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Two-stage energy management for networked microgrids with high renewable penetration

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HIGHLIGHTS

- Hybrid energy management is adopted for networked microgrids.
- Risk control is incorporated by introducing mean–variance Markowitz theory.
- Two-stage energy management is proposed to improve control accuracy.
- Uncertainties existing in the system are fully addressed.

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ABSTRACT

Networking of microgrids has received increasing attentions in recent years, which requires the uncertainty management associated with variations in the system. In this paper, a two-stage energy management strategy is developed for networked microgrids under the presence of high renewable resources. It decomposes the microgrids energy management into two stages to counteract the intra-day stochastic variations of renewable energy resources, electricity load and electricity prices. In the first stage (hourly time scale), a hierarchical hybrid control method is employed for networked microgrids, aiming to minimize the system operation cost. The mean–variance Markowitz theory is employed to assess the risk of operation cost variability due to the presence of uncertainties. In the second stage (5-min time scale), the components in microgrids are optimally adjusted to minimize the imbalance cost between day-ahead and real-time markets. Simulation study is conducted on an uncoordinated microgrids system as well as on the proposed networked system. According to the simulation results, the proposed method can identify optimal scheduling results, reduce operation costs of risk-aversion, and mitigate the impact of uncertainties.

1. Introduction

Heightened concerns about energy resource limits, climate change, as well as increasing energy prices, has led countries to increased integration of renewable energy sources (RESs) into modern power systems, primarily in the form of solar photovoltaic panels and wind turbines [1]. A transition from fossil-based and non-renewable fuels to renewable and sustainable energy is occurring around the world [2]. By the end of 2017, the global installed renewable capacity has reached 2180 GW, with solar capacity being around 390 GW and wind power capacity over 500 GW [3] In such a situation, microgrids (MGs), a cluster of various distributed generators, energy storage systems, loads and other onsite electric components, are emerging as an effective way to integrate the RESs in distribution networks and satisfy the end-user demands [4]. Microgrids have a critical role to play in transforming the existing power grid to a future smart grid, which usually operate in grid-connected modes to maximize benefits, and can also operate in islanded modes for enhancing system reliability in grid outage periods [5]. Multiple microgrids can be connected to form a networked system. Compared with the traditional individual microgrid, networked microgrids possess the capability of decreasing the network operation cost in grid-connected modes and reducing the amount of load shedding in islanded modes [6].

Energy management system (EMS) is used for optimally scheduling power resources and energy storage systems in microgrids to maintain supply-demand balance [4]. Numerous studies have examined the

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Nomenclature

Abbreviations

BESS battery energy storage system
CDG controllable distributed generator
DSO distribution system operator
EMS energy management system
MG microgrid
MGC microgrid community
RES renewable energy sources
SOC state of charge
VaR value-at-risk

Indices

t index of time (t = 1, 2, …, T)
i index of microgrid (i = 1, 2, …, I)
C index of microgrid community
k index of scenario (k = 1, 2, …, Ω_K)
$(\hat{\bullet})$ index of variables in real-time market

Parameters

a^{CG}/b^{CG} cost coefficients of CDG
a^{CL}/b^{CL} cost coefficients of controllable load
C_t^{CG} operation cost of CDG
C_t^{ES} operation cost of BESS
C_t^{CL} the cost of controllable load
C_{it}^{M} exchanged power cost of the ith microgrid
$C_t^{C,M}$ Cost of exchanged power in MGC
E_R^{ES} rated capacity of BESS
E_t^{ES} stored energy in BESS at time t
IC^{ES} investment cost of BESS
LCN BESS total life cycle number
$\eta^{ES,Dis}/\eta^{ES,Chr}$ BESS discharging/charging efficiencies
$\underline{P}^{CG}/\overline{P}^{CG}$ lower/upper limits of CDG power output
P_t^L electricity load
P_{it}^{RES} forecasted renewable power
$\overline{P}^{ES,Dis}/\overline{P}^{ES,Chr}$ upper limits of BESS discharging/charging power
$\underline{P}_i^M/\overline{P}_i^M$ lower/upper limits of exchanged power
$\underline{P}^{Exch}/\overline{P}^{Exch}$ lower/upper limits of interconnection exchange between a MGC and distribution network
ρ_{it} price of exchanged power at time t
ρ_t^C price of exchanged power between MGC and the distribution network
$Ramp_{CG}^{Up}/Ramp_{CG}^{Up}$ ramping up/down limits of CDG
$\underline{SOC}/\overline{SOC}$ lower/upper limits of state of charge
$SUC_{it}^{CG}/SDC_{it}^{CG}$ Start-up/shut-down costs of CDG
γ^{ES} battery lifetime depression coefficient
$\underline{\varsigma}/\overline{\varsigma}$ minimum/maximum ratio of controllable load

Variables

P_t^{CG} CDG power output
$P_t^{ES,Dis}/P_t^{ES,Chr}$ BESS discharging/charging power
P_t^{CL} the amount of controllable load
P_{it}^{M} exchanged power of the ith microgrid
$P_t^{C,M}$ exchanged power amount between MGC and the distribution network
χ_t^{CG} commitment status indicator of a CDG
$\chi_t^{ES,Dis}/\chi_t^{ES,Chr}$ BESS discharging/charging indicator
χ_t^{SU} / χ_t^{SD} start-up/shut-down indicator of a CDG

intelligent energy management of networked microgrids, which can be categorized into centralized EMS, decentralized EMS, and hybrid EMS based on the architecture. For instance, Olivares et al. present a centralized EMS for isolated microgrids, which use model predictive control technique to allow a proper dispatch of the energy storage units [7]. Wang et al. propose a decentralized energy management system for the coordinated operation of networked microgrids in a distribution system, which aim to minimize the operation cost in the grid-connected mode and maintain a reliable power supply in the island mode [8]. Wang and Mao investigate a hierarchical power scheduling approach to optimally manage power trading, storage, and distribution in a smart grid composed of a macrogrid and cooperative microgrids [9]. The merits and demerits of the three prevailing EMSs have been compared and summarized in [10].

Alternately, considering the increasing penetration of RESs, new challenges have been imposed on the scheduling of microgrids. RESs (i.e. solar and wind power) are intermittent and stochastic, which highly depend on environmental factors like solar irradiance and wind speed. Due to the uncertainty of renewable energy resources, uncertainty management in scheduling of MGs has become an active research area recent years. Commonly adopted methods in the literature for MGs uncertainty management are robust optimization [11–14] and stochastic optimization techniques [15,16]. Kuznetsova et al. present a robust optimization based optimal energy management strategy to improve system operation performance [11]. In [12], Gupta develops a robust optimization approach to accommodate wind power uncertainty and achieve cost minimization in MGs. In [13], a robust optimization approach is proposed to optimally operate MGs. By collaboratively scheduling energy storage and direct load control, the uncertain outputs of RESs are addressed. By reviewing the literature, it can be found that most works on MGs scheduling by robust optimization method focus on single microgrid operation. However, the form of networked MGs is emerging given its unprecedented benefits, which requires the optimal operation of MGs with uncertainty management taken into account. Under this circumstance, Hussain et al. design a robust optimization based scheduling method for multi-microgrids considering uncertainties in RESs and forecasted electric loads [14].

Stochastic optimization has also been widely used in the planning, operation, and control of MGs. Liang and Zhuang [15] present a detailed survey about stochastic modeling and optimization in a microgrid. In this survey, the key features of MGs are investigated and a comprehensive review on stochastic modeling and optimization tools for MGs is provided. In [16], a multi time-scale and multi energy-type coordinated microgrid scheduling solution is proposed. In the day-ahead scheduling model, the uncertainties of RESs are represented by multiple scenarios and the EMS objective is to minimize the microgrid operation cost. In a real-time dispatch model, the fluctuations of RESs are smoothed out by cooling loads and electrical energy. The prominent defects of applying stochastic optimization on MGs uncertainty management are the high computational requirements when the number of scenarios increases, as well as only providing probabilistic guarantees for constraint satisfaction [5]. In contrast, robust optimization is immune against all possible realizations of uncertain data within the uncertainty sets. However, shortcomings also exist in this method. Through optimizing the worst-case scenario, robust optimization approaches could result in over-conservative results in MGs operation [14].

Review of the literature has identified that some issues remain open in the scheduling and dispatching of MGs. In [11–13,16], the uncertainty management is conducted in an individual microgrid without realizing the emerging trends of networked MGs; and in others, although the uncertainty of RESs are considered in networked MGs, the authors only include it in day-ahead scheduling [14], but ignore RESs dynamic fluctuations in real-time operation. As for the uncertainties in MGs, most of the researchers only consider RESs output uncertainty and electric load uncertainty, and neglect the uncertainty in forecasted day-ahead electricity prices. Moreover, although stochastic optimization has been widely used in MGs energy management, to the best of the authors' knowledge, no researchers have carried out in-depth analysis of risks as well as their impacts on the scheduling and dispatch of networked MGs. Farzan et al. develop stochastic programming optimization models to optimally schedule MGs under uncertainty with risk neutral and risk averse options. Nevertheless, they only focus on the individual microgrid, without conducting risk analysis on networked microgrids.

Given no previous research have considered the above concerns in one work before, a comprehensive research on the noted issues is necessary for the economic and stable operation of networked MGs To close this research gap, this work is focused on developing a two-stage energy management strategy for networked microgrids under high penetration of RESs. Compared with previous microgrid scheduling and dispatching approaches, the distinguished features of the proposed method in this paper are summarized as follows:

(1) A hybrid energy management strategy is adopted for multi MGs. The individual microgrid is networked and regulated by a microgrid community (MGC) for enhancing the capability to accommodate the RESs fluctuations and improving layered privacy.
(2) Based on the mean-variance Markowitz theory [17], a risk component is introduced into the optimal energy management of a MGC to estimate profit. The risk-based decision making could greatly influence the scheduling and dispatching results in MGs.
(3) A two-stage senergy management strategy is proposed for networked microgrids considering the uncertainties of RESs outputs, electricity load and day-ahead prices. The operation costs are minimized in day-ahead scheduling control based on a hierarchical optimization method. The dynamic fluctuations of RESs and volatility of electricity load are smoothed out in the real-time dispatching stage.

The remainder of this paper is organized as follows. Section 2 presents the problem description. Section 3 introduces the components modeling. Section 4 provides the mathematical formulation of optimal networked MGs operation. Section 5 describes the numerical simulations to demonstrate the effectiveness of the proposed approach. Section 6 concludes the paper and suggests future research challenges.

2. Problem description

In this section, the problem is briefly described, which includes the components and configuration of networked MGs, and the proposed operational strategy in this paper.

2.1. Components and configuration of networked MGs

The basic components of a microgrid consist of RESs (i.e. photovoltaics system and wind turbine), controllable distributed generators (CDGs), battery energy storage systems (BESSs), and electric loads (i.e. both controllable and non-controllable loads). RESs are able to generate clean and sustainable energy; CDGs, such as micro turbines, can provide stable energy to meet MGs energy demand. BESSs can shift energy to alleviate energy management difficulties through adjusting charging/discharging status; the controllable part in electric loads can help maintain power balance through demand response programs. From the perspective of a microgrid, the general objective in grid connected mode is to minimize the operation cost or maximize the total benefit under certain operational constraints.

In practical scenarios, some geographically adjacent microgrids need to be coordinated controlled as a whole for certain goals, such as economy and reliability [18]. The rapid development of microgrids also leads to the emergence of microgrid community. In view of the merits and promising applications of MGC in recent years [19], the microgrids in this paper are networked under the regulation of MGC. As shown in Fig. 1, the individual MGs are connected in the MGC with close interaction among each other. Microgrids in MGC belong to different owners and may have different operation goals. A MGC consists of several microgrids and microgrid community level devices, including community distribution generation units and community BESS. Compared with an individual microgrid, a MGC has to consider the topology for interconnecting microgrid and has more levels of control to efficiently manage microgrids and community level devices. The distinct features and benefits of a MGC have been detailed in [19]. Note that the energy management in the MGC is achieved in a hybrid way, with better performances than completely decentralized control and centralized control. According to [10], the hybrid EMS is emerging as a trade-off between centralized EMSs and decentralized EMSs. It has better flexibility compared with centralized EMSs and lesser operation cost compared with decentralized EMSs.

2.2. Proposed strategy

In this paper, a two-stage energy management strategy is proposed for networked microgrids with high renewable penetration. The overall objective aims to minimize the operation cost of networked microgrids in grid connected modes and predefine the revenue risk into a certain level.

At the first stage, a day-ahead hourly scheduling is formulated for networked microgrids. In this stage, a hierarchical optimization strategy is adopted for the energy management of MGC. In the lower level, the optimization is focused on the individual microgrid and the objective is to minimize its operation cost. In this level, the problem is formulated as a deterministic issue without considering uncertainties in the microgrid. Through using the forecasted RESs output power, electrical load and electricity price, the lower level EMS determines the commitment status of CDGs, charging/discharging status of BESSs, and the shift or curtailment of controllable loads. Moreover, the exchanged power between the microgrid and MGC will be determined.

The upper level is to minimize the operation costs of the entire MGC with revenue risk considered. The uncertainties of each microgrid are collectively considered in the energy scheduling of microgrid community. Uncertainties including renewable resources and loads in individual microgrid are broadcast to microgrid community via information flow channels, and further incorporated into the risk control of networked microgrids. In addition, the uncertainties of electricity prices are taken into account at this level. The upper level EMS makes decisions about the power schedules of community level devices and the exchanged power with the utility grid.

At the second stage, a real-time dispatch is executed to balance the dynamic random fluctuations of renewables and load at 5 min temporal resolution. The real-time dispatch is required to minimize the imbalance cost considering the deviation between the day-ahead electricity and real-time electricity markets. A rolling horizon optimization strategy is employed in this stage for online optimization to enhance the control accuracy. The detailed procedures in each stage and their mathematical modelling are described in Section 4.

3. Components modeling

In this section, the modeling of various components in microgrids is given first, followed by the modeling of uncertainties and electricity market.

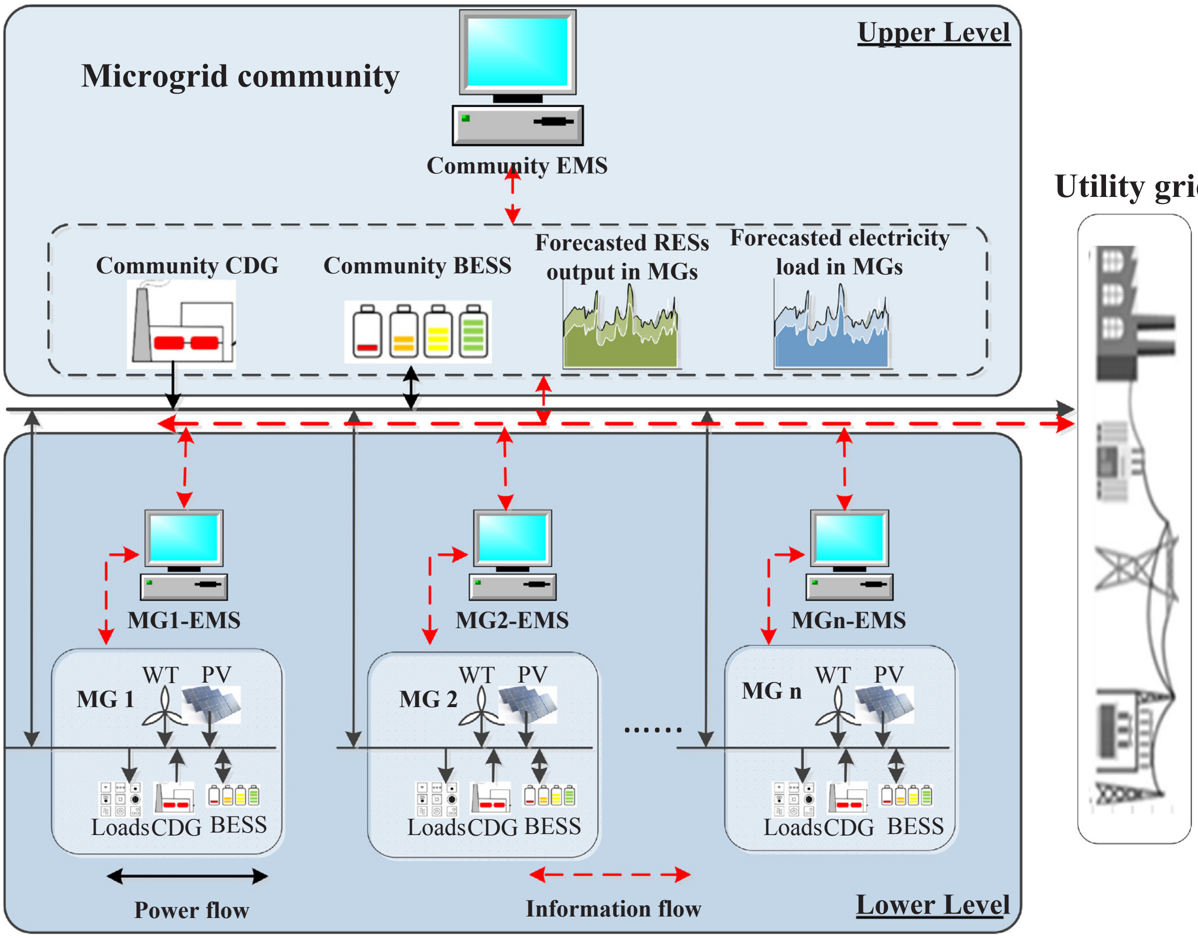

Fig. 1. The structure of networked microgrids.

3.1. Cdgs

CDGs are flexible components in a microgrid, which may refer to micro turbines, fuel cells, diesel generators, and other types of generation devices. In this paper, we use micro turbines to represent CDGs, whose fuel cost can be formulated as a linear function [12]:

$$C_t^{CG} = \chi_t^{CG} a^{CG} + b^{CG} P_t^{CG} \tag{1}$$

For other types of CDGs, such as diesel generators and gas-fired power generators, the fuel cost can be formulated as a quadratic function, which can be further approximated using piecewise linear functions.

The operation of a CDG should satisfy the following ramp rate limits and power constraints at each time period at each MG:

$$\underline{P}^{CG}\chi_t^{CG} \leqslant P_t^{CG} \leqslant \overline{P}^{CG}\chi_t^{CG};\quad \chi_t^{CG} \in \{0, 1\} \tag{2}$$

$$\begin{cases} P_t^{CG} - P_{t-1}^{CG} \leqslant Ramp_{CG}^{Up} \\ P_{t-1}^{CG} - P_t^{CG} \leqslant Ramp_{CG}^{Down} \end{cases} \tag{3}$$

$$\chi_t^{SU} + \chi_t^{SD} \leqslant 1;\quad \chi_t^{SU}, \chi_t^{SD} \in \{0, 1\} \tag{4}$$

$$\chi_t^{CG} - \chi_{t-1}^{CG} \leqslant \chi_t^{SU} - \chi_t^{SD} \tag{5}$$

where χ_t^{SU}, χ_t^{SD} are the start-up, shut-down indicator of a CDG (1 means it is in operation and 0 means it is not). Eq. (2) is the power constraints, Eq. (3) is the ramp rate limits, Eq. (4) shows that a CDG cannot be started up and shut down simultaneously at any time, Eq. (5) shows the relationship between the start-up indicator and shut-down indicator.

3.2. Besss

According to [20], the operation cost of BESSs usually refers to the maintenance cost, which can be formulated as a linear function as:

$$C_t^{ES} = \gamma^{ES} P_t^{ES,Dis} \Delta t + \gamma^{ES} E_t^{ES} \Delta t + \gamma^{ES} P_t^{ES,Chr} \Delta t \tag{6}$$

where, Δt is the time duration for converting power to energy. γ^{ES} is calculated as [20]:

$$\gamma^{ES} = \frac{IC^{ES}}{E_R^{ES} \cdot (LCN)} \tag{7}$$

BESSs should meet the following constraints during their operation:

$$E_{t+1}^{ES} = E_t^{ES} - P_t^{ES,Dis} \Delta t / \eta^{ES,Dis} + P_t^{ES,Chr} \Delta t \eta^{ES,Chr} \tag{8}$$

$$SOC_t = E_t^{ES} / E_R^{ES} \tag{9}$$

$$\underline{SOC} \leqslant SOC_t \leqslant \overline{SOC} \tag{10}$$

$$\begin{cases} 0 \leqslant P_t^{ES,Dis} \leqslant \chi_t^{ES,Dis} \overline{P}^{ES,Dis} \\ 0 \leqslant P_t^{ES,Chr} \leqslant \chi_t^{ES,Chr} \overline{P}^{ES,Chr} \end{cases} \tag{11}$$

$$\chi_t^{ES,Dis} + \chi_t^{ES,Chr} \leqslant 1;\quad \chi_t^{ES,Dis}, \chi_t^{ES,Chr} \in \{0, 1\} \tag{12}$$

$$E_t^{ES} = E_{INIT}^{ES}\, if \quad t = 1 \tag{13}$$

where, SOC_t is BESS state of charge (SOC) at time t; E_{INIT}^{ES} is the initial stored energy in a BESS. Eq. (8) shows BESS capacity change, which includes net energy injection and energy losses during charging/discharging process. Eqs. (9) and (10) define the BESS state of charge constraints. Eq. (11) limits BESS charging/discharging power capacity.

Eq. (12) means that a BESS cannot operate in charging mode and discharging mode simultaneously. Eq. (13) shows the initial energy stored in a BESS.

3.3. Controllable load

Demand response programs are considered in the EMS strategy for adjusting the peak load demand. The controllable load cost is assumed to be a function of controllable load amount and can be represented by a linear function given in [21]:

$$C_t^{CL} = a^{CL} + b^{CL} P_t^{CL} \tag{14}$$

The maximum ratio of controllable load is constrained by:

$$\underline{\varsigma} P_t^L \leqslant P_t^{CL} \leqslant \bar{\varsigma} P_t^L \tag{15}$$

3.4. Uncertain sets of RESs, load, and electricity prices

In this paper, RESs output, electricity load, and electricity price are regarded as uncertainties. The historical data in day-ahead market are used as correlated scenarios, hence allowing the correlated probability distributions to be estimated based on the statistical correlations among these uncertainties. Time-series-based methods, such as autoregressive integrated moving average model, are adopted here to generate correlated scenarios [22]. Wind power and solar power forecast errors can be modelled by the Beta distribution [23]:

$$f(\Delta P^{RES};\lambda_1,\lambda_2) = \Delta P^{RES\lambda_1 - 1}(1-\Delta P^{RES})^{\lambda_2 - 1} N \tag{16}$$

where, ΔP^{RES} is RESs output forecast error; λ_1, λ_2 are the Beta distribution shape parameters; N is the normalization error. Electricity price and load forecast errors can be modelled by the Gaussian distribution [20]:

$$f(\Delta x;\mu_x,\sigma_x^2) = \frac{1}{\sqrt{2\pi\sigma_x^2}} \exp\left[\frac{(\Delta x - \mu_x)^2}{2\sigma_x^2}\right] \tag{17}$$

where, Δx is electricity price or load forecast error; μ_x, σ_x^2 are the mean and standard deviation.

3.5. Market model

In a MGC system, power transactions are conducted between microgrids and MGC, MGC and the distribution system operator. Two different electricity price mechanisms are set among microgrids, MGC and distribution system operator. In the view of distribution system operator, MGC is regarded as a price-taker, meaning that the electricity price between MGC and distribution system operator will not be influenced by the scheduling strategy and be determined by the electricity market. The market price is uncertain and denoted by the above mentioned electricity price uncertain set. As for the electricity strike price between MGC and microgrids, the bilateral contract is built to reflect market participation. The market bidding strategies include many complex economic problems and are settled based on electricity generation, electricity load, and time-of-use electricity prices. The detailed steps for making the bilateral contract can be found in [19], which are not detailed here.

4. Proposed two-stage operation model

This section describes the mathematical formulation of the proposed two-stage operation model. The first stage is an hourly day-ahead optimal scheduling model, and the second stage is 5-min real-time dispatch model.

4.1. Hourly day-ahead optimal scheduling model

In this stage, considering the hierarchical control structure of a MGC, the hourly day-ahead scheduling is conducted by a two-level hierarchical control for the EMSs. The control structure is composed of the lower level microgrid energy management and the upper level MGC energy management, which is described below.

4.1.1. Lower level EMS

Objective function: The objective of the lower level EMS is to minimize the operation cost of individual microgrids in the MGC while satisfying some equality and inequality constraints, as shown below:

$$\min f_1 = \sum_{t=1}^{T} \begin{bmatrix} (C_{it}^{CG} + SUC_{it}^{CG}\chi_{it}^{SU} + SDC_{it}^{CG}\chi_{it}^{SD}) + \\ C_{it}^{ES} + C_{it}^{CL} + C_{it}^{M} \end{bmatrix} \tag{18}$$

The objective function in the individual microgrid is in a similar form with previous research [8,19], which is composed of four terms: the fuel consumption cost, the BESS operation cost, the controllable load cost, and the exchanged power cost. Notably, the fuel consumption cost includes the generation, startup, and shutdown costs of CDG.

The exchanged power cost of the ith microgrid is calculated as:

$$C_{it}^{M} = \rho_{it} P_{it}^{M} \tag{19}$$

where ρ_{it} is the price of exchanged power at time t, which can be derived from the bilateral contract. It is worth noting that when $P_{it}^M > 0$, P_{it}^M refers to the surplus power and ρ_{it} refers to the selling price; when $P_{it}^M < 0$, P_{it}^M refers to the power shortfall and ρ_{it} refers to the buying price.

The calculation of P_{it}^M is defined as:

$$P_{it}^{M} = P_{it}^{CG} + P_{it}^{ES,Chr} - P_{it}^{ES,Dis} + P_{it}^{RES} + P_{it}^{CL} - P_{it}^{L} \tag{20}$$

Constraints: To guarantee the stable operation of the MG, some equality and inequality constraints should be met.

(1) Power balance constraints:

For each MG, the total power generation from local sources and BESS should equal to the local demand and exchanged power with other MGs.

$$P_{it}^{CG} + P_{it}^{ES,Chr} - P_{it}^{ES,Dis} + P_{it}^{RES} = P_{it}^{M} + P_{it}^{L} - P_{it}^{CL} \tag{21}$$

(2) CDG constraints:

The operation of a CDG is limited in (2)–(5).

(3) BESS constraints:

The operational constraints of a BESS are specified in (8)–(13).

(4) Controllable load constraints:

The controllable load amount is constrained by the minimum and maximum ratios defined in (15).

(5) Exchanged power constraints:

The exchanged power should be constrained by:

$$\underline{P_i^M} \leqslant P_{it}^{M} \leqslant \overline{P_i^M} \tag{22}$$

After the optimization, the lower level EMS can decide the unit start-up/shut-down schedule of CDGs, charging/discharging status of BESS, shift or curtailment amount of controllable load, and the exchanged power at each time interval.

4.1.2. Upper level EMS

Objective Function: Similarly, the objective of the upper level EMS is to minimize the operation cost of a MGC by running a global optimization. In the meantime, given the uncertainties in the whole system, a risk control measure is introduced.

$$\min f_2 = \sum_{t=1}^{T} \begin{pmatrix} (C_t^{C,CG} + SUC_t^{C,CG}\chi_t^{C,SU} + SDC_t^{C,CG}\chi_t^{C,SD}) \\ + C_t^{C,ES} + C_t^{C,M} \end{pmatrix} \tag{23}$$

where C represents MG community. In the upper level objective function, there are three terms: the MG community fuel consumption cost, community BESS operation cost, and the cost of exchanged power with distribution system operator. Specially, the definitions of $C_t^{C,M}$ and $P_t^{C,M}$ are given by:

$$C_t^{C,M} = \rho_t^C P_t^{C,M} \tag{24}$$

$$P_t^{C,M} = P_t^{C,CG} + P_t^{C,ES} + \sum_{i=1}^{I} P_{it}^{RES} + \sum_{i=1}^{I} P_{it}^{M} - \sum_{i=1}^{I} (P_{it}^{L} - P_{it}^{CL}) \tag{25}$$

The uncertainties of RESs forecasting and electricity load forecasting in microgrids are combined managed in MGC, as observed in (25).

Given the uncertainties in the whole system, we formulate (23) into a probabilistic version to mitigate risky decision making. In addition, to improve the computational efficiency, the initial large set of scenarios is trimmed to a small number of representative scenarios. In this paper, an efficient scenarios reduction technique, i.e. backward method [23], is adopted to approximate the original scenario set. The risk associated with the cost variability is explicitly captured in the model through the mean-variance Markowitz theory [17]. Eq. (23) can be rewritten in a probabilistic version as:

$$\min E[O_1] + \varpi \cdot \sigma_{O_1} \tag{26}$$

where $E[O_1]$ is the expected operation cost, σ_{O_1} is the standard deviation, $\varpi \in [0, +\infty]$ is the weighting factor for the inclusion of risk in the objective function. It should be noted that the higher the value of ϖ, the more risk averse. When $\varpi = 0$, the strategy is risk neutral. The calculations of $E[O_1]$ and σ_{O_1} are given by:

$$E[O_1] = \sum_{k \in \Omega_K} \mathrm{Pr}_k \cdot f_{2k} \tag{27}$$

$$\sigma_{O_1}^2 = E[O_1^2] - E^2[O_1] = \sum_{k \in \Omega_K} \mathrm{Pr}_k \cdot f_{2k}^2 - \left(\sum_{k \in \Omega_K} \mathrm{Pr}_k \cdot f_{2k} \right)^2 \tag{28}$$

where Pr_k is the probability of scenario k, f_{2k} refers to the cost function f_2 under scenario k, Ω_K is the set of reduced representative scenarios. The linearization of quadratic function in (28) has been widely investigated in the literature [24–26], therefore it is not detailed here.

Constraints: In each scenario k, some equality and inequality constraints should be met for the stable operation of a MGC. The CDG constraints and BESS constraints are the same with the lower level EMS, i.e. (2)–(5), (8)–(13). The different parts with the lower level EMS are given below:

1) Power balance constraints:

$$P_{tk}^{C,CG} + P_{tk}^{C,ES} + \sum_{i=1}^{I} P_{itk}^{RES} = P_{tk}^{C,M} - \sum_{i=1}^{I} P_{itk}^{M} + \sum_{i=1}^{I} (P_{itk}^{L} - P_{itk}^{CL}) \tag{29}$$

2) Exchanged power constraints:

$$\underline{P}^{Exch} \leqslant P_{tk}^{C,M} \leqslant \overline{P}^{Exch} \tag{30}$$

After performing the global optimization, the upper level EMS can decide the unit commitment of community CDGs, charging/discharging status of community BESSs, and the power exchange amount with the distribution network.

4.2. 5-minute real-time dispatch model

In real-time dispatch, the dynamic fluctuations of RESs and the volatility of electricity demand are accommodated in the operation of microgrids. Note that the real-time dispatch interval could be any short uniform time interval (e.g. 15-min interval and 5-min interval). In this paper, the proposed dispatching interval is assumed to be 5 min. For real-time electricity dispatch, a rolling horizon optimization strategy is employed to derive a more accurate value [16]. In rolling horizon optimization scheme, the model inputs are updated at each time step. And at each time step, the model is optimized, with the schedule results derived for all the remaining intervals. Under this circumstance, the schedules in the first interval are mandatory, while the other intervals are only used as references. At the next time step, the control window is moved forward, updating the model inputs and repeating the above procedures until the end of time horizon [27]. As the time scale is 5 min, the time window of the dispatch covers 288 intervals (i.e. 24 h).

In this stage, the objective is to minimize the imbalance cost owing to the deviation between the first stage day-ahead electricity market and the second stage real-time electricity market, defined in a similar form as [28]:

$$\min f_3 = \sum_{t=1}^{NT} (C_t^{C,M} - \hat{C}_t^{C,M}) \tag{31}$$

where NT is the total number of dispatch intervals in the real-time market; $\hat{P}_t^{C,M}$ is the real-time dispatched power; $\hat{C}_t^{C,M}$ is the cost of exchanged power in real-time market. Note that $(\hat{\cdot})$ is used to denote the variables in real-time market. The calculation of $\hat{C}_t^{C,M}$ is given in (32), (33):

$$\hat{C}_t^{C,M} = \hat{\rho}_t^{C} \cdot \hat{P}_t^{C,M} \tag{32}$$

$$\hat{P}_t^{C,M} = \hat{P}_t^{C,CG} + \hat{P}_t^{C,ES} + \sum_{i=1}^{I} \hat{P}_{it}^{RES} + \sum_{i=1}^{I} \hat{P}_{it}^{M} - \sum_{i=1}^{I} (\hat{P}_{it}^{L} - \hat{P}_{it}^{CL}) \tag{33}$$

The complete constraints of (31) include (2), (5), (8)–(13), and (15). In real-time dispatch, slight imbalances in each interval can be handled by automatic generation control or emergency demand response (i.e., instantaneous control).

The step-by-step procedure for carrying out the whole optimization is summarized in Fig. 2. The formulated problems are based on mixed integer linear programming, which can be easily implemented through commercial software like CPLEX and academic software like MATLAB.

5. Case studies

5.1. Set up

The proposed approach is tested on an artificial situation, which is based on a modified MGC system composed of three MGs in [29]. The system configuration is denoted in Fig. 1 as well, specifying the power flow and information flow direction. By verifying the proposed method in an academic microgrid community, it could verify the feasibility of applying the approach into more complex real microgrid community applications in future. For instance, a university can be regarded as a microgrid community connected to a low voltage grid. Hospitals, student apartments, dining rooms, etc., equipped with renewable resources, BESSs, and CDGs can be taken as geographically adjacent microgrids in the microgrid community.

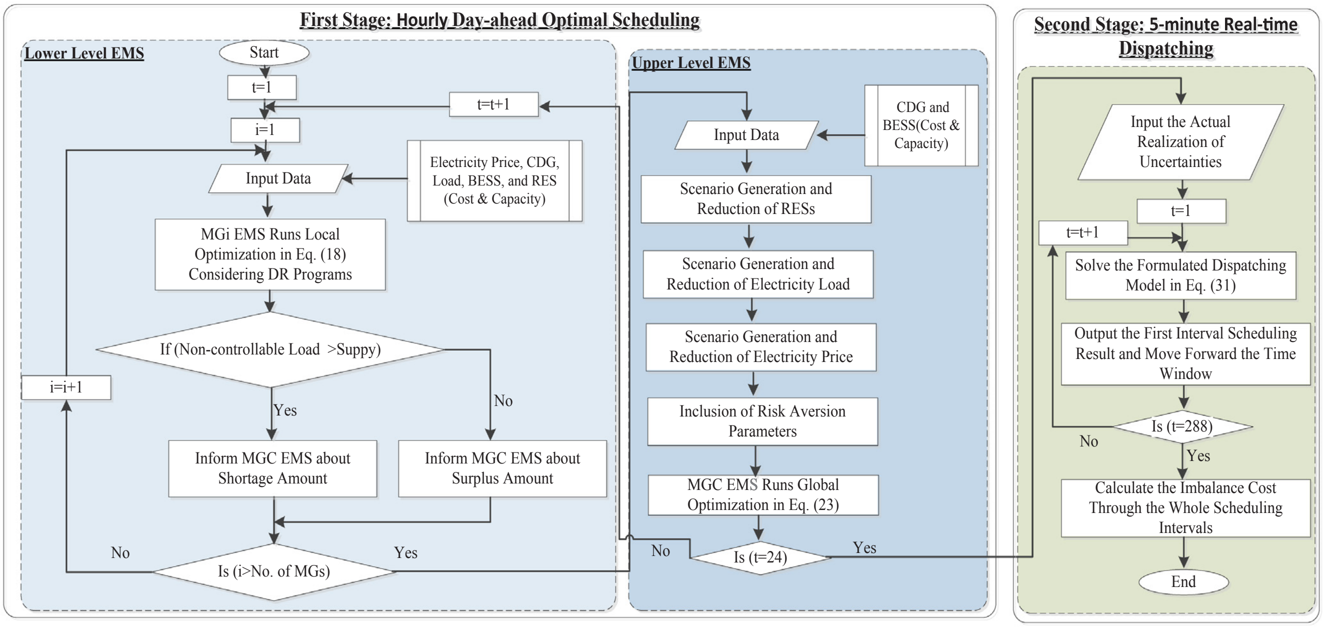

Fig. 2. Flowchart of proposed multi-time scale energy management strategy.

Table 1
Parameters of CDGs in each microgrid and MGC [31].

Parameters	Controllable distributed generators			
	MG1	MG2	MG3	MGC
a^{CG}, b^{CG} ($/kWh)	0.30, 0.05	0.22, 0.03	0.43, 0.04	0.31, 0.06
$\underline{P}^{CG}$, $\overline{P}^{CG}$ (kW)	0, 200	0, 180	0, 160	0, 500
$Ramp^{Up}_{CG}$, $Ramp^{Down}_{CG}$ (kW/h)	80, 85	75, 75	70, 80	220, 230
SUC^{CG}, SDC^{CG} ($)	0.32, 0.15	0.34, 0.18	0.35, 0.15	0.30, 0.20

The load in microgrids mainly includes domestic appliances, lighting load, air-conditioning load in the buildings, and system devices, such as SCADA device and server. It is assumed that controllable load, such as thermostatically controlled load, exists in every microgrid and the minimum/maximum ratios are set to be 0 and 20%. The cost coefficients of controllable load a^{CL}, b^{CL} are set as $0.33/kWh and $0.05 based on the information provided in [21]. The lower and upper limits for exchanged power capacity in the MG are ± 500 kW, and the values are ± 1500 kW in the MGC. The parameters related to CDGs of each microgrid and MGC are tabulated in Table 1. BESS parameters in microgrids and MGC are shown in Table 2. The simulation is coded on a 64-bit PC with 2.40 GHz processor and 8 GB RAM using MOSEK toolbox [30] in MATLAB platform.

Table 2
Parameters of BESSs in each microgrid and MGC [32].

Parameters	Battery energy storage systems			
	MG1	MG2	MG3	MGC
IC^{ES} ($), LCN (times)	80 E_R^{ES}, 2000	80 E_R^{ES}, 2000	80 E_R^{ES}, 2000	80 E_R^{ES}, 2000
E_R^{ES}, E_{INIT}^{ES} (kWh)	200, 50	180, 40	220, 60	420, 150
$\overline{P}^{ES,Dis}$, $\overline{P}^{ES,Chr}$ (kW)	150	125	160	200
$\underline{SOC}$, $\overline{SOC}$	20%,80%	20%,80%	20%,80%	20%,80%
$\eta^{ES,Dis}$, $\eta^{ES,Chr}$	0.95, 0.97	0.98, 0.96	0.95, 0.95	0.98, 0.95

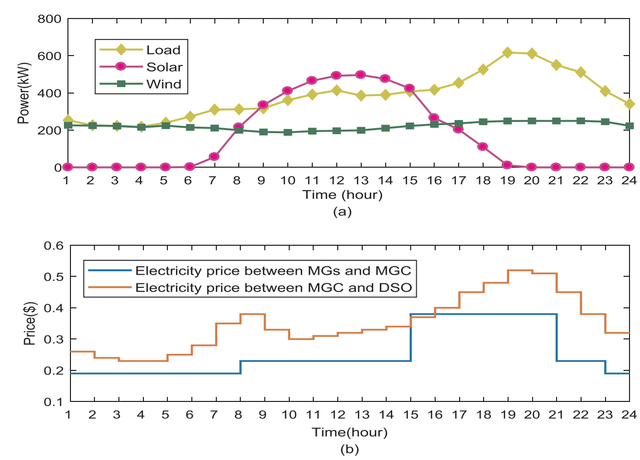

Fig. 3. Day-ahead forecasted profiles (a) forecasted electricity load and RESs generation (b) forecasted electricity prices.

Fig. 3 denotes the day-ahead forecasted electricity load, RESs generation, and electricity prices over 24 h on a typical day, which is based on data from the Australian Energy Market Operator [33]. Notably, in Fig. 3(a), the electricity load and RESs generation refer to the cumulative value in three microgrids. As clearly observed from Fig. 3(a), there is energy surplus during the daytime and energy shortage during night-time periods. For Fig. 3(b), the electricity price between microgrids and the MGC is determined by the bilateral contract, which is a fixed value even in the real-time market. As for the electricity price between the MGC and the distribution network operator (DSO), the value is forecasted and uncertain in the real-time market.

5.2. Results and discussion

To verify the effectiveness of the proposed approach, two cases are compared: (i) **Case 1**: An uncoordinated operation strategy. The individual microgrid operates strategically as the price-taker in the electricity market, aiming to minimize their operation costs. The system total operation cost is the summation of individual's cost. The imbalance cost is calculated after the realization of scenarios. (ii) **Case 2**:

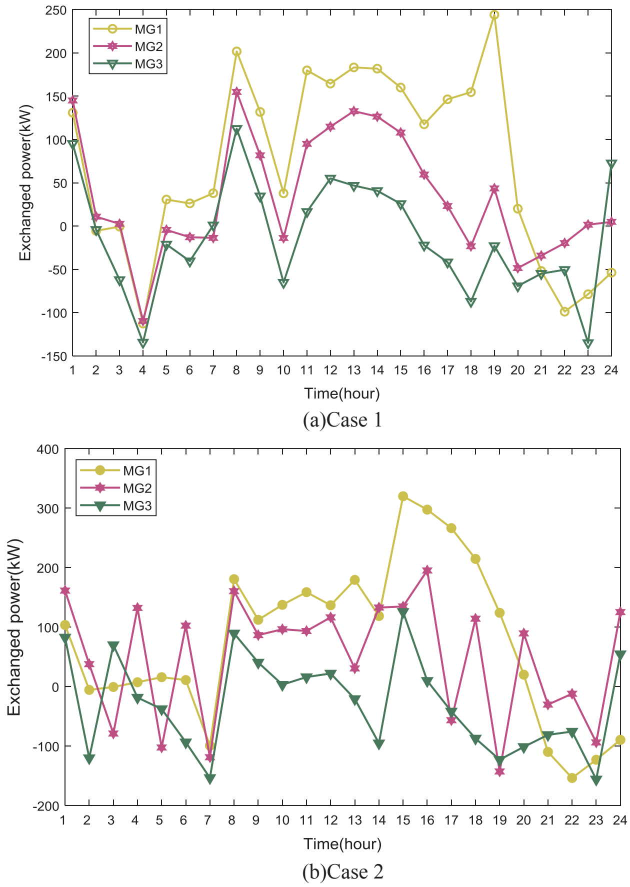

Fig. 4. Exchanged power results in microgrids in Case 1 and Case 2.

The proposed networked microgrids scheduling approach.

Fig. 4(a) demonstrates the exchanged power scheduling results in three microgrids in Case 1. The exchanged power schedules in coordinated mode are presented in Fig. 4(b). In uncoordinated mode, microgrids will exchange power directly with distribution system operator without the coordination of MGC. In the figure, a positive value means MGs have surplus energy and can sell it to the distribution system operator/MGC, while a negative value denotes that MGs have a shortfall and need to buy the corresponding amount with real-time electricity price externally. As observed, microgrids in Case 2 have more surplus energy over the whole periods. By trading power in the MGC, MGs can support each other with a lower operation cost. As shown in Fig. 4(b), MG1 and MG2 sells the surplus energy most of the time during the day, while MG3 needs to purchase energy at most periods.

By trial and error methods [20], the weighting factor ϖ is set to be 3.6 in this paper. The system operation cost distributions in day-ahead market is illustrated in Fig. 5, which includes uncoordinated microgrids overall operation cost distribution and networked microgrids operation cost distribution. In the proposed control scheme, after the local optimization, the exchanged power value is sent to the upper level as constraints for global optimization. For the upper level EMS, the correlated scenarios of electricity load, RESs outputs, and electricity prices are based on the day-ahead data. The mean operation cost in Case 2 is −$347.92 and the standard deviation is 93.35. In contrast, the mean operation cost in Case 1 is only −226.70 and the standard deviation is 97.14, which is higher than the standard deviation in Case 1. In addition, the Value-at-Risk (VaR) at the 95% confidence level is adopted for

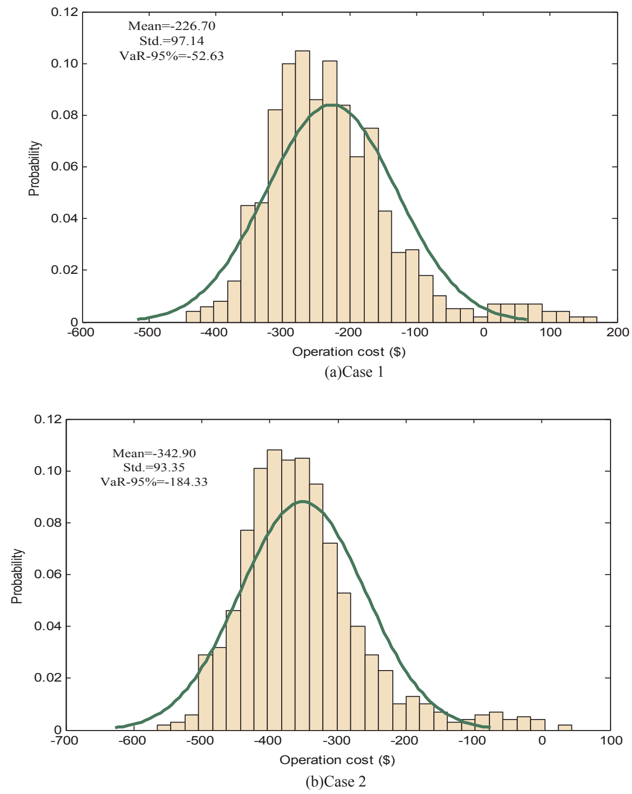

Fig. 5. Distributions of system operation cost in day-ahead market in Case 1 and Case 2.

evaluating the risk of different operation strategies. The VaR-95% means the expected value of the 5% scenarios with the lowest operation cost, which is −$184.33 in Case 2 and −$52.63 in Case 1.

The power scheduling results of the BESS, CDG and controllable load in both cases in day-ahead market are shown in Fig. 6. In both cases, the BESS works in charging mode when electricity prices are relatively lower (i.e. early morning and late afternoon). Instead, BESSs are discharging at morning and evening peak periods, when electricity prices are relatively higher. Therefore, the profits made by BESSs are derived from the differences between on-peak and off-peak periods. It can be observed that more controllable load and CDG are used in Case 2. This is because for networked microgrids operation, CDGs and controllable load are more frequently used to balance the power balance. Through the coordinated operation of various components of the microgrids, the total power production follows the load curve.

Fig. 7 illustrates the exchanged power between the system and the distribution system operator in deterministic day-ahead scheduling, risk-controlled day-ahead scheduling, and real-time dispatch under two cases. Due to the inclusion of risk hedging parameters in risk-controlled day-ahead scheduling, the deterministic scheduling has more surplus energy for selling and less shortage amount for purchasing in both cases. The deviations between real-time exchanged power and risk-controlled day-ahead exchanged power are caused by the dynamic fluctuations of RESs in real time, and the forecast errors in electricity load and electricity price. Compared to Case 1, the results in Case 2 have more surplus power to trade in the electricity market. Hence, more profits are expected via the proposed approach. The real-time community BESS state of charge status change is denoted in Fig. 7(b). Similarly to day-ahead results, the BESS charging/discharging status corresponds to the real-time electricity price change.

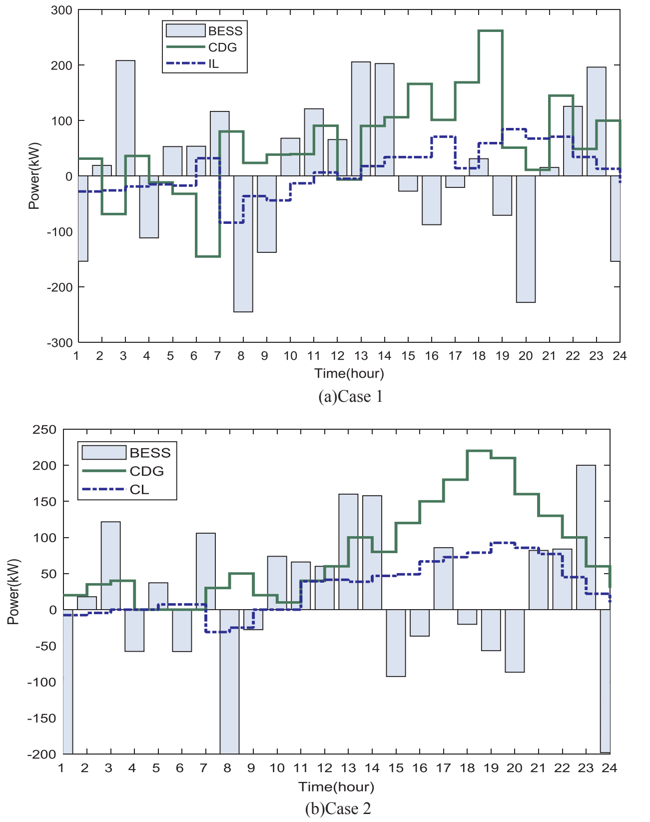

Fig. 6. (a) Summation of power scheduling of BESS, CDG, and controllable load in three microgrids (b) power scheduling of BESS, CDG, and controllable load in MGC.

The expected operation costs in the day-ahead and real-time markets for both cases are given in Tables 3 and 4. It can be found that the net operation cost in Case 1 is −$211.87 and the net operation cost in Case 2 is −$331.558. Therefore, more profits can be made by the proposed approach and the economic superiority is verified.

6. Conclusions and future research challenge

This paper proposes a two-stage, i.e. an hourly day-ahead scheduling and 5-min real-time dispatch, energy management strategy for networked MGs in the presence of high renewable penetration. In the day-ahead scheduling stage, a hybrid energy management system control method is adopted considering the hierarchical structure of networked microgrids The control objective is to minimize the operation cost on a daily basis and the operation cost variations are captured by incorporating mean-variance Markowitz theory into the objective function. Uncertainties on renewable energy resources output, electricity load, and electricity price are addressed in the first stage. In real-time dispatch stage, the objective is to minimize the imbalance cost given the deviations in the day-ahead and real-time markets. According to the simulation results, the proposed method identifies a techno-economic plan for network microgrids under the regulation of microgrid community as well as provides a risk-hedging strategy. Compared with previous research, it is advantageous in, (1) adopting a hybrid energy management system for networked microgrids with the presence of microgrid community; (2) in depth analyzing the risks of low profit scenarios by incorporating mean-variance Markowitz theory based risk factors; (3) comprehensively evaluating uncertainties in the operation system and mitigating dynamic fluctuations of renewable resources in real-time dispatch stage.

Considering current testing system is in an academic situation, future research can be done towards more complex practical systems. In

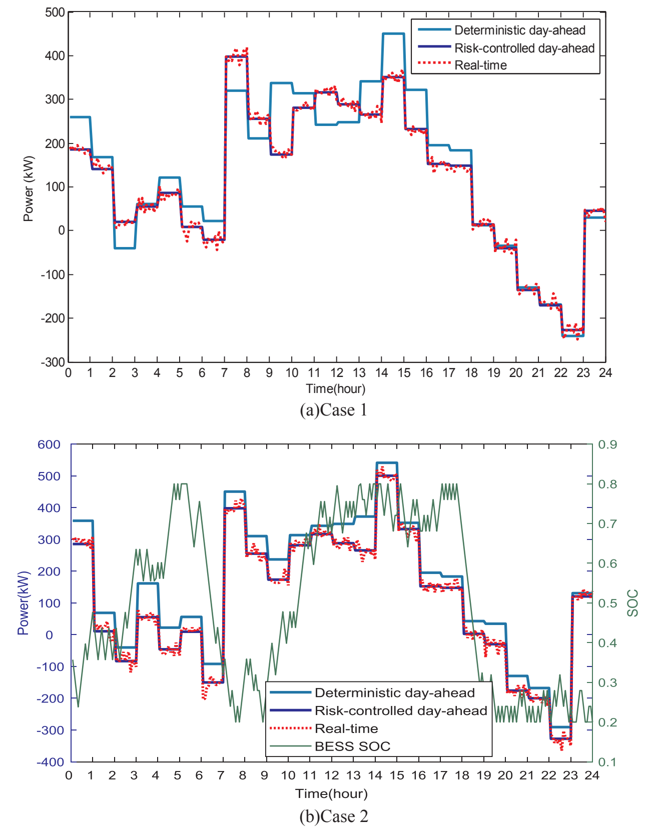

Fig. 7. (a) Summation of exchanged power in individual microgrids in day-ahead market and real-time market. (b) MGC exchanged power amount in day-ahead market and real-time market and community BESS state of charge change in real-time market.

Table 3
Operation cost for microgrids components in Case 1.

	CDG	BESS	Controllable load	Total
Expected operation cost ($)	−96.3683	−90.1748	−47.0369	−233.58
Imbalance cost ($)	2.5271	4.4124	14.7697	21.71
Net operation cost ($)	−93.8412	−85.7624	−32.2672	−211.87

Table 4
Operation cost for microgrids components in Case 2.

	CDG	BESS	Controllable load	Total
Expected operation cost ($)	−164.907	−98.8394	−89.6634	−353.41
Imbalance cost ($)	4.2996	1.1404	16.4120	21.85217
Net operation cost ($)	−160.608	−97.699	−73.2513	−331.558

addition, with more microgrids participating in the energy trading system, a blockchain based transactive energy platform can be designed to efficiently share resources in a peer-to-peer manner [34].

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