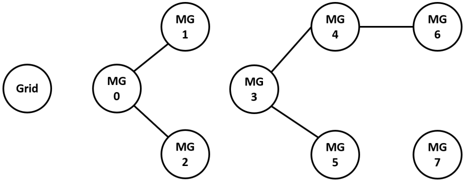




IEEE 33-bus Distribution System: Effect of Preference Mechanism

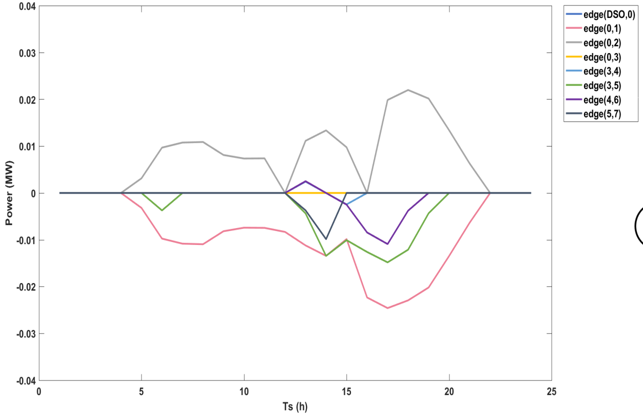
Case 2: grid-connected mode

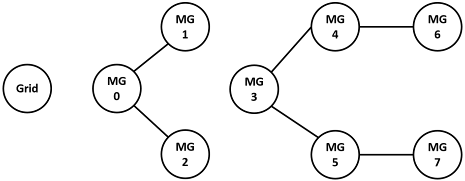




IEEE 33-bus Distribution System: Effect of Preference Mechanism

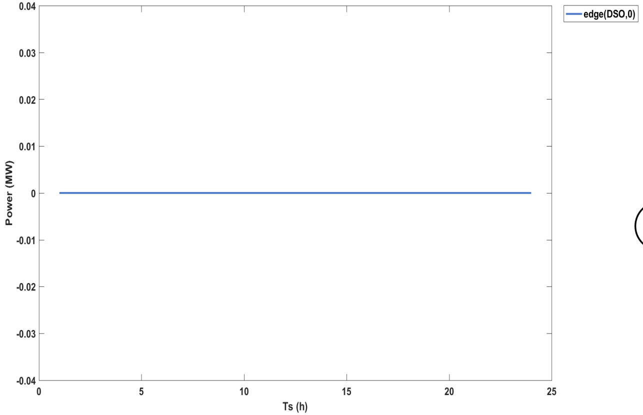
Case 2: grid-connected mode

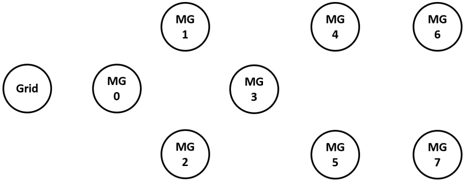




IEEE 33-bus Distribution System: Effect of Preference Mechanism

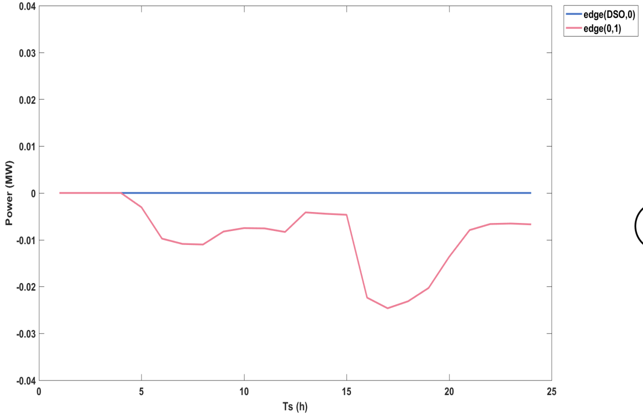
Case 2: Islanding mode $\kappa = 20$

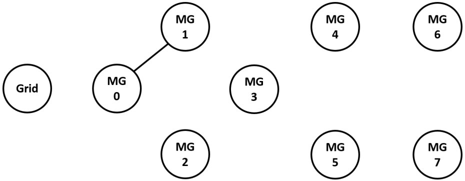




IEEE 33-bus Distribution System: Effect of Preference Mechanism

Case 2: Islanding mode $\kappa = 20$





IEEE 33-bus Distribution System: Effect of Preference Mechanism

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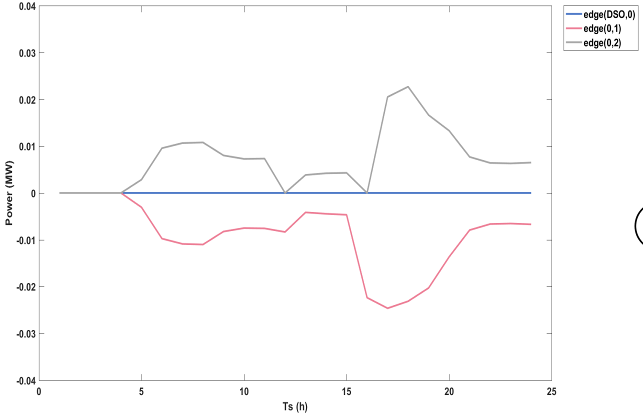
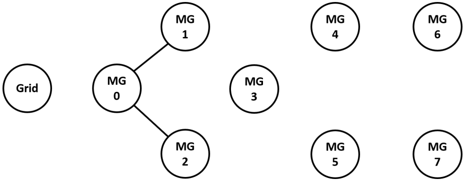
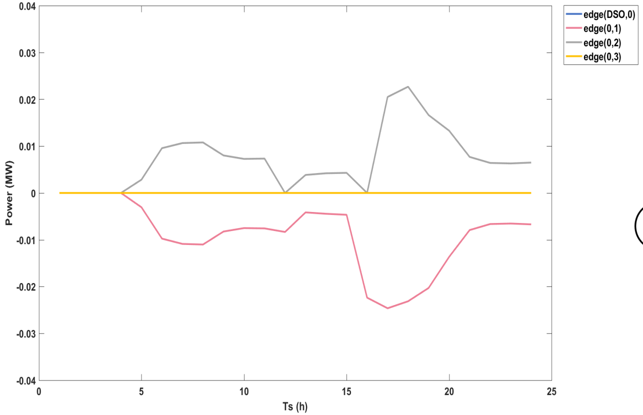
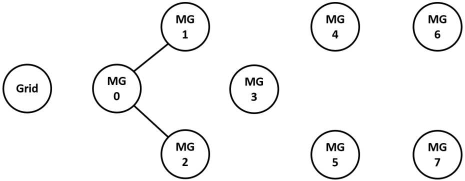




IEEE 33-bus Distribution System: Effect of Preference Mechanism

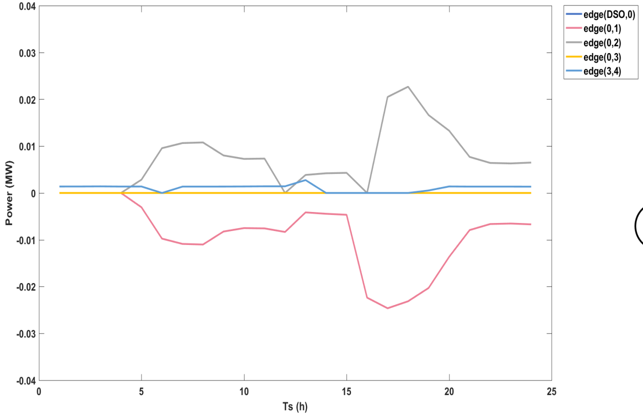
Case 2: Islanding mode $\kappa = 20$

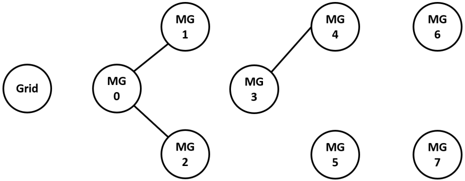




IEEE 33-bus Distribution System: Effect of Preference Mechanism

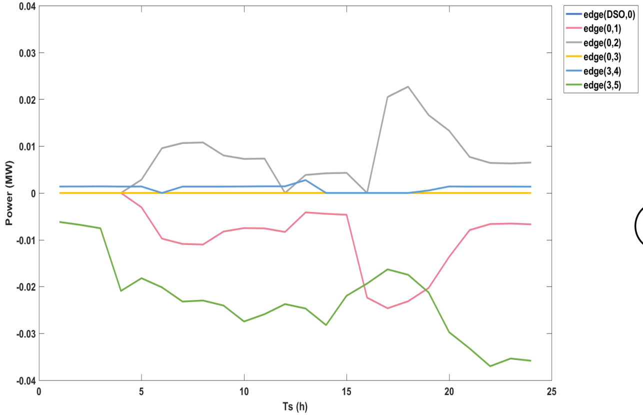
Case 2: Islanding mode $\kappa = 20$

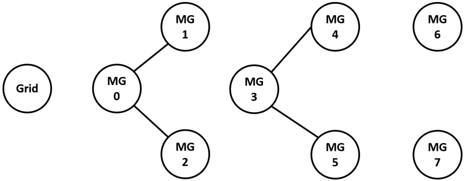




IEEE 33-bus Distribution System: Effect of Preference Mechanism

Case 2: Islanding mode $\kappa = 20$





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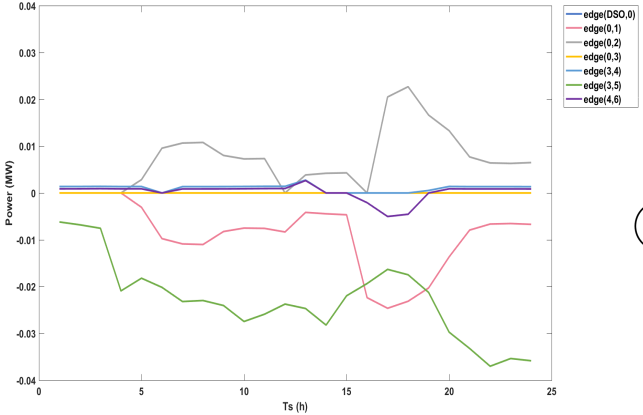

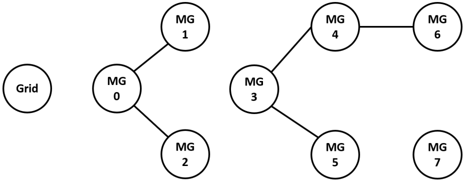

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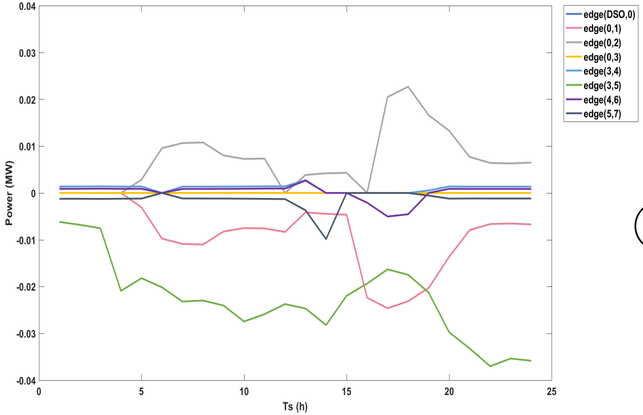
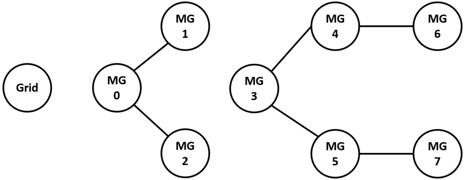
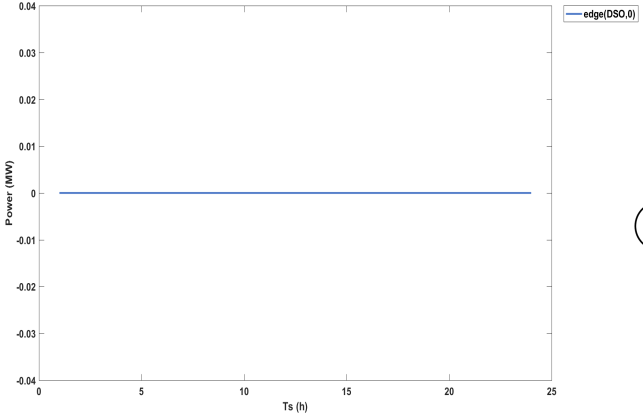
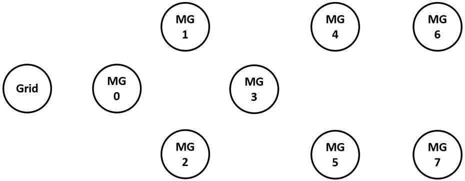




IEEE 33-bus Distribution System: Effect of Preference Mechanism

Case 2: Islanding mode $\kappa = 60$





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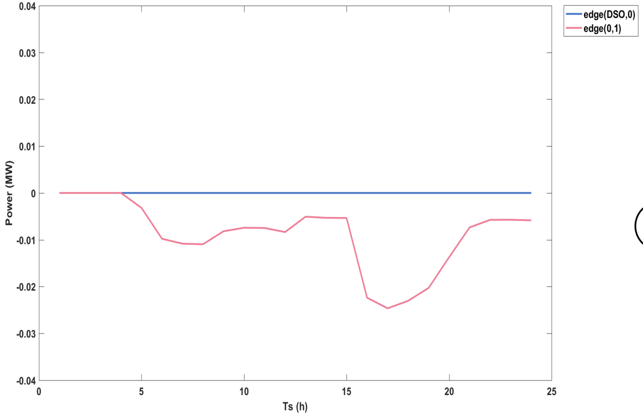

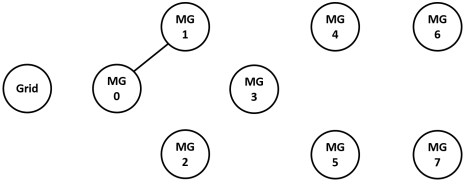

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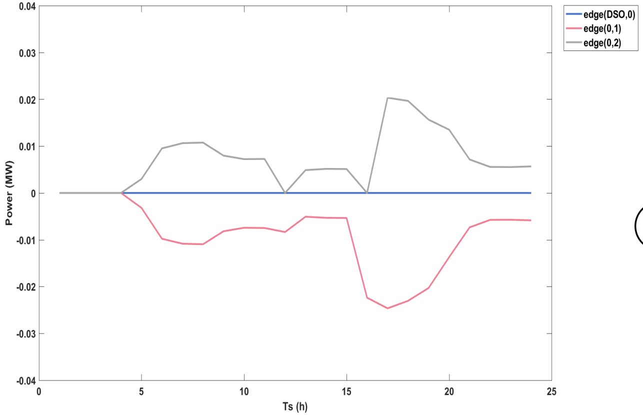

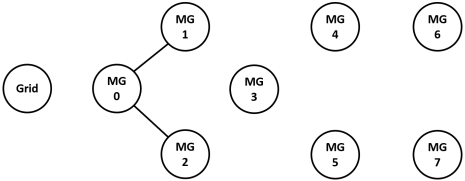

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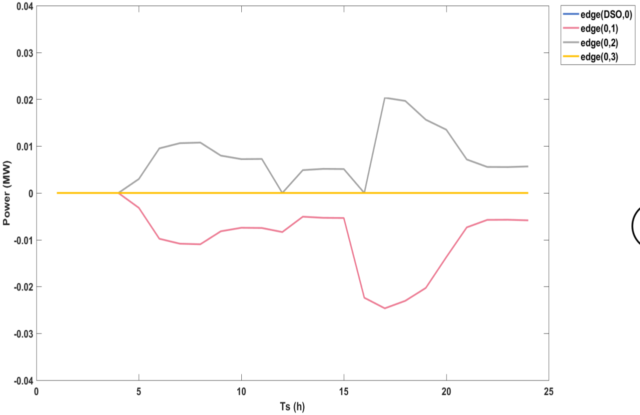

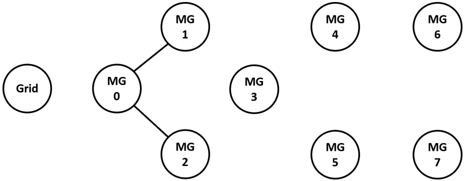

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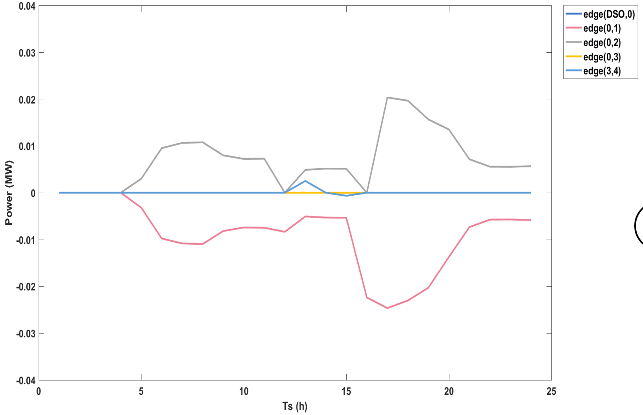

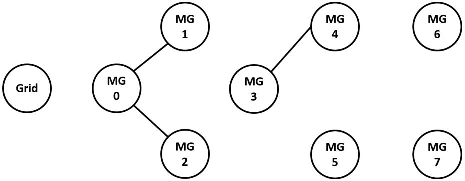

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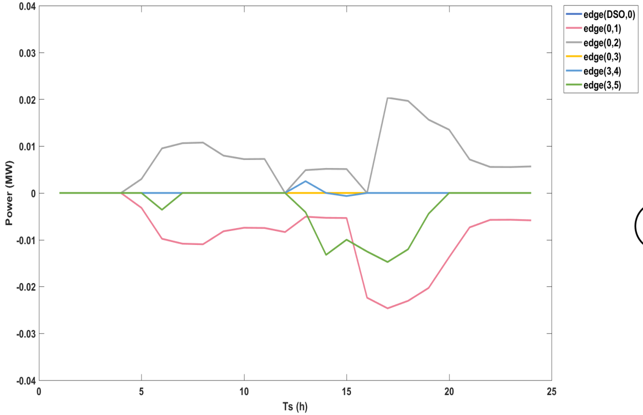

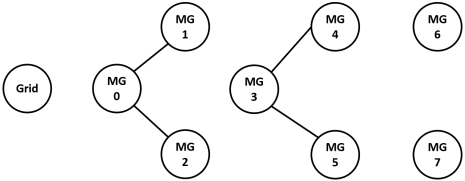

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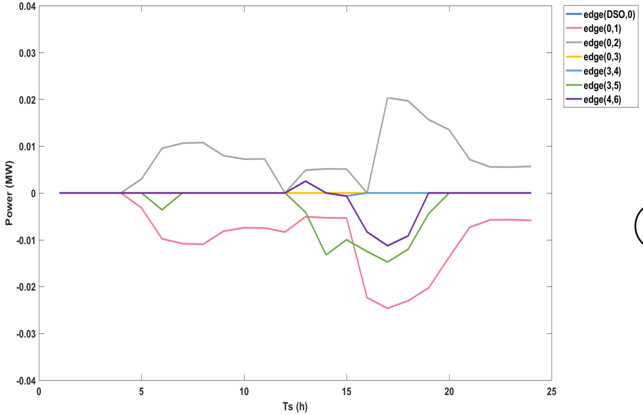

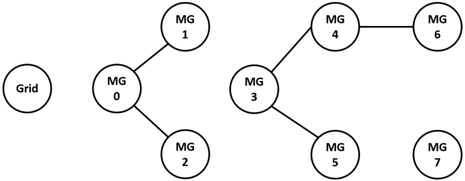

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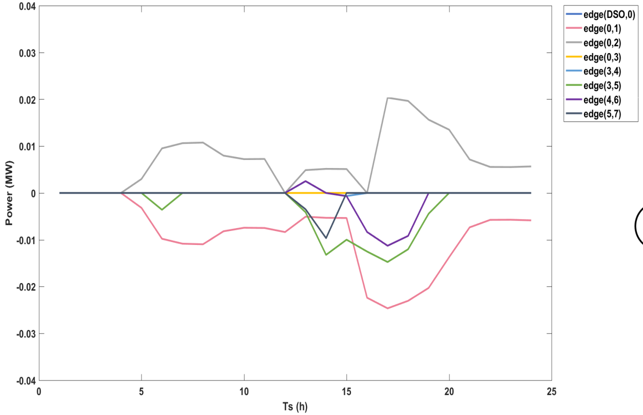
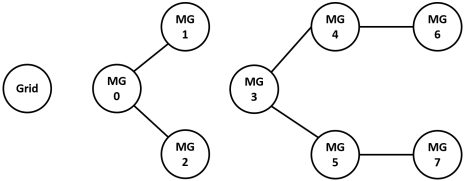
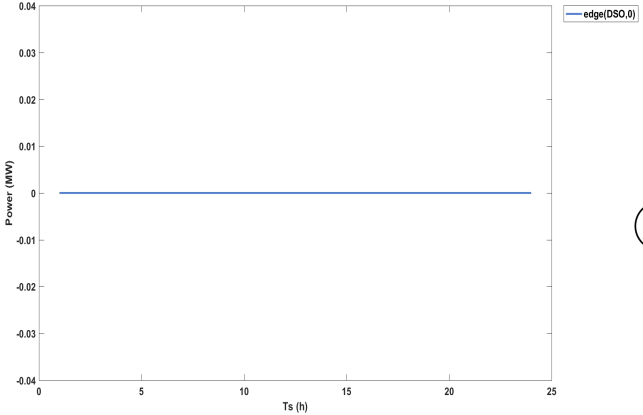
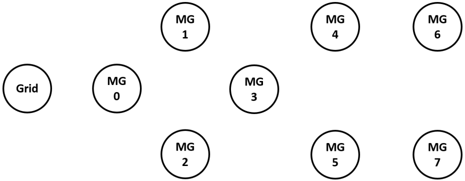




IEEE 33-bus Distribution System: Effect of Preference Mechanism

Case 2: Islanding mode $\kappa = 100$





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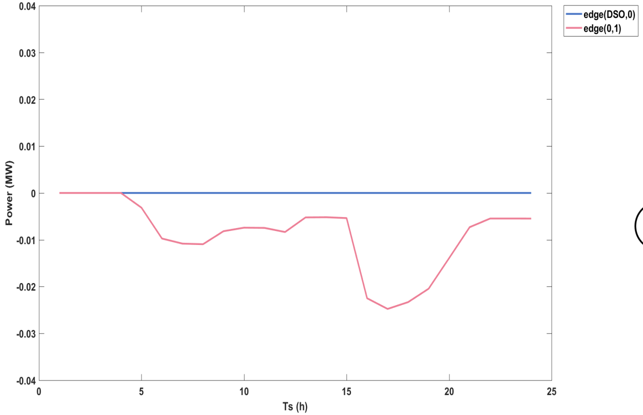

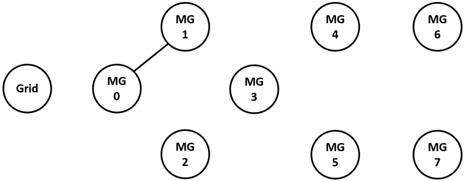

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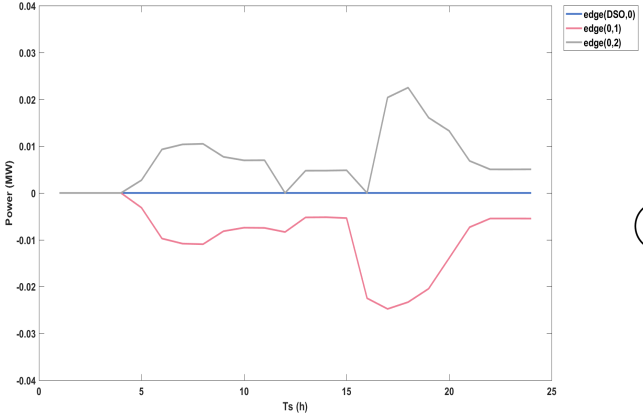

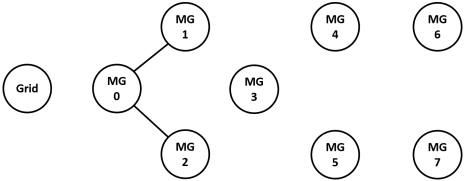

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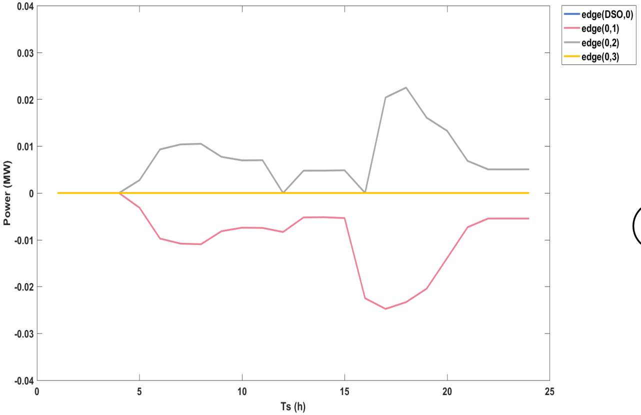

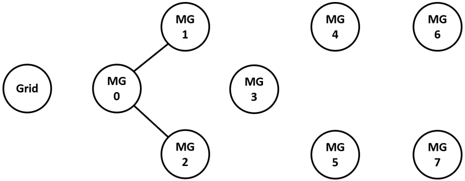

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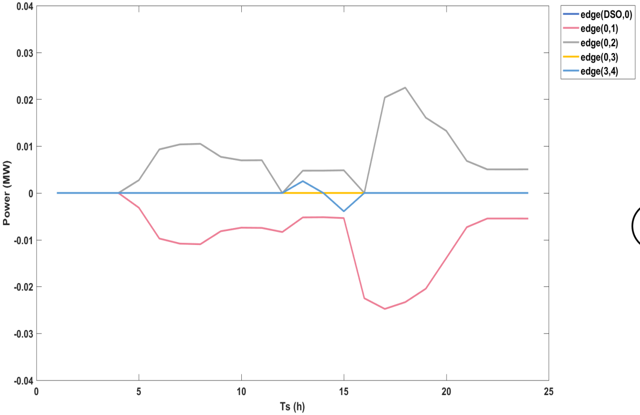

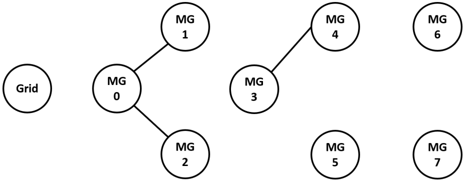

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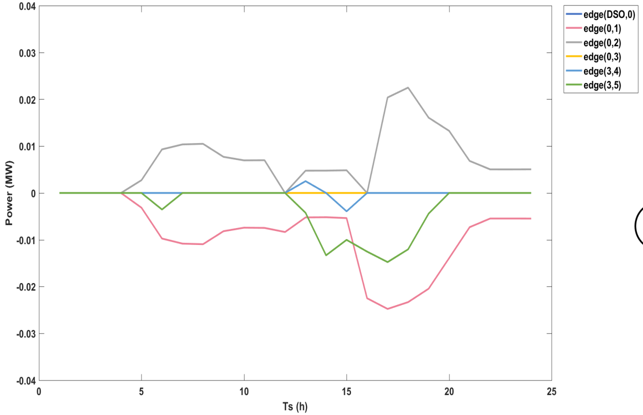

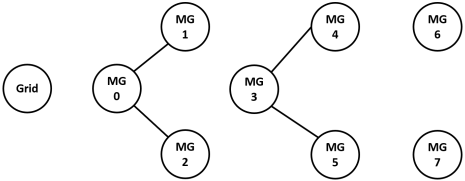

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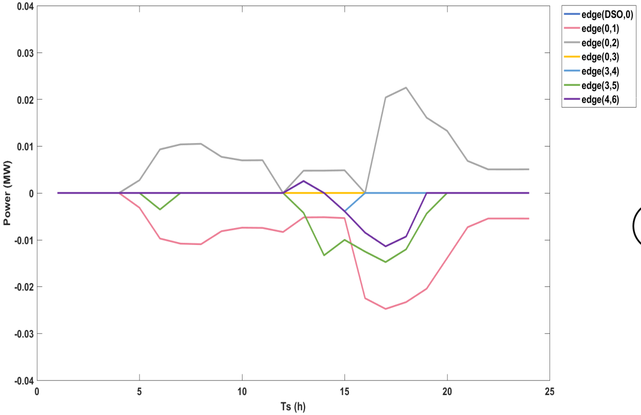

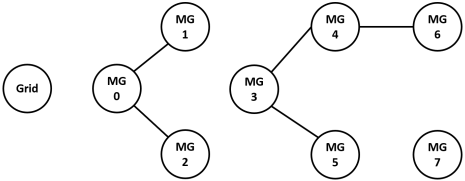

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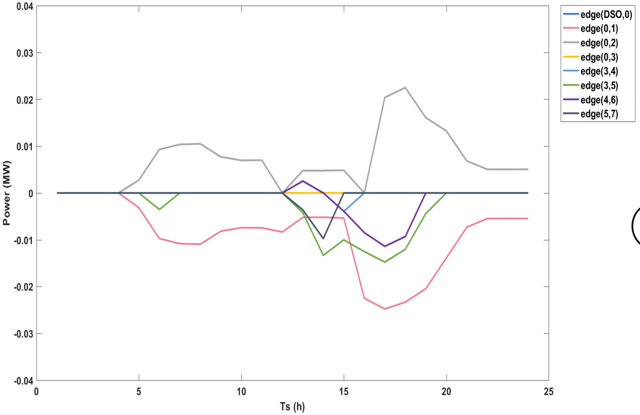
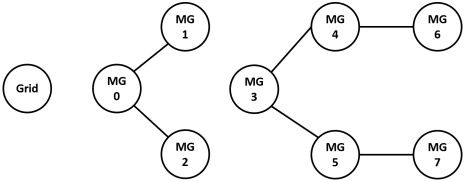
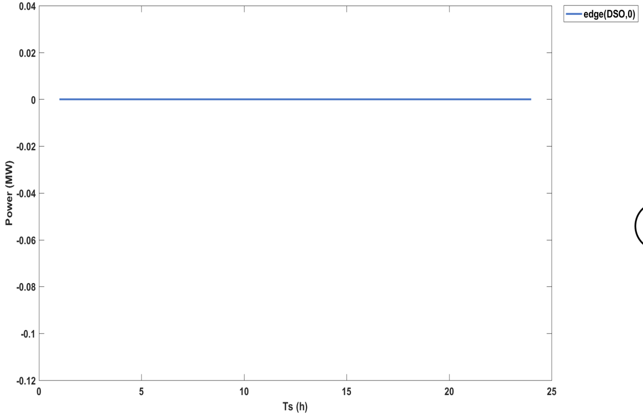
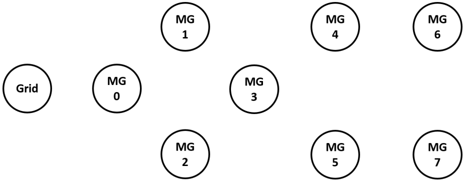




IEEE 33-bus Distribution System: Effect of Preference Mechanism

Case 2: Islanding mode with a time-varying κ





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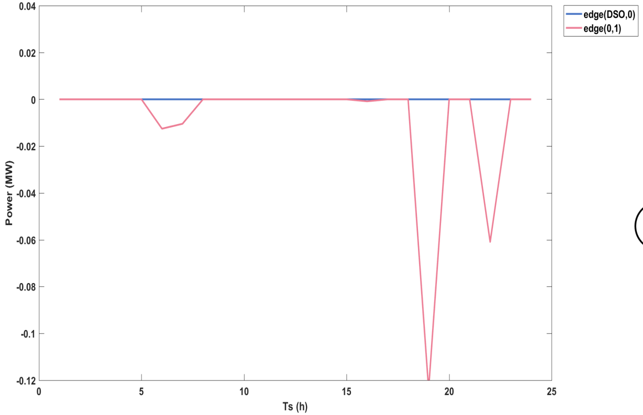

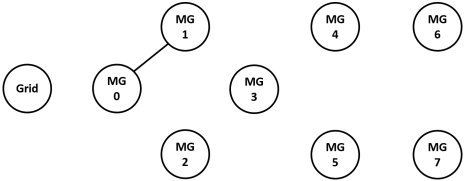

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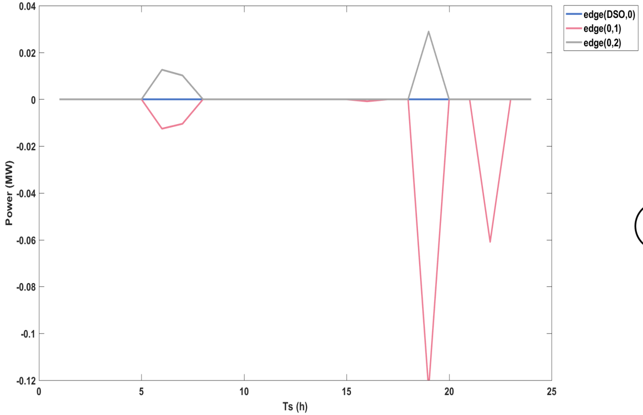

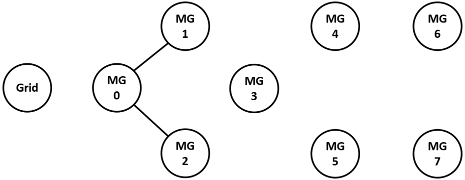

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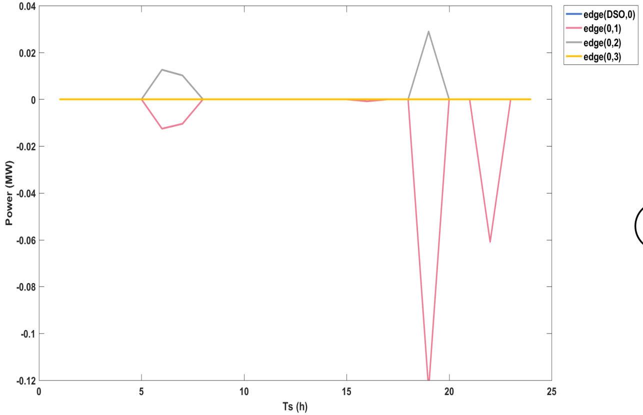

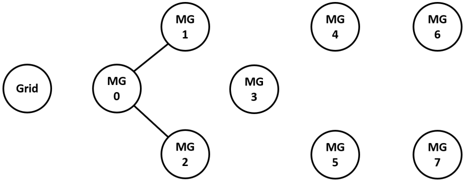

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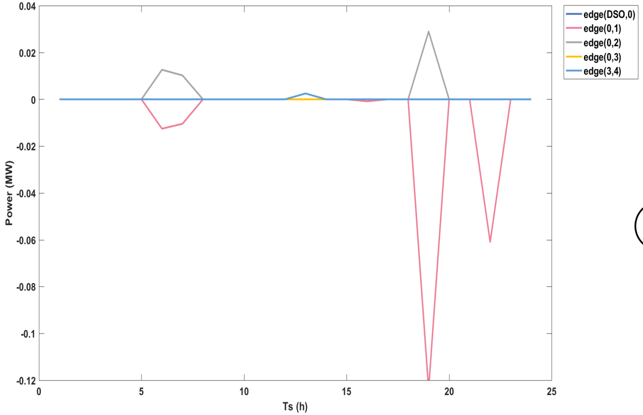

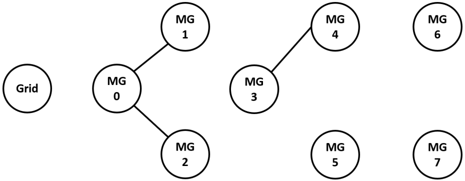

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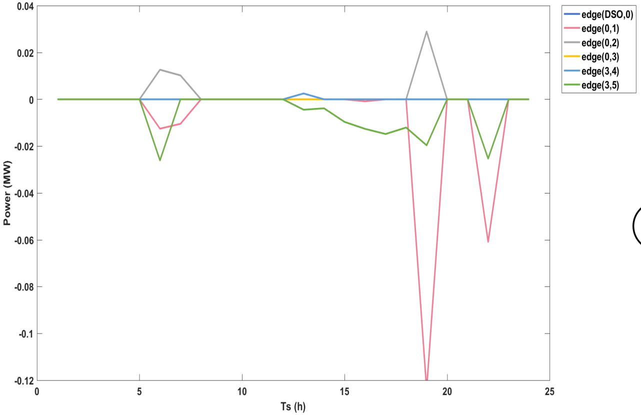

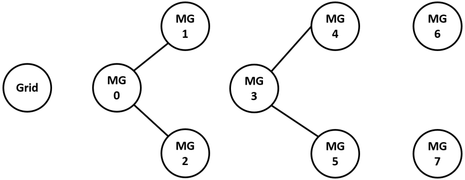

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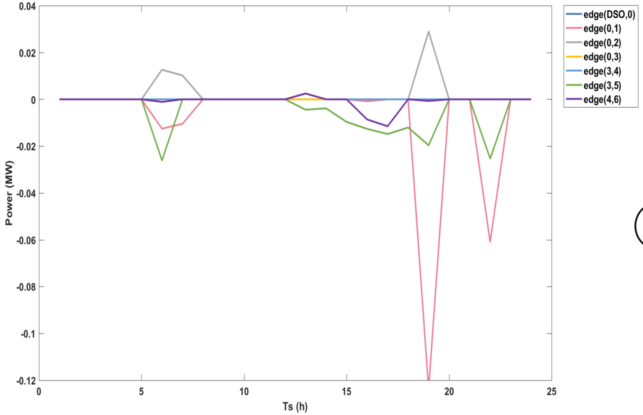

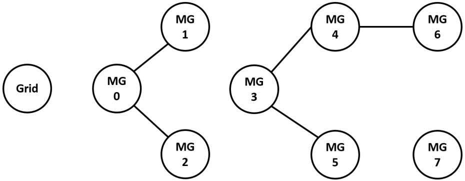

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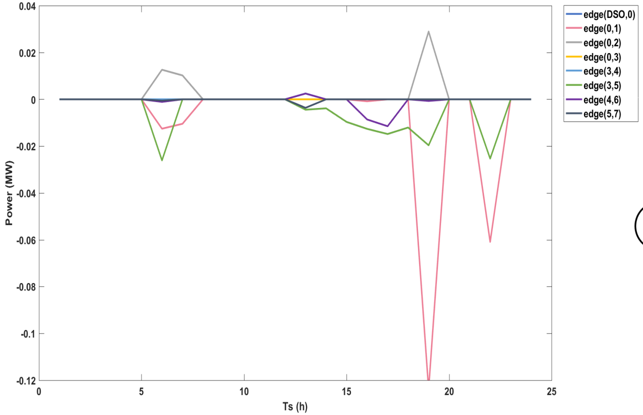
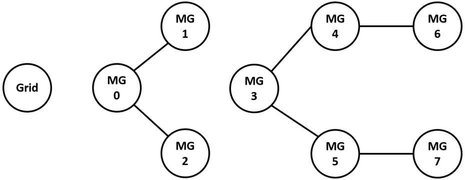
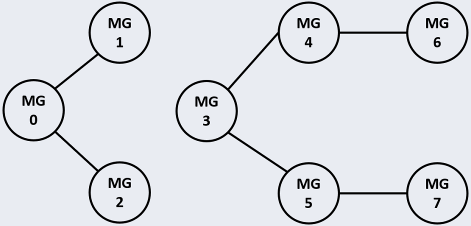




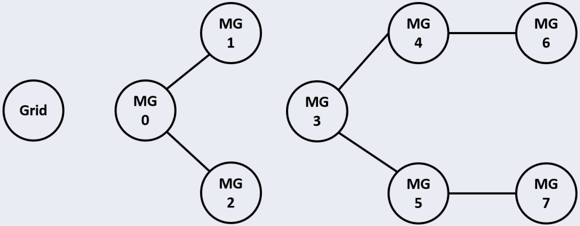
IEEE 33-bus Distribution System: Effect of Preference Mechanism

Case 2: grid-connected mode or islanding mode

Case 2: 2 desired clusters

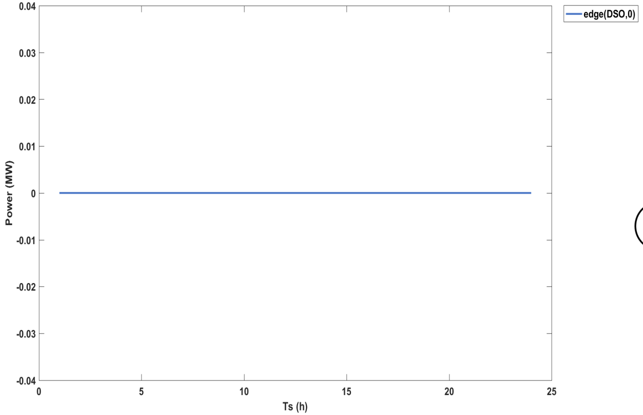


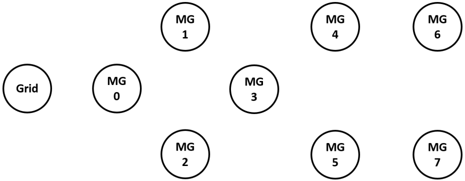
Case 2: Results



IEEE 33-bus Distribution System: Effect of Preference Mechanism

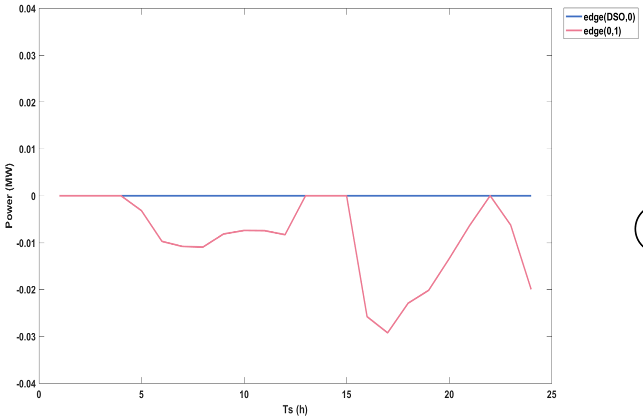
Case 3: grid-connected mode

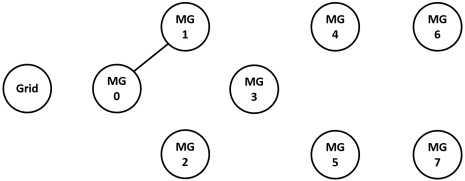




IEEE 33-bus Distribution System: Effect of Preference Mechanism

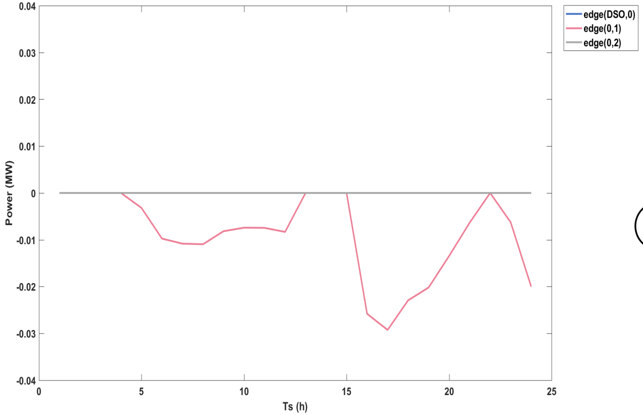
Case 3: grid-connected mode

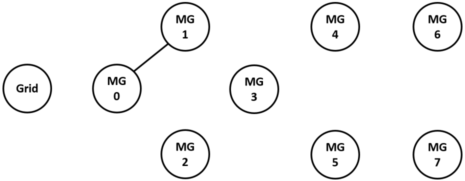




IEEE 33-bus Distribution System: Effect of Preference Mechanism

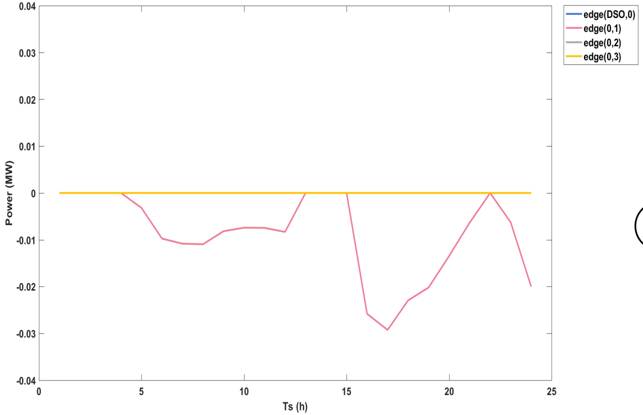
Case 3: grid-connected mode

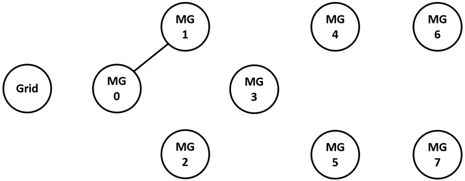




IEEE 33-bus Distribution System: Effect of Preference Mechanism

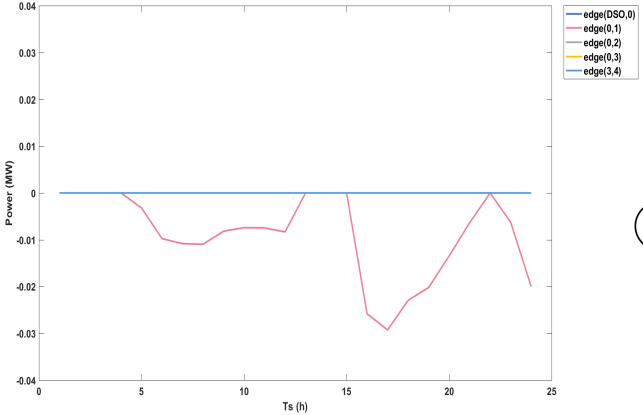
Case 3: grid-connected mode

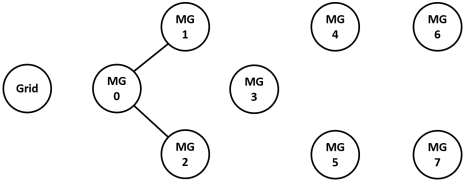




IEEE 33-bus Distribution System: Effect of Preference Mechanism

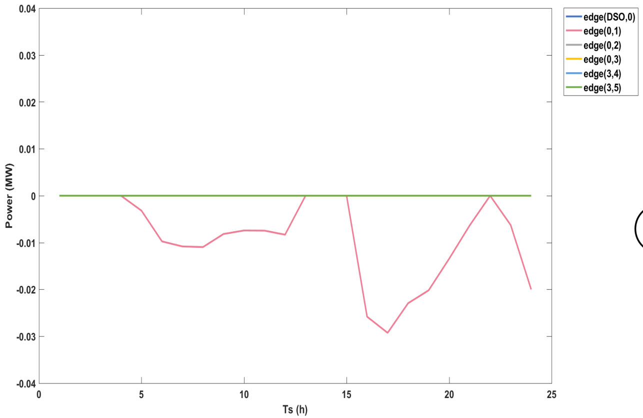
Case 3: grid-connected mode

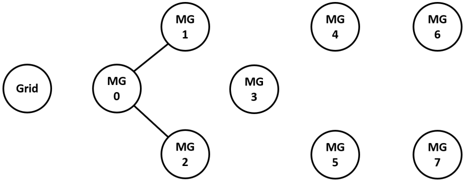




IEEE 33-bus Distribution System: Effect of Preference Mechanism

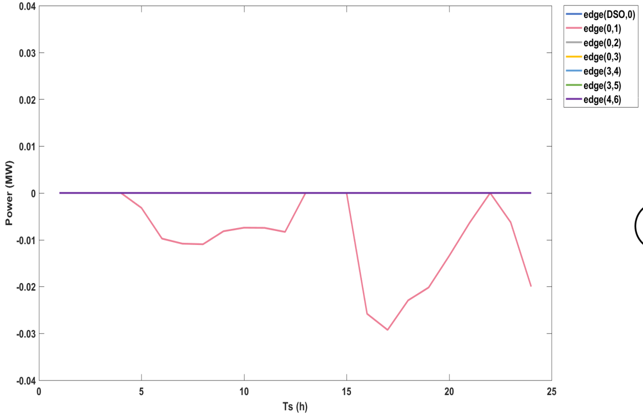
Case 3: grid-connected mode

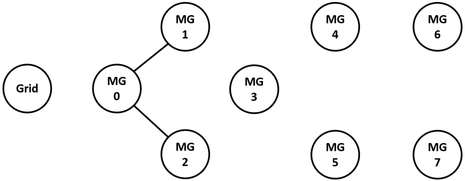




IEEE 33-bus Distribution System: Effect of Preference Mechanism

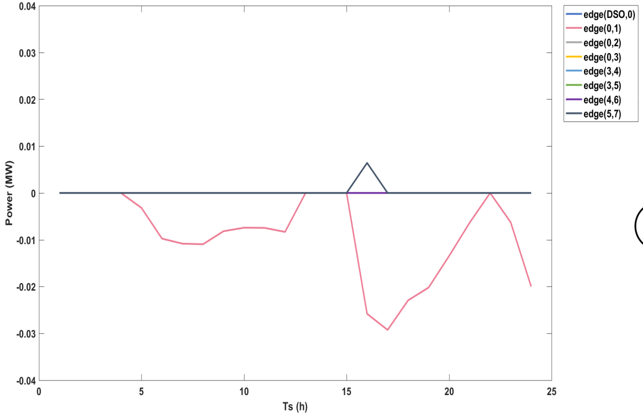
Case 3: grid-connected mode

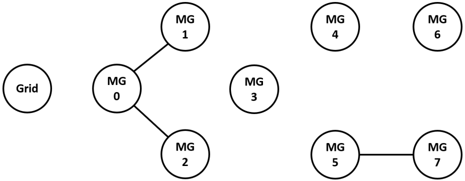




IEEE 33-bus Distribution System: Effect of Preference Mechanism

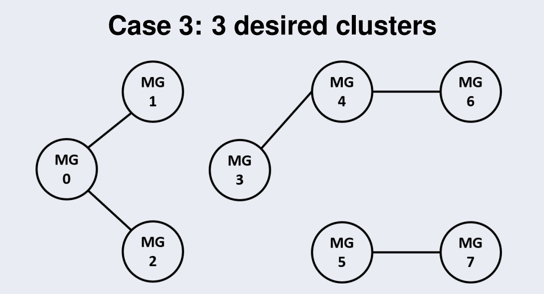
Case 3: grid-connected mode

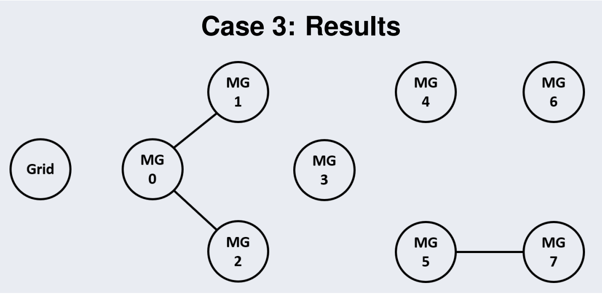




IEEE 33-bus Distribution System: Effect of Preference Mechanism

Case 3: grid-connected mode





IEEE 33-bus Distribution System: Effect of Preference Mechanism

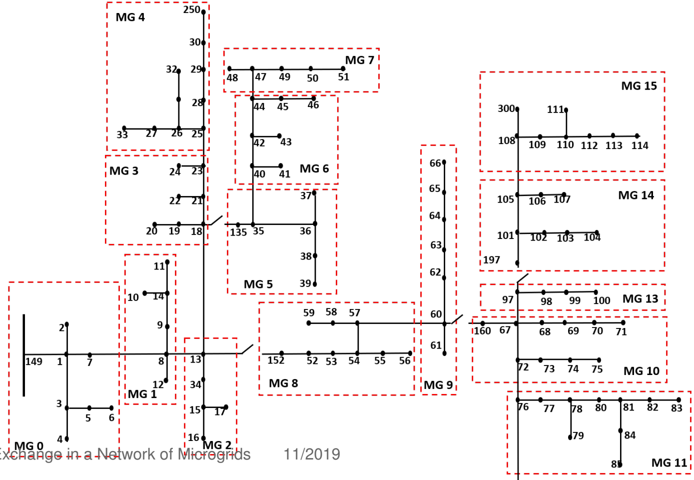
Conclusion

The preference mechanism is imposed onto P2P power trading while it exerts great effects on the resulting power flow within a network of microgrids. Three case studies validated that different preferences help to achieve different desired power flow within a network of microgrids.

IEEE 123-bus Distribution System: Convergence Performance

Simulations

- Selection of step size parameters ρ_1 and ρ_2
- Effect of the size of the network of microgrids
- Effect of the time scale



IEEE 123-bus Distribution System: Convergence Performance

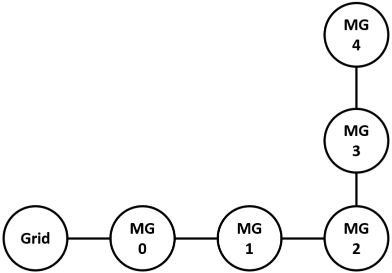
Simulations

- Selection of step size parameters ρ_1 and ρ_2
  - ρ_1: the step size related to virtual coupling constraint
  - ρ_2: the step size related to physical coupling constraint
- Effect of the size of the network of microgrids
- Effect of the time scale

IEEE 123-bus Distribution System: Convergence Performance

Simulations

- Selection of step size parameters ρ_1 and ρ_2
- Effect of the size of the network of microgrids
- Effect of the time scale

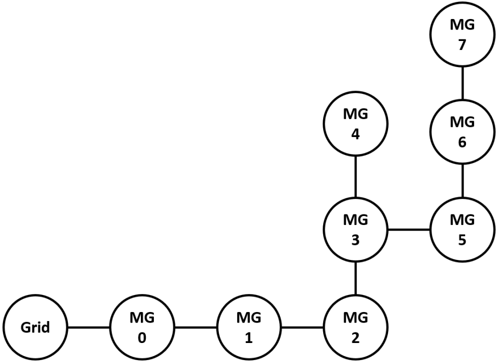


A network of 5 microgrids

IEEE 123-bus Distribution System: Convergence Performance

Simulations

- Selection of step size parameters ρ_1 and ρ_2
- Effect of the size of the network of microgrids
- Effect of the time scale

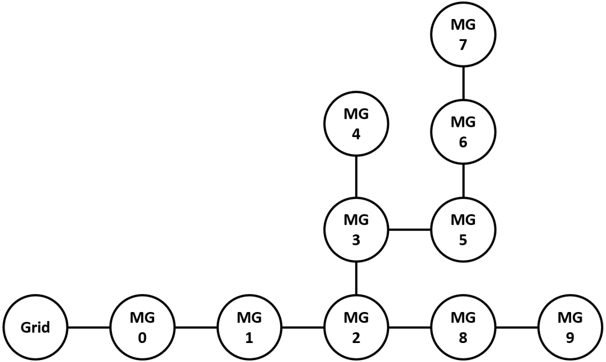


A network of 8 microgrids

IEEE 123-bus Distribution System: Convergence Performance

Simulations

- Selection of step size parameters ρ_1 and ρ_2
- Effect of the size of the network of microgrids
- Effect of the time scale

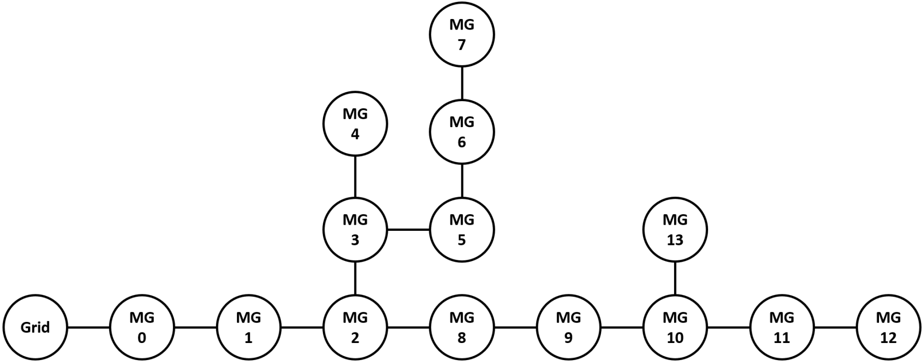


A network of 10 microgrids

IEEE 123-bus Distribution System: Convergence Performance

Simulations

- Selection of step size parameters ρ_1 and ρ_2
- Effect of the size of the network of microgrids
- Effect of the time scale

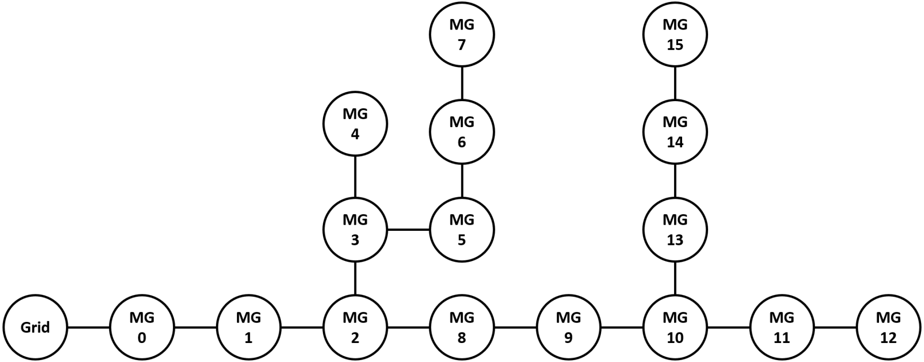


A network of 14 microgrids

IEEE 123-bus Distribution System: Convergence Performance

Simulations

- Selection of step size parameters ρ_1 and ρ_2
- Effect of the size of the network of microgrids
- Effect of the time scale



A network of 16 microgrids

IEEE 123-bus Distribution System: Convergence Performance

Simulations

- Selection of step size parameters ρ_1 and ρ_2
- Effect of the size of the network of microgrids
- Effect of the time scale
  $Ts = [1, 2, 4, 8, 12, 16, 20, 24, 28, 32, 36, 40, 44, 48]$

IEEE 123-bus Distribution System: Convergence Performance

Simulations

- Selection of step size parameters ρ_1 and ρ_2
- Effect of the size of the network of microgrids
- Effect of the time scale

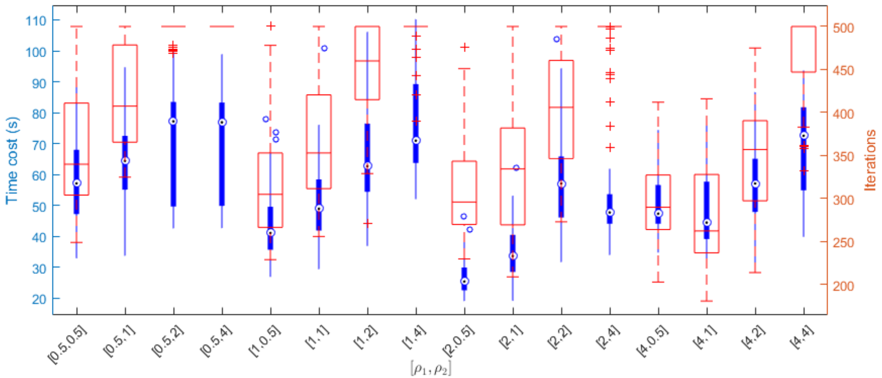
Evaluation indices

- Average iteration of convergence
- Average time cost of convergence

IEEE 123-bus Distribution System: Convergence Performance

Simulations

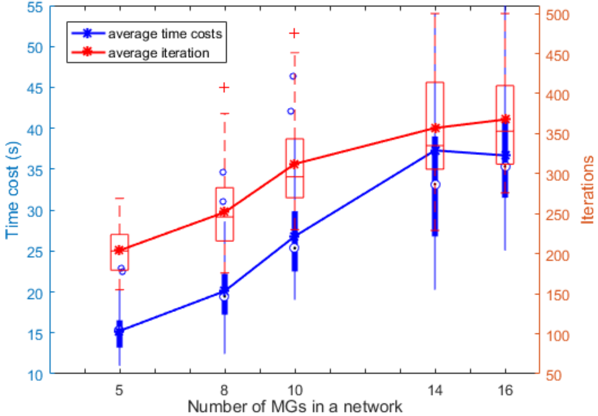
- Selection of step size parameters ρ_1 and ρ_2
  Optimal parameters: $\rho_1 = 2, \rho_2 = 0.5$.
- Effect of the size of the network of microgrids
- Effect of the time scale



IEEE 123-bus Distribution System: Convergence Performance

Simulations

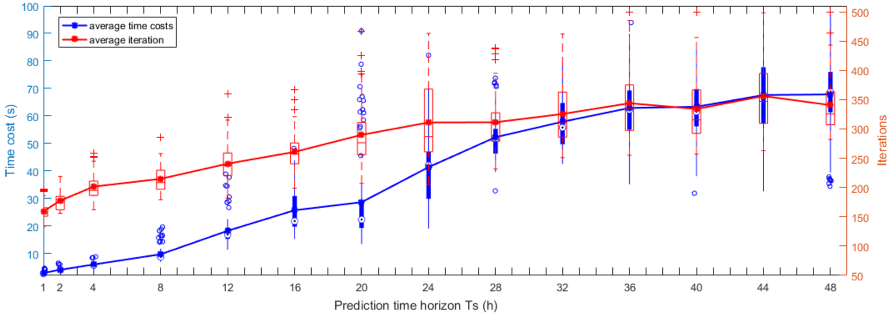
- Selection of step size parameters ρ_1 and ρ_2
- Effect of the size of the network of microgrids
- Effect of the time scale



IEEE 123-bus Distribution System: Convergence Performance

Simulations

- Selection of step size parameters ρ_1 and ρ_2
- Effect of the size of the network of microgrids
- Effect of the time scale



IEEE 123-bus Distribution System: Convergence Performance

Conclusion

The results show that the time cost of convergence and the iteration of convergence increase almost linearly with the size of the network and the time horizon.

Section 5

Wind Power Forecasting

- Wind Power Forecast Using Deep Learning Methods
- Wind Power Reconciliation

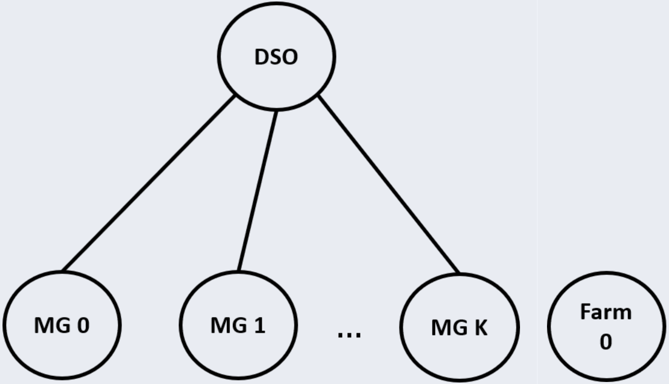
jump

Wind Power Forecasting

Convolutional neural network (CNN) models

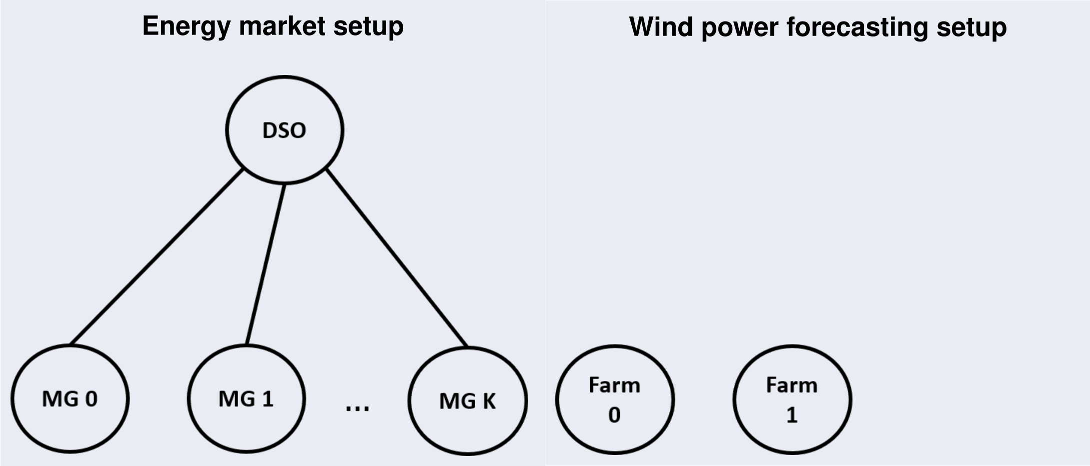
Energy market setup

Wind power forecasting setup



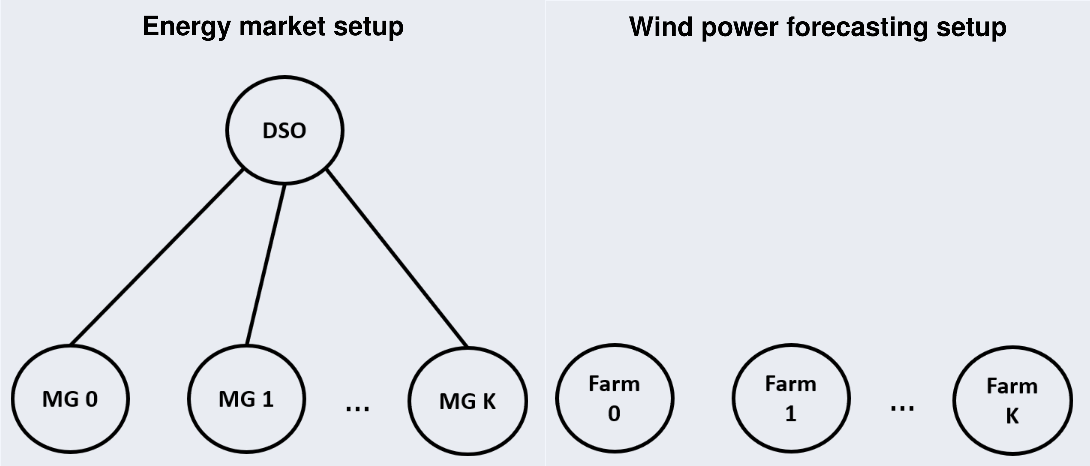
Wind Power Forecasting

Convolutional neural network (CNN) models



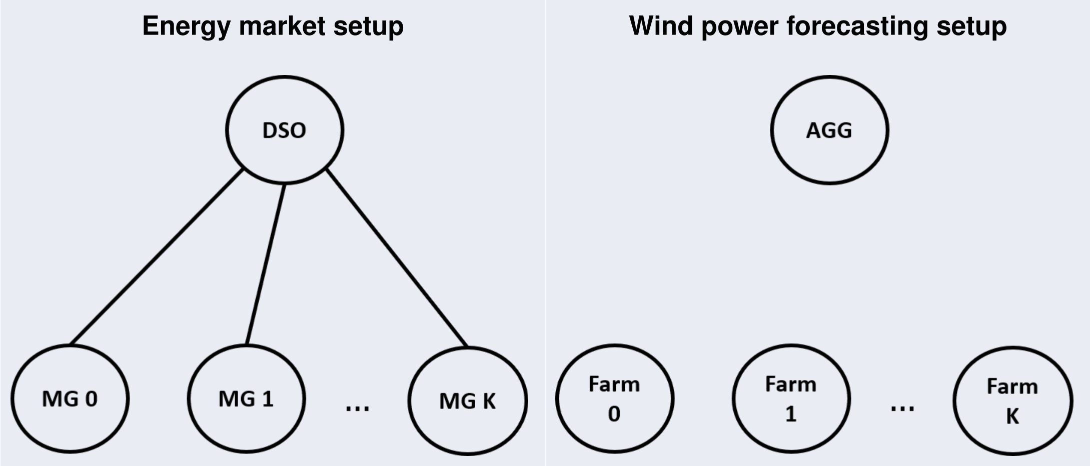
Wind Power Forecasting

Convolutional neural network (CNN) models



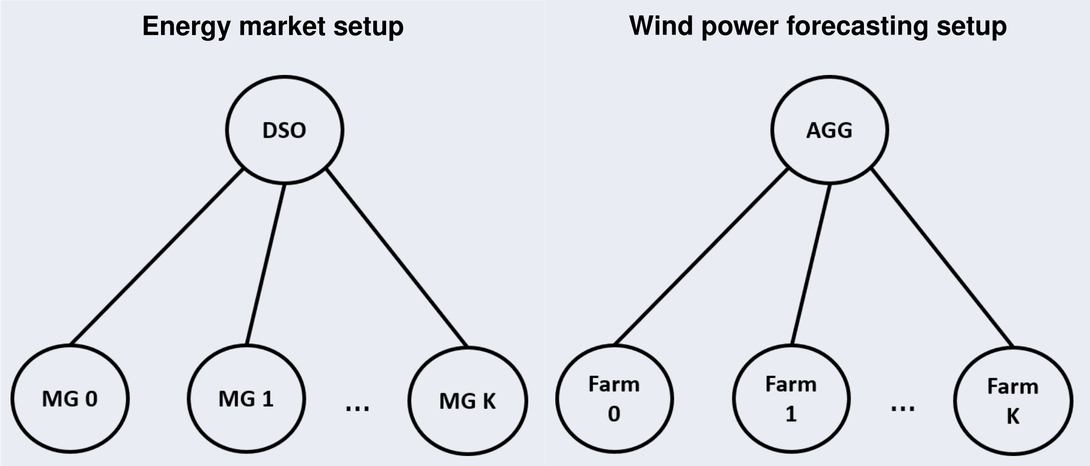
Wind Power Forecasting

Convolutional neural network (CNN) models



Wind Power Forecasting

Convolutional neural network (CNN) models



Wind Power Forecast Using Deep Learning Methods

State of art of short-term wind power forecasting

- Physical methods
- Statistical methods
- Artificial intelligence methods: explore information from large datasets

Available datasets

- Wind speed forecasts in 2 directions at 12 altitudes
- Wind Power outputs
- 4 individual wind farms (installed power capacities: 27.2MW, 56MW, 46.75MW and 51MW)
- 17312 hourly data (2 years)

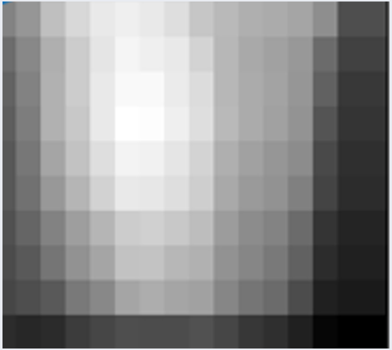
Wind Power Forecast Using Deep Learning Methods

Convolutional neural network (CNN) models

Wind data

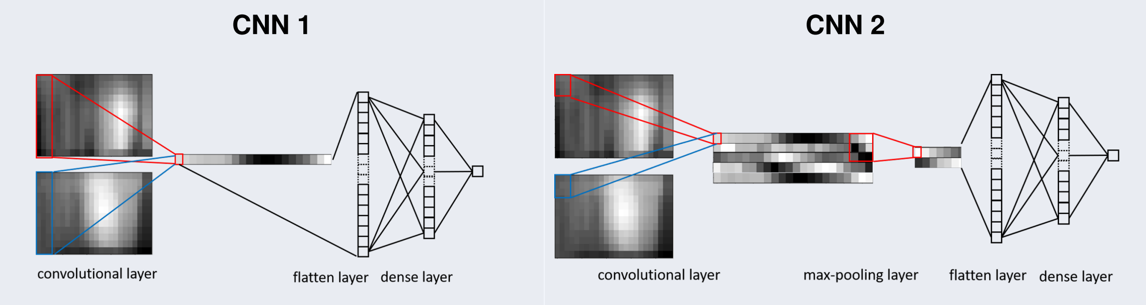
Altitude	$t-K$	$t-K+1$	$t-K+2$	$\dots$	$t-1$	t
10m	W^{10}_{t-K}	W^{10}_{t-K+1}	W^{10}_{t-K+2}	$\dots$	W^{10}_{t-1}	W^{10}_{t}
30m	W^{30}_{t-K}	W^{30}_{t-K+1}	W^{30}_{t-K+2}	$\dots$	W^{30}_{t-1}	W^{30}_{t}
80m	W^{80}_{t-K}	W^{80}_{t-K+1}	W^{80}_{t-K+2}	$\dots$	W^{80}_{t-1}	W^{80}_{t}
100m	W^{100}_{t-K}	W^{100}_{t-K+1}	W^{100}_{t-K+2}	$\dots$	W^{100}_{t-1}	W^{100}_{t}
120m	W^{120}_{t-K}	W^{120}_{t-K+1}	W^{120}_{t-K+2}	$\dots$	W^{120}_{t-1}	W^{120}_{t}
150m	W^{150}_{t-K}	W^{150}_{t-K+1}	W^{150}_{t-K+2}	$\dots$	W^{150}_{t-1}	W^{150}_{t}
170m	W^{170}_{t-K}	W^{170}_{t-K+1}	W^{170}_{t-K+2}	$\dots$	W^{170}_{t-1}	W^{170}_{t}
220m	W^{220}_{t-K}	W^{220}_{t-K+1}	W^{220}_{t-K+2}	$\dots$	W^{220}_{t-1}	W^{220}_{t}
250m	W^{250}_{t-K}	W^{250}_{t-K+1}	W^{250}_{t-K+2}	$\dots$	W^{250}_{t-1}	W^{250}_{t}
300m	W^{300}_{t-K}	W^{300}_{t-K+1}	W^{300}_{t-K+2}	$\dots$	W^{300}_{t-1}	W^{300}_{t}
500m	W^{500}_{t-K}	W^{500}_{t-K+1}	W^{500}_{t-K+2}	$\dots$	W^{500}_{t-1}	W^{500}_{t}

Wind Picture



Wind Power Forecast Using Deep Learning Methods

Convolutional neural network (CNN) models



Wind Power Forecast Using Deep Learning Methods

Benchmarks

Methods	Abbreviation
CNN1 with identity activation function	NOCNN1
CNN1 with sigmoid function	SGMCNN1
CNN1 with tanh function	TANHCNN1
CNN1 with ReLU function	RLCNN1
CNN2 with identity activation function	NOCNN2
CNN2 with sigmoid function	SGMCNN2
CNN2 with tanh function	TANHCNN2
CNN2 with ReLu function	RLCNN2
Radial Basic Function (RBF) based support vector regression(SVR)	RBFSVR
Polynomial kernel based SVR	PolySVR
RBF based NN	RBFNN
Sigmoid function based NN	SGMNN

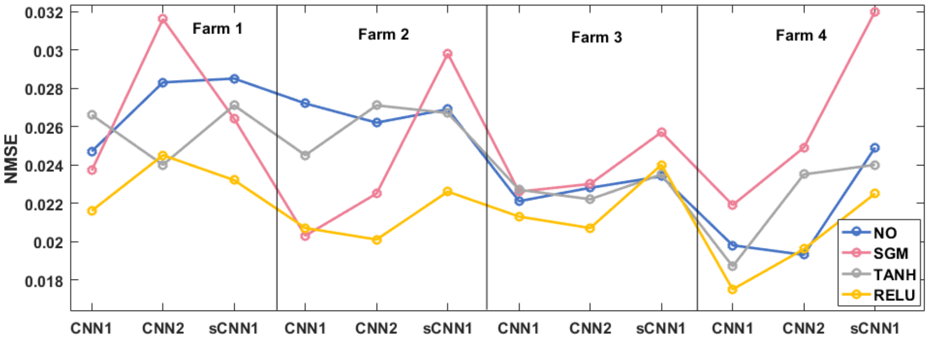
Evaluation indices

Normalized Mean Square Error: $NMSE = \frac{1}{N}\sum_{n=1}^{N}(\hat{P}_n - P_n)^2$

Normalized Mean Absolute Error:$NMAE = \frac{1}{N}\sum_{n=1}^{N}\left|\hat{P}_n - P_n\right|$

Wind Power Forecast Using Deep Learning Methods

CNN comparison (using wind amplitude)

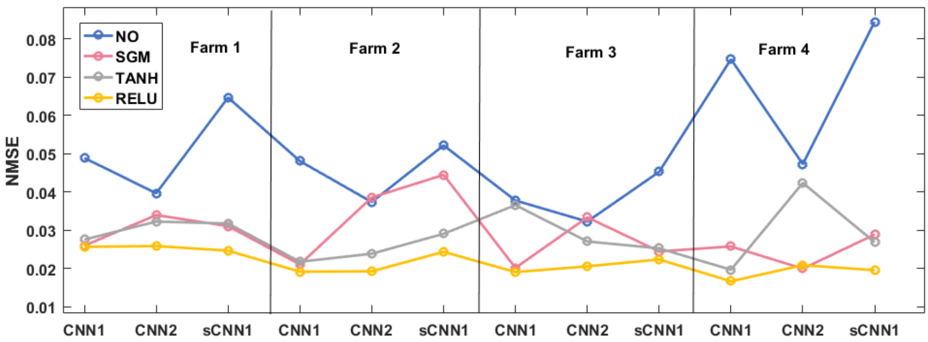


Result

ReLU activation function in CNNs provides better performance than any other activation function.

Wind Power Forecast Using Deep Learning Methods

CNN comparison (using wind directions)



Result

ReLU activation function in CNNs provides better performance than any other activation function.

Wind Power Forecast Using Deep Learning Methods

Comparison between CNNs and others

Wind farm 1

Methods	Activation function	wind direction	altitudes	NMSE	NMAE
CNN1	ReLU	1	multiple	0.0236	0.1103
SVR	Poly	1	single	0.0293	0.1195
NN	RBF	2	multiple	0.0218	0.1023

Wind farm 2

Methods	activation function	wind direction	altitudes	NMSE	NMAE
CNN1	ReLU	2	multiple	0.0191	0.0947
SVR	Poly	1	multiple	0.0279	0.1331
NN	RBF	2	multiple	0.0204	0.1067

Wind Power Forecast Using Deep Learning Methods

Comparison between CNNs and others

Wind farm 3

Methods	Activation function	wind direction	altitudes	NMSE	NMAE
CNN1	ReLU	2	multiple	0.0190	0.0956
SVR	Poly	1	single	0.0253	0.1151
NN	RBF	2	multiple	0.0198	0.0964

Wind farm 4

Methods	activation function	wind direction	altitudes	NMSE	NMAE
CNN1	ReLU	2	multiple	0.0166	0.0880
SVR	Poly	1	multiple	0.0236	0.1103
NN	RBF	2	multiple	0.0192	0.0914

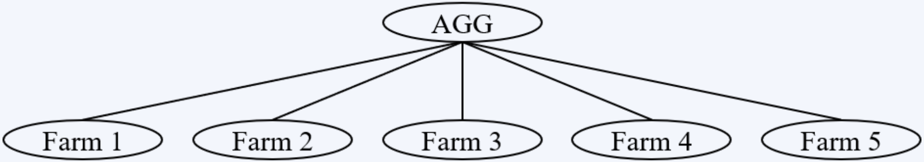
Wind Power Forecast Using Deep Learning Methods

Conclusion

CNNs provide slight advantages over RBFNNs and PolySVRs in the last 3 case studies, while PolySVRs perform worst in all 4 datasets.

Wind Power Reconciliation

Forecast reconciliation problem

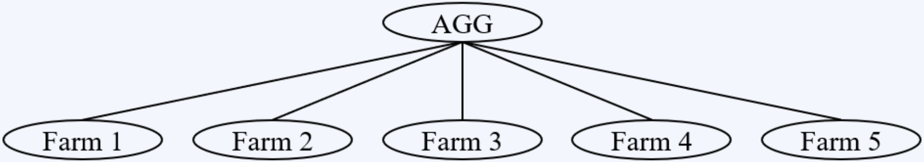


$$\begin{bmatrix} y_{\mathrm{AGG},t} \\ y_{1,t} \\ y_{2,t} \\ y_{3,t} \\ y_{4,t} \\ y_{5,t} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} y_{1,t} \\ y_{2,t} \\ y_{3,t} \\ y_{4,t} \\ y_{5,t}, \end{bmatrix}, \quad \forall t. \Longrightarrow Y_t = SY_t^b, \quad \forall t$$

Aggregation consistency of basic forecasts : $\hat{Y}_t \neq S\hat{Y}_t^b$
Aggregation consistency of reconciled forecasts: $\tilde{Y}_t = S\tilde{Y}_t^b$
y denotes the actual value, $\hat{y}$ denotes the basic forecast value and $\tilde{y}$ denotes the reconciled forecast value.

Wind Power Reconciliation

Forecast reconciliation problem



$$\hat{Y}_t \Longrightarrow \tilde{Y}_t$$

Motivation of reconciliation problem

- The basic forecasts do not follow aggregation consistency constraints $\longrightarrow$ **Reconciliation**
- Multi-owned wind farms are not willing to share information $\longrightarrow$ **Distributed Reconciliation**

Wind Power Reconciliation

Generalized least squares (GLS) reconciliation problem

A base forecast can be written as $\hat{Y}_{t+h|t} = S\beta_{t+h|t} + \mathcal{E}_{t+h|t}$,

- $\beta_{t+h|t} = \mathbb{E}[Y^b_{t+h}|\Theta_t]$ is the h-step-ahead expectation at instant t of the bottom level
- $\mathcal{E}_{t+h|t}$ is the reconciled error with zero-mean and covariance matrix $\Sigma_{t+h|t}$
- Θ_t is the information set available at t for the forecast

GLS estimation: $\hat{\beta}_{t+h|t} = (S^\top \Sigma^+_{t+h|t} S)^{-1} S^\top \Sigma^+_{t+h|t} \hat{Y}_{t+h|t}$

GLS reconciled forecasts: $\tilde{Y}_{t+h|t} = S\hat{\beta}_{t+h|t} = S(S^\top \Sigma^+_{t+h|t} S)^{-1} S^\top \Sigma^+_{t+h|t} \hat{Y}_{t+h|t}$

Trace minimization (MinT) reconciliation problem

$$\hat{\mathcal{E}}_{t+h|t} = Y_{t+h} - \hat{Y}_{t+h|t} \qquad \tilde{\mathcal{E}}_{t+h|t} = Y_{t+h} - \tilde{Y}_{t+h|t}$$

- $\hat{Y}_{t+h|t}$ and $\tilde{Y}_{t+h|t}$ are h-step-ahead base and reconciled forecasts
- Y_{t+h}: the observed values of all series at time $t+h$.
- $\hat{\mathcal{E}}_{t+h|t}$ and $\tilde{\mathcal{E}}_{t+h|t}$ are h-step-ahead base and reconciled forecast errors
- $W_{t+h|t}$ is the covariance matrix of $\hat{\mathcal{E}}_{t+h|t}$

MinT reconciled forecasts: $\tilde{Y}_{t+h|t} = S(S^\top W^+_{t+h|t} S)^{-1} S^\top W^+_{t+h|t} \hat{Y}_{t+h|t}$.

Wind Power Reconciliation

Generalized least squares (GLS) reconciliation estimation

$$\tilde{Y}_{t+h|t} = S(S^\top \Sigma_{t+h|t}{}^{+} S)^{-1} S^\top \Sigma^{+}_{t+h|t} \hat{Y}_{t+h|t}$$

Trace minimization (MinT) reconciliation estimation

$$\tilde{Y}_{t+h|t} = S(S^\top W_{t+h|t}{}^{+} S)^{-1} S^\top W^{+}_{t+h|t} \hat{Y}_{t+h|t}.$$

Covariance matrix

$\Sigma_{t+h|t}$: the covariance matrix of the reconciled errors; hard to identify
$W_{t+h|t}$: the covariance matrix of base forecast errors; can be estimated.

Estimator	Covariance matrix	Matrix property
Ordinary Least Squares (OLS)	Identity matrix	diagonal matrix
Weighted Least Squares (WLS)	$\mathrm{diag}(W^e_{t+h\|t})$	diagonal matrix
Hierarchical Least Squares (HLS)	SI	full matrix
Minimum Trace (MinT)	$W^e_{t+h\|t}$	full matrix
Minimum Trace Shrinkage (MinT_srk)	$\lambda \mathrm{diag}(W^e_{t+h\|t}) + (1-\lambda) W^e_{t+h\|t}$	full matrix

$W^e_{t+h|t} = \frac{1}{t} \sum_{n=1}^{t} \hat{\mathcal{E}}_{n+h|n} \hat{\mathcal{E}}^\top_{n+h|n}$

Wind Power Reconciliation

Game theoretical optimal (GTOP) reconciliation

A minmax optimization problem

$V = \min_{\tilde{Y}_{t+h|t} \in \mathcal{A}} \max_{Y_{t+h} \in \mathcal{A} \cap \mathcal{B}} L(Y_{t+h}, \tilde{Y}_{t+h|t}) - L(Y_{t+h}, \hat{Y}_{t+h|t})$

- $\mathcal{A}$: the hyperplane determined by the aggregated consistency constraint
- $\mathcal{B}$: extra available knowledge on the data
- L: loss function (L_2 norm))
- A: diagonal matrix accounting for the weighting factors, $A = \mathrm{diag}(\sqrt{a_{\mathrm{AGG}}}, \sqrt{a_1}, \ldots, \sqrt{a_K})$

$\tilde{Y}^{\mathrm{GTOP}}_{t+h|t} = \mathrm{argmin}_{\tilde{Y}_{t+h|t} \in \mathcal{A} \cap \mathcal{B}} \left\| A\tilde{Y}_{t+h|t} - A\hat{Y}_{t+h|t} \right\|_2^2$

Constrained GTOP problem

$$\arg\min_{\tilde{y}_1, \ldots, \tilde{y}_K} \sum_{k=1}^{K} a_k f_k(\tilde{y}_k - \hat{y}_k) + a_{\mathrm{AGG}} f_{\mathrm{AGG}}(\tilde{y}_{\mathrm{AGG}} - \hat{y}_{\mathrm{AGG}})$$

$$\text{s.t.} \quad \mathcal{A} : \sum_{k=1}^{K} \tilde{y}_k = \tilde{y}_{\mathrm{AGG}} \qquad \mathcal{B} : b_k^{\mathrm{low}} \le \tilde{y}_k - \hat{y}_k \le b_k^{\mathrm{up}}, \qquad k = 1, \ldots, K\,.$$

Wind Power Reconciliation

Constrained GTOP problem

$$\arg\min_{\tilde{y}_1,\ldots,\tilde{y}_K} \sum_{k=1}^{K} a_k f_k(\tilde{y}_k - \hat{y}_k) + a_{\mathrm{AGG}} f_{\mathrm{AGG}}(\tilde{y}_{\mathrm{AGG}} - \hat{y}_{\mathrm{AGG}})$$

$$\text{s.t.} \quad \mathcal{A} : \sum_{k=1}^{K} \tilde{y}_k = \tilde{y}_{\mathrm{AGG}}$$

$$\mathcal{B} : b_k^{\mathrm{low}} \leq \tilde{y}_k - \hat{y}_k \leq b_k^{\mathrm{up}}, \qquad k = 1, \ldots, K\,.$$

Online estimation of weight matrix A and constraint $\mathcal{B}$

ADMM-based distribution algorithm

Distribution algorithms for constrained GTOP problems

- OLS-CADMM
- WLS-CADMM

Wind Power Reconciliation

Case studies: dataset description

Dataset	Wind speeds	Power output
Simulated dataset	Randomly generated	Simulated
NREL dataset	Provided	Simulated
Sardinia dataset	Provided	Measured

Case studies: evaluation indices

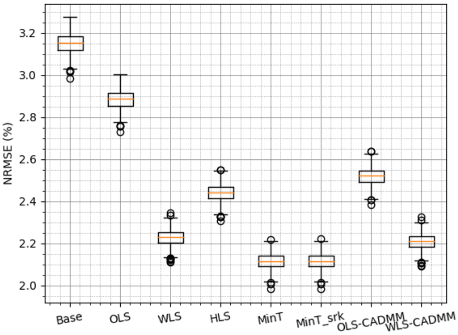
- NRMSE: normalized root square error
- NMAE: normalized mean absolute error
- IRMSE: improvement of RMSE

$$\mathrm{IRMSE_x} = \frac{\mathrm{RMSE_{Base}} - \mathrm{RMSE_x}}{\mathrm{RMSE_{Base}}}$$

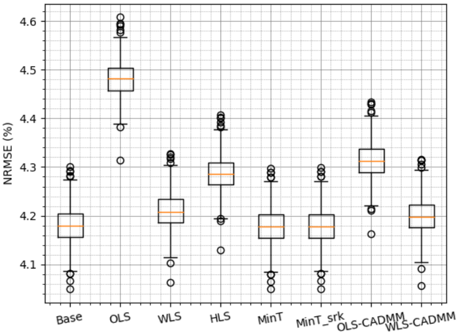
Wind Power Reconciliation

NRMSEs on the simulated dataset

NRMSE of Node “AGG”



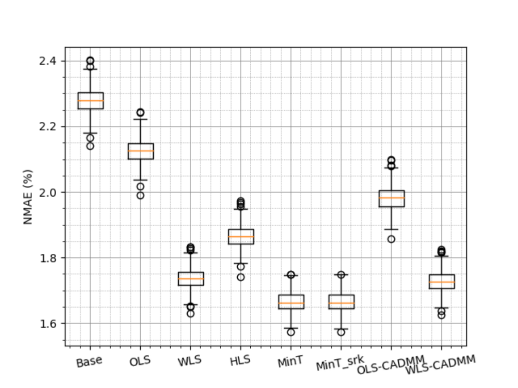
NRMSE at bottom level



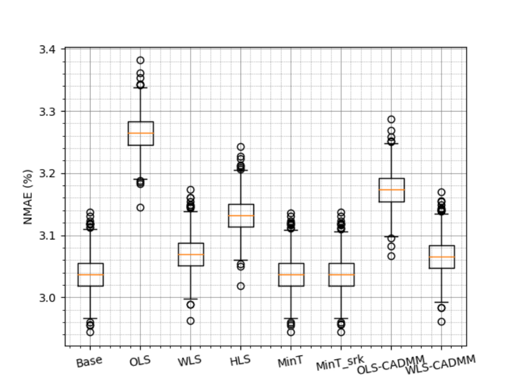
Wind Power Reconciliation

NMAEs on the simulated dataset

NMAE of Node "AGG"



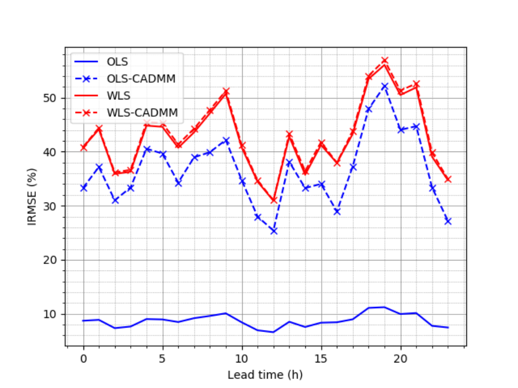
NMAE at bottom level



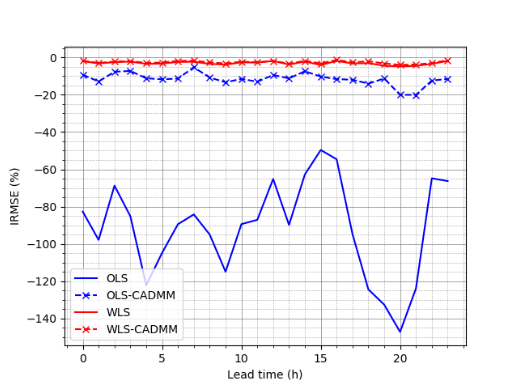
Wind Power Reconciliation

IRMSEs on the NREL dataset

IRMSEs of Node “AGG”



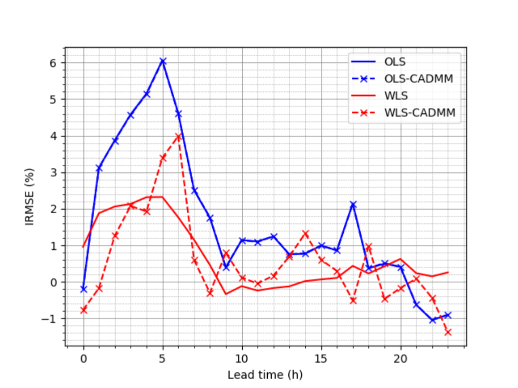
IRMSEs at bottom level



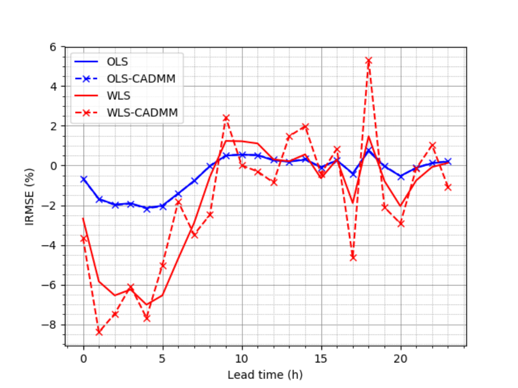
Wind Power Reconciliation

IRMSEs on the Sardinia dataset

IRMSEs of Node “AGG”



IRMSEs at bottom level



Wind Power Reconciliation

Conclusion

- Min_T provides the best performance by considering the correlation among different agents in a centralized way.
- Reconciliation can be solved in a distributed manner in the framework of (WLS-) GTOP.

Section 6

Communication Techniques: Power Line Communication

jump

Power Line Communication (PLC)

Motivations of PLC

- PLC is an attractive communication technique in smart grid, and one of the information and communication techniques in energy trading realization
- Power line channels are highly interfered by strong impulsive noise (IN), degrading data transmission performance.

Motivations of IN mitigation work

- The usually used sparse IN model does not fit for IN bursts in the specific channels.
- Already existing methods may not offer good performance

Power Line Communication (PLC)

Orthogonal frequency division multiplexing (OFDM) PLC system model in the frequency domain

$$R = Fs + Fi + Fw = Fs + I + W$$

- F is FFT matrix
- s is the desired signal in the time domain
- I and W are impulsive noise and background noise in the frequency domain
- R is the received signal in the frequency domain

Not all the subcarriers are used for signal transmission in the frequency domain.

OFDM PLC system model on null subcarriers in the frequency domain

$$R_{null} = I_{null} + W_{null} = F_{null} i + W_{null}$$

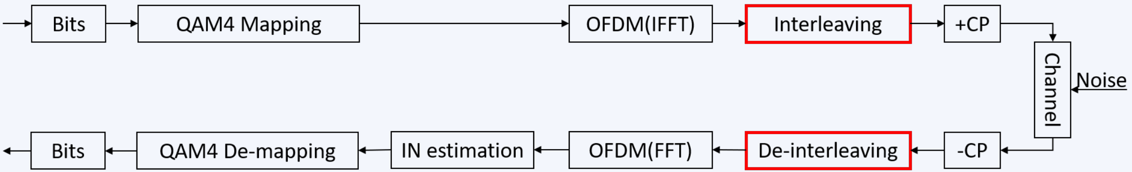
- F_{null} is FFT submatrix on null subcarriers
- I_{null} and W_{null} are the subvectors of impulsive noise I and background noise W in the frequency domain
- R_{null} is the submatrix of the received signal R in the frequency domain

Power Line Communication (PLC)

IN mitigation

- Sparsify IN bursts in the time domain
- Identify IN supports
- Estimate IN magnitude

OFDM PLC systems

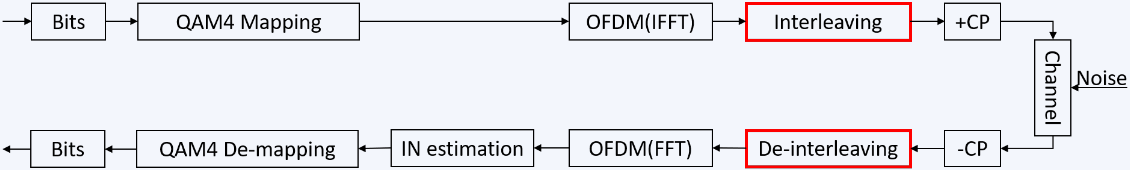


Power Line Communication (PLC)

IN mitigation

- Sparsify IN bursts in the time domain
- Identify IN supports
- Estimate IN magnitude

Orthogonal frequency division multiplexing (OFDM) PLC systems



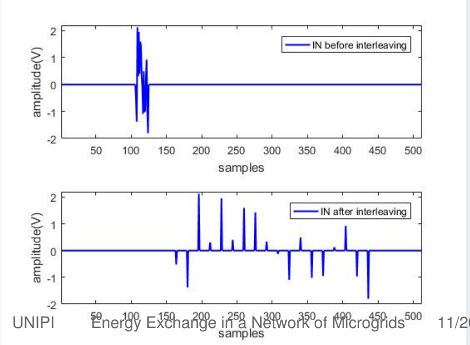
Power Line Communication (PLC)

Proposed IN mitigation algorithm

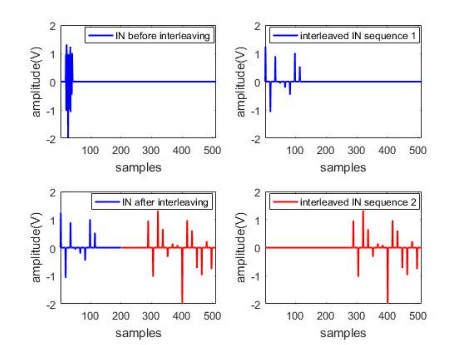
- Sparsify IN bursts in the time domain
- Identify IN supports
- Estimate IN magnitude

Orthogonal frequency division multiplexing (OFDM) PLC systems

Case 1: IN bursts



Case 2: IN bursts

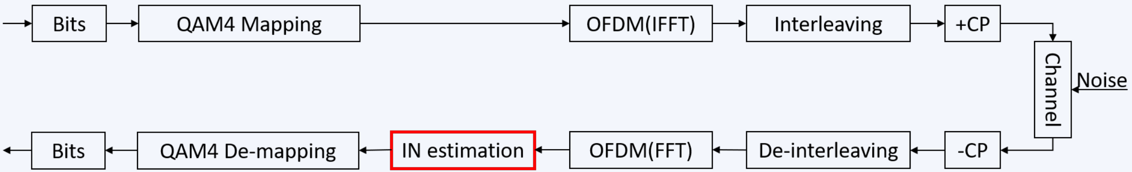


Power Line Communication (PLC)

IN mitigation

- Sparsify IN bursts in the time domain
- Identify IN supports: multiple signal classification (MUSIC)
- Estimate IN magnitude
  - Least squares (LS)
  - Sparse Bayesian learning (SBL)

Orthogonal frequency division multiplexing (OFDM) PLC systems



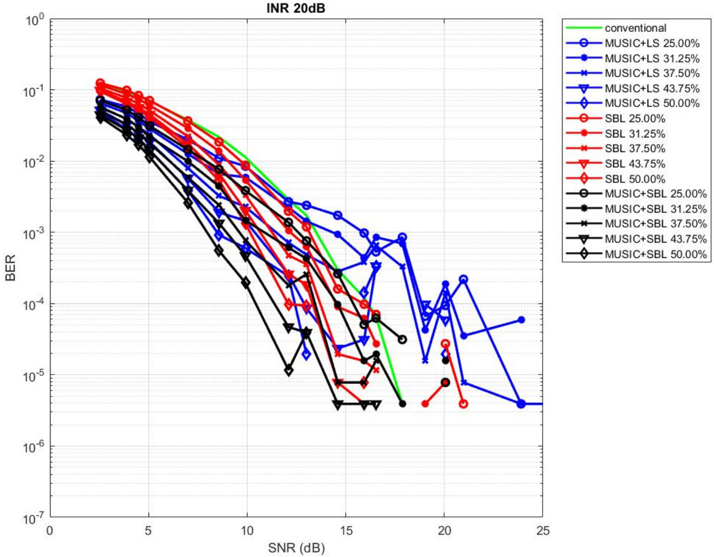
Power Line Communication (PLC)

Simulation

- Null subcarriers $[25\%, 31.25\%, 37.5\%, 43.75\%, 50\%]$
- Ratio of IN to background power (INR) $[20, 30, 40]$ dB
- Channels: Ideal channel and frequency-selective channel
- Methods
  - MUSIC+LS
  - MUSIC+SBL
  - SBL
- Evaluation indice: bit error rate (BER)

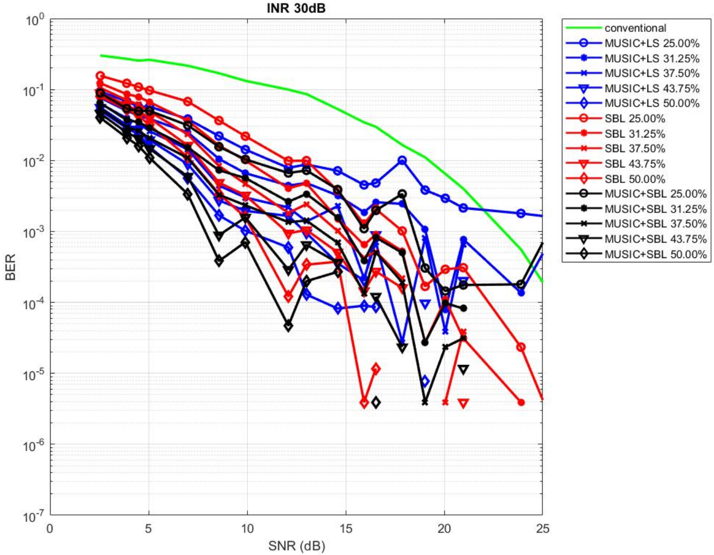
Power Line Communication (PLC)

Simulation: ideal channels INR=20dB



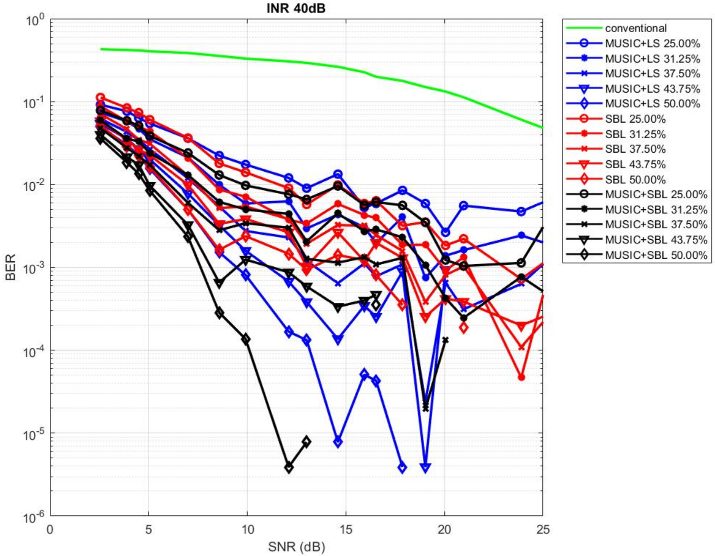
Power Line Communication (PLC)

Simulation: ideal channels INR=30dB



Power Line Communication (PLC)

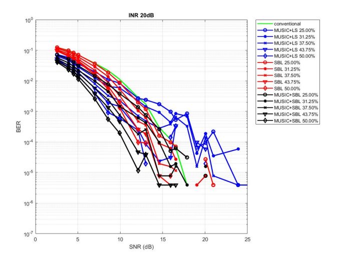
Simulation: ideal channels INR=40dB



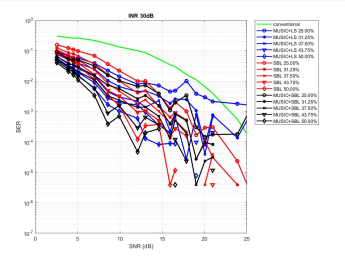
Power Line Communication (PLC)

Simulation: ideal channels

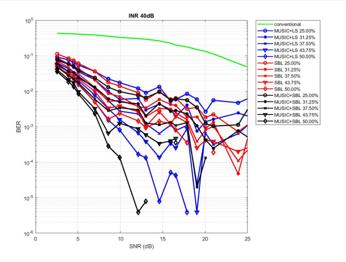
INR=20dB



INR=30dB



INR=40dB

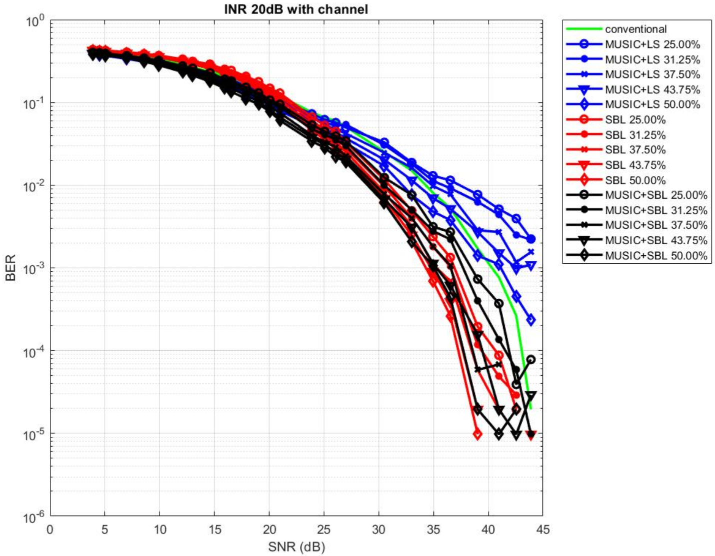


Conclusion

In ideal channels, the proposed MUSIC+SBL method performs best among all 3 methods under different INRs and null subcarriers.

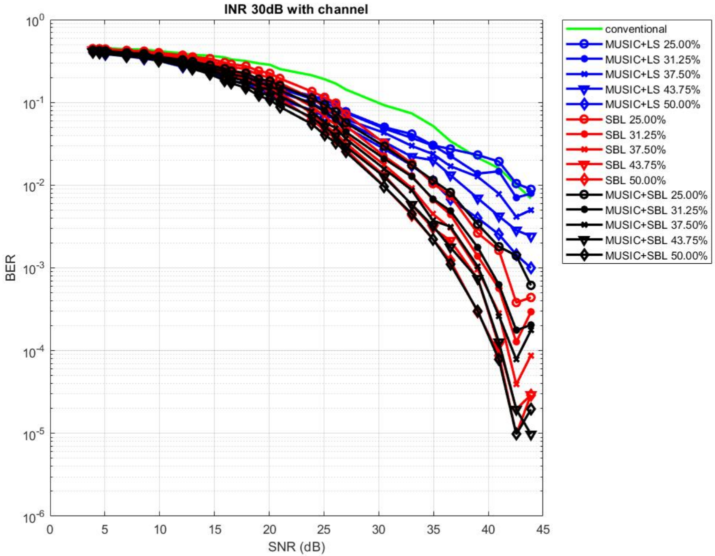
Power Line Communication (PLC)

Simulation: frequency-selective channels INR=20dB



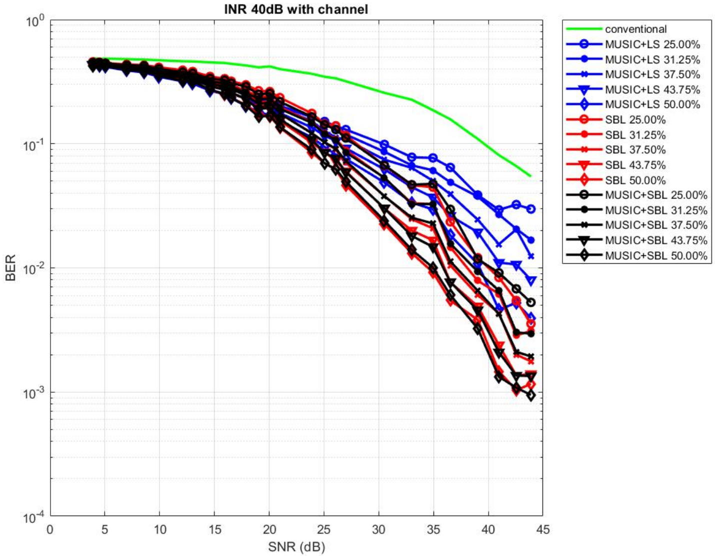
Power Line Communication (PLC)

Simulation: frequency-selective channels INR=30dB



Power Line Communication (PLC)

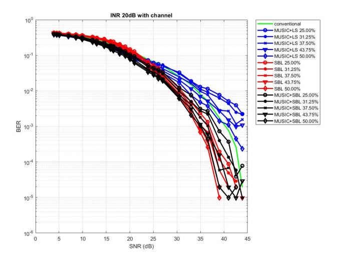
Simulation: frequency-selective channels INR=40dB



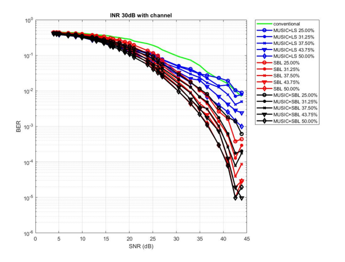
Power Line Communication (PLC)

Simulation: frequency-selective channels

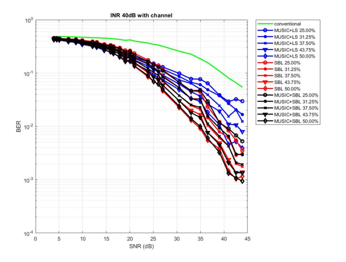
INR=20dB



INR=30dB



INR=40dB



Conclusion

In frequency-selective channels, MUSIC+SBL provides slight advantages over SBL algorithm, far better than MUSIC+LS method.

Power Line Communication (PLC)

Conclusion

In frequency-selective channels, MUSIC+SBL provides slight advantages over SBL algorithm, far better than MUSIC+LS method.

Section 7

Conclusions

- Summary
- Open Questions and Proposed Future Works

jump

Summary

P2P energy trading

- A preference mechanism was adapted into P2P energy trading for a network of microgrids;
- All the physical constraints regarding power flow were included in the model;
- The effect of preference mechanism on the resulting power flow was analyzed for achieving the desired power flow or a predefined network configuration;
- A distributed algorithm was developed to realize such a P2P energy trading market model.

Summary

Wind power forecasting

- Wind power forecast for a single wind farm was investigated using deep-learning (i.e., CNN) algorithms;
- Wind power forecast reconciliation among a 2-layer hierarchy was investigated in a distributed manner for data privacy preserving.

Summary

Communication techniques

- An algorithm for IN mitigation was proposed to improve the data transmission performance;
- The proposed algorithm was examined in both ideal and frequency-selective channels;
- The results showed that the proposed algorithm provides slight advantage in the frequency-selective channels.

Open Questions and Proposed Future Works

P2P energy trading

- Convergence scale: convergence speed may need to be reconsidered in a large scale problem;
- Heterogeneity: heterogeneous objective functions are used to fully encompass diversity of all the microgrids;
- DSO: the role of DSO needs to be reconsidered in the future electricity markets;
- Reactive power and ancillary services can be taken into account in future energy trading design.

Wind power forecasting

The uncertainty of renewable energy sources was not considered in our model. The integration of uncertainty into energy trading models may provide valuable information for DERs management for microgrids.

Open Questions and Proposed Future Works

Communication techniques

- In practical applications, more techniques should be considered and combined at both the transmitter and the receiver to combat impulsive noise;
- As impulsive noise is asynchronous to the mains period, an efficient method to estimate the arriving of IN could be helpful to allocate the time resources for data transmission;
- In general, impulsive noise is assumed to be generated by the devices connected to the network. If possible, the states of the connecting devices can be considered for the IN arriving and duration estimation, and thus the impact of impulsive noise may be dramatically reduced.

Section 8

Activities and Publications

Activities and Publications

Courses

- Model Predictive Control, IMT, Lucca, Italy, 2019, April
- Game Theory and Distribution Control, Paris, France, 2018, March

Visiting Period

3-month visit Prof. Pierre Pinson at the Technical University of Denmark

Presentation

- IFAC LSS 2019, oral report, Delft, Netherlands
- PIERS 2019, poster, Rome, Italy
- IEEE PESGM 2019, oral report and poster, Atlanta, USA
- EEEIC 2017, oral report, Milan, Italy

Workshop

- Second Public event for the Energy Collective project, Svalin, Denmark
- EEC 2019 workshop, Analytics for the sharing economy, Naples, Italy

Activities and Publications

Publications: Journals

- **L. Bai**, D. Thomopulos, E. Crisostomi, Preference-based Energy Exchange in a Network of Microgrids, Applied energy, 2019 (Under review)
- **L. Bai**, E. Crisostomi, M. Raugi, M. Tucc, Wind Turbine Power Curve Estimation Based on Earth Mover Distance and Artificial Neural Network, IET Renewable Power Generation, 2019
- **L. Bai**, P. Pinson, Distributed Reconciliation in Day-Ahead Wind Power Forecasting, Energies, 2019
- **L. Bai**, M. Tucci, M. Raugi. Impulsive Noise Mitigation with Interleaving Based on MUSIC in Power Line Communication, IEEE Transactions on Smart Grid, 2018
- **L. Bai**, M. Tucci, S. Barmada, M. Raugi, T. Zheng. Impulsive Noise Characterization in Narrowband Power Line Communication, Energies, 2018

Activities and Publications

Publications: Conferences

- **L. Bai**, E. Crisostomi, Distribution Loss Allocation in Peer-to-Peer Energy Trading in a Network of Microgrids, IEEE PESGM, 2020 (Submitted)
- **L. Bai**, E. Crisostomi, M. Raugi, M. Tucc, Wind Power Forecast Using Wind Forecasts at Different Altitudes in Convolutional Neural Networks, IEEE PES General Meeting, 2019
- M. Tucci, M. Raugi, **L. Bai**, S. Barmada,T. Zheng. Analysis of noise in in-home channels for narrowband power line communications, EEEIC, 2017

thank you!