IOWA STATE UNIVERSITY

EE 653 Power distribution system modeling, optimization and simulation

Microgrids (Part I)
Introduction and Energy Management

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The Concept of MG

A MG is a localized small-scale power system that clusters and manages distributed energy resources (DERs) and loads within a defined electrical boundary and point of common coupling (PCC).

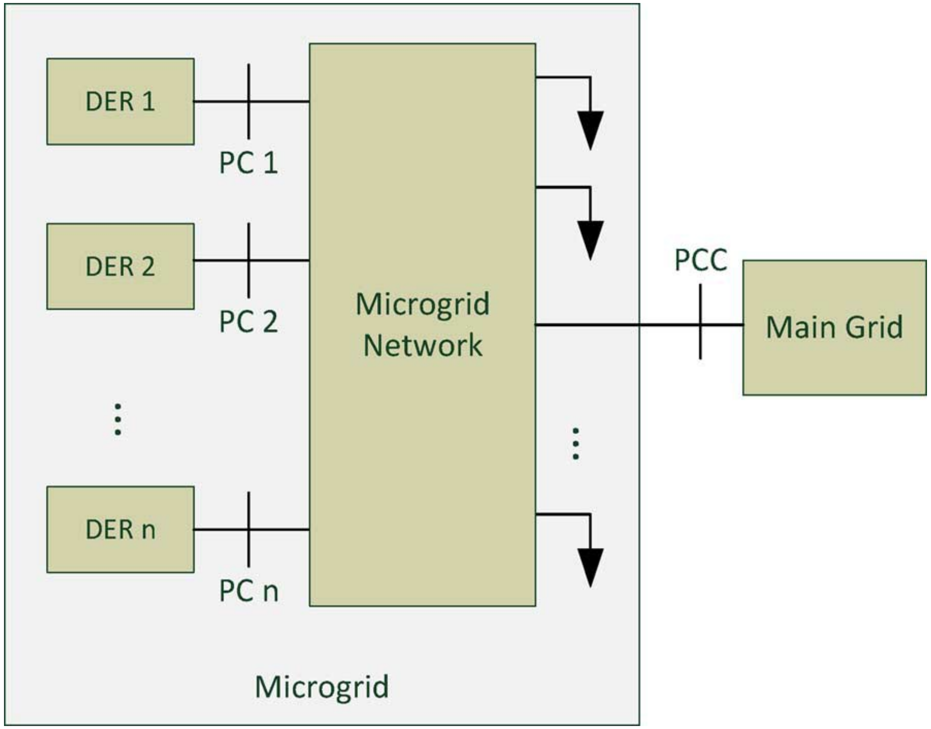


Fig. 1 Schematic diagram of a generic multiple-DER MG [1]

[1] D. E. Olivares *et al*., "Trends in Microgrid Control," in *IEEE Transactions on Smart Grid*, vol. 5, no. 4, pp. 1905-1919, July 2014.

Basic MG Components

The MG components to be modeled in the MG optimal scheduling/operation/control problem include loads, local generating units, and energy storage systems connected through an low voltage (LV) distribution network [1].

1. *Local Generations*

- A MG presents various types of generation sources that feed electricity, heating, and cooling to users.
- These sources are divided into two major groups: (i) thermal energy sources (e.g,. natural gas or biogas generators or micro combined heat and power); (ii) renewable generation sources (e.g., wind turbines, solar generations).

2. *Loads*

- In a MG, consumption simply refers to elements that consume electricity, heat, and cooling which range from single devices to lighting, heating system of buildings, commercial centers, etc. In the case of controllable loads, the electricity consumption can be modified in demand of the network.

[1] D. E. Olivares *et al.*, "Trends in Microgrid Control," in *IEEE Transactions on Smart Grid*, vol. 5, no. 4, pp. 1905-1919, July 2014.

3. Energy Storages

(i) The primary application of energy storage systems is to coordinate with generation resources to guarantee the MG generation adequacy.

(ii) Energy storage systems can also be used for load shifting, where the stored energy at times of low prices is generated back to the MG when the market price is high. This action is analogous to shifting the load from high price hours to low price hours.

(iii) Energy storage systems also play a major role in MG islanding application.

4. Point of Common Coupling

(i) It is the point in the electric circuit where a MG is connected to a main grid.

(ii) MGs that do not have a PCC are called isolated MGs which are usually presented in the case of remote sites

[1] D. E. Olivares *et al*., "Trends in Microgrid Control," in *IEEE Transactions on Smart Grid*, vol. 5, no. 4, pp. 1905-1919, July 2014.

Typical Configuration of MG

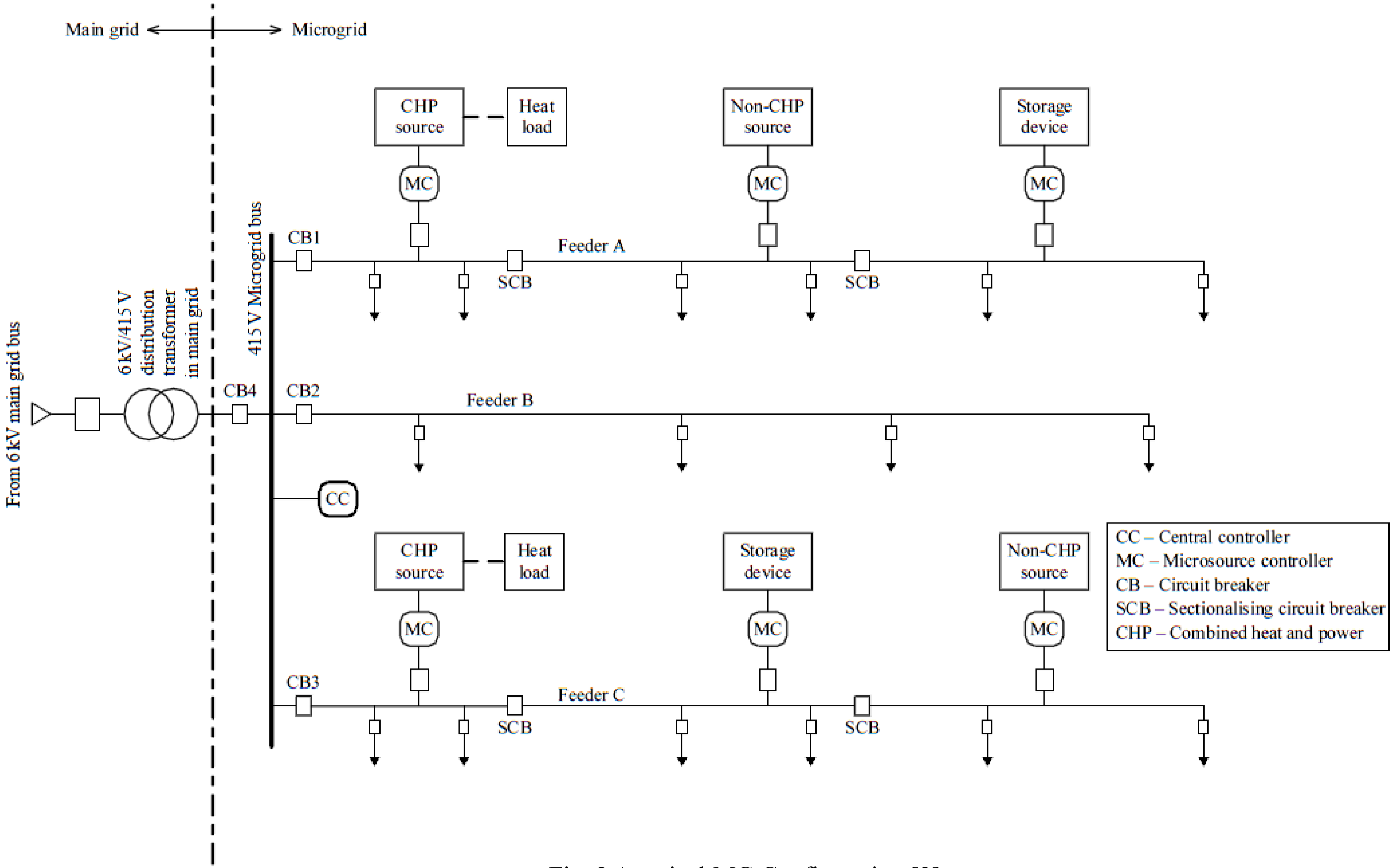


Fig. 2 A typical MG Configuration [2]

[2] Series, I. R. E. "Microgrids and active distribution networks." *The Institution of Engineering and Technology*, 2009

MG Configuration

- A MG is coupled with the main utility grid (denoted as ‘main grid’) through the PCC circuit breaker.

- A MG is operated in two modes: (1) grid-connected and (2) standalone [2].
  - In grid-connected mode, a MG remains connected to the main grid either totally or partially, and imports or exports power from or to the main grid.
  - In case of any disturbance in the main gird, the MG switches over to stand-alone mode while still feeding power to the priority loads.

[2] Series, I. R. E. "Microgrids and active distribution networks." *The Institution of Engineering and Technology*, 2009

Typical Configuration of hybrid AC/DC MG

Compared to conventional AC and DC MG, hybrid can provide a more effective solution for the integration of system components that are inherently AC and DC oriented. A typical configuration of a hybrid AC/DC can be divided into two components:

- an AC-based subgrid connected with diesel generator, wind turbines and AC loads
- an DC-based subgrid integrating fuel cells, PVs, electric vehicles and DC loads

The two subgrids are linked by a bi-directional converters.

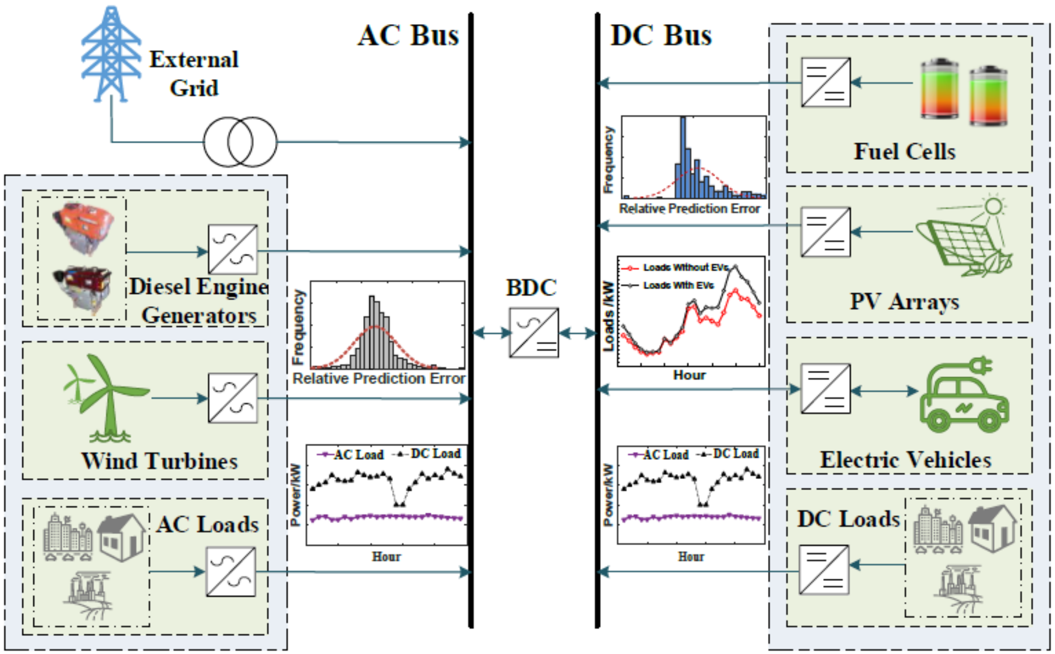


Fig. 3 A typical hybrid AC/DC MG [3]

Advantages of Hybrid AC/DC MGs :

- Reduce investment costs by greatly reducing the number of electronic power converters
- Minimize conversion loss by eliminating unnecessary multi-conversion processes
- Enhance nodal reliability because of the availability of alternative resources
- Maximize the utilization of renewable power generation
- Realize power mutual-balance through the bi-directional converter between the AC and DC subgrids

[3] Z. Liang, H. Chen, X. Wang, S. Chen and C. Zhang, "A Risk-Based Uncertainty Set Optimization Method for the Energy Management of Hybrid AC/DC Microgrids with Uncertain Renewable Generation," in *IEEE Transactions on Smart Grid*, Early access.

Typical Configuration of hybrid AC/DC MG

The bi-directional converter (BDC) has a critical role in balancing power flow between the AC and DC subgrids. The detailed constraints of the BDC are presented as follows:

$$I_{BDC,t}^{ac/dc} + I_{BDC,t}^{dc/ac} \leq 1, I_{BDC,t}^{ac/dc}, I_{BDC,t}^{dc/ac} \in \{0,1\}$$

BDC state constraint, which ensures that power does not flow in both direction simultaneously

$$0 \leq P_{BDC,t}^{ac/dc} \leq I_{BDC,t}^{ac/dc} * P_{BDC,t}^{ac/dc,Cap}$$

$$0 \leq P_{BDC,t}^{dc/ac} \leq I_{BDC,t}^{dc/ac} * P_{BDC,t}^{dc/ac,Cap}$$

Constraints of the range of the BDC exchange power

$$-\Delta t * Ramp_{BDC,t}^{ac/dc} \leq P_{BDC,t}^{ac/dc} - P_{BDC,t-1}^{ac/dc} \leq \Delta t * Ramp_{BDC,t}^{ac/dc}$$

$$-\Delta t * Ramp_{BDC,t}^{dc/ac} \leq P_{BDC,t}^{dc/ac} - P_{BDC,t-1}^{dc/ac} \leq \Delta t * Ramp_{BDC,t}^{dc/ac}$$

Constraints of the ramping power exchange limits of the BDC

The exchange power between the AC and DC subgrids is associated with the BDC conversion efficiency $\eta_{BDC,t}^{ac/dc}$ and the BDC utilization ration $\omega_{BDC,t}^{ac/dc}$

$$P_{BDC,t}^{dc} = \eta_{BDC,t}^{ac/dc} * P_{BDC,t}^{ac/dc}$$

$$P_{BDC,t}^{ac} = \eta_{BDC,t}^{dc/ac} * P_{BDC,t}^{dc/ac}$$

$$\eta_{BDC,t}^{ac/dc} = \sum_{j=0}^{m} a_j \left(\omega_{BDC,t}^{ac/dc}\right)^j$$

$$\eta_{BDC,t}^{dc/ac} = \sum_{j=0}^{m} a_j \left(\omega_{BDC,t}^{dc/ac}\right)^j$$

$$\omega_{BDC,t}^{ac/dc} = P_{BDC,t}^{ac/dc} / P_{BDC,t}^{ac/dc,Cap}$$

$$\omega_{BDC,t}^{dc/ac} = P_{BDC,t}^{dc/ac} / P_{BDC,t}^{dc/ac,Cap}$$

Calculate the power from the BDC to the AC and DC subgrids

[3] Z. Liang, H. Chen, X. Wang, S. Chen and C. Zhang, "A Risk-Based Uncertainty Set Optimization Method for the Energy Management of Hybrid AC/DC Microgrids with Uncertain Renewable Generation," in *IEEE Transactions on Smart Grid*, Early access.

MG Categories

Most MGs can be further described by the following four categories [4]:

(1) Campus Environment/Institutional MG

The focus of campus micro-grids is aggregating existing on-site generation with multiple loads that located in tight geography in which owner easily manage them.

(2) Remote Off-grid MGs

These micro-grids never connect to the macro-grid and instead operate in an island mode at all times because of economical issue or geography position. Typically, an "off-grid" micro-grid is built in areas that are far distant from any transmission and distribution infrastructure and, therefore, have no connection to the utility grid.

(3) Military Base MGs

These MGs are being actively deployed with focus on both physical and cyber security for military facilities in order to assure reliable power without relying on the macro-grid.

[4] Ward Bower, Dan Ton, Ross Guttromson, “The Advanced Micro-grid Integration and Interoperability,“ Sandia National Laboratories, 2014

MG Categories

(4) Commercial and Industrial MGs

These types of micro-grids are maturing quickly in North America and Asia Pacific; however, the lack of well –known standards for these types of micro-grids limits them globally. Main reasons for the installation of an industrial micro-grid are power supply security and its reliability. There are many manufacturing processes in which an interruption of the power supply may cause high revenue losses and long start-up time.

Tab. 1 DOE MG Program Application-Power Categories [4]

Commercial	>50kW, three-phase and functionally expandable
Community/Campus	1-10 MW may be modular or single rating
Utility Scale	>10 MW possibly using multiple interconnected micro-grid

[4] Ward Bower, Dan Ton, Ross Guttromson, "The Advanced Micro-grid Integration and Interoperability," Sandia National Laboratories, 2014

Technical and Economical Advantages of MG

The development of MG is very promising for the electric energy industry because of the following advantages [2]:

1. ***Environmental issues*** – It is needless to say that MGs would have much lesser environmental impact than the large conventional thermal power stations. However, it must be mentioned that the successful implementation of carbon capture and storage schemes for thermal power plants will drastically reduce the environmental impacts. Nevertheless, some of the benefits of MG in this regard are as follows:

(i) Reduction in gaseous and particulate emissions due to close control of the combustion process may ultimately help combat global warming
(ii) Physical proximity of customers with microsources may help to increase the awareness of customers towards judicious energy usage.

[2] Series, I. R. E. "Microgrids and active distribution networks." *The Institution of Engineering and Technology*, 2009

Technical and Economical Advantages of MG

2. *Operation and investment issues* – Reduction of physical and electrical distance between microsource and loads can contribute to:

- (i) Improvement of reactive support of the whole system, thus enhancing the voltage profile.
- (ii) Reduction of Transmission & Distribution (T & D) feeder congestion.
- (iii) Reduction of T & D losses.
- (iv) Reduction/postponement of investments in the expansion of transmission and generation systems by proper asset management.

3. *Resilience and reliability* – Improvement in power resilience and reliability is achieved due to :

- (i) Decentralization of supply.
- (ii) Better match of supply and demand.
- (iii) Reduction of the impact of large-scale transmission and generation outages.
- (iv) Minimization of downtimes and enhancement of the restoration process through black start operations of microsources.

[2] Series, I. R. E. "Microgrids and active distribution networks." *The Institution of Engineering and Technology*, 2009

Challenges and Disadvantages of MG's Development

In spite of potential benefits, development of MGs suffers from several challenges and potential drawback as follows [1], [2]:

1. Bidirectional power flows:

- While distribution feeders were initially designed for unidirectional power flow, integration of DG units at low voltage levels can cause reverse power flows and lead to complications in protection coordination, undesirable power flow patterns, fault current distribution, and voltage control.

2. Stability issues:

- Local oscillations may emerge from the interaction of the control systems of DG units, requiring a thorough small-disturbance stability analysis. Moreover, transient stability analyses are required to ensure seamless transition between the grid-connected and stand-alone modes of operation in a MG.

[1] D. E. Olivares *et al.*, "Trends in Microgrid Control," in *IEEE Transactions on Smart Grid*, vol. 5, no. 4, pp. 1905-1919, July 2014.
[2] Series, I. R. E. "Microgrids and active distribution networks." *The Institution of Engineering and Technology*, 2009

Challenges and Disadvantages of MG's Development

3. Low inertia

- Unlike bulk power systems where high number of synchronous generators ensures a relatively large inertia, MGs might show a low-inertia characteristic, especially if there is a significant share of power electronic-interfaced DG units. Although such an interface can enhance the system dynamic performance, the low inertia in the system can lead to severe frequency deviations in stand-alone operation if a proper control mechanism is not implemented.
- Grid-forming virtual inertia devices are developed for fast frequency response for low inertia system.

4. Uncertainty

- Taking into account the uncertainty of parameters such as load profile and weather forecast. This uncertainty is higher than those in bulk power systems, due to the reduced number of loads and highly correlated variations of available energy resources (limited averaging effect).

[1] D. E. Olivares *et al*., "Trends in Microgrid Control," in *IEEE Transactions on Smart Grid*, vol. 5, no. 4, pp. 1905-1919, July 2014.
[2] Series, I. R. E. "Microgrids and active distribution networks." *The Institution of Engineering and Technology*, 2009

Challenges and Disadvantages of MG's Development

5. High costs of distributed energy resources

- The high installation cost for MGs is a great disadvantage. This can be reduced by arranging some form of subsidies from government bodies to encourage investments.

6. Administrative and legal barriers

- In most counties, no standard legislation and regulations are available to regulate the operation of MGs. Governments of some countries are encouraging the establishment of green power MGs, but standard regulations are yet to be framed for implementation in future.

7. Market monopoly

- In the MGs are allowed to supply energy autonomously to priority loads during any main grid contingency, the main question that arises is who will then control energy supply prices during the period over when main grid is not available. Since the main grid will be disconnected and the current electricity market will lose its control on the energy price. However, MGs might retail energy at a very high price exploiting market monopoly.

[1] D. E. Olivares *et al.*, "Trends in Microgrid Control," in *IEEE Transactions on Smart Grid*, vol. 5, no. 4, pp. 1905-1919, July 2014.
[2] Series, I. R. E. "Microgrids and active distribution networks." *The Institution of Engineering and Technology*, 2009

MG Control

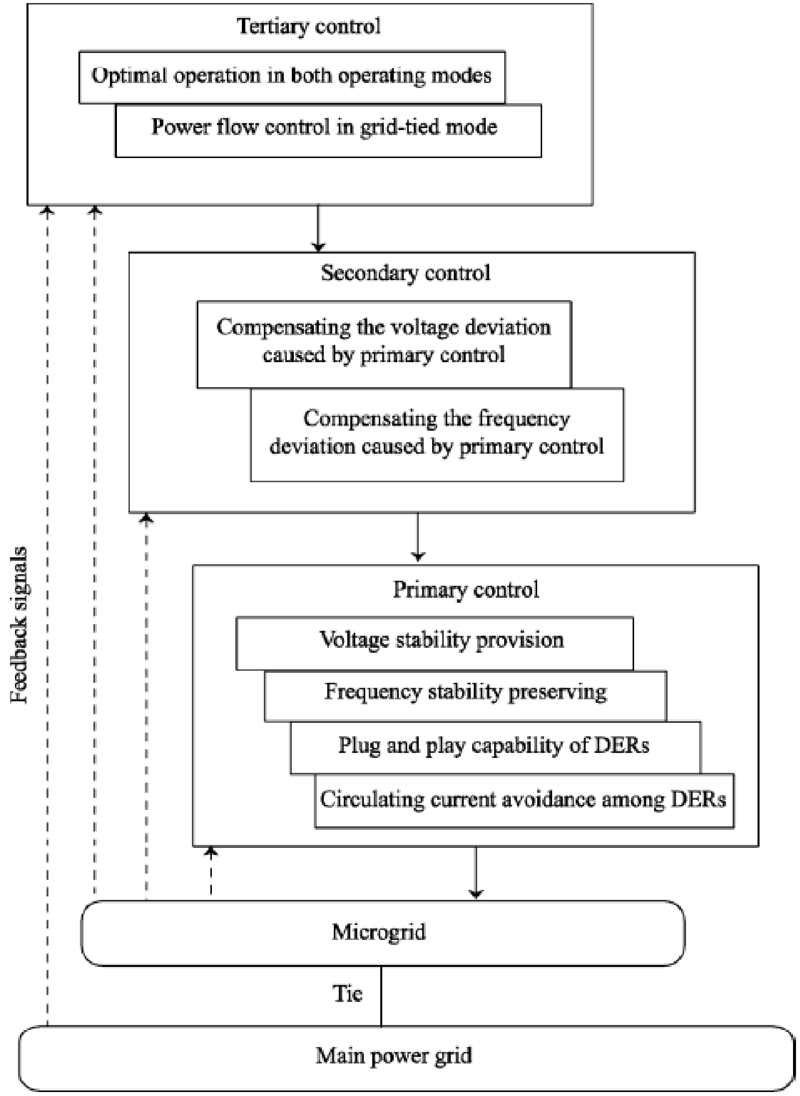


Fig. 4.1 Hierarchical control levels of a MG [5]

- The primary control maintains voltage and frequency stability of the microgrid subsequent to the islanding process.
- The secondary control compensates for the voltage and frequency deviations caused by the operation of the primary controls.
- The tertiary control manages the power flow between the microgrid and the main grid and facilitates an economically optimal operation.

[5] A. Bidram and A. Davoudi, "Hierarchical Structure of Microgrids Control System," in *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 1963-1976, Dec. 2012.

MG Control

As seen in Fig. 4, the MG control system can be categorized into three levels, namely, primary, secondary and tertiary [5]:

1. ***Primary control***
   - To stabilize the voltage and frequency. Subsequent to an islanding event, the MG may lose its voltage and frequency stability due to the mismatch between the power generated and consumed.
   - To offer plug and play capability for DERs and properly share the active and reactive power among them, preferably, without any communication links.
   - To provide the reference points for the control loops of DERs.
2. ***Secondary control***
   - As a centralized controller, secondary control restores the MG voltage and frequency and compensate for the deviations caused by the primary control.
   - Secondary control is designed to have slower dynamics response than that of the primary.

[5] A. Bidram and A. Davoudi, "Hierarchical Structure of Microgrids Control System," in *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 1963-1976, Dec. 2012.

3. Tertiary control

- Tertiary control is the last and the slowest control level that considers the economical concerns in the optimal operation of the MG, and manages the power flow between MG and main grid.

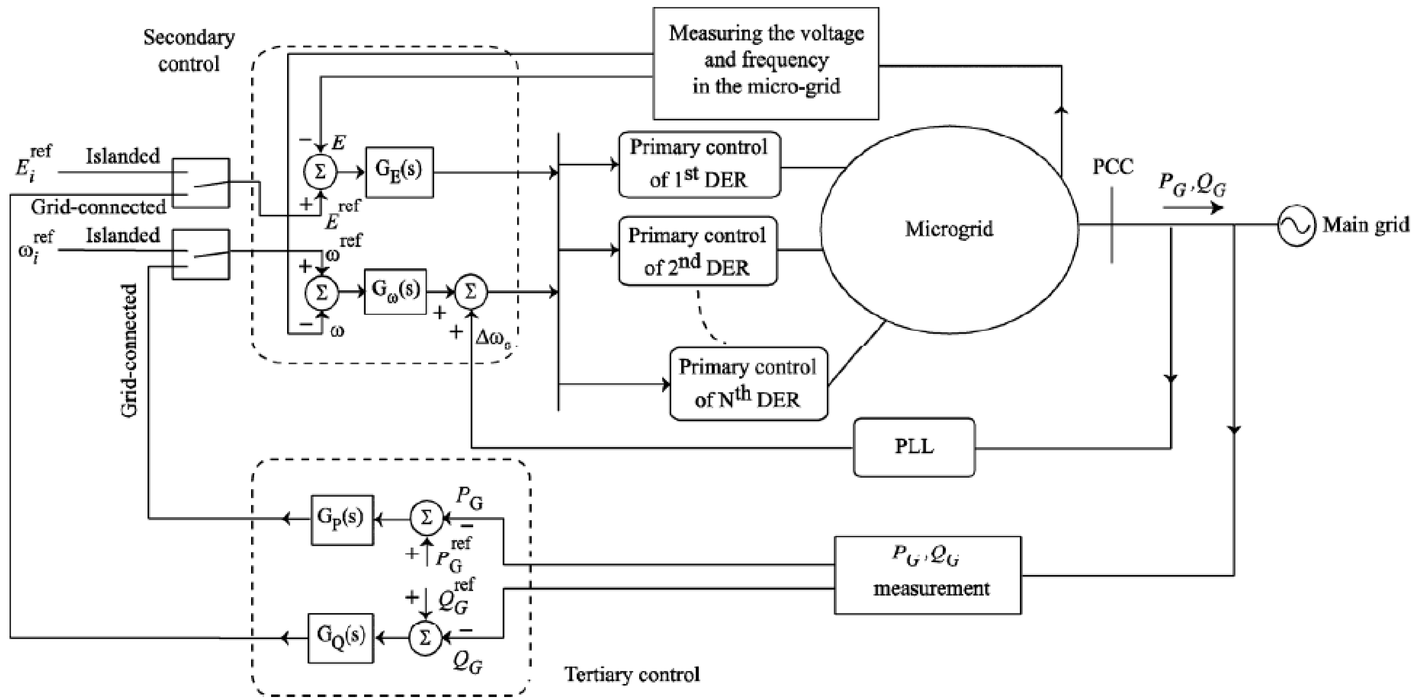


Fig. 4.2 Hierarchical control levels of a MG [5]

[5] A. Bidram and A. Davoudi, "Hierarchical Structure of Microgrids Control System," in *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 1963-1976, Dec. 2012.

Research topic: Networked MGs

- Optimization-based decision making
  - Centralized coordination of networked MGs
  - Decentralized coordination of networked MGs
  - Decentralized coordination of MGs for self-healing operation
  - Restoration with networked microgrids formation
- Learning-based decision making
  - Power management of networked MGs under incomplete information

Networked MGs

- Networked microgrids can support and interchange power with each other
- Highly desirable when utilities are not accessible (e.g., in an island or a military base) or lost (e.g., utility grids are down)

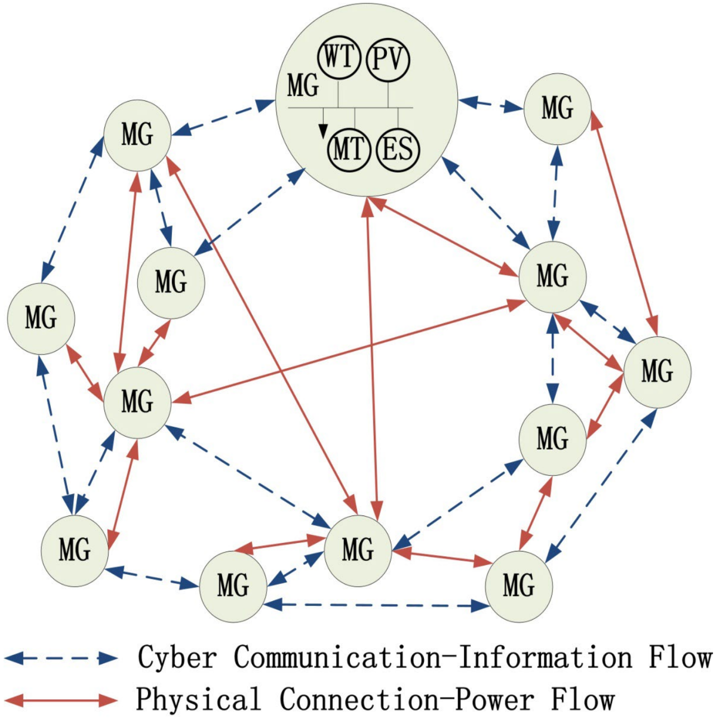


Fig. 5 Concept of networked MGs [6]

➢Economic energy exchange in normal operation
➢Energy support for self-healing

[6] Z. Wang, B. Chen, J. Wang and C. Chen, "Networked Microgrids for Self-Healing Power Systems," in *IEEE Transactions on Smart Grid*, vol. 7, no. 1, pp. 310-319, Jan. 2016.

Centralized Coordination of Networked MGs

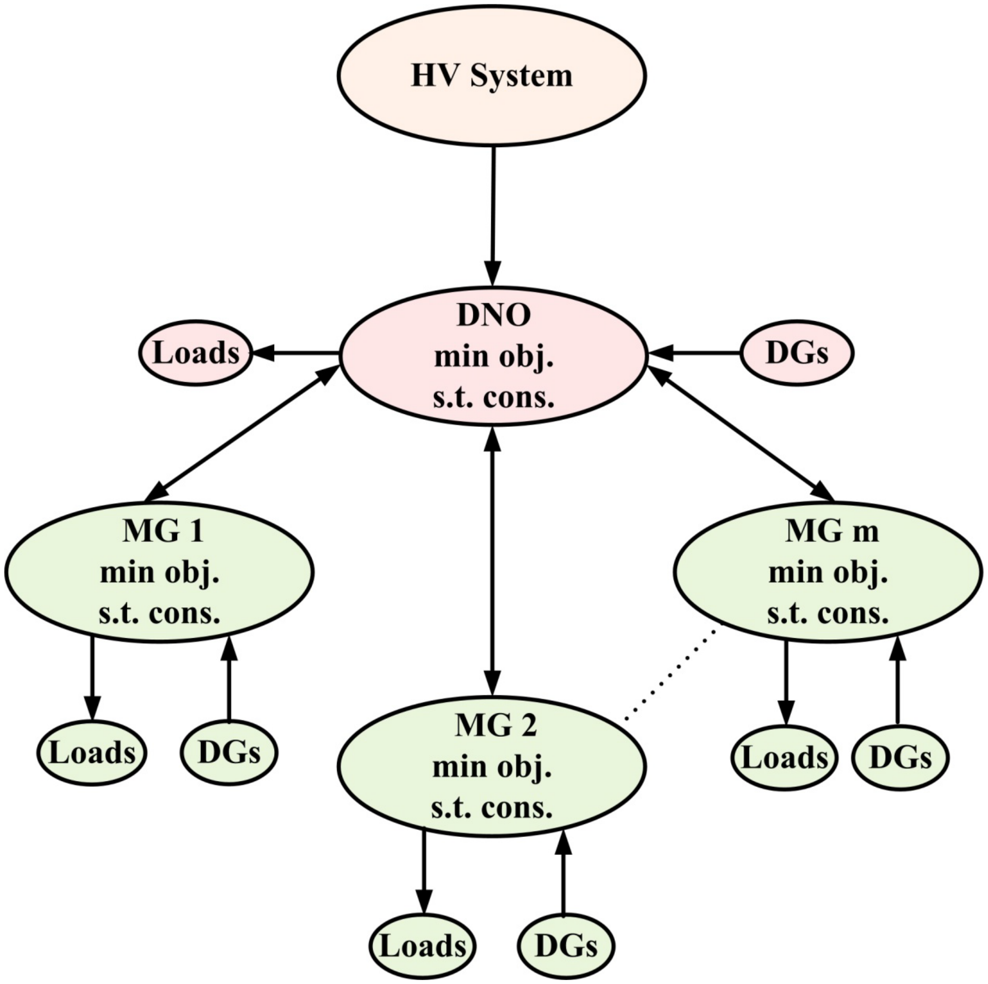


Fig. 6 Interactions between DNO and multiple MGs [7]

Each entity:
Min (operation costs-revenues)
s.t.

- power flow constraints
- voltage constraints
- DG capacity constraints

KKT

Min (objective function of distribution network operator)
s.t.

- constraints of DNO
- complementarity constraints of ALL MGs

[7] Z. Wang, B. Chen, J. Wang, M. Begovic, and C. Chen, "Coordinated Energy Management of Networked Microgrids in Distribution Systems," IEEE Transactions on Smart Grid, vol. 6, no. 1, pp. 45-53, January 2015.

Coordinated Energy Management of Networked MGs

A. Sets

$\mathcal{S}$	Set of scenarios
G	G= $\{WT, PV\}$
$D\,/\,M$	Set of nodes in DNOs/MGs

B. Acronyms

WT	Wind turbine
PV	Photovoltaic generator
MT	Micro turbine
MG	Microgrid

C. Parameters

$m1$	Point of common coupling (PCC) of m th MG
$r_i\,/\,x_i$	Line resistance/reactance between nodes i and $i+1$
$p_i^D\,/\,q_i^D$	Active/reactive demand at node i
$p_{i,g}^R$	Predicted active power output of a RES-based DG at node i, $g \in$ G
$p_i^{\max}\,/\,q_i^{\max}$	Maximum allowed active/reactive output of the MT at node i
ε	Maximum allowed voltage deviation
γ_s	Probability of s th scenario
$c^G\,/\,c^{\Delta G}$	Generation/redispatch cost of a MT ($/kW)
p_i^{rd}	Maximum allowable redispatchable generation of the MT at node i
$c^{S,MG}\,/\,c^{B,MG}$	MG price for selling/buying electricity to/from DNO ($/kWh)
$c^{D,MG}\,/\,c^{D,DNO}$	MG/DNO price for selling electricity to consumers within the MG/DNO ($/kWh)
$c^{S,DNO}\,/\,c^{B,DNO}$	DNO price for selling/buying electricity to/from HV system ($/kWh)
$\Delta p_{i,s,g}^R$	Prediction error of output of type-g DG at node i in scenario s

D. Variables

V_i	Voltage magnitude at node i
$P_i\,/\,Q_i$	Active/reactive power flow from node i to $i+1$
$p_i^g\,/\,q_i^g$	Active/reactive power generation at node i
$p_i^G\,/\,q_i^G$	Base active/reactive power output of the MT at node i
$\eta_1\,/\,\eta_{m1}$	Power deficiency of DNO/ m th MG
$\theta_1\,/\,\theta_{m1}$	Power surplus of DNO/ m th MG
$C_{i,s}^{rd}$	Redispatch cost of a MT at node i in scenario s ($)
$\Delta(\cdot)_s$	Adjustment of $(\cdot)$ in scenario s

DNO

$$\min \sum_{i\in D} c^G p_i^G + (c^{B,DNO}\eta_1 + \sum_m c^{S,MG}\theta_{m1} - c^{S,DNO}\theta_1 - \sum_m c^{B,MG}\eta_{m1}) \\ + \sum_s \gamma_s \sum_{i\in D}(c^G \Delta p_{i,s}^G + C_{i,s}^{rd}) + \sum_s \gamma_s (c^{B,DNO}\Delta\eta_{1,s} + \sum_m c^{S,MG}\Delta\theta_{m1,s} - c^{S,DNO}\Delta\theta_{1,s} - \sum_m c^{B,MG}\Delta\eta_{m1,s}) \quad (1)$$

Power flow & voltage

$$s.t.\ P_{i+1} = P_i - p_{i+1}^D + \sum_g p_{i+1,g}^R + p_{i+1}^G,\ \forall i \in D \cup M \quad (2)$$

$$Q_{i+1} = Q_i - q_{i+1}^D + q_{i+1}^G,\ \forall i \in D \cup M \quad (3)$$

$$V_{i+1} = V_i - (r_i P_i + x_i Q_i)/V_1,\ \forall i \in D \cup M \quad (4)$$

$$1-\varepsilon \le V_i \le 1+\varepsilon,\ \forall i \in D \cup M \quad (5)$$

MT

$$0 \le p_i^G \le p_i^{\max},\ \forall i \in D \quad (6)$$

Second stage

$$\Delta P_{i+1,s} = \Delta P_{i,s} + \sum_g \Delta p_{i+1,s,g}^R + \Delta p_{i+1,s}^G,\ \forall i \in D \cup M,\ \forall s \in \mathcal{S} \quad (7)$$

$$\Delta Q_{i+1,s} = \Delta Q_{i,s} + \Delta q_{i+1,s}^G,\ \forall i \in D \cup M,\ \forall s \in \mathcal{S} \quad (8)$$

$$\Delta V_{i+1,s} = \Delta V_{i,s} - (r_i \Delta P_{i,s} + x_i \Delta Q_{i,s})/V_1,\ \forall i \in D \cup M,\ \forall s \in \mathcal{S} \quad (9)$$

$$1-\varepsilon \le V_i + \Delta V_{i,s} \le 1+\varepsilon,\ \forall i \in D \cup M,\ \forall s \in \mathcal{S} \quad (10)$$

$$0 \le p_i^G + \Delta p_{i,s}^G \le p_i^{\max},\ \forall i \in D,\ \forall s \in \mathcal{S} \quad (11)$$

$$-p_i^{rd} \le \Delta p_{i,s}^G \le p_i^{rd},\ \forall i \in D,\ \forall s \in \mathcal{S} \quad (12)$$

$$C_{i,s}^{rd} \ge c^{\Delta G}\Delta p_{i,s}^G,\ \forall i \in D,\ \forall s \in \mathcal{S} \quad (13)$$

$$C_{i,s}^{rd} \ge -c^{\Delta G}\Delta p_{i,s}^G,\ \forall i \in D,\ \forall s \in \mathcal{S} \quad (14)$$

MG

$$\min \sum_{i\in M} c^G p_i^G + (c^{B,MG}\eta_{m1} - c^{S,MG}\theta_{m1}) + \sum_s \gamma_s \sum_{i\in M}(c^G \Delta p_{i,s}^G + C_{i,s}^{rd}) + \sum_s \gamma_s (c^{B,MG}\Delta\eta_{m_1,s} - c^{S,MG}\Delta\theta_{m1,s}) \quad (1)$$

$$s.t.\ 0 \le p_i^G \le p_i^{\max},\ \forall i \in M \quad (2)$$

$$-p_i^{rd} \le \Delta p_{i,s}^G \le p_i^{rd},\ \forall i \in M,\ \forall s \in \mathcal{S} \quad (3)$$

$$0 \le p_i^G + \Delta p_{i,s}^G \le p_i^{\max},\ \forall i \in M,\ \forall s \in \mathcal{S} \quad (4)$$

$$C_{i,s}^{rd} \ge c^{\Delta G}\Delta p_{i,s}^G,\ \forall i \in M,\ \forall s \in \mathcal{S} \quad (5)$$

$$C_{i,s}^{rd} \ge -c^{\Delta G}\Delta p_{i,s}^G,\ \forall i \in M,\ \forall s \in \mathcal{S} \quad (6)$$

Coordinated Energy Management of Networked MGs

Each entity has min (operation costs-revenues)
s.t.
(1)power flow constraints
(2)voltage constraints
(3)generator capacity constraints

KKT

Min (objective function of DNO)
s.t.
(1)constraints of DNO
(2)complementarity constraints of ALL microgrids

$$f_{p_{i,t}^{pred}}(x) = x^{\alpha-1}(1-x)^{\beta-1}$$

$$P_i^{pred} / S_{base} = \alpha_i / (\alpha_i + \beta_i)$$

$$\sigma_i^2 = \alpha_i \beta_i / (\alpha_i + \beta_i)^2 (\alpha_i + \beta_i + 1)$$

$$\sigma_i = 0.2 \times P_i^{pred} / P_i^{\max} + 0.21$$

Scenario generation by Monte-Carlo simulations

Scenario reduction by simultaneous backward reduction method

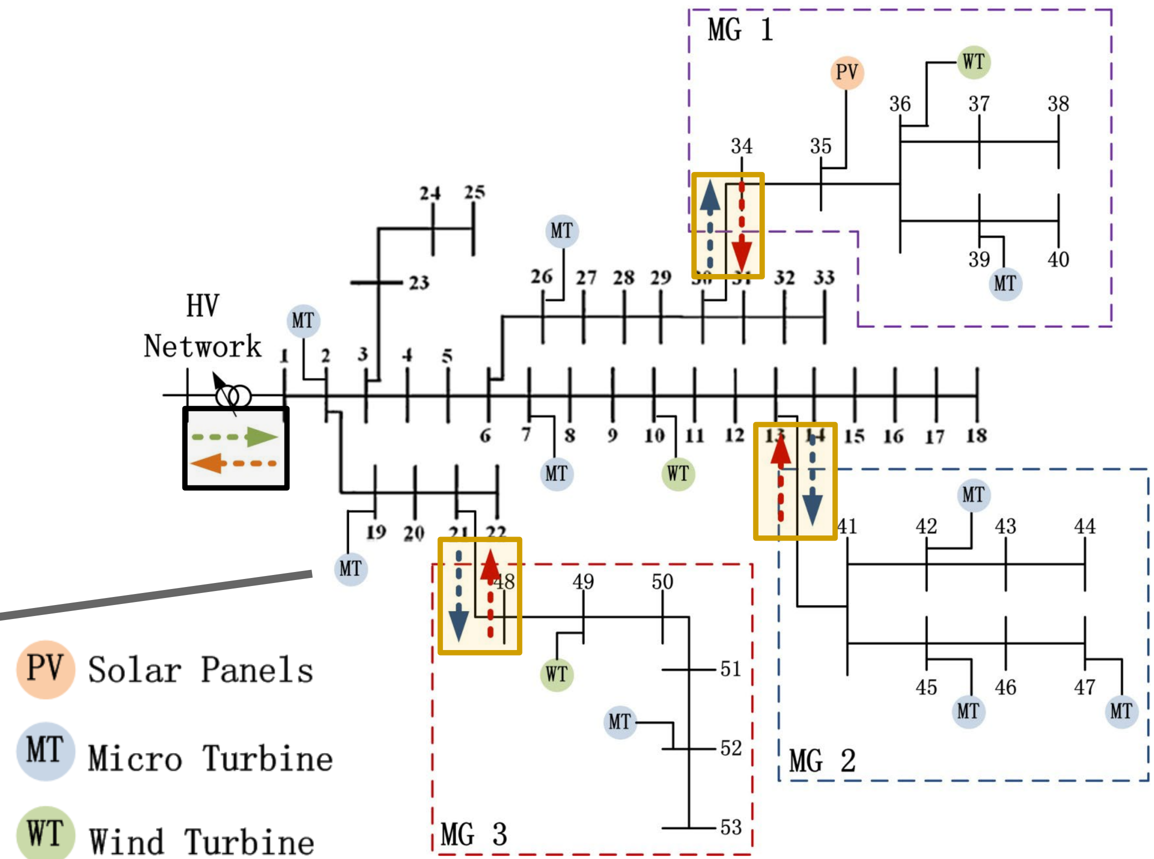
Coordinated Energy Management of Networked MGs

green arrow →	$0.28/kWh
orange arrow ←	$0.30/kWh

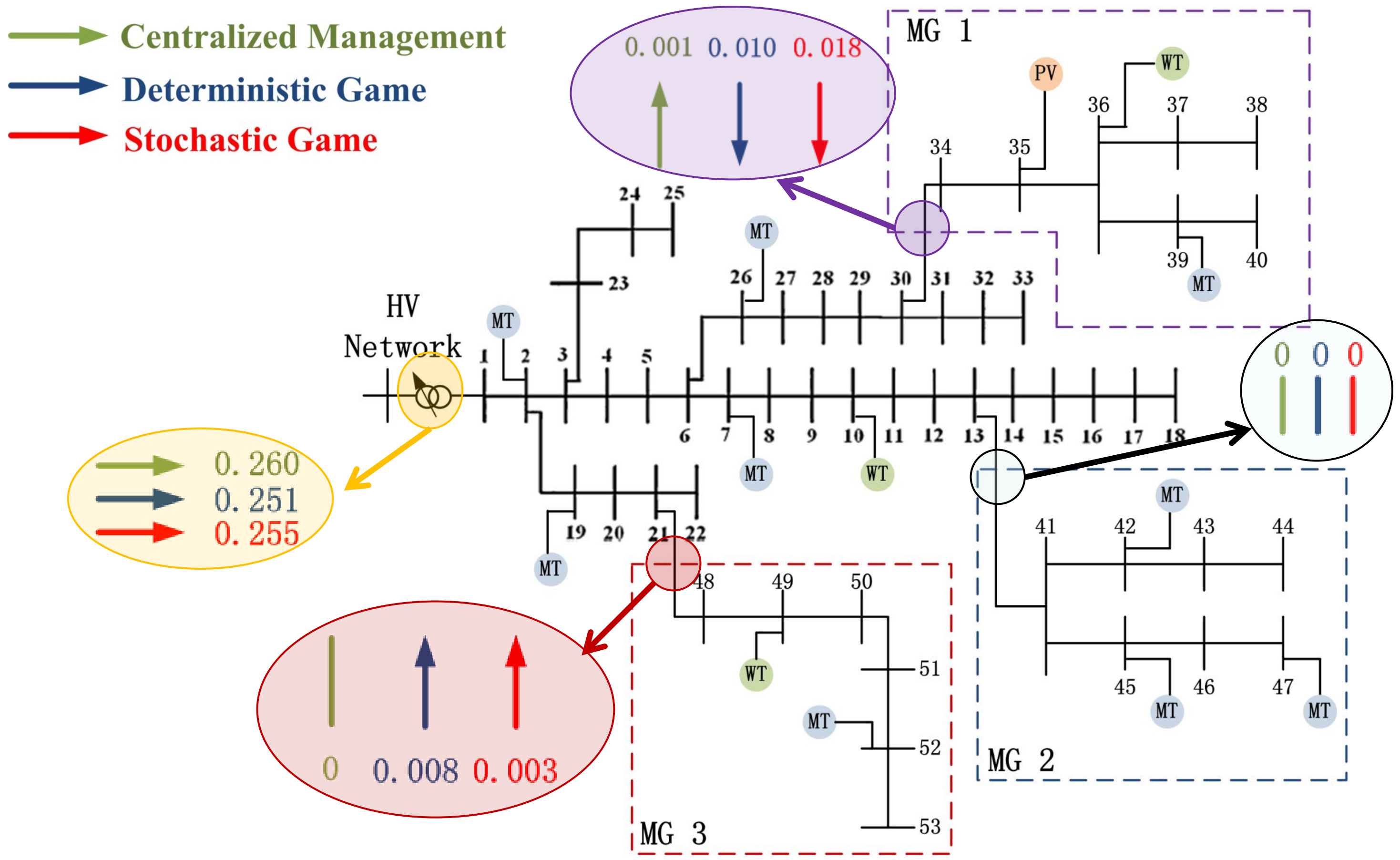
blue arrow →	$0.30/kWh
red arrow ←	$0.25/kWh

Electricity price
- **MG Loads: $0.20/kWh**
- **DNO Loads: $0.30/kWh**

MT generation cost: $0.10/kWh
MT redispatch cost: $0.15/kWh

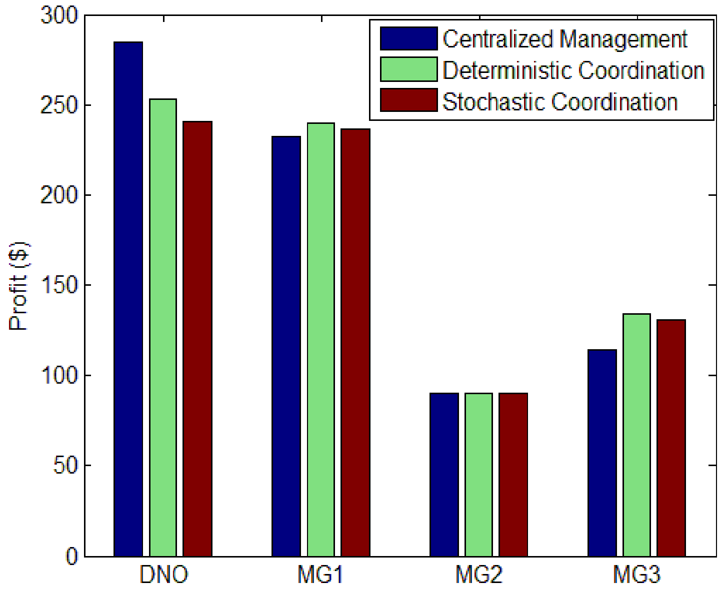


Coordinated Energy Management of Networked MGs

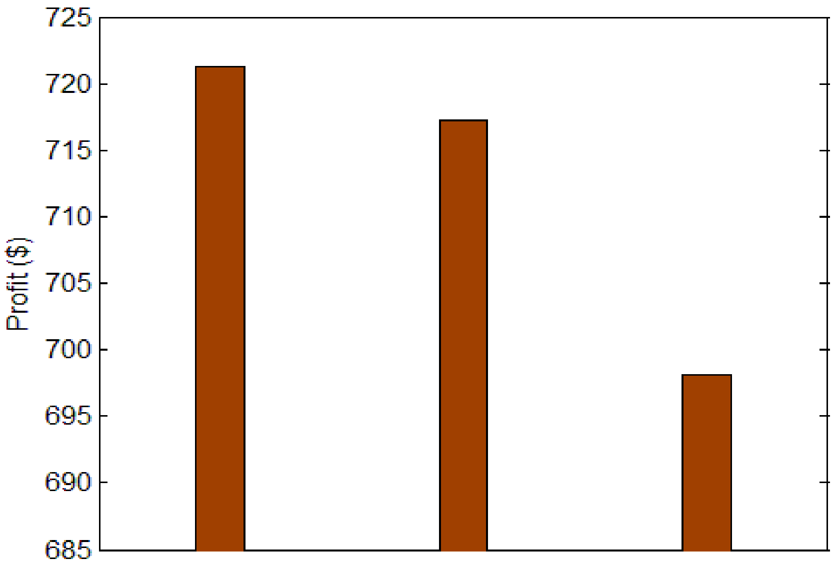


Coordinated Energy Management of Networked MGs

Profits of Each Entity



Total Profit of All Entities



Centralized Management **Deterministic Coordination** **Stochastic Coordination**

Decentralized Coordination of Networked MGs

- **Problem statement:** in previous slides, we introduced our work on centralized coordination of networked MGs. Here the problem that we want to solve is to coordinate the operation of MGs and distribution systems in a ***completely decentralized*** fashion.
- **Proposed solution:** A decentralized bi-level stochastic optimization algorithm that offers autonomy to each entity to optimize its own objectives subject to an entity-specific set of constraints.
- The algorithm has two levels:
  - The first level is to solve the optimization problem of each entity and conduct negotiations based on the current penalty factor until no further negotiations can be achieved.
  - The second level is to update the penalty functions representing the mutual impacts between different entities until the optimal coordinated operation point is found.

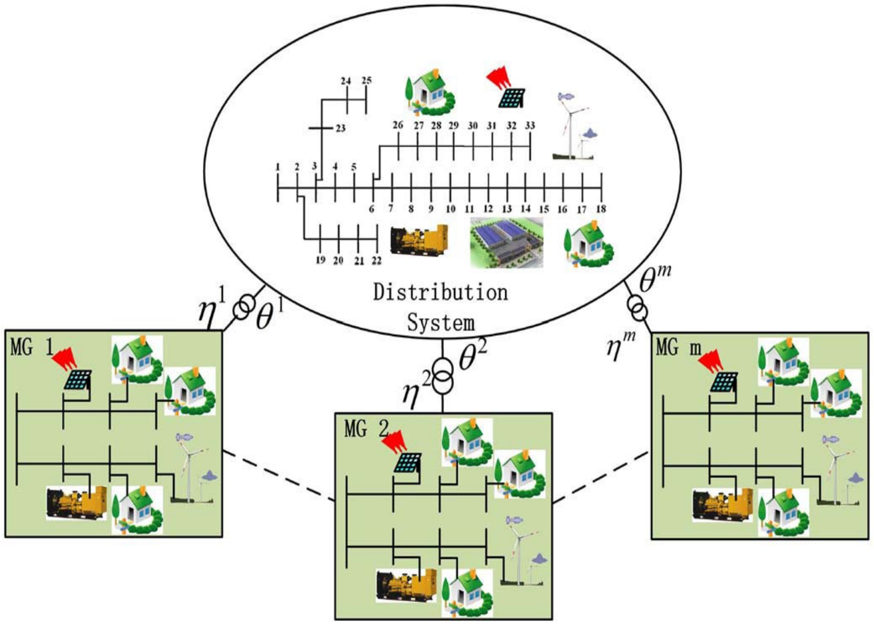
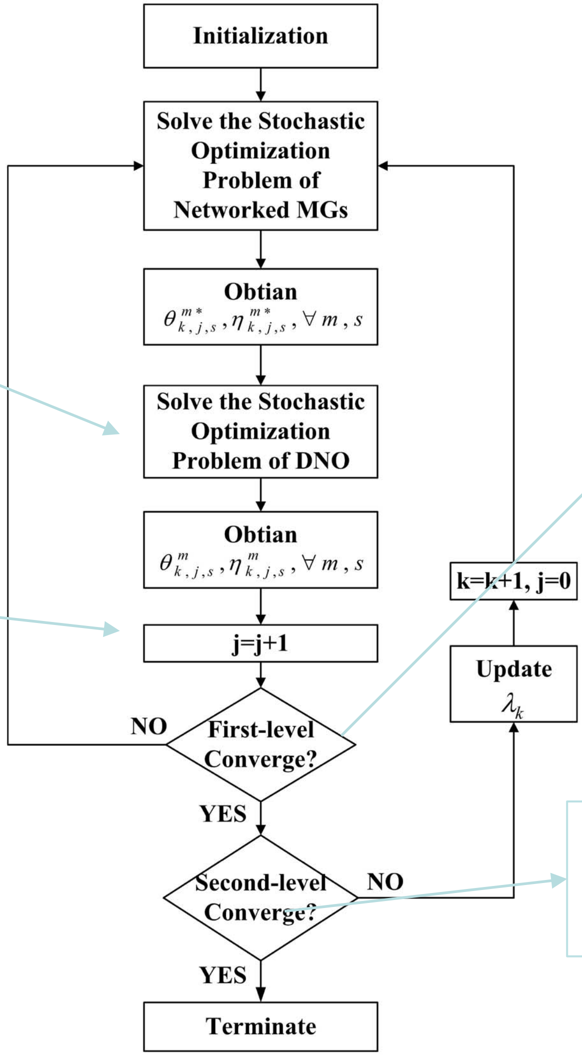


Fig. 7 Distribution system with networked MGs [8]

[8] Z. Wang, B. Chen, J. Wang, and J. Kim, "Decentralized Energy Management System for Networked Microgrids in Grid-connected and Islanded Modes," *IEEE Transactions on Smart Grid*, vol. 7, no. 2, pp. 1097-1105, March 2016.

Decentralized Coordination of Networked MGs



Power exchange requested by individual MGs

Power exchange requested by DNO

Check convergence within entities

$$\left|\theta^{m*}_{k,j,s} - \theta^{m*}_{k,j-1,s}\right| \le \varsigma_1$$
$$\left|\eta^{m*}_{k,j,s} - \eta^{m*}_{k,j-1,s}\right| \le \varsigma_1, \quad \forall m, s$$
$$\left|\theta^{m}_{k,j,s} - \theta^{m}_{k,j-1,s}\right| \le \varsigma_1$$
$$\left|\eta^{m}_{k,j,s} - \eta^{m}_{k,j-1,s}\right| \le \varsigma_1, \quad \forall m, s.$$

Check convergence between MGs and DNO

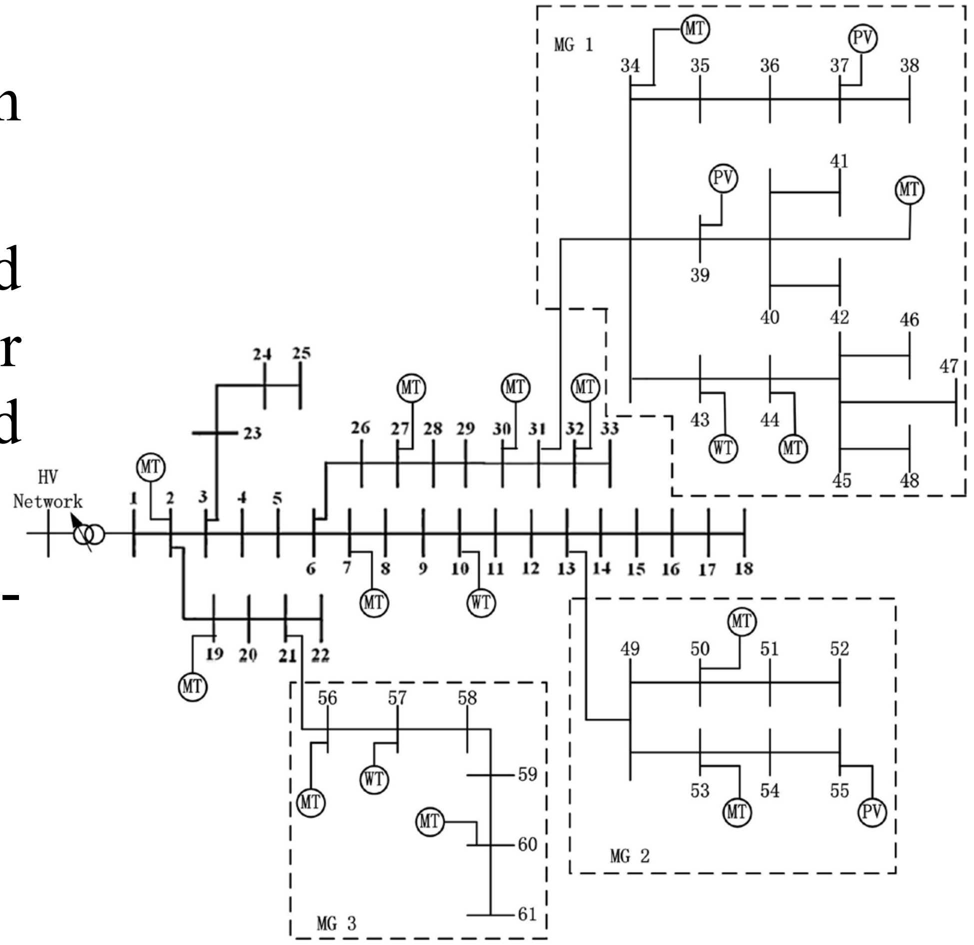
$$\left|\theta^{m*}_{k,j,s} - \theta^{m}_{k,j,s}\right| \le \varsigma_2, \left|\eta^{m*}_{k,j,s} - \eta^{m}_{k,j,s}\right| \le \varsigma_2, \quad \forall m, s.$$

$\theta^{m*}_{k,j,s}$ and $\eta^{m*}_{k,j,s}$ represent the power exchange requested by the *mth* MG in the *sth* scenario in the current iteration

$\theta^{m}_{k,j-1,s}$ and $\eta^{m}_{k,j-1,s}$ represent the power exchange requested by the DNO in the previous first-level iteration

Decentralized Coordination of Networked MGs

- A test distribution system with three networked MGs
- Consider uncertainties of wind turbine (WT) generation, solar PV (PV) generation and load demand
- Consider controllable micro-turbines (MT)



Decentralized Coordination of Networked MGs

Tab.2 Convergence of power exchange between distribution network operator (DNO) and MGs

Entity	Bus. No.	Exchange in Iteration 1	Exchange in Iteration 2	Exchange in Iteration 3
DNO	1	0.0080	0.0480	0.0480
MG1	31	0.1960	0.0690	0.0690
MG2	13	0.1200	0.1501	0.1501
MG3	21	-0.0240	-0.0142	-0.0142

Tab.3 Convergence of micro-turbine dispatches

MT (Node)	Iteration No.						
	1	2	3	4	5	6	7
	Active Power Generation (p.u.)						
MT2	0.1505	0.1422	0.1410	0.0987	0.0901	0.0901	0.0901
MT7	0.1508	0.1510	0.1507	0.1503	0.1500	0.1500	0.1500
MT19	0.1500	0.1488	0.1412	0.1005	0.0901	0.0901	0.0901
MT27	0.1500	0.1514	0.1427	0.0725	0.0106	0.0106	0.0106
MT30	0.1509	0.1515	0.1508	0.1505	0.1500	0.1500	0.1500
MT32	0.1500	0.1500	0.1452	0.0210	0.0011	0.0011	0.0011
MT34	0.1506	0.1509	0.1504	0.1503	0.1500	0.1500	0.1500
MT39	0.0650	0.0678	0.0674	0.0669	0.0663	0.0663	0.0663
MT44	0.0003	0.0002	0.0004	0.0005	0.0017	0.0017	0.0017
MT50	0.0566	0.0532	0.0529	0.0527	0.0525	0.0525	0.0525
MT53	0.0547	0.0536	0.0532	0.0526	0.0525	0.0525	0.0525
MT56	0.1500	0.1485	0.1441	0.0821	0.0639	0.0639	0.0639
MT60	0.0128	0.0158	0.0149	0.0146	0.0140	0.0140	0.0140

Decentralized Coordination of Networked MGs

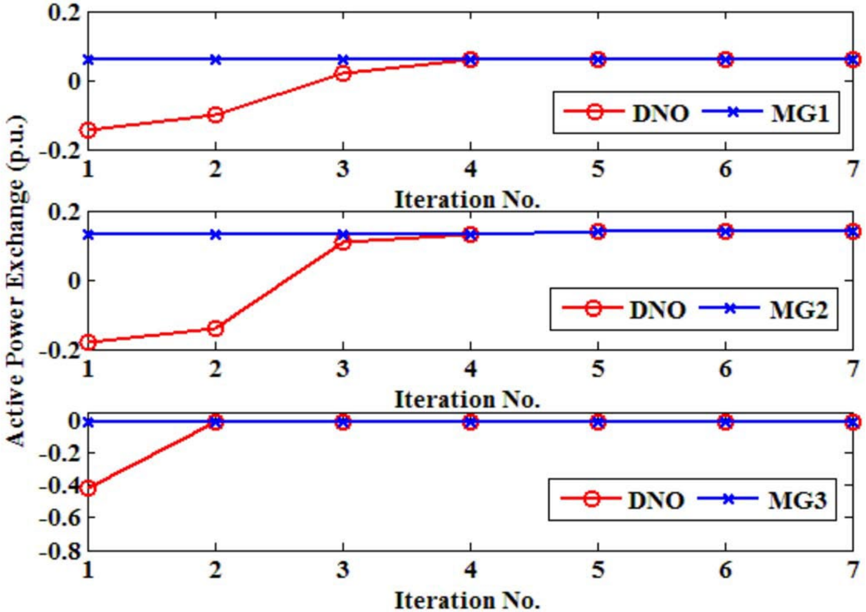


Fig. 8 Convergence of power exchange between distribution network operator (DNO) and MGs

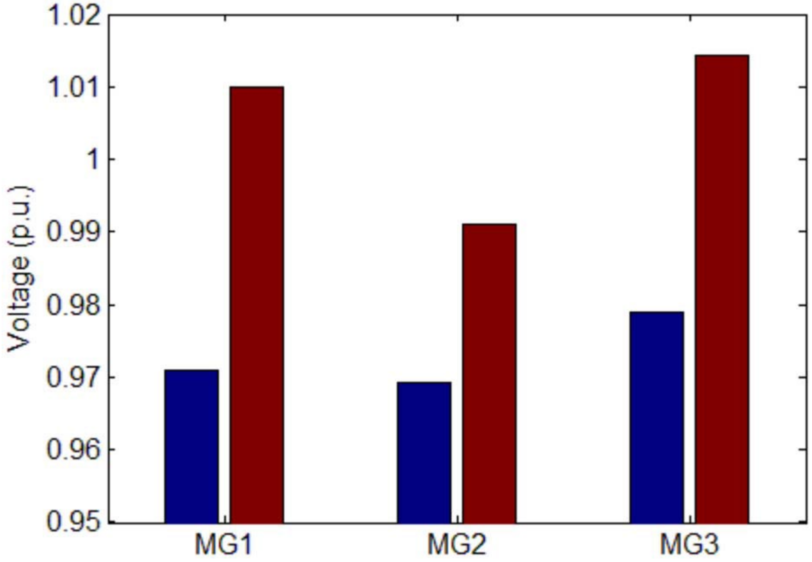


Fig. 9 Highest and lowest voltage levels in individual MGs

Scope of Power System Resilience Research

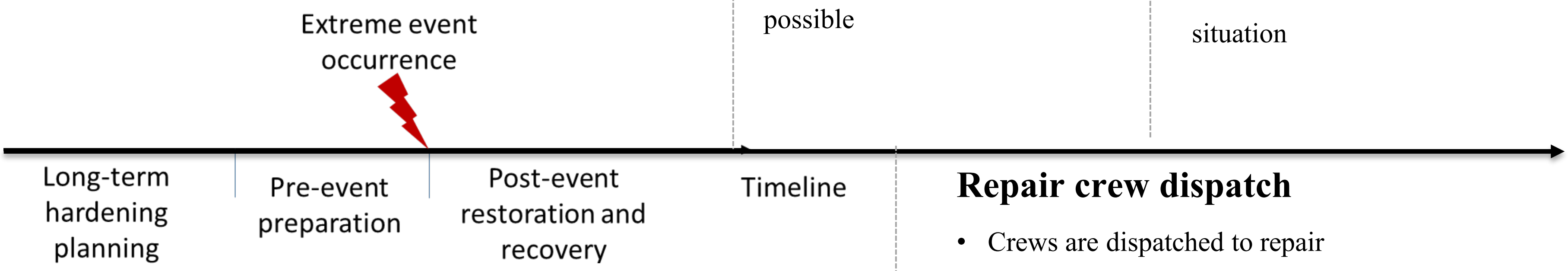
- Aim: efficient post-event restoration
- Proposed resilience strategies:

Microgrid formation

Divide the fault impacted area into several microgrids, restoring as much load as possible

Networked microgrid operation

- The operation of networked microgrid in emergency situation



Repair crew dispatch

- Crews are dispatched to repair the damaged components

Restoration with Dynamic Microgrid Formation

Problem statement:

- Propose a self-healing strategy to sectionalize the on-outage portion of a distribution system into <u>self-supplied networked microgrids</u>

- ➢ A portion of larger distribution system
- ➢ Decouple itself from main grid when the latter is under duress
- ➢ Maintain the supply-demand balance for extended times
- ➢ Can reattach itself to main grid after normal operation is resumed

Why to sectionalize?

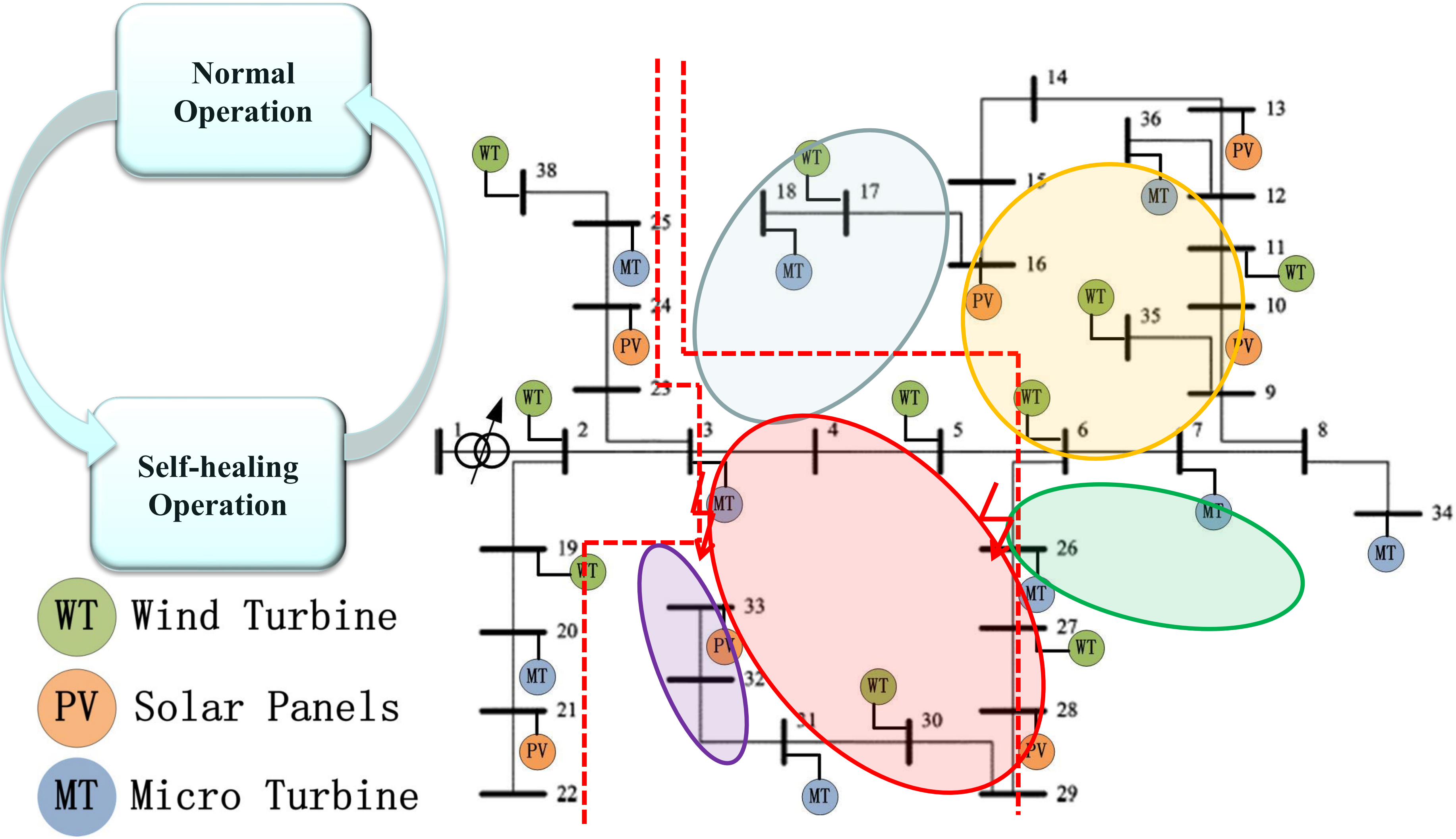
- Reduce time of restoration
- Maintain power supply to critical loads using local capacity
- Prevent possible cascading faults and cascading inverter trips

Challenges?

- Dynamic nature of formation and dissolution considering uncertainties of renewable generations and loads

[8] Z. Wang and J. Wang, "Self-healing Resilient Distribution Systems based on Sectionalization into Microgrids," *IEEE Transactions on Power Systems*, vol. 30, no. 6, pp.3139-3149, November 2015.

Restoration with Dynamic Microgrid Formation



Restoration with Dynamic MG Formation

- Static MGs vs. dynamic MGs
- A distribution grid can be automatically divided into several autonomous MGs surrounding local energy resources in response to power outage in the system. The configuration of these MGs can be changed dynamically.

Static MGs	Dynamic MGs
Static electric boundaries and connection point with external system	Dynamic electric boundaries and connection point with external system
Energy resources and managed in a static group	Energy resources need to be grouped dynamically
Operation as a single entity	Coordinated operation is required

Restoration with Dynamic MG Formation

- Objective function: maximize weighted load picked up

$$\max_{s_i, c_{ij}, v_{ik}, \gamma_{ik}, P_i^k, Q_i^k, V_i^k, \delta_i^k} \sum_{i \in \bar{\mathcal{N}}} w_i \cdot \sum_{k \in \mathcal{K}} \gamma_{ik} \cdot p_i$$

- Constraints for MGs Formation in MILP
  - 1) Node clustering constraints
  - 2) MG connectivity constraints. For a radial (tree) distribution network, each microgrid can be viewed as a subtree network with the root node being the node where the DG is installed.
  - 3) MG branch-node constraints. Each node/line must belong to a certain MG
  - 4) MG load pickup constraints
  - 5) MG operation constraints: Linearized DistFlow model
  - 6) Distribution system condition constraints

Restoration with Dynamic MG Formation

- The on-outage area will be optimally sectionalized into networked self-adequate MGs which can autonomously provide reliable power supply to a maximum number of affected customers.
- An optimization problem is formulated and solved to obtain optimal decisions over the optimization window. However, only the decision for the first time interval in the window is implemented in practice. The solutions for other time intervals will be discarded. The above process is repeated.

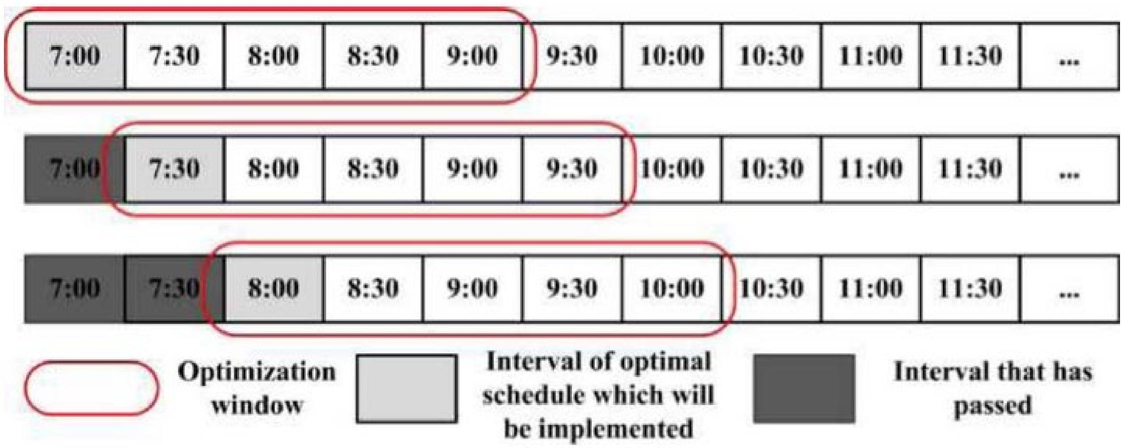


Fig. 10 Demonstration of rolling-horizon optimization

Restoration with Dynamic MG Formation

- A rolling-horizon optimization method is used to schedule the outputs of dispatchable DGs based on forecasts.
- In the self-healing mode, the on-outage portion of the distribution system will be optimally sectionalized into networked self-supplied MGs so as to provide reliable power supply to the maximum loads continuously.
- In order to take into account the uncertainties of DG outputs and load consumptions, we formulate the problems as a stochastic program.

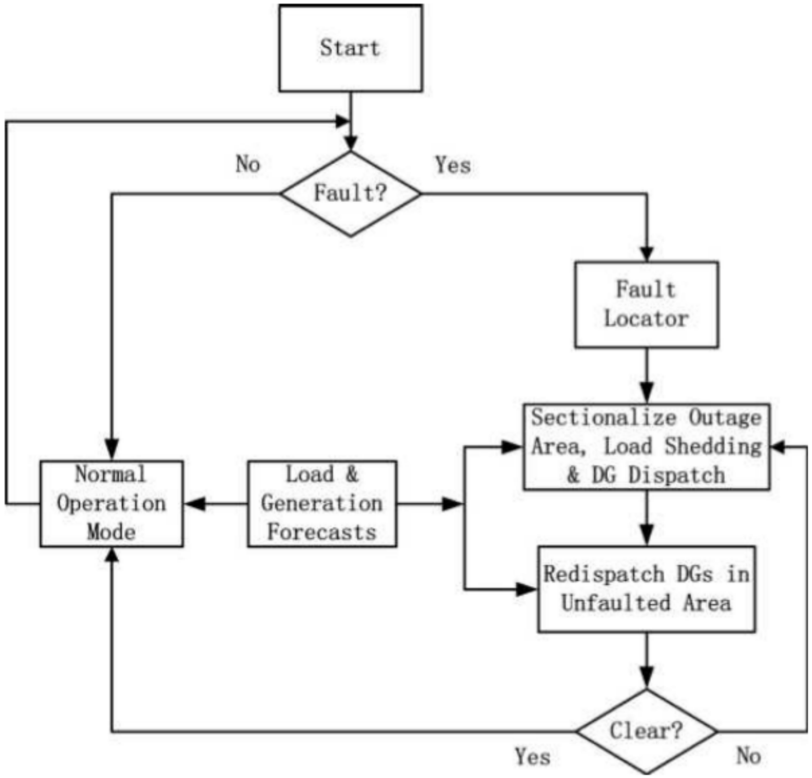
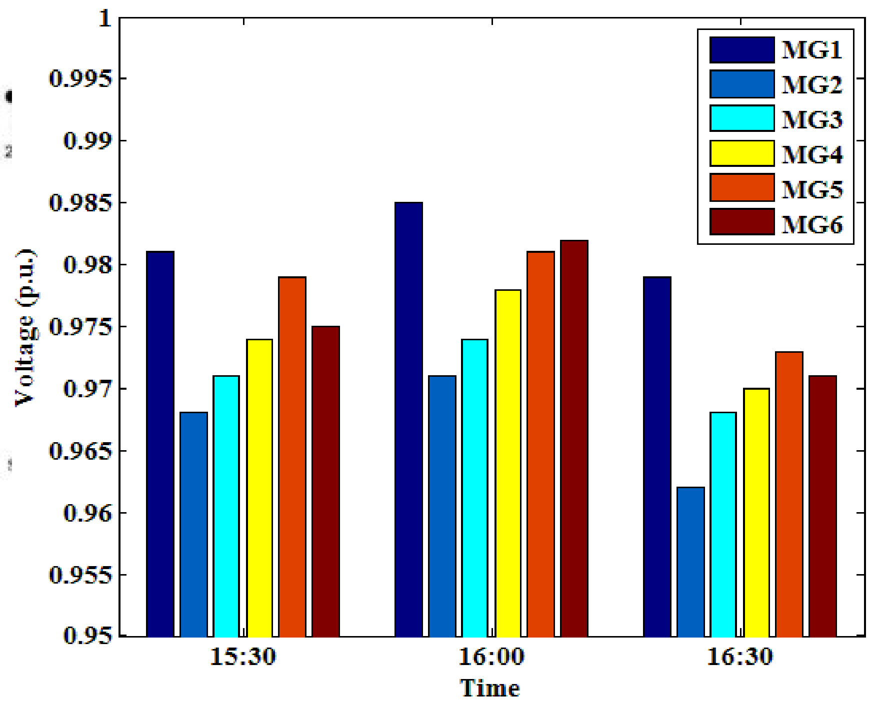


Fig. 11 Flowchart of the proposed operation and self-healing strategy [9]

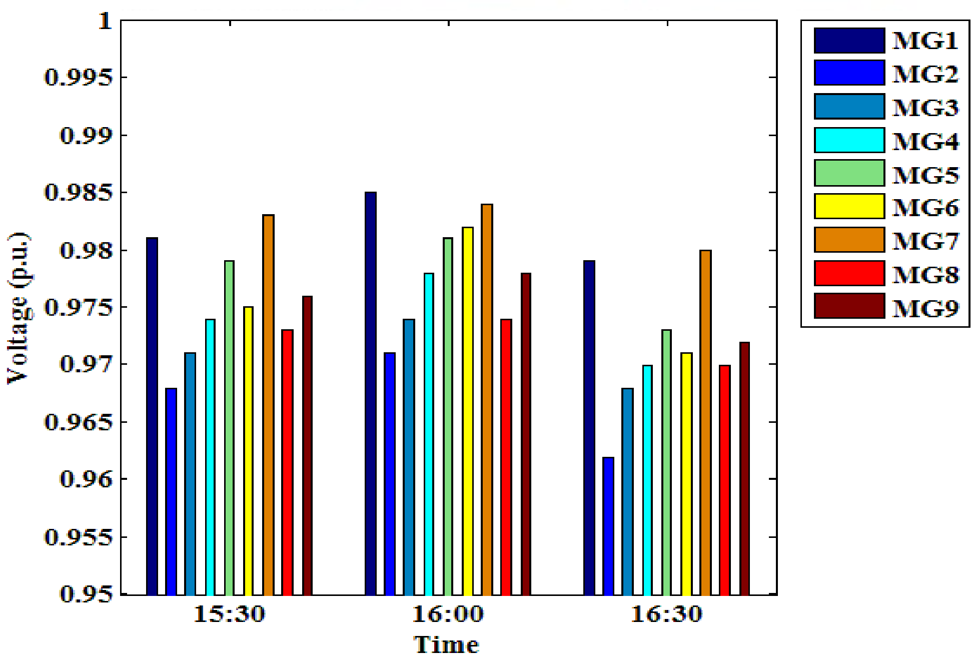
[9] Z. Wang and J. Wang, "Self-healing Resilient Distribution Systems based on Sectionalization into Microgrids," *IEEE Transactions on Power Systems*, vol. 30, no. 6, pp.3139-3149, November 2015.

Restoration with Dynamic MG Formation

Self-Healing Mode for a Single Fault



Self-Healing Mode for Multiple Faults



Networked MGs for Self-Healing Power Systems

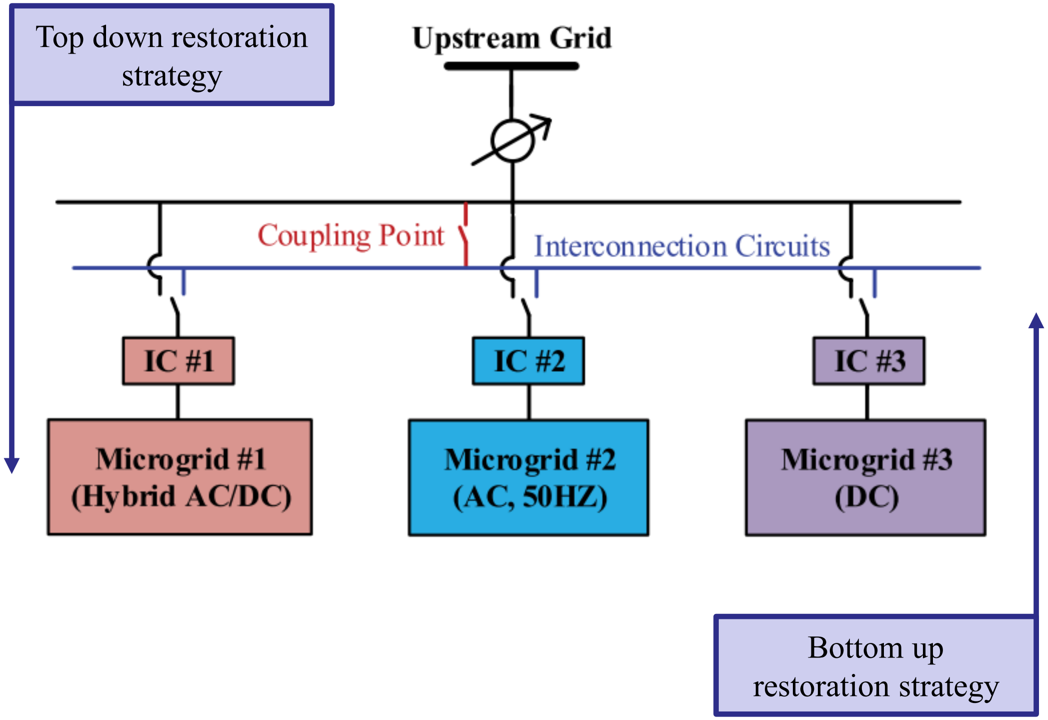


Fig. 12 Configuration of networked MGs

Concept: A power distribution system can host a number of MGs that are networked to form a MG cluster.

Feature: Networked MGs operate cooperatively by sharing critical DER resources in order to overcome potential power deficiencies in MG clusters.

Networked MGs for Self-Healing Power Systems

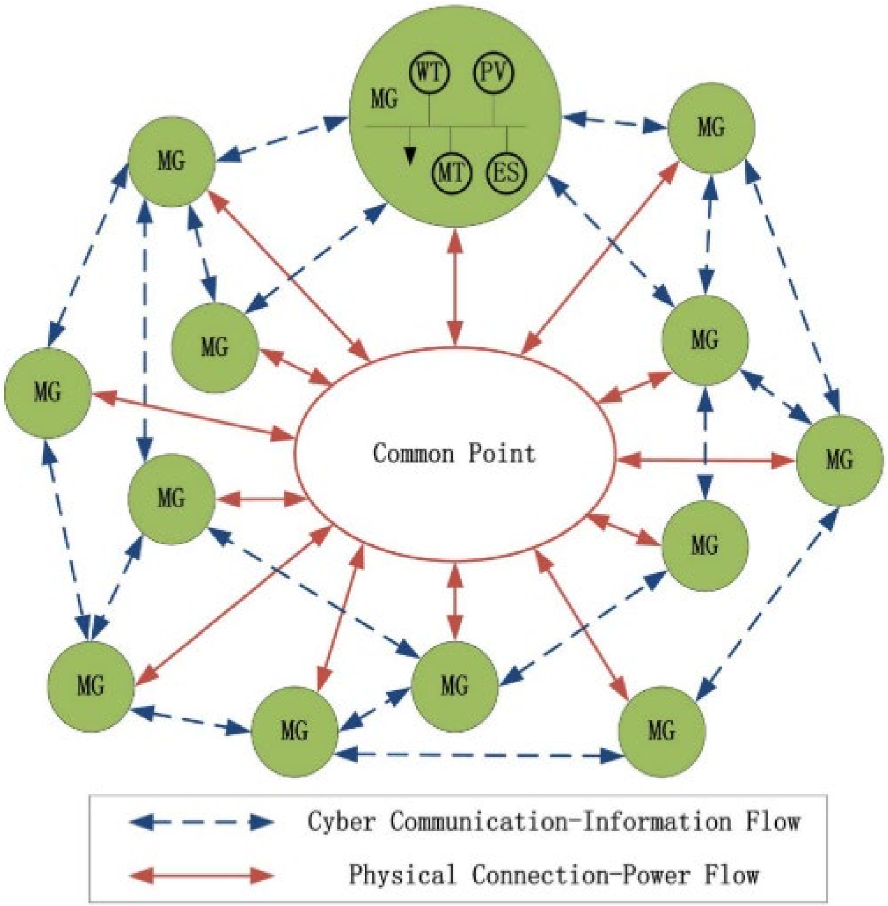


Fig. 5 Concept of networked MGs [6]

- The networked MGs are connected by a physical common bus and a designed two-layer cyber communication network.
- In the self- healing mode, the local generation capacities of other MGs can be used to support the on-emergency portion of the system.
- A consensus algorithm is used to distribute portions of the desired power support to each individual MG in a decentralized way.

[6] Z. Wang, B. Chen, J. Wang, and C. Chen, "Networked Microgrids for Self-healing Power Systems," *IEEE Transactions on Smart Grid*, vol. 7, no. 1, pp. 310-319, January 2016.

Networked MGs for Self-Healing Power Systems

- Normal operation

$$\min \sum_{t} \left(\sum_{i \in G_n} F_i(P_{i,t}) + \rho_e(\theta^p_{n,t} + \theta^q_{n,t}) + \rho_l \sum_{i \in D2_n} v_{i,t} TL^P_{i,t} \right)$$

The objective function minimizes the operation costs and generation-demand mismatch of the nth MG.

- Self-healing operation

$$\min(\theta^p_{n,t} - \mu^p_{n,t})^2 + (\theta^q_{n,t} - \mu^q_{n,t})^2$$

The operation objective is to make the power exchange with the common point approach μ as closely as possible.

- Constraints:

Power balance constraints, ramp up/down constraints, etc.

Networked MGs for Self-Healing Power Systems

Case study:

It is assumed that the six MGs are connected via a ring cyber network.

- Each MG starts the iteration with its own total generation, and exchanges information with its neighboring MGs in the ring-connected cyber network.
- The algorithm converges to the same value 5.963 MW, which is the averaged generation of all normally-operating MGs, in 14 iterations.

a single fault happens on the line sections 13–18 in MG1 at 18:00

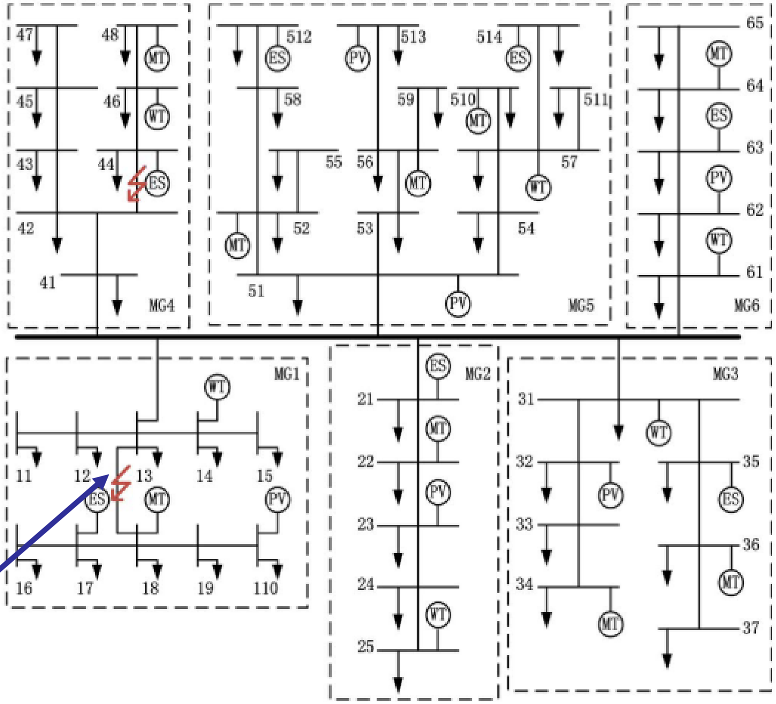


Fig. 13 Test system with six networked MGs [6]

[6] Z. Wang, B. Chen, J. Wang, and C. Chen, "Networked Microgrids for Self-healing Power Systems," *IEEE Transactions on Smart Grid*, vol. 7, no. 1, pp. 310-319, January 2016.

Networked MGs for Self-Healing Power Systems

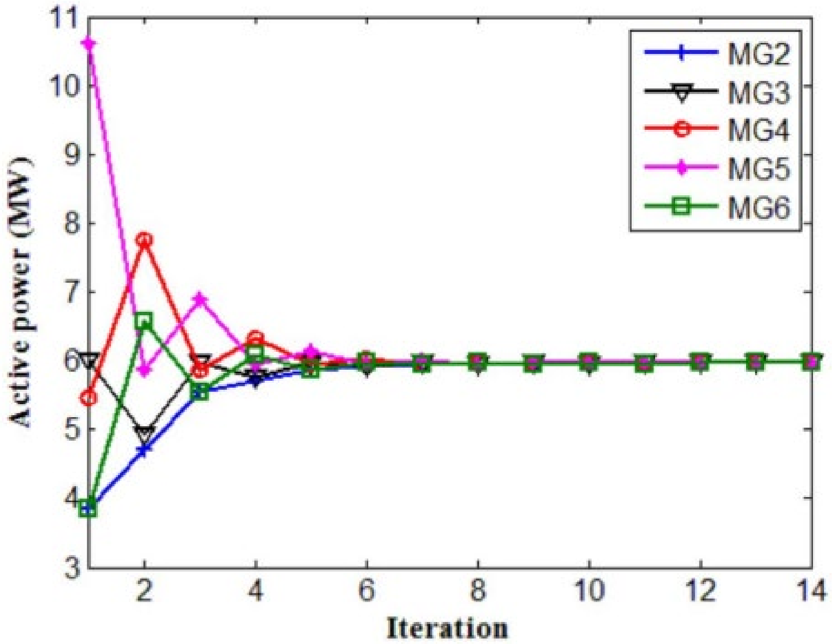


Fig. 14 Iteration of total active power output of DGs in all normally-operation MGs at 18:00

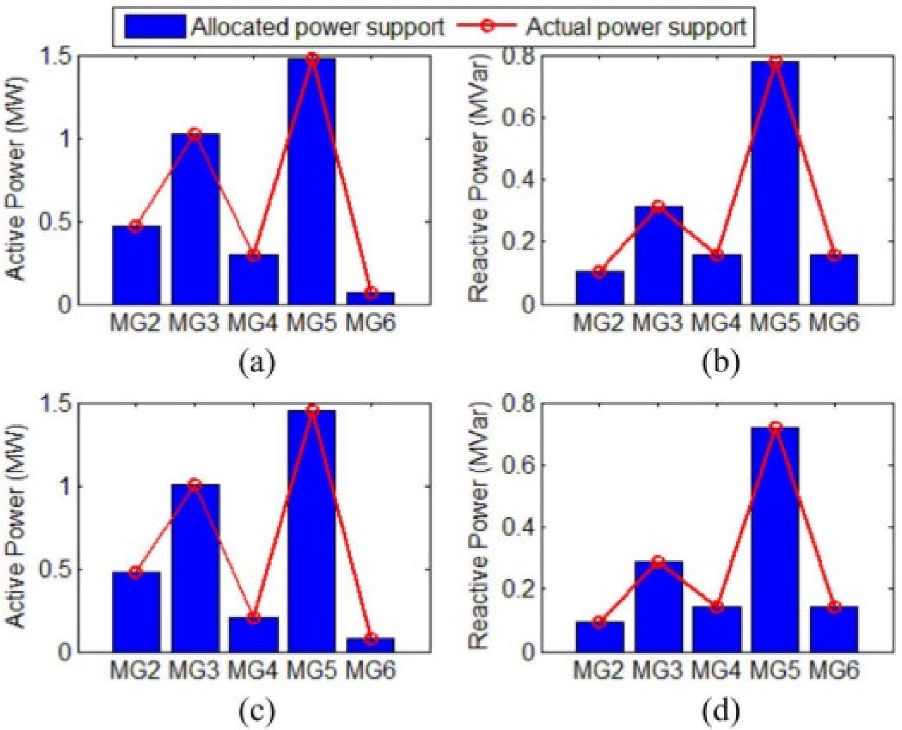


Fig. 15 Allocated power support request and actual power support of each MG in Case 2. (a) and (b) Active and reactive power support at 18:00, respectively. (c) and (d) Active and reactive power support at 19:00, respectively.

Literature Review

A wide range of methods have been applied to solve optimal power management problem of networked MGs:

- Centralized decision models
- Distributed optimization methods
- Heuristic techniques

Model-based method

- Solve a large-scale optimization problem
- Need complete information of MG physical models
- Not adaptive to system parameter changes (such as, fuel price for diesel generators)

Need a method to address above challenges

Solution

Reinforcement Learning (RL) ⇨ Power management of Networked MGs

- Markov decision process (S_t, A_t, P_t, R_t)
- Repeated interactions
- Maximize the expected cumulative reward

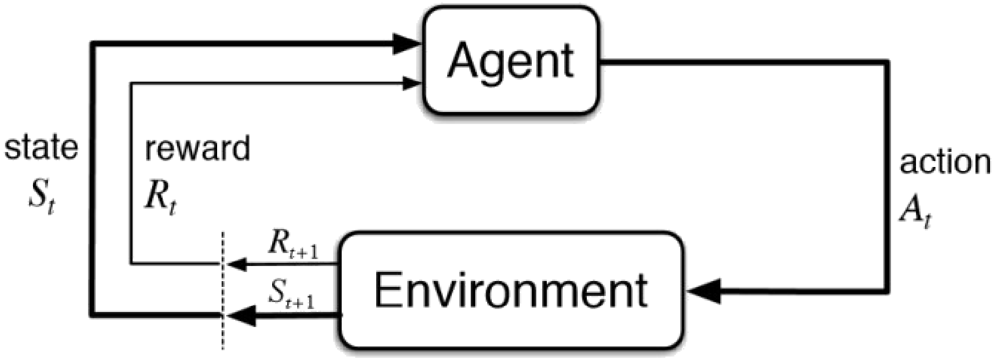


Fig. 16 Concept of RL [10]

- **Agent can solve the problem with incomplete information of Environment**
- **Computational time (After the model is well trained)**
- **Adaptability**

[10] R. S. Sutton and A. G. Barto, "Reinforcement Learning: An Introduction", The MIT Press, London, England, 2017.

Cooperative business model

To ensure the long-term sustainability and encourage economic development in rural communities, the feasibility of cooperative business models for rural system electrification was analyzed in literatures.

It has been shown that a non-profit cooperative can act as an intermediary agent between the rural MGs and the wholesale market.

- The power is exchanged between the MGs and the cooperative at a retail rate, and the revenue from electricity sales in the wholesale market is returned to MGs.

- The retail energy pricing program can be used to influence the MGs' behavior based on the availability of resources.

This paper was motivated to address power management of several privately-owned MGs that are members of a cooperative, under data privacy and ownership constraints. The data access constraint can hinder the feasibility of cooperative power management.

To address this issue, we have proposed a reinforcement learning (RL)-based method that enables optimal resource allocation within the cooperative model, while maintaining the data ownership of the participating MGs.

Contributions

In summary, the main contributions of [11] can be listed as follows:

- The proposed power management system can handle the current limitations raised from data privacy and ownership in the cooperative setting. Considering the **model-free nature of our RL-based method**, the **data privacy of MGs** and the **data confidentiality of customers** are maintained. The power management problem is solved with access to only minimal and **aggregated data**.

- The proposed RL solver is faster than conventional optimization solvers since the learned state-action value function acts similar to a **memory** that recalls from the cooperative agent's past experiences to estimate new optimal solutions. This is done by updating the state values at each decision window and without re-solving the decision problem.

- The RL framework is trained using a **regularized recursive least square methodology** with a **forgetting factor**, which enables the decision model to be adaptive to changes in system parameters which are excluded from the cooperative agent's state set.

[11] Q. Zhang, K. Dehghanpour, Z. Wang, Q. Huang, "A Learning based Power Management for Networked Under Incomplete Information", in *IEEE Trans. Smart Grid*, Early Access.

Bi-level RL-based Networked MGs Power Management

Level I - RL-based Distribution System Control:

The cooperative agent employs an adaptive model-free RL method.

- Develop a regularized recursive least square function approximation methodology.
- Find the optimal retail price signals for the MGs based on the latest system states.

Level II - MG Power Management:

The MGCC agents receive the price signal for a look-ahead moving decision window.

- Each MGCC agent solves a Mixed Integer Nonlinear Programming (MINLP) to dispatch their local generation/ storage assets to maximize their revenue in the price-based environment, subject to full AC power flow constraints.

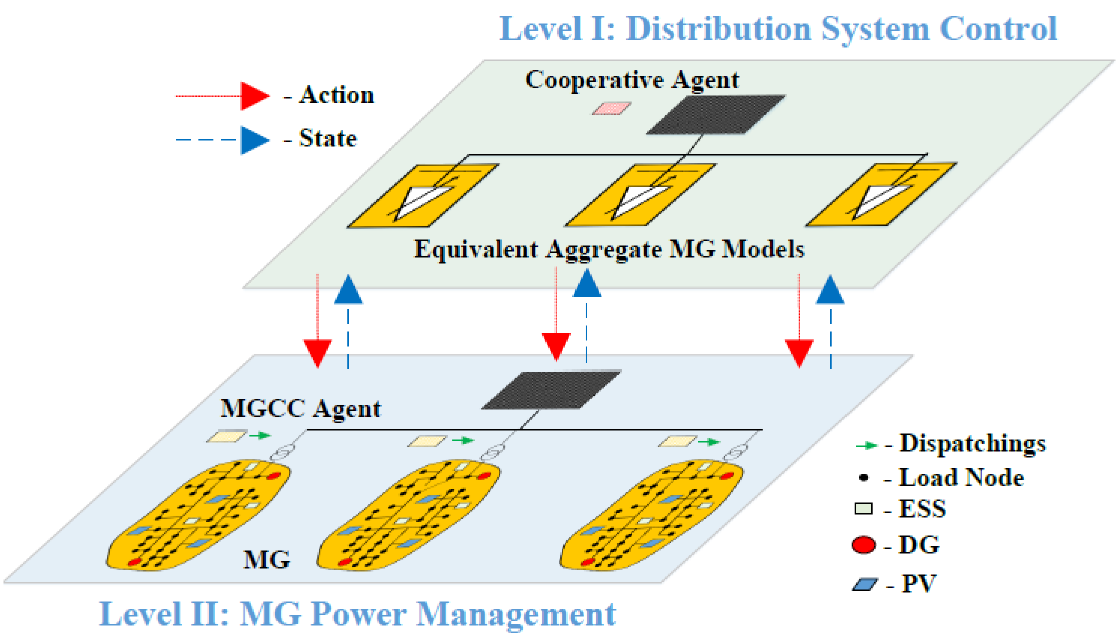


Fig. 17 The architecture of the bi-level networked MGs power management

[11] Q. Zhang, K. Dehghanpour, Z. Wang, Q. Huang, "A Learning based Power Management for Networked Under Incomplete Information", in *IEEE Trans. Smart Grid*, Early Access.

Bi-level RL-based Networked MGs Power Management

Action of cooperative agent ($\boldsymbol{a}$):

- Locational retail price

State ($\boldsymbol{S}$):

- Aggregated level (for each MG) active load and solar information

Unknown information for utility agent:

- MG physical models behind PCCs

Objective:

- Maximize the profit of the cooperative agent (non-profit agent)
- Minimize the operational cost of individual MGs

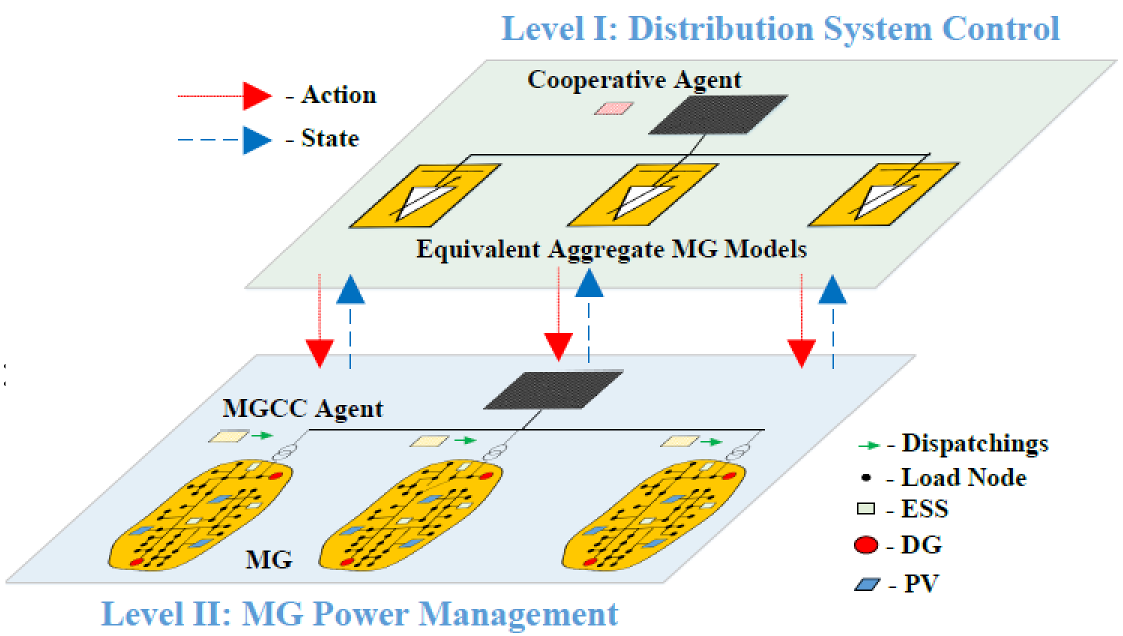


Fig. 17 The architecture of the bi-level networked MGs power management

Level I: Adaptive RL-based Distribution System Control

- Maximize the **reward** function (R-function)
  s.t. MGs response

$$R(t) = \sum_{t'=0}^{T-1} \gamma^{t'} \left(\lambda_{t+t'}^{W} P_{t+t'}^{W} - \sum_{n=1}^{N} \lambda_{t+t',n}^{R} P_{t+t',n}^{PCC} \right)$$

where λ^W is wholesale price, P^W is exchanged power with the wholesale market, λ^R is retail prices at the PCCs, P^{PCC} is the exchanged power at the PCCs.

- The **state-action** value function (Q-function)

$$Q_t(\boldsymbol{S}, \boldsymbol{a}) = E\left\{ \overbrace{\sum_{t'=0}^{T-1} \gamma^{t'} \pi(t+t') | \boldsymbol{S}(t) = \boldsymbol{S}, \boldsymbol{a}(t) = \boldsymbol{a}}^{\textbf{Expected cumulative reward}} \right\}$$

where the revenue is $\pi(t) = \lambda_t^W P_t^W - \sum_{n=1}^{N} \lambda_{t,n}^R P_{t,n}^{PCC}$

- **Parameterize** the state-action value function with multivariate regression **parameters** $\boldsymbol{\theta}$

$$Q_t(\boldsymbol{S}, \boldsymbol{a}) \approx \hat{Q}_t(\boldsymbol{S}, \boldsymbol{a}|\boldsymbol{\theta}) = Q_{\boldsymbol{S}\cdot\boldsymbol{a}}(t|\boldsymbol{\theta}) + Q_{\boldsymbol{S}}(t|\boldsymbol{\theta}) + Q_{\boldsymbol{a}}(t|\boldsymbol{\theta})$$

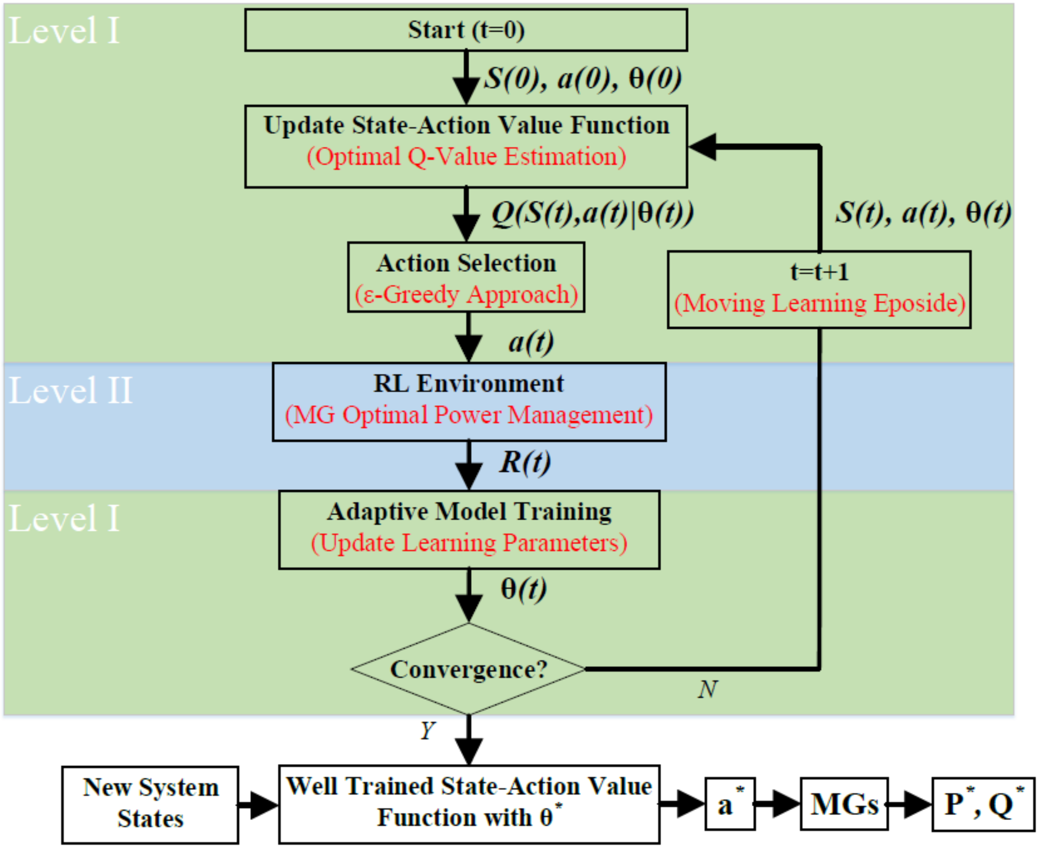


Fig. 18 Flowchart of the proposed RL-based method

Level I: Multivariate polynomial regression model

Given the regression parameter vector , $Q_{\boldsymbol{S}\cdot\boldsymbol{a}}$, $Q_{\boldsymbol{S}}$, and $Q_{\boldsymbol{a}}$ are the parameterized sub-components that quantify the impacts of state-action interaction $Q_{\boldsymbol{S}\cdot\boldsymbol{a}}(t|\boldsymbol{\theta})$, state values $Q_{\boldsymbol{S}}(t|\boldsymbol{\theta})$, and action values $Q_{\boldsymbol{a}}(t|\boldsymbol{\theta})$, respectively.

$$Q_t(\boldsymbol{S},\boldsymbol{a}) \approx \hat{Q}_t(\boldsymbol{S},\boldsymbol{a}|\boldsymbol{\theta}) = Q_{\boldsymbol{S}\cdot\boldsymbol{a}}(t|\boldsymbol{\theta}) + Q_{\boldsymbol{S}}(t|\boldsymbol{\theta}) + Q_{\boldsymbol{a}}(t|\boldsymbol{\theta})$$

These regression sub-components in multivariate polynomial regression model are defined as follows:

$$Q_{\boldsymbol{S}\cdot\boldsymbol{a}}(t|\boldsymbol{\theta}) = \sum_{n=1}^{N} \theta_{t,n}^{1}\,\lambda_{t,n}^{R}\hat{I}_{PV}(t,n) + \sum_{n=1}^{N} \theta_{t,n}^{2}\,\lambda_{t,n}^{R}\hat{P}_{D}(t,n)$$

$$Q_{\boldsymbol{S}}(t|\boldsymbol{\theta}) = \sum_{n=1}^{N} \theta_{t,n}^{3}\,\hat{I}_{PV}(t,n) + \sum_{n=1}^{N} \theta_{t,n}^{4}\,\hat{P}_{D}(t,n)$$

$$Q_{\boldsymbol{a}}(t|\boldsymbol{\theta}) = \sum_{n=1}^{N} \theta_{t,n}^{5}\,\lambda_{t,n}^{R} + \theta^{6}$$

where $\hat{I}_{PV}$ and $\hat{P}_{D}$ are the system state vectors of solar irradiance and active load demand estimations.

Level I: Learning Process

Action selection: ϵ-greedy method

$$\boldsymbol{a}_{\boldsymbol{opt}}(t') = \arg\max_{\boldsymbol{a}'} Q_{t'}(\boldsymbol{S}(t'), \boldsymbol{a}')$$

$$a(t) = \begin{cases} \boldsymbol{a}_{\boldsymbol{opt}}(t), & if\ r \geq \varepsilon \\ \lambda_{t,i}^{R} \sim U\{\rho_\lambda\}, & if\ r < \varepsilon \end{cases} \qquad \begin{array}{l} 0 \leq \varepsilon \ll 1 \\ r \sim U\{[0,1]\} \end{array}$$

- Reduce the risk of sub-optimality
- Promote continuous exploration of action space

Update θ: gradient descent approach and regularized recursive least squares algorithm

Learning rule : $\theta\,(t+1) \leftarrow \theta(t) + \delta\{R(t) - \hat{Q}_t(\boldsymbol{S}, \boldsymbol{a}|\boldsymbol{\theta})\}\nabla_\theta \hat{Q}_t(\boldsymbol{S}, \boldsymbol{a}|\boldsymbol{\theta})$

$$\theta(t+1) \leftarrow \theta(t) + \Delta(t)x(t)\{R(t) - \hat{Q}_t(\boldsymbol{S}, \boldsymbol{a}|\boldsymbol{\theta})\}$$

$$\Delta(t+1) \leftarrow \hat{\Delta}(t+1)\left(I + \mu\hat{\Delta}(t+1)\right)^{-1}$$

$$\hat{\Delta}(t+1) \leftarrow \frac{1}{1-\phi}\left(\Delta(t) - \frac{\Delta(t)x(t)x^T(t)\Delta(t)}{1 + x^T(t)\Delta(t)x(t)}\right)$$

- Avoid overfitting: regularization factor μ
- Adaptive to changes: forgetting factor ϕ

Level II: MGCC Agent Power Management

To simulate the environment, each MG receives the price signals as action from the utility to solve the constrained power management problem within a moving decision window.

$$\min_{x_p, x_q} \sum_{t}^{T+t} \left(-\lambda_{t,n}^{R} P_{t,n}^{PCC} + \lambda_{i,t,n}^{F} F_{i,t,n}\right)$$

The objective minimize each MG's total cost of operation.

s.t.

$$F_{i,t,n} = a_f \left(P_{i,t,n}^{DG}\right)^2 + b_f P_{i,t,n}^{DG} + c_f$$

The fuel consumption of diesel generators (DGs) can be expressed as a quadratic polynomial function.

$$\left|P_{t,n}^{PCC}\right| \le P_{t,n}^{PCC,M}$$

$$\left|Q_{t,n}^{PCC}\right| \le Q_{t,n}^{PCC,M}$$

Power exchange limit between the MG and the upstream utility grid

$$0 \le P_{i,t,n}^{DG} \le P_{i,t,n}^{DG,M}$$

$$0 \le Q_{i,t,n}^{DG} \le Q_{i,t,n}^{DG,M}$$

$$\left|P_{i,t,n}^{DG} - P_{i,t-1,n}^{DG}\right| \le P_{i,n}^{DG,R}$$

DG active/reactive power output limits, and DG ramping constraint

$$P_{t,n}^{ij} = V_{t,n}^{i} \left(V_{t,n}^{i} G_{n}^{ij} - V_{t,n}^{j}\left(G_{n}^{ij} \cos\left(\theta_{t,n}^{ij}\right) + B_{n}^{ij} \sin\left(\theta_{t,n}^{ij}\right)\right)\right)$$

$$Q_{t,n}^{ij} = -V_{t,n}^{i} \left(V_{t,n}^{i} B_{n}^{ij} + V_{t,n}^{j}\left(G_{n}^{ij} \cos\left(\theta_{t,n}^{ij}\right) - B_{n}^{ij} \sin\left(\theta_{t,n}^{ij}\right)\right)\right)$$

$$\left(P_{t,n}^{ij}\right)^2 + \left(Q_{t,n}^{ij}\right)^2 \le \left(S_{t,n}^{ij,M}\right)^2$$

Line active/reactive flow calculations, and line flow limit constraint

Level II: MGCC Agent Power Management

$$\sum_{i,j\in k}^{K} P_{t,n}^{ij} = \sum_{j,i\in k}^{K} P_{t,n}^{ji} - p_{i,t,n}$$

$$\sum_{i,j\in k}^{K} Q_{t,n}^{ij} = \sum_{j,i\in k}^{K} Q_{t,n}^{ji} - q_{i,t,n}$$

$$p_{i,t,n} = P_{i,t,n}^{D,e} - P_{i,t,n}^{DG} - P_{i,t,n}^{PV,e} + P_{i,t,n}^{Ch} - P_{i,t,n}^{Dis}$$

$$P_{i,t,n}^{D} = P_{i,t,n}^{D,e} - \varepsilon_{i,t,n}^{D}, P_{i,t,n}^{PV} = P_{i,t,n}^{PV,e} - \varepsilon_{i,t,n}^{PV}$$

$$q_{i,t,n} = Q_{i,t,n}^{D} - Q_{i,t,n}^{DG} - Q_{i,t,n}^{PV} + Q_{i,t,n}^{ESS}$$

Nodal active/reactive power balance constraints

$$V_{t,n}^{PCC} = V_{t,n}^{PCC,E}$$

$$V_{i,n}^{m} \le V_{i,t,n} \le V_{i,n}^{M}$$

Nodal voltage constraints

$$\left|Q_{i,t,n}^{PV}\right| \le Q_{i,n}^{PV,M}$$

PV reactive power output limit

$$E_{i,t,n} = E_{i,t-1,n} + \Delta t\left(P_{i,t,n}^{Ch}\eta_{Ch} - P_{i,t,n}^{Dis}/\eta_{Dis}\right)/E_{i,n}^{Cap}$$

$$E_{i,n}^{m} \le E_{i,t,n} \le E_{i,n}^{M}$$

$$0 \le P_{i,t,n}^{Ch} \le \mu_{i,t,n}^{Ch} P_{i,n}^{Ch,M}$$

$$0 \le P_{i,t,n}^{Dis} \le \mu_{i,t,n}^{Dis} P_{i,n}^{Dis,M}$$

$$0 \le \mu_{i,t,n}^{Ch} + \mu_{i,t,n}^{Dis} \le 1, \mu_{i,t,n}^{Ch}, \mu_{i,t,n}^{Dis} \in \{0,1\}$$

ESS operational constraints

Level II: MGCC Agent Power Management

The steps of the interactive power flow solution are as follows:

Step I. Receive input signals from Level I: The MGs receive the retail price signals at the PCCs, $\lambda_{t,n}^{R}$, from the cooperative agent.

Step II. Solve individual MG optimal power management problem: Given $\lambda_{t,n}^{R}$ and the estimated voltage at PCC, the power management problem is solved independently by each MGCC, and the exchanged active and reactive powers at the PCCs are obtained for each MG.

Step III. Solve power flow problem over distribution system: Treating MGs as fixed PQ loads in the external distribution system, power flow is solved over the network connecting the MGs. The total substation exchanged power, P_{t}^{W} , and voltage values at PCCs, $V_{t,n}^{PCC}$, are updated based on the power flow solution.

Step IV. Check convergence: Go back to Step III to update PQ values corresponding to each MG, until the changes in voltage values at MG PCCs are smaller than a threshold value V_{Th}.

Case Study

The case study has of four MGs (33-bus network and 13-bus network) in Fig. 19.

- Tab. 4 presents all setting parameters for the proposed RL-based method.
- Both load demands and PV generations data with 15-min time resolution are obtained from smart meters to provide realistic numerical experiments in Fig. 20a and Fig. 20b.
- The wholesale market prices used in the numerical case study have been shown in Fig. 20c.

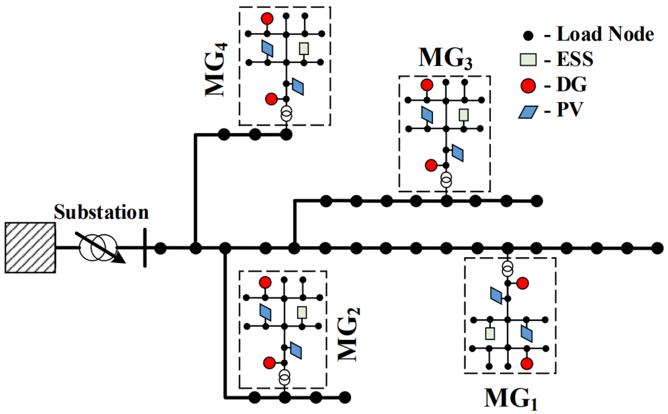
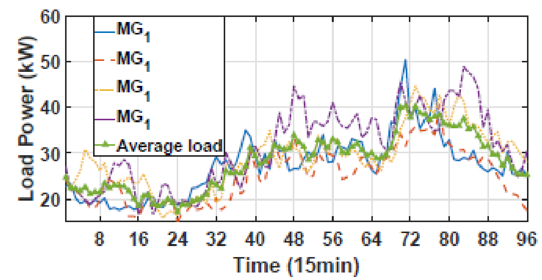


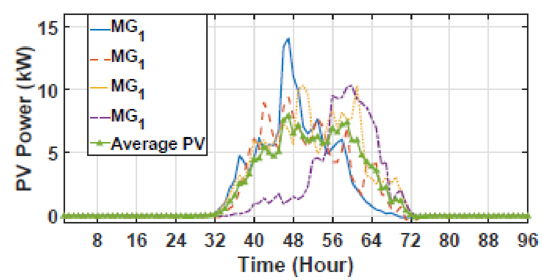
Fig. 19 Test system under study

Tab. 4 Test system under study

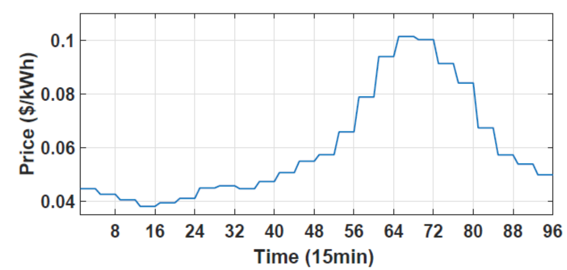
Parameters	γ	δ	μ	ϕ	ϵ
Values	0.99	0.01	1×10^{-5}	0.01	0.1



(a) Aggregate active load profile of the MGs



(b) Aggregate PV power of the MGs



(c) Wholesale market price

Fig. 20 Input data for the case study

Numerical Results

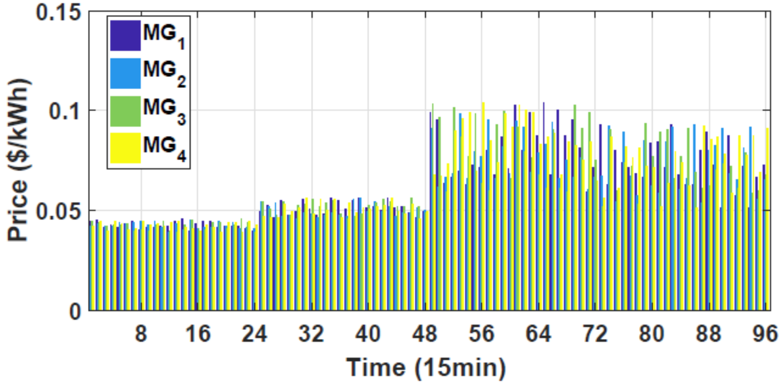
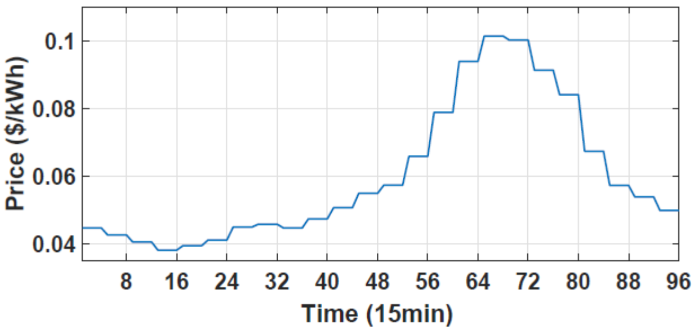


Fig. 21 Optimal locational retail price signals



(c) Wholesale market price

Fig. 20 Input data for the case study

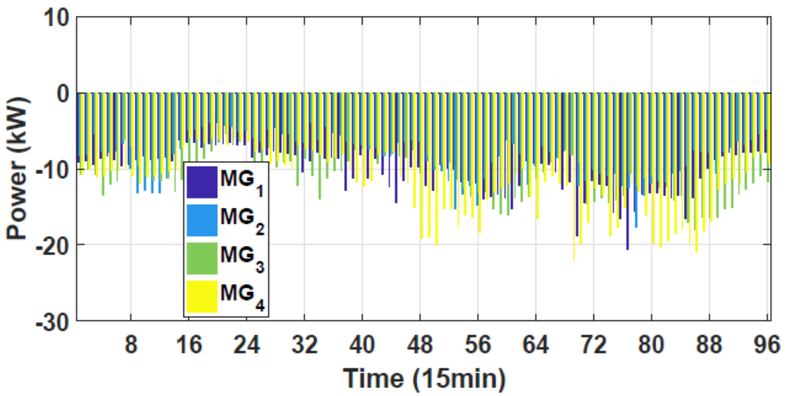


Fig. 22 Optimal power transferred through PCC of MGs

- Fig. 21 and Fig. 22 show the correlations and mutual impacts between the optimal retail price signals from Level I and optimal MGs' behaviors from Level II, respectively.

- As the wholesale price increases, the cooperative agent increases the retail prices to encourage the MGs to produce more power to reduce the costs of power purchase from the wholesale market.

Benefits of RL-based Method: comparison

A numerical comparison between a centralized solver (complete information) versus the proposed RL-based method (incomplete information).

Tab. 5 Comparison with A Centralized Optimization Method

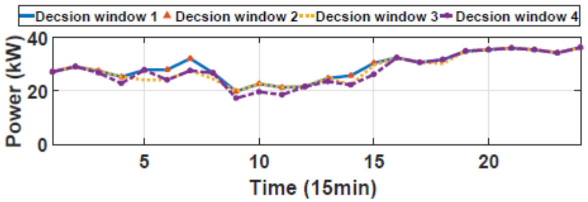
	RL-based method	Centralized Opt.
Social welfare ($)	4232.264	4212.372
Computational time (s)	9.64	116.35
MG privacy maintenance	Yes	No

As can be seen in Tab.5:

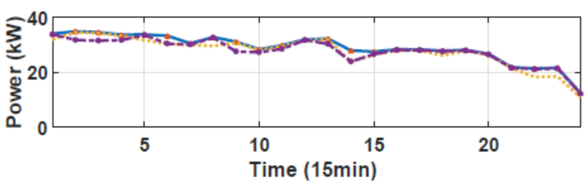
- The difference between the solutions obtained by the centralized solver and the proposed RL is less than 0.5% of the total achieved welfare.
- The decision time of the proposed RL-based method is much smaller than that of a centralized optimization method.
- The proposed method maintains the privacy of MGs physical model.

Benefits of RL-based Method: memory effect

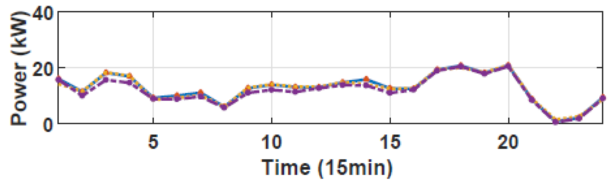
To demonstrate the memory effect of RL-based method, we have performed numerical experiments in which the trained state-action value functions of three different decision window have been used for new decision window without re-training.



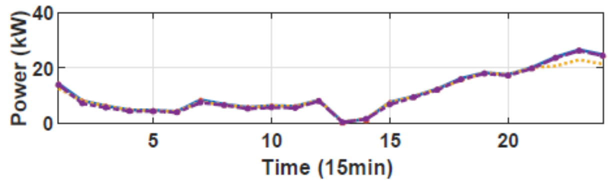
(a) Optimal action for decision window 1, using the trained models of decision windows 2, 3, and 4 for comparison



(b) Optimal action for decision window 2, using the trained models of decision windows 1, 3, and 4 for comparison



(c) Optimal action for decision window 3, using the traine models of decision windows 1, 2, and 4 for comparison



(d) Optimal action for decision window 4, using the traine models of decision windows 1, 2, and 3 for comparison

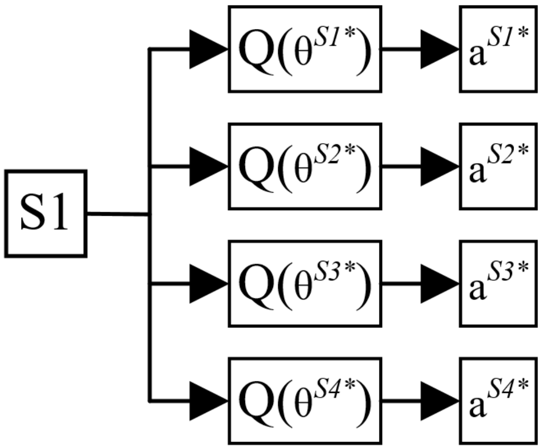


Fig. 23 Verifying the memory effect of the proposed Q-function and $\boldsymbol{\theta}^*$

Therefore, it shows that the trained Q-function and $\boldsymbol{\theta}^*$ having general applicability for different scenarios (with similar state type).

Benefits of RL-based Method

Therefore, the RL-based method has two fundamental advantages over centralized optimization method:

RL is model-free

- unlike centralized optimization approaches, the proposed RL-based method does not require detailed private knowledge of MG systems to reach the optimal solution.

RL is much faster compared to centralized solvers

- since the trained state-action value function (parameterized Q-function), which acts similar to a memory, is able to leverage the cooperative agents past experiences to obtain new optimal solutions by generalizing to new unseen states.

Performance of the proposed reward function approximation

To verify the functionality of the RL framework, the estimated reward (value of parameterized Q-function) obtained from the multiple linear regression is compared with the actual reward (value of R-function) at each episode, as shown in Fig. 24.

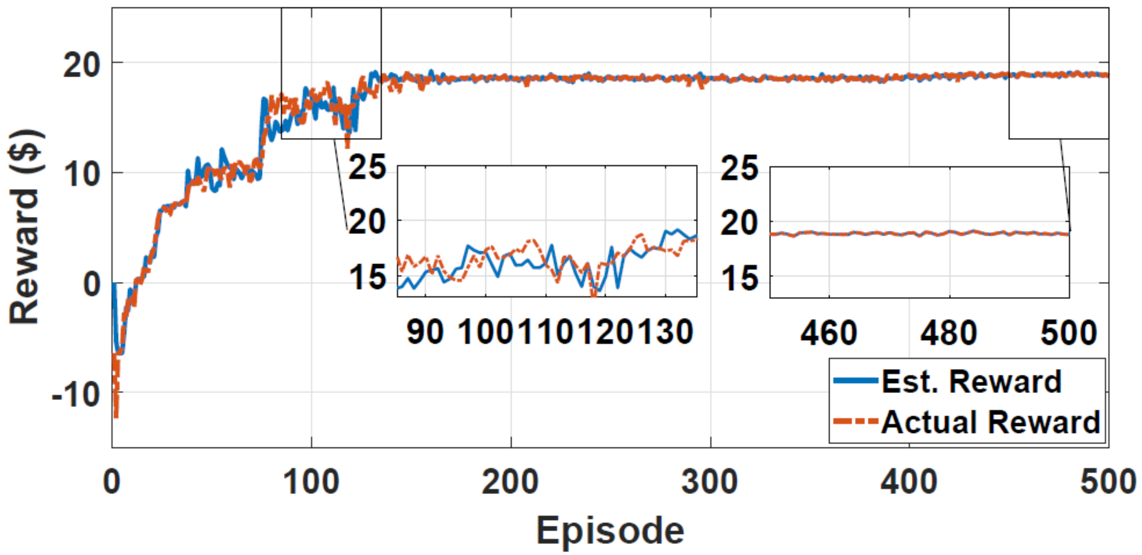


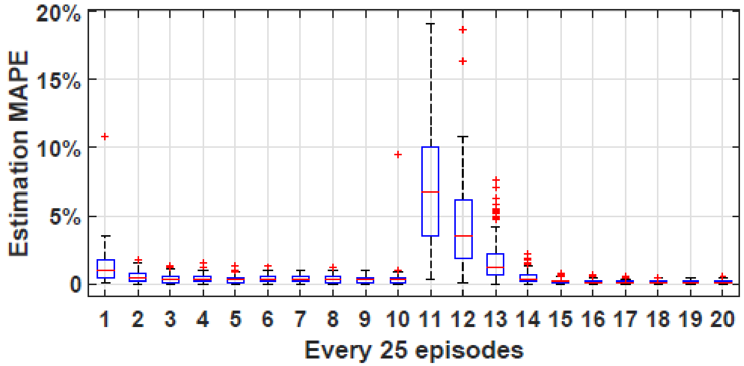
Fig. 24 Estimated utility reward VS actual received reward

- At the earlier stages of the learning process, the difference between the estimated reward and the real reward is relatively high.
- However, as the number of episodes increases, this difference drops to within an acceptable range.

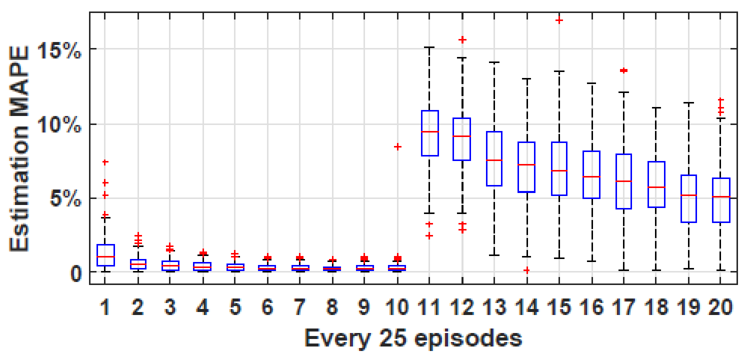
The results imply that the cooperative agent is able to accurately estimate the response of MGs to control actions.

Adaptive RL Results

To test the adaptability of the learning framework against changes in parameters (non-state parameters).



(a) Estimation MAPE with forgetting factor (Highly adaptive)



(b) Estimation MAPE without forgetting factor (Slow adaptation)

Fig. 25 Adaptability of the proposed RL-based method

- When episode=250, the DG fuel price is doubled.

- The proposed RL-based method (with forgetting factor) can track the actual reward signal with the sudden parameter changes.

- While, the conventional RL-based (without forgetting factor) method shows slow adaptation to changes in parameters.

- For this case, our proposed RL-based method is able to achieve 25% overall improvement in the convergence constant over conventional RL method.

Adaptive RL Results

In Fig. 26, the impact of forgetting factor on the convergence of the RL framework is demonstrated.

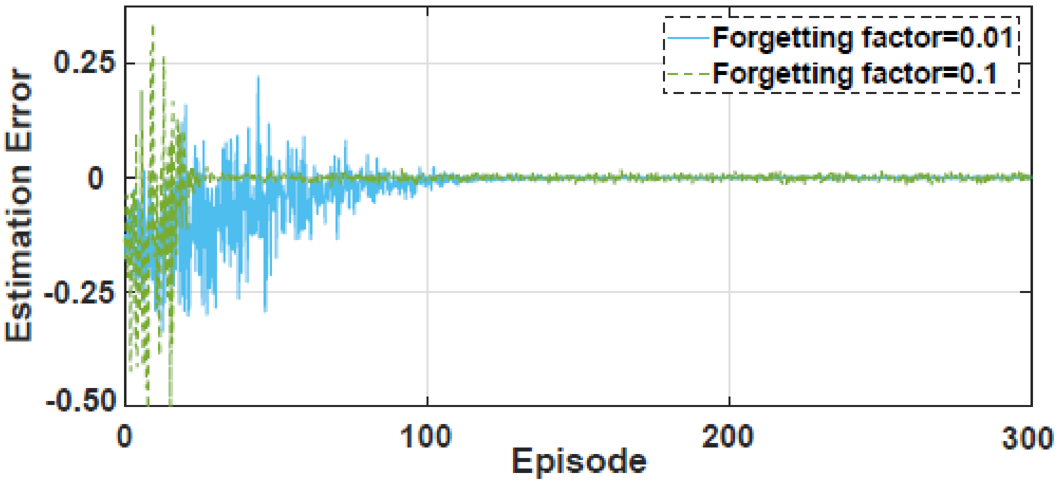


Fig. 26 Impact of forgetting factor on RL convergence

- As the forgetting factor increases from 0.01 to 0.1, the convergence speed of the RL framework has been improved.
- However, a tradeoff exists between the rate of convergence and the accuracy of the solution.
- Higher forgetting factors also lead to higher variances in the estimation error signal.

Conclusion

To summarize, the proposed decision model shows better adaptability, solution quality, and computational time compared to conventional centralized optimization methods.

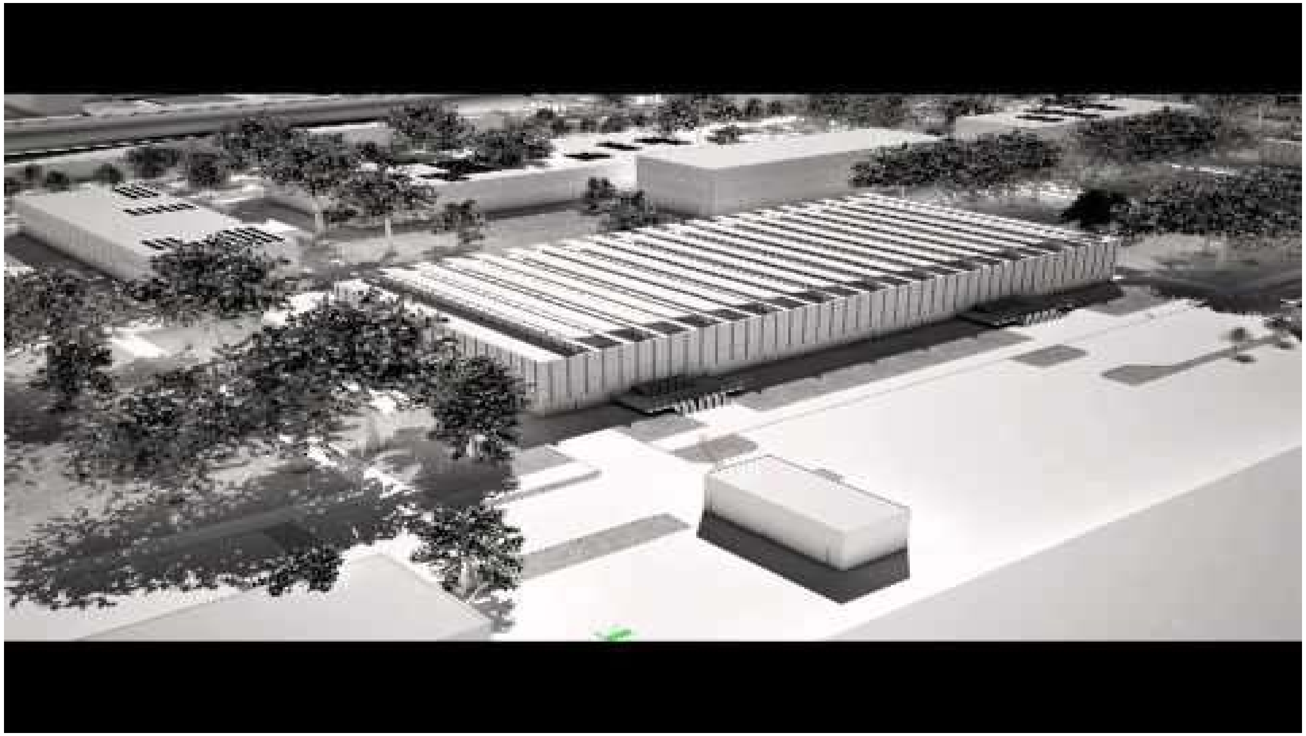
- Using the proposed decision method, a cooperative agent is able to accurately track the behavior of multiple networked MGs under incomplete knowledge of operation variables behind the PCCs.

- The proposed RL-based method is able to generalize from its past experiences to estimate optimal solutions in new situations without re-training from random initial conditions (i.e., fast response under evolving system conditions). This immensely speeds up the power management computational process.

- The framework is shown to be adaptive against the changes happening to unobserved parameters that are excluded from cooperative agent's state set. The learning model has been tested and verified using extensive numerical scenarios.

Case Study: MG Project at Illinois Institute of Technology

The $14 million project has equipped IIT's MG with a high-reliability distribution system for enhancing reliability, new sustainable energy sources (roof-top solar panels, wind generation units, flow batteries and charging stations for electric vehicles), and smart building automation technology (building controllers, Zigbee sensors, controllable loads) for energy efficiency and demand response.



[12] Micro-grid Project at IIT. http://iitmicrogrid.net/microgrid.aspx

Case Study: MG Project at Illinois Institute of Technology

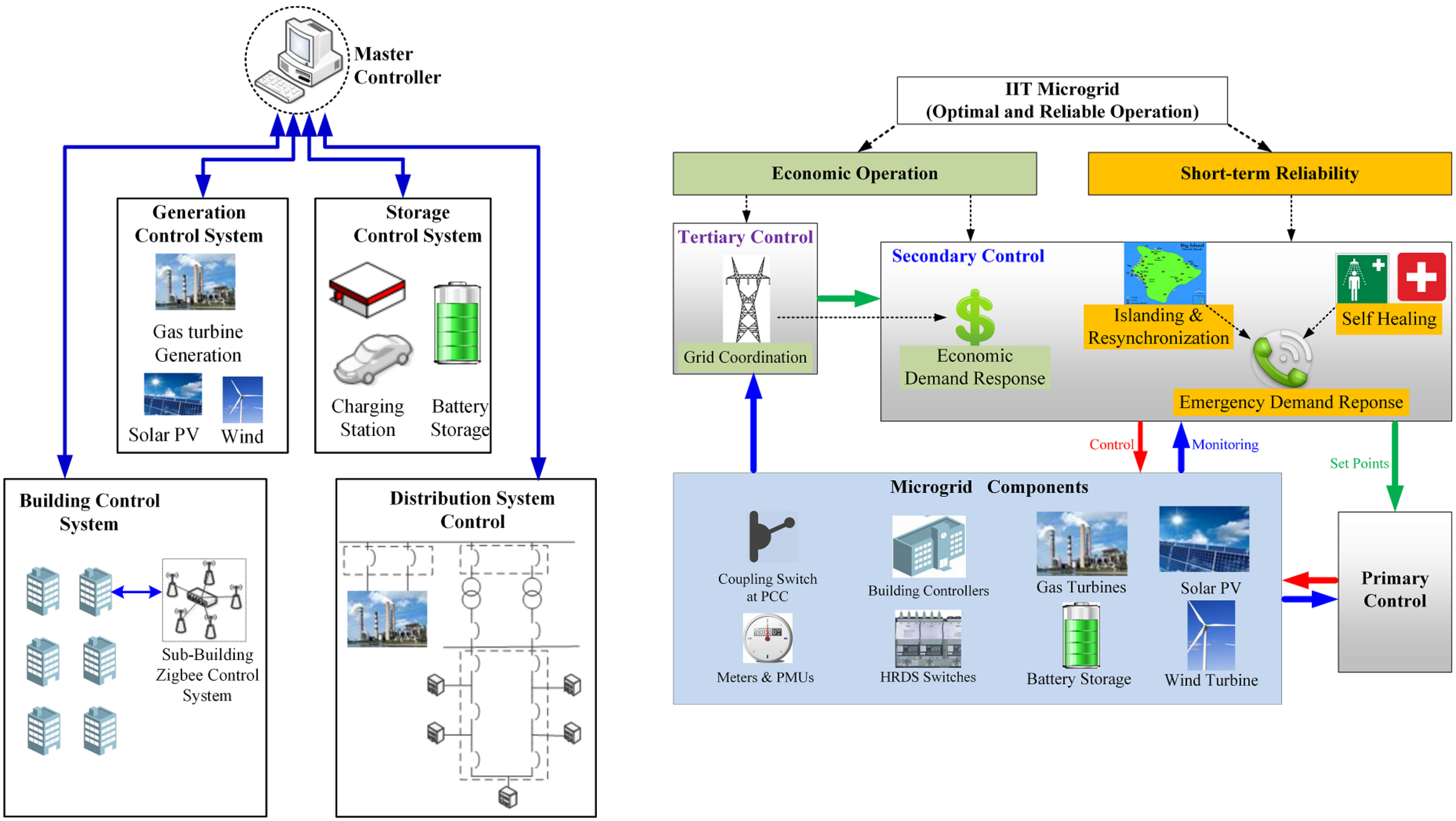


Fig. 27 General configuration of MG project at Illinois Institute of Technology [12]

[12] Micro-grid Project at IIT. http://iitmicrogrid.net/microgrid.aspx

Case Study: IIT-Bronzeville Networked MGs

The Bronzeville community MG [13] is adjacent to an existing MG on the campus of the Illinois Institute of Technology, which owns, manages, and operates its electric distribution system.

Phase I
- ~ 362 customers
- 2.5 MW of load
- Battery storage and solar PV
- Mobile generation used for testing purposes

Phase II
- ~ 748 customers in total
- 5.2 incremental MW of load
- Sufficient DER to meet the load
- Connected with the IIT MG to form a MG cluster

[13] M. Shahidehpour, Z. Li, S. Bahramirad, Z. Li and W. Tian, "Networked Microgrids: Exploring the Possibilities of the IIT-Bronzeville Grid," in *IEEE Power and Energy Magazine*, vol. 15, no. 4, pp. 63-71, July-Aug. 2017.

Case Study: IIT-Bronzeville Networked MGs

To explore the possibility and benefits of networking MGs, two adjacent MGs, IIT campus MG (ICM) and Bronzeville community MG (BCM) are physically tied together.

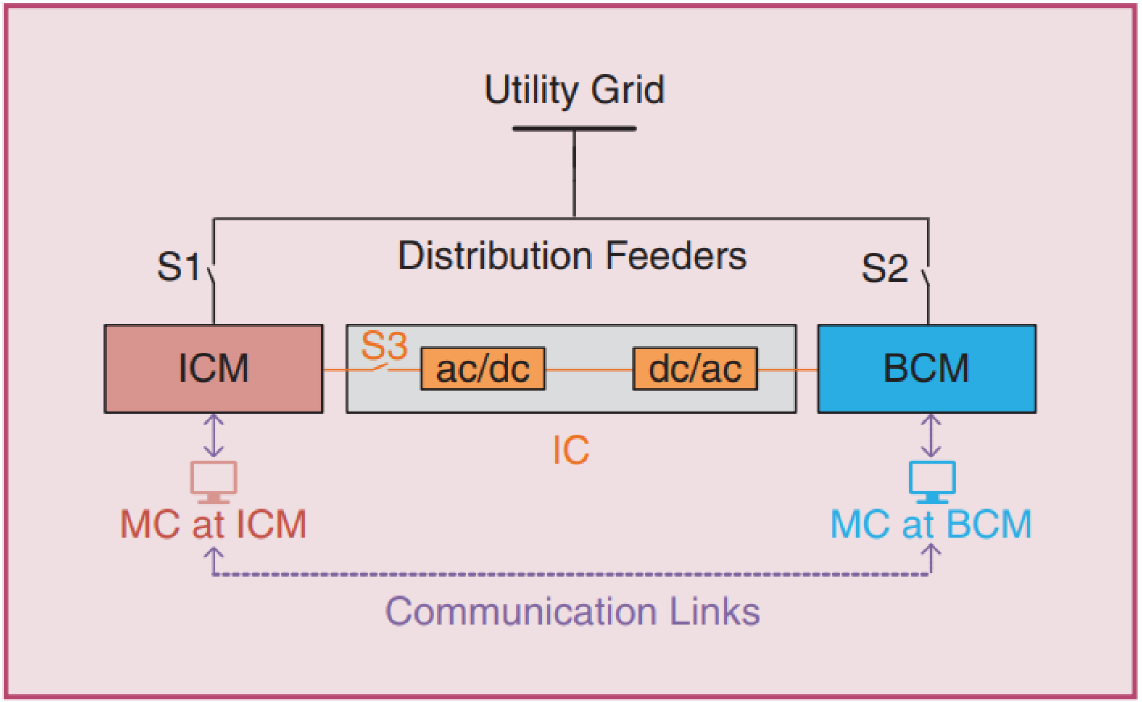


Fig. 28 A conceptual integration of the IIT-Bronzeville networked MGs [13]

[13] M. Shahidehpour, Z. Li, S. Bahramirad, Z. Li and W. Tian, "Networked Microgrids: Exploring the Possibilities of the IIT-Bronzeville Grid," in *IEEE Power and Energy Magazine*, vol. 15, no. 4, pp. 63-71, July-Aug. 2017.

Case Study: IIT-Bronzeville Networked MGs

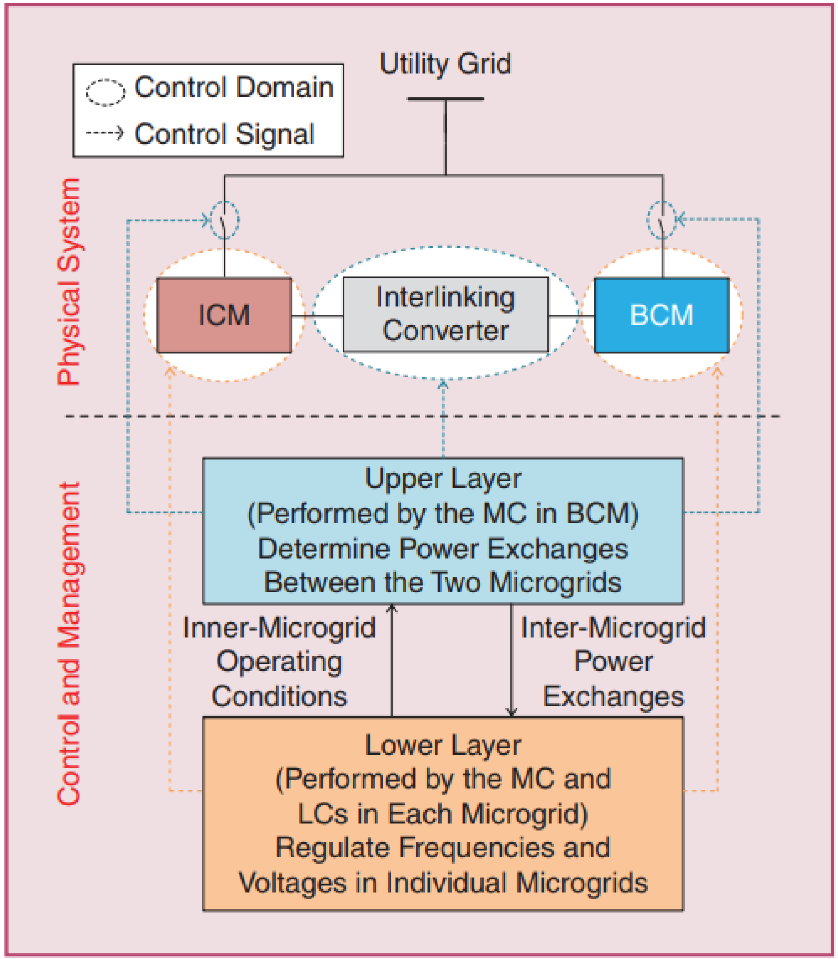


Fig. 29 Two-layer energy management for networked MGs [13]

Fig.29 shows the composition of the proposed coordinated control mechanism, which is divided into two coordinated layers for facilitating the operation of the networked MGs.

- Upper layer: the MC in the BCM determines the optimal exchange of power with the utility grid and between the two MGs.

- Lower layer: the MC in each MG manages operation independently for satisfying the designated power exchanges. Each MC will communicate with its LCs in response to any changes in real-time operating conditions to regulate MG frequency and voltages.

[13] M. Shahidehpour, Z. Li, S. Bahramirad, Z. Li and W. Tian, "Networked Microgrids: Exploring the Possibilities of the IIT-Bronzeville Grid," in *IEEE Power and Energy Magazine*, vol. 15, no. 4, pp. 63-71, July-Aug. 2017.

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[11] Q. Zhang, K. Dehghanpour, Z. Wang, Q. Huang, "A Learning based Power Management for Networked Under Incomplete Information", in *IEEE Trans. Smart Grid*, Early Access.
[12] Micro-grid Project at IIT. http://iitmicrogrid.net/microgrid.aspx
[13] M. Shahidehpour, Z. Li, S. Bahramirad, Z. Li and W. Tian, "Networked Microgrids: Exploring the Possibilities of the IIT-Bronzeville Grid," in *IEEE Power and Energy Magazine*, vol. 15, no. 4, pp. 63-71, July-Aug. 2017.

Thank you!