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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 ($k = 1, 2, \ldots, \Omega_K$)
$(\hat{\cdot})$	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