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RESEARCH PAPER

A Data-Driven Adjustable Robust Optimization Model for Energy Management of Networked Microgrids

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Abstract

Environmental pollution, rapid depletion of fossil fuels, and high energy losses during transmission-distribution are the main problems of traditional power grids. This motivates the development of microgrids (MGs), which are a localized network of fossil fuel and renewable generators, energy storage systems, and electrical loads. Due to the limited operational capacity of individual MGs, multiple adjacent MGs can be networked to form a cluster of interconnected MGs. This paper develops a robust energy management and scheduling model for the co-optimization of internal network operation inside MGs and external energy sharing between MGs. The uncertainty of renewable energy sources is handled by proposing a data-driven robust optimization model with a self-adaptive uncertainty set. This set is constructed by the kernel density estimation method based on the distributional information extracted from uncertainty data. To account for the multi-level and sequential decision-making process of scheduling, the energy management model is formulated as an adjustable robust optimization problem by incorporating wait-and-see decision variables. The results show that compared to conventional robust optimization models, the proposed model is more effective in dealing with uncertainty and can ensure the robustness of scheduling decisions at a lower cost.

Keywords:
Multiple microgrids; Data-driven optimization; Renewable energy; Energy trading; Robust optimization

Introduction

In traditional power systems, electricity is generated in large-scale power plants using fossil fuels and distributed over long distances to meet load demands. The result of this is increased environmental pollution, rapid depletion of fossil fuel resources, and loss of significant amounts of energy during transmission and distribution [1]. This motivates the development of microgrids (MGs), which are an interconnected network of dispatchable fossil-fuel-based generators (such as microturbines, diesel engines, and fuel cells), non-dispatchable renewable energy resources (such as wind turbines and photovoltaic systems) and energy storage systems with the purpose of serving residential, commercial, and industrial loads within a small geographical area [2]. The increasing use of renewable energy has spawned the concept of networked MGs or multi-MGs, referring to a cluster of multiple self-governed MGs that are geographically close to each other. The networking strategy enables MGs to exchange power with one another, thus increasing the reliability of individual MGs and allowing them to meet their power needs with renewable, cheaper energy sources [3]. Moreover, it reduces reliance on the main power grid and provides improved power supply reliability for critical loads during emergencies [4].

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Despite the above advantages, it is difficult to achieve the reliable and stable operation of networked MGs due to several reasons. First, the optimal scheduling and planning of networked MGs is challenging because it requires both the local energy management of multiple energy generation resources with different characteristics within MGs and the coordination of energy sharing between MGs [5]. Second, the intermittent nature of renewable energy generation and the time-variability of consumer demands make it difficult to maintain dynamic supply-demand balances. Unless these uncertainty sources are handled properly inside each of the MGs, they can propagate throughout the network and adversely affect overall performance [6].

As a result of the challenges mentioned above, researchers have been driven to develop diverse energy management and optimization models that can be applied to a wide array of conditions. In energy management models, the main function is to optimize energy generated by dispatchable generators, consumed by controllable loads, transferred between MGs, and charged or discharged by storage units. With a well-designed energy management model, microgrids can optimally coordinate and manage their internal resources while effectively interacting with the main grid and other MGs. It offers multiple benefits such as (1) reducing the overall costs of operation, (2) maintaining supply and demand balances, (3) providing customers with reliable power supplies, and (4) utilizing renewable energy resources more efficiently [5].

To capture uncertainty in the energy management models of networked MGs, three main paradigms have been used in the literature: stochastic programming, robust optimization, and data-driven robust optimization (DDRO). Stochastic programming quantifies uncertainty using probability distributions that are assumed to be exactly known. This approach requires the exact distribution of uncertainty, which is difficult or even impossible to accurately estimate based on available historical data. To cope with this problem, probability distributions are approximated by a set of discrete scenarios. A scenario reduction approach is usually needed due to the exponential growth of scenarios with the increase in the number of uncertain parameters [7]. Even though removing scenarios could reduce computational complexity, it might put system security at risk because of power imbalance in case of unseen scenarios [8]. By contrast, robust optimization assumes little information concerning the lower and upper bounds of uncertain parameters when modeling uncertainty. Conventional robust optimization approaches utilize fixed-shaped uncertainty sets without being able to capture the distributional structure of underlying uncertainty data, which leads to over-conservative robust scheduling decisions with a high cost of robustness. Motivated by the shortcomings of robust optimization and stochastic programming, DDRO emerges as an intermediate approach that bridges the gap between these two approaches. In DDRO, an ambiguity set is constructed as a family of probability distributions that share the same statistical metrics, and the solution is immunized against the worst-case distribution within the ambiguity set [9]. Since DDRO considers a set of probability distributions rather than a single distribution, it outperforms stochastic programming in terms of robustness against distribution errors resulting from raw and incomplete historical data. Moreover, DDRO provides less conservative results than robust optimization due to the fact that it captures partial stochastic information that robust optimization ignores. Several approaches have been developed in the literature for the extraction of probability distributions from uncertainty data and the construction of data-driven uncertainty sets, for example, statistical distance and moment-based methods [10], Dirichlet process mixture modeling [11], and support vector clustering [12]. Even with the attractive features of these approaches, most existing DDRO models are unable to effectively reduce distribution estimation errors, especially when dealing with complex uncertainty data.

In order to ensure the optimal and reliable performance of multi-MG systems, this paper develops a data-driven energy management model that optimizes two different kinds of operations simultaneously: internal decisions on how MGs will interact with each other and external decisions on how energy supply and demand will be coordinated within MGs. The external and internal decisions are coupled together since energy sharing between MGs affects the amount of energy needed by every MG to meet local demands. Due to its location-dependent and time-varying nature, renewable power generation is subject to a high level of uncertainty. An adaptive DDRO model empowered with machine learning is developed to cope with uncertainty. The merits of the developed DDRO model lie in the following two aspects. First, compared to static robust optimization making all scheduling decisions at once, the proposed model is cast as an adaptive optimization problem that allows corrective actions after observing the realization of uncertainty. This feature mitigates the cost of robustness and results in less conservative solutions. Second, the robust kernel density estimation (RKDE) is employed to construct an uncertainty set that is self-adaptive to the intrinsic structure of uncertainty data. Moreover, the RKDE can extract distributional information even from messy data, which improves the accuracy of the resulting robust solution.

This paper helps practitioners and researchers to form a cluster of MGs for efficient utilization of dispatchable energy generators (such as diesel generators and microturbines), non-dispatchable generators (such as wind turbines and photovoltaic systems), and energy storage units within a geographical area. Networking multiple MGs is a viable solution to not only enhance the overall performance of MGs but also provide each individual MG with enhanced security, increased stability, and reduced costs by cooperating with other MGs.

Literature Review

Robust optimization has been extensively used in previous studies to handle the uncertainties associated with the energy management problems of MGs. Ref. [13] optimizes the day-ahead planning of a multi-MG system by a two-layer framework, where the upper level minimizes the total system cost and determines the price and quantity of the exchanged energy between MGs, and the lower level deals with the uncertainties resulting from renewable energy sources and loads using a two-stage robust optimization model under the box uncertainty set. By integrating non-cooperative game theory and box-set-induced robust optimization, Ref. [14] coordinates energy trading between MGs while suppressing the impact of uncertainty on the optimal performance of market players. To address the over-conservatism caused by the box uncertainty set, a large number of studies utilize the polyhedral uncertainty set that can control the degree of robustness and its cost. For example, Ref. [15] develops a polyhedral set-based adaptive robust optimization model to guarantee the collaborative and economic operation of networked MGs under the worst-case scenarios of photovoltaic output. In Ref. [16], the optimal design and scheduling scheme for multiple interconnected MGs is determined using a two-stage robust optimization model, where the first stage focuses on the deployment of distributed energy resources in MGs and the second stage minimizes the system cost while ensuring robustness against all possible realizations of renewable energy uncertainty within a polyhedral uncertainty set. Using the same uncertainty set, Ref. [17] proposes a robust bilevel programming model to determine interactive strategies and energy transaction prices under the uncertainties of energy demand and renewable energy resources. To improve the robustness of scheduling decisions against the uncertainty of loads and renewable generation in an MG, Ref. [18] designs a transactive energy-sharing scheme with a decentralized robust optimization model formulated using the polyhedral uncertainty set. Ref. [19] minimizes the operation cost of renewable energy resources, conventional generators, load shifting and shedding, and energy storage units in an islanded MG while ensuring solution robustness under the worst situation of uncertainty described using a time-dependent polyhedral uncertainty set. Despite its ability to make a trade-off between the cost of robustness and the degree of conservatism, the polyhedral uncertainty set is not capable of extracting useful information from available data. To overcome this problem, Ref. [20] employs the Imprecise Dirichlet Model for the construction of an ambiguity set based on information extraction from electric vehicles and wind power generation in a single MG. To manage the uncertainty of renewable energy generation and the integrated demand response, Ref. [21] develops a distributionally robust scheduling model under an ambiguity set with a confidence interval based on the 1-norm and the ∞-norm of uncertainty data. Ref. [22] constructs a data-driven multi-ellipsoidal uncertainty set to capture the temporal correlation and conditional correlation of forecast errors associated with the power output of wind turbines in a single MG. For the resilient operation of an integrated energy system against extreme weather events, Ref. [23] develops a DDRO model under an ambiguity set formed by incorporating the Wasserstein metric and moment information of uncertainty. A data-driven economic dispatch model for a distribution system with multiple MGs is proposed in Ref. [24], where the ∞-norm and 1-norm are adopted to build the ambiguity set based on the probability distributions of uncertain renewable power generation. Ref. [25] optimizes network operation and power trading for a multi-MG system and employs the Wasserstein metric to formulate a data-driven distributionally robust model that effectively deals with the uncertainty of renewable generation and load.

In spite of strenuous efforts, there are still several important research gaps in existing studies. First, a large number of robust energy management models use box and polyhedral uncertainty sets. These classical sets have a fixed shape without sufficient flexibility in adapting to the structure of uncertainty data, which undermines the quality of the resulting robust solution. Second, most existing DDRO-based energy management models are designed for one MG due to computational tractability. In practice, MGs that operate independently face a number of problems, including frequent exchange of power with the main grid, limited use of local renewable power generation, and high operation costs [15]. Third, several studies rely on a static robust formulation that assumes all scheduling decisions must be made at once prior to observing the realization of uncertainty. In general, this leads to over-conservative solutions because many decisions can be adjusted based on the actual values of uncertain parameters. The goal of this paper is to fill these gaps by developing a DDRO model for co-optimizing internal network operation within MGs and external power sharing between MGs. By employing the RKDE, the proposed model integrates robust optimization and machine learning to form a self-adjustable uncertainty set that accurately extracts uncertainty information from historical data and greatly reduces the unnecessary conservatism of robust scheduling decisions. Moreover, this approach can handle noisy and large-scale historical data, yielding a computationally tractable counterpart formulation [26]. The proposed model is formulated as an adaptive robust optimization problem to allow the adjustments of a subset of decisions after uncertainty is realized. Table 1 provides an overview of robust optimization models for the energy management of MGs.

Problem Statement

As shown in Fig. 1, this paper considers a common architecture for a network of multiple interconnected MGs, indexed by $\mathcal{M} = \{1, \dots, M\}$. In addition to being connected to the main power grid, these MGs are connected with each other, exchanging information and power using a communication network and a power bus. Each MG incorporates the following components: dispatchable distributed generators (DDGs), energy storage systems (ESSs), renewable energy generates (REGs), and local loads (both non-controllable and controllable loads). DDGs (e.g., microturbines) are capable of providing stable energy to meet the energy needs of MGs, and REGs (e.g., wind turbines and photovoltaic systems) generate sustainable and clean energy. With ESSs, intermittent renewable energy generation can be smoothed out and the power load can be flattened by charging during low-load periods and discharging during peak-load periods.

Moreover, the controllable loads can contribute to maintaining power balance because their schedules can flexibly be adjusted over time according to demand response programs.

Table 1. An overview of robust energy management models for MGs

	System structure		Robust formulation		Uncertainty set						
Ref.	**Single MG**	**Networked MGs**	**Static**	**Adaptive**	**Box set**	**Polyhedral set**	**Moment information**	**Wasserstein metric**	**Dirichlet model**	**Multi ellipsoidal set**	**Kernel density estimation**
[13]		*		*		*					
[14]		*	*		*						
[15]		*		*		*					
[16]		*		*		*					
[17]		*	*			*					
[18]	*			*		*					
[19]	*		*			*			*		
[20]	*			*							
[21]	*			*			*				
[22]	*		*							*	
[23]	*			*			*	*			
[24]		*	*				*				
[25]		*		*				*			
This work		*		*							*

The optimal and reliable operation of the system described above is ensured by developing a two-stage adaptive DDRO model, where the first-stage decisions have to be made before observing the realizations of uncertainty and the second-stage decisions can be adjusted after uncertainty is realized. The first stage determines the day-ahead scheduling decisions about the power output of DDGs and ESSs, the upward/downward reserve of DDGs, the charging/discharging status of ESSs, and the exchanged power between MGs. The second stage focuses on the power adjustment of DDGs in real-time operation and minimizes the power imbalance that may be caused due to the difference between the actual and scheduled outputs of REGs.

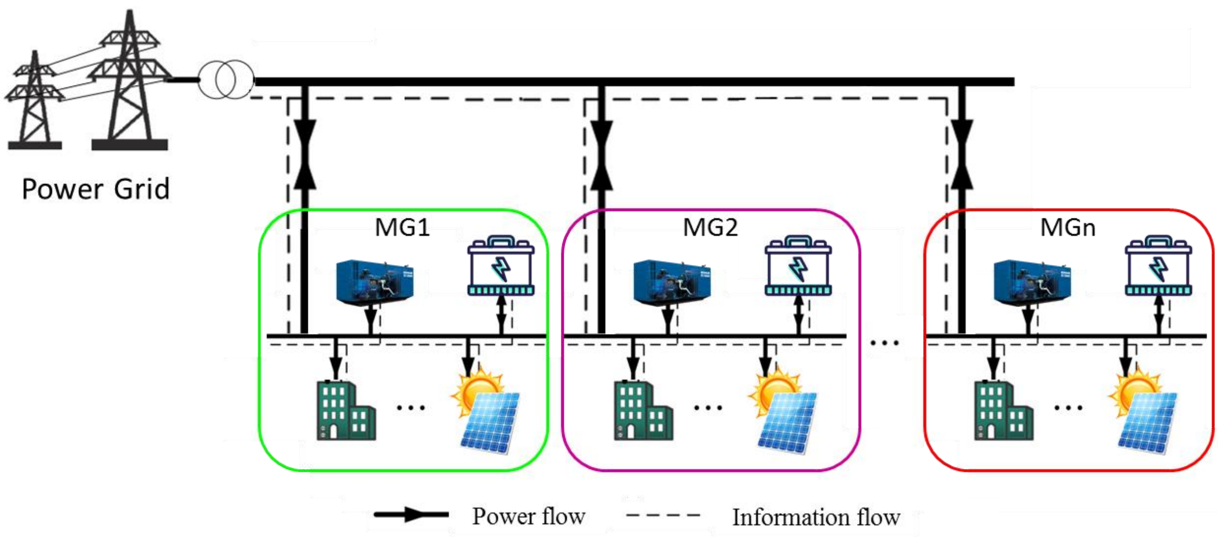


Fig. 1. A basic structure of multiple networked MGs

Mathematical Formulation

This section presents a two-stage adaptive DDRO model to determine the optimal energy scheduling and sharing strategy of networked MGs. A list of indices/sets, decision variables, and parameters is provided in the Nomenclature.

Nomenclature

Indices and Sets	
$\mathcal{M}$	Set of MGs
m/t	Index of MGs/periods
Parameters	
a, b, c	DDG's cost function coefficients
C^R	DDG's reserve cost per unit
pr_t^b	Power buying price from the main grid at time t
pr_t^s	Power selling price to the main grid at time t
pr_t^{ex}	Power exchange price between MGs at time t
ρ^l	Penalty cost for power shortage
ρ^r	Penalty cost for power surplus
$\mathcal{N}_m^r$	Set of buses of REGs in MG m
$\mathcal{N}_m^g$	Set of buses of DDGs in MG m
$\overline{P}^c$	Charging capacity at each period
$\overline{P}^{dc}$	Discharging capacity at each period
$\overline{E}$	Upper bound on power storage
$\underline{E}$	Lower bound on power storage
η^c	ESS's charging efficiency
η^{dc}	ESS's discharging efficiency
D_m^c	The aggregate controllable load in MG m
$d_{m,t}^c$	Controllable load in MG m at time t
$d_{m,t}^{nc}$	Non-controllable load in MG m at time t
$\underline{D}_{m,t}^c$	Lower bound of controllable load in MG m at time t
$P_{m,t}^r$	REG's predicted output in MG m at time t
$\overline{D}_{m,t}^c$	Upper bound of controllable load in MG m at time t
$\underline{P}_m^g$	DDG's minimum generation capacity in MG m
$\overline{P}_m^g$	DDG's maximum generation capacity in MG m
$\underline{Ra}^g$	DDG's ramping up limit
$\overline{Ra}^g$	DDG's ramping down limit
Variables	
$P_{m,t}^g$	DDG's power generation in MG m at time t
$\overline{R}_{m,t}^g$	DDG's upward reserve in MG m at time t
$\underline{R}_{m,t}^g$	DDG's downward reserve in MG m at time t
$P_{m,t}^s$	Power sold to the main grid by MG m at time t
$P_{m,t}^b$	Power bought from the main grid by MG m at time t
$P_{m,n,t}^{ex}$	Power exchanged from MG m to MG n at time t
$\Delta P_{m,t}^g$	DDG's real-time power adjustment in MG m at time t
$\Delta P_{m,t}^+$	Power surplus in MG m at time t
$\Delta P_{m,t}^-$	Power shortage in MG m at time t
$E_{m,t}^{es}$	Power storage in MG m at time t
$P_{m,t}^c$	Power charging in MG m at time t
$P_{m,t}^{dc}$	Power discharging in MG m at time t
$d_{m,t}^c$	Actual controllable load in MG m at time t
$\xi_{m,t}$	REG's predicted error in MG m at time t
Binary variables	
$\alpha_{m,t}^c$	ESS's charging status in MG m at time t
$\alpha_{m,t}^{dc}$	ESS's charging status in MG m at time t

Objective function

Objective function (1) minimizes the total system cost that consists of five parts: the first three parts are associated with day-ahead scheduling costs and are independent of uncertainty, the last part is associated with real-time power adjustment costs and is influenced by uncertainty.

$$\min_{x} \sum_{m\in\mathcal{M}} \sum_{t\in\mathcal{T}} \left\{ f_{m,t}^{g}(\boldsymbol{x}) - f_{m,t}^{m}(\boldsymbol{x}) - f_{m,t}^{ex}(\boldsymbol{x}) + f_{m,t}^{d}(\boldsymbol{x}) + \max_{\boldsymbol{\xi}\in U} \min_{y\in\Omega(x,\boldsymbol{\xi})} f_{m,t}^{ad}(\boldsymbol{y},\boldsymbol{\xi}) \right\} \tag{1}$$

here, $\boldsymbol{x}$ and $\boldsymbol{y}$ are the vectors of first-stage (here-and-now) and second-stage (wait-and-see) decision variables, respectively, Ω is the feasible region of second-stage variables, and δ is the vector of random variables whose realizations belong to uncertainty set U. $f_{m,t}^{g}$ is the power generation cost of DDGs and is approximated using a quadratic function as follows:

$$f_{m,t}^{g} = \left(a.{P_{m,t}^{g}}^{2} + b.P_{m,t}^{g} + c\right) + C^{R}\left(\overline{R}_{m,t}^{g} + \underline{R}_{m,t}^{g}\right) \tag{2}$$

as represented by (3), $f_{m,t}^{m}$ is the revenue (cost) of each MG from selling (buying) power to (from) the main grid. Similarly, $f_{m,t}^{ex}$ is the revenue (cost) of each MG from power trading and is expressed in (4). If MG m buys power from MG n in time t, then $P_{m,n,t}^{ex} < 0$; otherwise, MG m sells power MG n and $P_{m,n,t}^{ex} > 0$. Eq. (5) indicates discomfort costs that occur when actual power consumption deviates from the desired power consumption. As expressed in (6), the last part of the objective function is the cost of power adjustment at the real-time stage and is associated with possible power surplus or shortage after uncertainty realization.

$$f_{m,t}^{m} = pr_{t}^{s}P_{m,t}^{s} - pr_{t}^{b}P_{m,t}^{b} \tag{3}$$

$$f_{m,t}^{ex} = \sum_{n\in\mathcal{M}\backslash m} pr_{t}^{ex}P_{m,n,t}^{ex} \tag{4}$$

$$f_{m,t}^{d} = \left(P_{m,t}^{il} - P_{m,t}^{dl}\right)^{2} \tag{5}$$

$$f_{m,t}^{ad} = \rho^{l}\Delta P_{m,t}^{-} + \rho^{r}\Delta P_{m,t}^{+} \tag{6}$$

Constraints

Eq. (7) shows the dynamics of power storage in MG m based on net power injection and losses during the process of charging and discharging. The upper and lower limits on the power stored in each MG are expressed by constraint (8). The amount of the power charged and discharged at each period is limited by constraints (9) and (10), respectively. Constraint (11) guarantees that each ESS cannot charge and discharge at the same time.

$$E_{m,t}^{es} = E_{m,t-1}^{es} + \eta^{c}P_{m,t}^{c} - P_{m,t}^{dc}/\eta^{dc} \quad \forall m\in\mathcal{M}, t\in\mathcal{T} \tag{7}$$

$$\underline{E} \leq E_{m,t}^{es} \leq \overline{E} \quad \forall m\in\mathcal{M}, t\in\mathcal{T} \tag{8}$$

$$0 \leq P_{m,t}^{c} \leq \alpha_{m,t}^{c}\overline{P}^{c} \quad \forall m\in\mathcal{M}, t\in\mathcal{T} \tag{9}$$

$$0 \leq P_{m,t}^{dc} \leq \alpha_{m,t}^{dc}\overline{P}^{dc} \quad \forall m\in\mathcal{M}, t\in\mathcal{T} \tag{10}$$

$$\alpha_{m,t}^{c} + \alpha_{m,t}^{dc} \leq 1 \quad \forall m\in\mathcal{M}, t\in\mathcal{T} \tag{11}$$

Demand response constraints

While non-controllable loads cannot be shifted over time, controllable loads can be arranged flexibly in accordance with the constraints of the demand response program. Constraint (12) states that the sum of controllable loads over the entire scheduling horizon should be equal to the total power demand. Constraint (13) imposes the upper and lower bound on the amount of controllable loads at each period.

$$\sum_{t\in\mathcal{T}} d^{c}_{m,t} = D^{c}_{m} \quad \forall m \in \mathcal{M} \tag{12}$$

$$\underline{D}^{c}_{m,t} \le d^{c}_{m,t} \le \overline{D}^{c}_{m,t} \quad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{13}$$

Power generation constraints

Constraint (14) states that the power output of each DDG minus its downward reserve cannot come below the minimum generation capacity. The power output of each DDG plus its upward reserve cannot exceed the maximum generation capacity, as enforced by constraint (15). Constraint (16) ensures that variations in the power output of each DDG do not violate its upward and downward reserves. Constraints (17) and (18) impose the upper and lower bounds on the ramp rate of DDGs.

$$P^{g}_{m,t} - \underline{R}^{g}_{m,t} \ge \underline{P}^{g}_{m} \quad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{14}$$

$$P^{g}_{m,t} + \overline{R}^{g}_{m,t} \le \overline{P}^{g}_{m} \quad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{15}$$

$$\underline{R}^{g}_{m,t} \le \Delta P^{g}_{m,t} \le \overline{R}^{g}_{m,t} \quad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{16}$$

$$P^{g}_{m,t} + \Delta P^{g}_{m,t} - P^{g}_{m,t-1} - \Delta P^{g}_{m,t-1} \le \overline{Ra}^{g} \quad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{17}$$

$$P^{g}_{m,t-1} + \Delta P^{g}_{m,t-1} - P^{g}_{m,t} - \Delta P^{g}_{m,t} \le \underline{Ra}^{g} \quad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{18}$$

Power balance constraints

It is assumed that MGs are near each other, so there is no significant loss of power exchange. The power balance constraint for each MG at the day-ahead stage is expressed by Eq. (19). The power output of REGs is subject to uncertainty and is modeled as the sum of the predicted output $P^{r}_{m,t}$ and the prediction error $\xi_{m,t}$. To keep the power balance in each MG, DDGs compensate for the prediction error of REGs in the real-time stage. Possible power shortage and surplus are measured by constraint (20) and penalized in the objective function.

$$P^{g}_{m,t} + P^{r}_{m,t} + P^{b}_{m,t} + P^{dc}_{m,t} = P^{s}_{m,t} + P^{c}_{m,t} + d^{c}_{m,t} + d^{nc}_{m,t} \quad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{19}$$

$$\Delta P^{g}_{m,t} + \xi_{m,t} \le \Delta P^{+}_{m,t} - \Delta P^{-}_{m,t} \quad \forall m \in \mathcal{M}, t \in \mathcal{T} \tag{20}$$

Uncertainty set construction

Let $\xi_{(1)}, \dots, \xi_{(N)}$ be a set of N data samples, each of which is an uncertainty realization in R^{d}. A probability density function for ξ can be estimated using the kernel density estimation (KDE) method, which is formulated as follows:

$$\hat{f}_{KDE}(\xi) = \frac{1}{N}\sum_{i=1}^{N} K_{\beta}\left(\xi, \xi_{(N)}\right) \tag{21}$$

where K_{β} is a kernel function whose bandwidth is denoted by the parameter β. Since there is no noticeable difference in density estimation between various kernel functions [26], the Gaussian kernel function is adopted in this study.

$$K_{\beta}\left(\xi, \xi_{(i)}\right) = \left(1/\sqrt{2\pi}\beta\right) exp\left(-\left\|\xi - \xi_{(i)}\right\|^{2}/2\beta^{2}\right) \tag{22}$$

in a positive semi-definite kernel like the Gaussian kernel, there exists a mapping Ω from R^{d} to the Hilbert space H as $K_{\beta}\left(\xi, \xi_{(i)}\right) = \langle \Omega(\xi), \Omega\left(\xi_{(i)}\right)\rangle$. It is proved that $\hat{f}_{KDE}(\xi)$ equals an optimal solution of the following optimization problem:

$$\min_{S\in H}\sum_{i=1}^{N}\left\|\Omega\left(\xi_{(i)}\right)-S\right\|^2 \tag{23}$$

where S is an arbitrary function in the space H. Due to the high sensitivity of the quadratic loss function in (23) to outliers, the RKDE method has been proposed to estimate S as follows:

$$\min_{S\in H} J(S)=\sum_{i=1}^{N}\vartheta\left(\left\|\Omega\left(\xi_{(i)}\right)-S\right\|\right) \tag{24}$$

here, $\vartheta(.)$ denote a robust loss function such as the Huber loss function. Problem (24) cannot be directly solved with conventional optimizers since its solution is a function of probability densities. In order to solve the above, we use the kernelized reweighted least squares algorithm whose pseudocode is provided in Algorithm 1 [27]. This algorithm has been shown to be efficient at solving the above problem and ensures the convergence to the global optimum for the Huber function [28]. In Algorithm 1, η is the first-order derivative of ϑ and $\left\|\Omega\left(\xi_{(i)}\right)-S^{(k)}\right\|$ is calculated by,

$$\left\|\Omega\left(\xi_{(i)}\right)-S^{(k)}\right\|=\sqrt{\langle\Omega\left(\xi_{(i)}\right),\Omega\left(\xi_{(i)}\right)\rangle-2\langle\Omega\left(\xi_{(i)}\right),S^{(k)}\rangle+\langle S^{(k)},S^{(k)}\rangle} \tag{25}$$

where the right-hand side terms can be computed using the kernel trick as follows:

$$\langle\Omega\left(\xi_{(i)}\right),\Omega\left(\xi_{(i)}\right)\rangle=K_\beta\left(\xi_{(i)},\xi_{(i)}\right) \tag{26}$$

$$\langle\Omega\left(\xi_{(i)}\right),\xi^{(r)}\rangle=\sum_{j=1}^{N}\mathrm{w}_j^{(k-1)}K_\beta\left(\xi_{(i)},\xi_{(j)}\right) \tag{27}$$

$$\langle S^{(k)},S^{(k)}\rangle=\sum_{n=1}^{N}\sum_{z=1}^{N}\mathrm{w}_n^{(k-1)}\mathrm{w}_z^{(k-1)}K_\beta\left(\xi_{(n)},\xi_{(z)}\right) \tag{28}$$

Algorithm 1
Input: Initial guesses $\mathrm{w}_i^{(0)}\geq 0$ such that $\sum_{i=1}^{n}\mathrm{w}_i^{(0)}=1$, and tolerance ϵ
while $\left|\left[J\left(S^{(k)}\right)-J\left(S^{(k-1)}\right)\right]/J\left(S^{(k-1)}\right)\right|>\epsilon$ **do**
1: update $S^{(k)}\leftarrow\sum_{i=1}^{N}\mathrm{w}_i^{(k-1)}\Omega\left(\xi_{(i)}\right)$
2: update $L\left(S^{(k)}\right)\leftarrow\sum_{i=1}^{N}\vartheta\left(\left\|\Omega\left(\xi_{(i)}\right)-S^{(k)}\right\|\right)$
3: update $\mathrm{w}_i^{(k)}\leftarrow\eta\left(\left\|\Omega\left(\xi_{(i)}\right)-S^{(k)}\right\|\right)/\sum_{j=1}^{N}\eta\left(\left\|\Omega\left(\xi_{(i)}\right)-S^{(k)}\right\|\right)$
4: $k\leftarrow k+1$
end while
return $\hat{f}_{RKDE}=S^{(k)}$

After estimating the density function $\hat{f}_{RKDE}$, the cumulative density function $\hat{F}_{RKDE}^{(i)}(\xi_i)$ for the *i*-th component of uncertainty vector $\boldsymbol{\xi}$ is constructed. In order to determine the confidence region of ξ_i given a predetermined confidence level, the quantile function is defined as follows:

$$\hat{F}_{RKDE}^{(i)\,-1}(\gamma)=\min\left\{\xi_i\in\mathbb{R}|\hat{F}_{RKDE}^{(i)}(\xi_i)\geq\gamma\right\} \tag{29}$$

where the confidence level is set at $1-2\gamma$. Using the function estimated above, the data-driven uncertainty set is formulated as follows:

$$U = \left\{ \boldsymbol{\xi} \middle| \begin{array}{c} \hat{F}_{RKDE}^{(i)\,-1}(\gamma) \le \xi_i \le \hat{F}_{RKDE}^{(i)\,-1}(1-\gamma) \quad \forall i \\ \sum_i (1-\omega_i \phi)\xi_i^0 \le \sum_i \xi_i \le \sum_i (1+\omega_i \phi)\xi_i^0 \end{array} \right\} \tag{30}$$

where ϕ denotes the normalized uncertainty parameter introduced to adjust the level of conservatism. ξ_i^0 and ω_i are the center of the uncertainty set and its variation range, respectively, which can be computed as follows:

$$\xi_i^0 = \left[\hat{F}_{RKDE}^{(i)\,-1}(\gamma) + \hat{F}_{RKDE}^{(i)\,-1}(1-\gamma)\right]/2 \tag{32}$$
$$\omega_i = \left[\hat{F}_{RKDE}^{(i)\,-1}(1-\gamma) - \xi_i^0\right]/\xi_i^0 \tag{33}$$

Robust counterpart model

This subsection discusses how to derive the tractable robust counterpart of the data-driven energy management model (1)-(20) under the uncertainty set (30). The vector representation of the model is presented first in order to simplify the notation:

$$\begin{aligned} &\min_{x} \mathbf{c}'\mathbf{x} + \max_{\boldsymbol{\xi}\in U} \min_{y\in\Omega(x,\boldsymbol{\xi})} \sum_{t\in\mathcal{T}} \mathbf{d}_{\mathrm{t}}' \mathbf{y}_{\mathrm{t}}(\boldsymbol{\xi}) \\ &s.t.\ \mathbf{W}_{\boldsymbol{m}}'\mathbf{x} + \sum_{t\in\mathcal{T}} \mathbf{V}_{\boldsymbol{tm}}'\mathbf{y}_t(\boldsymbol{\xi}) \le \mathbf{h}_{\boldsymbol{m}}'(\boldsymbol{\xi}) \qquad \forall\boldsymbol{\xi}\in U, m\in\mathcal{M} \\ &\text{over} \left\{ \begin{array}{c} \mathbf{x} = P_{m,t}^{g}\overline{R}_{m,t}^{g}\underline{R}_{m,t}^{g}P_{m,t}^{s}P_{m,t}^{b}P_{m,n,t}^{ex}E_{m,t}^{es}P_{m,t}^{c}P_{m,t}^{dc}\alpha_{m,t}^{c}\alpha_{m,t}^{dc} \\ \mathbf{y} = \Delta P_{m,t}^{g}\Delta P_{m,t}^{+}\ \Delta P_{m,t}^{-} \end{array} \right\} \end{aligned} \tag{34}$$

here, $\mathbf{x}$ and $\mathbf{y}$ are the vectors of the second-stage and the second-stage decisions, respectively, and $\mathrm{h}(\boldsymbol{\xi})$ denotes uncertainty $\xi_{m,t}$ moved from the left to the right-hand side of constraint (20). Problem (34) involves enumerating uncertainty retaliations within the uncertainty set U, making it computationally intractable. It is possible to solve this problem by adopting the affine decision rule approximation, which assumes the second-stage decisions are affinely affected by uncertainty:

$$\mathbf{y}_t(\boldsymbol{\xi}) = \mathbf{Q}_t\boldsymbol{\xi} + \mathbf{e}_t \tag{35}$$

where $\mathbf{Q}$ and $\mathbf{e}$ are continuous decision variables that are optimized by the model, and $\boldsymbol{\xi} = [\boldsymbol{\xi}_1', \dots, \boldsymbol{\xi}_T']$. Moreover, it is assumed that the right-hand-side vector $\mathbf{h}$ affinely responds to uncertainty. By plugging the decision rules into the model (34) and transforming the uncertainty in the objective function into a constraint, we arrive at the following optimization problem:

$$\min_{x,Q,e,R}\ R \tag{36a}$$
$$\mathbf{c}'\mathbf{x} + \sum_{t\in\mathcal{T}} \mathbf{d}_{\mathrm{t}}'(\mathbf{Q}_t\boldsymbol{\xi} + \mathbf{e}_t) \le R \quad \forall\boldsymbol{\xi}\in U \tag{36b}$$
$$s.t.\ \mathbf{W}_{\boldsymbol{m}}'\mathbf{x} + \sum_{t\in\mathcal{T}} \mathbf{V}_{\boldsymbol{tm}}'(\mathbf{Q}_t\boldsymbol{\xi} + \mathbf{e}_t) \le \mathbf{h}_{\boldsymbol{m}}'\boldsymbol{\xi} + \mathrm{h}_m^0 \quad \forall\boldsymbol{\xi}\in U, m\in\mathcal{M} \tag{36c}$$

To ensure the feasibility of constraints (36b) and (36c) for all realizations of uncertainty within U, the worst-case realization of $\boldsymbol{\xi}$ is considered by reformulating (36) as follows:

$$\min_{x,Q,e,R}\ R \tag{37a}$$
$$s.t.\ \max_{\boldsymbol{\xi}\in U} \left\{ \left(\sum_{t\in\mathcal{T}} \mathbf{d}_t'\mathbf{Q}_t \right).\boldsymbol{\xi} \right\} \le R - \mathbf{c}'\mathbf{x} - \sum_{t\in\mathcal{T}} \mathbf{d}_t'\mathbf{e}_t \tag{37b}$$
$$\max_{\boldsymbol{\xi}\in U} \left\{ \left(\sum_{t\in\mathcal{T}} \mathbf{V}_{tm}'\mathbf{Q}_t - \mathbf{h}_m' \right).\boldsymbol{\xi} \right\} \le \mathrm{h}_m^0 - \mathbf{W}_{\boldsymbol{m}}'\mathbf{x} - \sum_{t\in\mathcal{T}} \mathbf{V}_t'\mathbf{e}_t \quad \forall m\in\mathcal{M} \tag{37c}$$

where the inner maximization problems in (37b) and (37c) involve the following constraints:

$$\xi_{it} \leq \hat{F}_{RKDE}^{(it)\,-1}(1-\gamma) \tag{38}$$
$$-\xi_{it} \leq -\hat{F}_{RKDE}^{(it)\,-1}(\gamma) \tag{39}$$
$$\sum_{i}\sum_{t}\xi_{it} \leq \sum_{i}\sum_{t}(1+\omega_{it}\phi)\xi_{it}^{0} \tag{40}$$
$$-\sum_{i}\sum_{t}\xi_{it} \leq -\sum_{i}\sum_{t}(1-\omega_{it}\phi)\xi_{it}^{0} \tag{41}$$

here, ξ_{it} is the i-th component of $\boldsymbol{\xi}_t$. The inner maximization problems are linear with respect to variable $\boldsymbol{\xi}$ and can equivalently be replaced with its dual form, resulting in the following robust counterpart model:

$$\min_{x,Q,e,R,\theta,\lambda} \; R \tag{42a}$$
$$\begin{aligned} s.t.\; & \bar{\lambda}_{it}\hat{F}_{RKDE}^{(it)\,-1}(1-\gamma) - \underline{\lambda}_{it}\hat{F}_{RKDE}^{(it)\,-1}(\gamma) + \bar{\lambda}^{0}\sum_{i}\sum_{t}(1+\omega_{it}\phi)\xi_{it}^{0} - \underline{\lambda}^{0}\sum_{i}\sum_{t}(1-\omega_{it}\phi)\xi_{it}^{0} \\ & \leq R - \mathbf{c}'\mathbf{x} - \sum_{t}\mathbf{d}_t'\mathbf{e}_t \end{aligned} \tag{42b}$$
$$\bar{\lambda}_{it} - \underline{\lambda}_{it} + \bar{\lambda}^{0} - \lambda^{0} = \left[\sum_{k}\mathbf{d}_k'\mathbf{Q}_k\right]_{i+(t-1).l} \quad \forall i,t \tag{42c}$$
$$\begin{aligned} & \bar{\theta}_{it}\hat{F}_{RKDE}^{(it)\,-1}(1-\gamma) - \underline{\theta}_{it}\hat{F}_{RKDE}^{(it)\,-1}(\gamma) + \bar{\theta}^{0}\sum_{i}\sum_{t}(1+\omega_{it}\phi)\xi_{it}^{0} - \underline{\theta}^{0}\sum_{i}\sum_{t}(1-\omega_{it}\phi)\xi_{it}^{0} \\ & \leq \mathrm{h}_m^0 - \mathbf{W}_m'\mathbf{x} - \sum_{t}\mathbf{V}_t'\mathbf{e}_t \quad \forall m \in \mathcal{M} \end{aligned} \tag{42d}$$
$$\bar{\theta}_{it} - \underline{\theta}_{it} + \bar{\theta}^{0} - \underline{\theta}^{0} = \left[\sum_{k}\mathbf{Q}_{\boldsymbol{k}}'\mathbf{V}_k - \mathbf{h}_{\boldsymbol{m}}\right]_{i+(t-1).l} \quad \forall m,i,t \tag{42e}$$

where $\boldsymbol{\lambda}$ and $\boldsymbol{\theta}$ are the vectors of positive dual variables associated with constraints (38)-(41), $[\mathbf{x}]$ returns the i-component of the vector $\mathbf{x}$ and l denotes the dimension of $\boldsymbol{\xi}_t$.

Case Study

To evaluate its performance, the proposed data-driven robust energy management model is tested on a multi-MG system with three interconnected MGs [29]. This system has a radial topology similar to that represented in Fig. 1. MGs accommodate REGs, DDGs, ESSs, and internal loads. Each MG is responsible for determining its scheduling decisions as an independent entity. MGs can compensate for possible deviations between their generation and demand by exchanging energy between themselves. At the same time, they are allowed to sell/purchase energy to/from the main grid. Due to the fact that the scheduling decisions of MGs are correlated with each other, they must be coordinated so that the entire system operates efficiently.

By employing this common benchmark test system, we will be able to compare the results of the proposed model with previous models and confirm its suitability for use in future MG community applications that are more complex. In addition to non-controllable loads, every MG includes controllable loads with the lower and upper bounds of 0 and 20%, respectively. Table 2 summarizes the parameters of ESSs and DDGs used in MG1, MG2, and MG3. Fig.2 illustrates the day-ahead prediction for electricity price, renewable power generation, and loads on a typical day. The prediction error of REGs is represented by generating random samples from Gaussian distributions with zero mean and standard deviation of 10% [25]. All optimization problems are solved using GAMS on a PC with an Intel Core i5 CPU and 8 GB RAM.

Table 2. Parameters of ESS and DDG

Unit	parameter	MG1	MG1	MG1	Ref.
ESS	$\overline{P}^{c}/\overline{P}^{dc}(kW)$	150	125	160	[29]
	$\overline{E}/\underline{E}$	80%, 20%	80%, 20%	80%, 20%	[29]
	η^{c}/η^{dc}	0.97, 0.95	0.96, 0.98	0.95, 0.95	[29]
DDG	a ($\$/kWh^2$)	0.00003	0.00003	0.00003	[30]
	b ($\$/kWh$)	0.30	0.30	0.30	[30]
	c ($\$$)	0	0	0	[30]
	$\overline{P}_{m}^{g}/\underline{P}_{m}^{g}$	200, 0	180, 0	160, 0	[29]
	$\underline{Ra}^{g}/\overline{Ra}^{g}$	85, 80	75, 75	80, 70	[29]

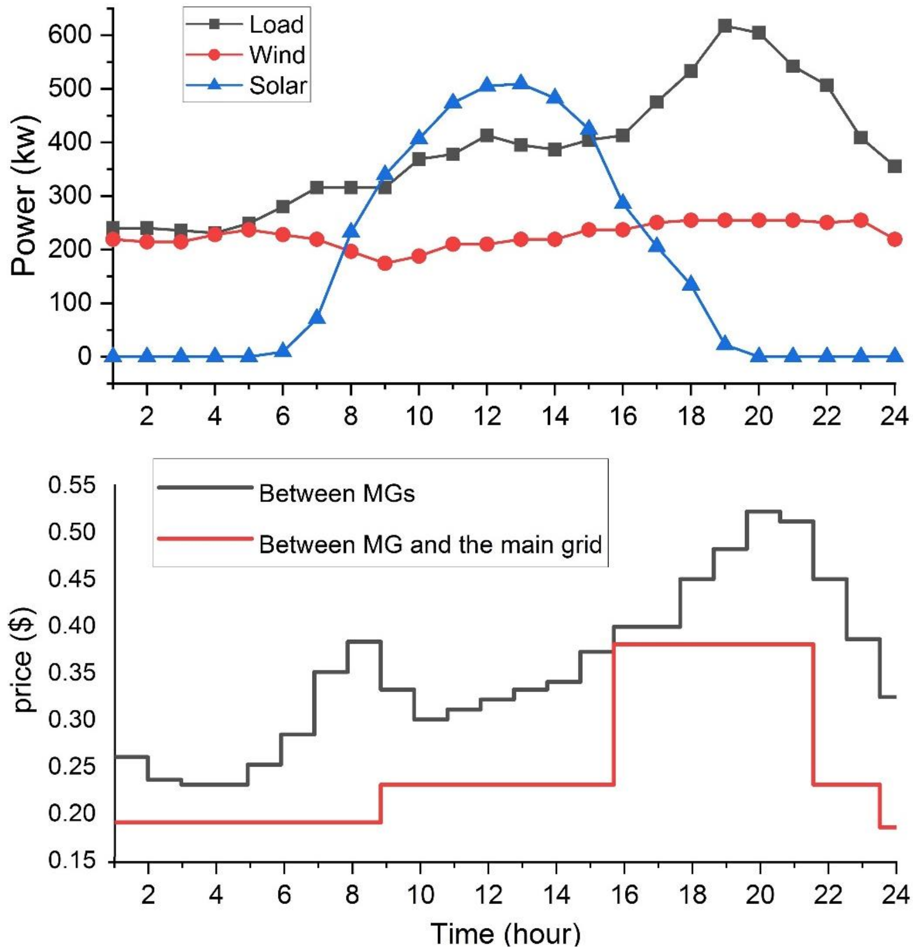


Fig. 2. Forecasted data of renewable energy, load, and electricity price

Comparison of economic performance

To analyze the economic results of the proposed DDRO model, two alternative models are utilized for comparison: (1) the deterministic model that ignores random fluctuations in the output power of renewable generators energy or assumes them to be fixed values, and (2) the polyhedral set-based robust optimization (PRO) model that is commonly used for uncertainty treatment in the energy management of networked MGs due to its ability to adjust the conservatism of the resulting robust solution [31]. To make a fair comparison, the reliability level of both robust optimization models is set at the same value (about 90%). The cost of robustness (CR) is used as an index to measure how much optimality is sacrificed to guarantee solution robustness. This index is calculated as $CR = (OR - OD)/OD$, where OR and OD are the optimal costs of the robust and deterministic models, respectively. It is preferred to have a lower value of CR since it means less cost must be paid for robustness.

It can be seen from Fig. 3 (a) that the deterministic model has the lowest operational cost, but it does not provide a hedge against uncertainty and leads to solutions that may become infeasible by small variations in renewable power generation. The power imbalance caused by the determinist solution increases real-time adjustment costs because the price of selling (buying) energy in the day-ahead market is usually higher (lower) than that in the real-time market. On the other hand, the robust models reduce the probability of violation of the real-time power balance constraints and subsequently avoid renewable generation curtailment and load shedding for almost all possible uncertainty realizations. Based on the comparison of the costs of the robust models, the proposed DDRO model demonstrates superiority over the PRO model by providing robust scheduling solutions at a lower cost. To be more specific, the CR of the proposed model for MG1, MG2, and MG3 are 12%, 11%, and 7%, respectively, which are about half the CR returned by the PRO model.

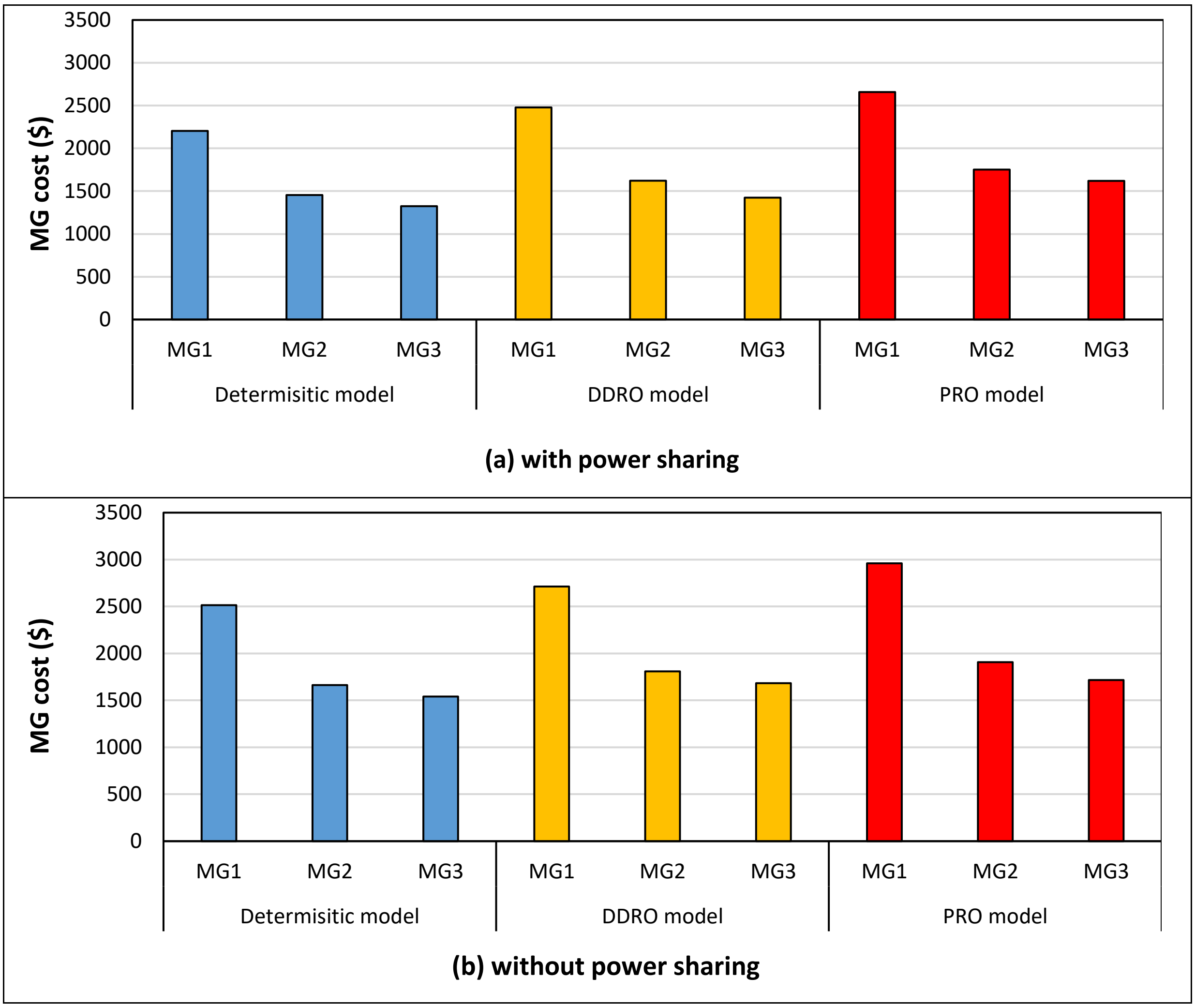


Fig. 3. The cost of MGs with/without power-sharing based on different optimization approaches

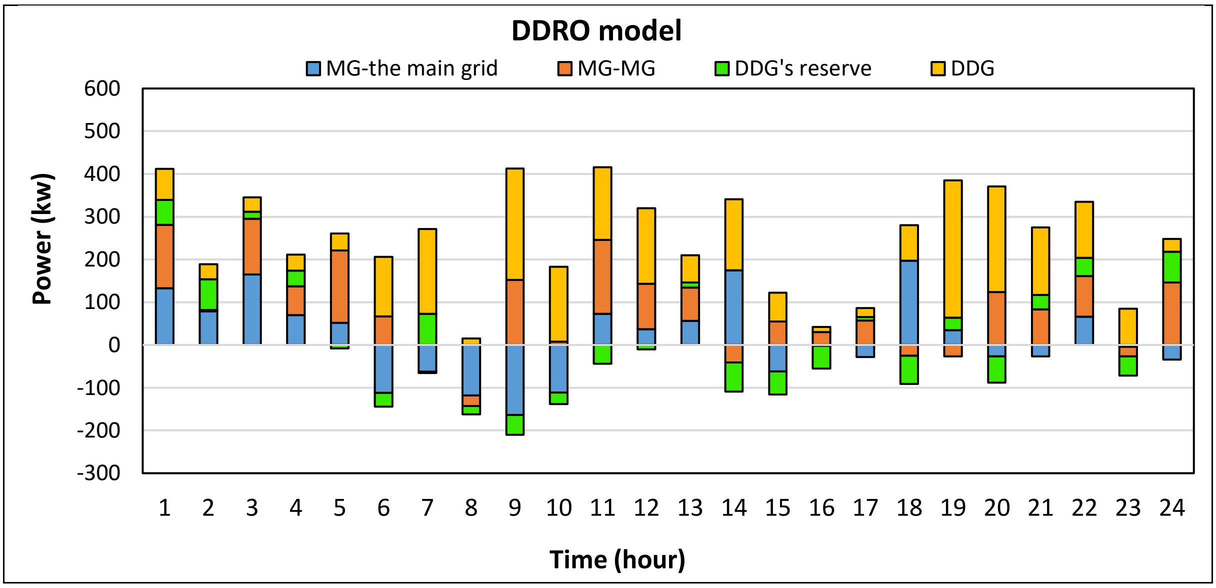
To evaluate the merits of power trading between MGs, we also solve the energy management models while setting the variables of $P_{m,n,t}^{ex}$ equal to zero. Fig. 3 (b) shows that every MG can benefit from power trading. For example, the cost of MG1 is reduced by more than 14%, 15%, and 16% after allowing MG-to-MG power exchange in the deterministic, DDRO, and PRO models. Table 2 summarizes the computational time of different energy management models. From the table, the deterministic optimization problem takes much less time to solve than the others due to a much smaller problem size. The computational time of the DDRO model with trading is about 245 s, which is slightly higher than that of the PRO model. The results also show that the case without trading has a shorter computational time compared to the case with trading. This is expected because power trading between MGs makes a connection between the optimization problems of individual MGs and increases the number of variables and constraints involved in the energy management problem.

Table 3. The computational time of different energy management models

	Mode	Deterministic model	DDRO model	PRO model
CPU time (s)	With trading	12.5	245.9	235.5
	Without trading	6.2	196.6	185.9

Optimal energy scheduling

This subsection compares optimal scheduling schemes determined by the DDRO and PRO models. Fig. 4 shows the scheduling results of power trading and the power generation and reserve of DDGs for MG1. In this figure, negative values indicate that MG1 sells excess power to the main grid or other MGs, while positive values indicate that it buys power to compensate for power shortages. In comparison with the PRO model, the DDRO model reduces the amount of power generated and reserved by DDGs. It can also be seen that with the DDRO model, MG1 needs to buy less power from other entities or has more excess power to sell. The reason is that the polyhedral set used by the PRO model has a fixed structure and may include the worst-case outputs of REGs that have little or no chance of being realized. This requires MG1 to generate more power from DDGs, buy more power from others, or make up for the deviation of REGs from their predicted output. On the other hand, the DDRO employs an uncertainty set that is self-adaptive to the uncertainty data of REGs and hedges against those worst-case power generation scenarios that are likely to happen in practice. As a result of incorporating realistic uncertainty realizations in the DDRO model, MG1 more efficiently utilizes REGs and needs less power to buy or generate from DDGs.



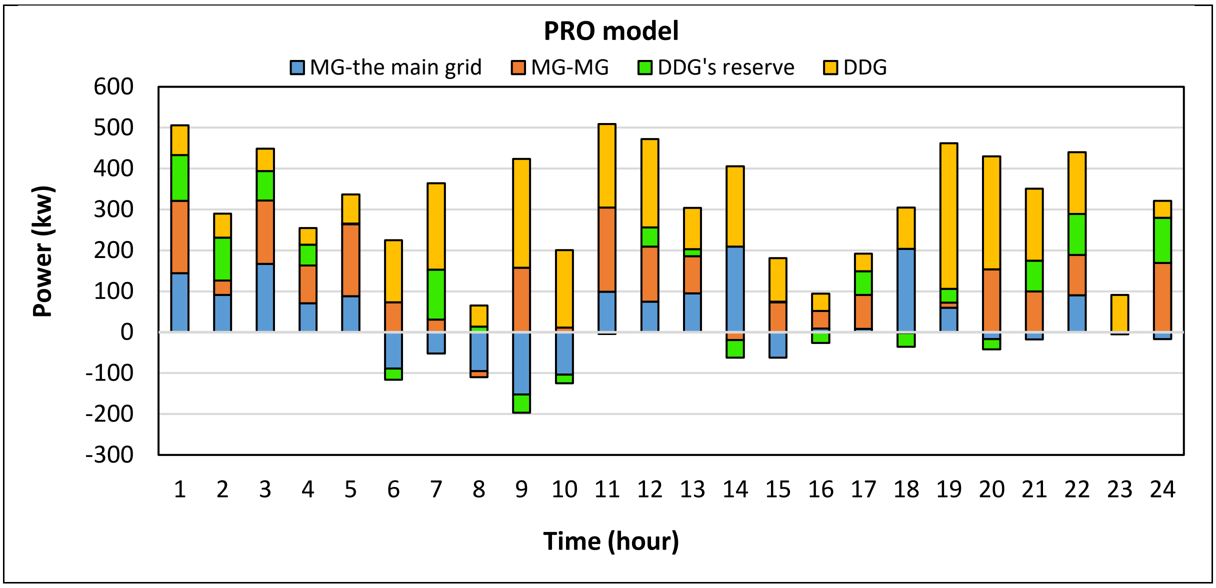


Fig. 4. Optimal scheduling of DDGs and power-sharing based on the DDRO and PRO models

Robustness verification

In this subsection, a quantitative evaluation is performed using Monte Carlo simulations to investigate how much the robustness ensured by the DDRO and PRO models will be achieved in practice [32]. This simulation evaluates the quality of different robust solutions obtained by changing the conservatism level of the DDRO and PRO models. The conservatism level of the PRO model is adjusted by a parameter named the budget of uncertainty that controls the number of uncertain parameters taking their worst-case values. For the DDRO model, the resulting solution becomes less conservative when the normalized uncertainty parameter ϕ of the confidence level $1 - 2\gamma$ decreases. Each robust solution is evaluated individually using the following procedure:

Stage 1: 1000 samples are randomly generated from Gaussian distribution to represent the prediction error of REGs (i.e., $\xi_{m,t}$) [25].

Stage 2: Using the generated samples, the DDRO and PRO model are respectively solved, and their first-stage decisions are fixed as parameters because they cannot change after the actual value of uncertain parameters becomes known.

Stage 3: An additional 500 samples are generated for the evaluation of the out-of-sample performance.

Stage 4: The optimization problem (42) with fixed first-stage decisions is solved for each random sample collected in stage 3 and the objective function value (total system cost) is calculated.

Stage 5: The mean value of the total system costs calculated over all samples is computed. Moreover, the reliability level is calculated based on the probability of violation of real-time power adjustment constraints.

The results of the above simulation for solutions with different conservatism levels are summarized in Fig. 5. Under the same reliability level, lower system costs indicate that less cost is incurred to ensure the robustness of scheduling decisions. Therefore, the DDRO model significantly outperforms the PRO model in terms of robustness cost. For example, the cost of the DRO model is 16% lower than that of the PRO model when the reliability level is around 95%. This superiority is due to the fact that the DDRO model uses a compact uncertainty set constructed based on the distributional structure captured from uncertainty data, while the PRO model uses a fixed-shape uncertainty set without considering the geometry of uncertainty data. This means the PRO model must choose a large uncertainty set with a high robustness cost to achieve the same level of reliability as the DDRO model. The results also show that both models have almost the same performance when the reliability level decreases. This is expected because in such cases, the uncertainty set of the DDRO model is not large enough to encapsulate all data samples and its performance becomes similar to the polyhedral set that only utilizes the lower and upper bounds of data samples.

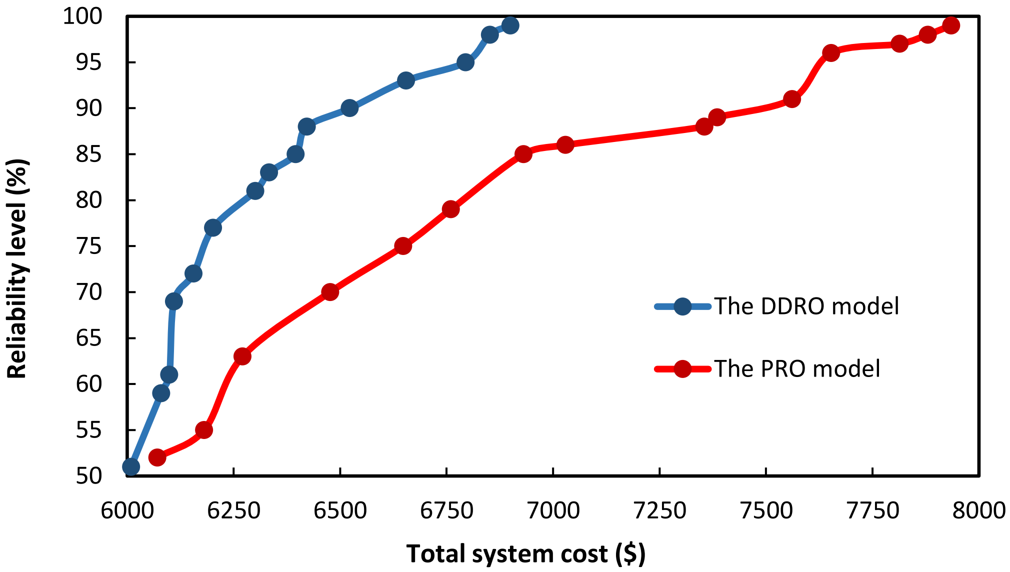


Fig. 5. Comparison of total system cost and reliability level of two robust optimization models

Conclusions

This paper develops a data-driven robust energy management model for co-optimizing the system operation and energy trading of multiple interconnected MGs. The proposed model determines robust scheduling decisions about the power generation and reserve of DDGs, the charging/discharging of ESSs, the sharing of power between MGs and the output of REGs while taking into account the uncertainties of wind turbines and photovoltaic systems simultaneously. These uncertainties are handled by a DDRO model under a data-driven uncertainty set constructed using the RKDE approach. Different from conventional uncertainty sets whose structure is fixed and has little or no connection with the probability distribution of uncertainty data, the constructed set accurately captures the region where uncertainty realizations may be located. To account for the multi-level and sequential decision-making process of scheduling, the energy management model is formulated as an adjustable robust optimization problem by incorporating wait-and-see decision variables, and the corresponding tractable formulation is obtained by adopting the affine decision rule approximation.

The managerial insights obtained from testing the proposed model on a system with three interconnected MGs are summarized as follows. Using the proposed DDRO model, the decision-maker can ensure the robust performance of MGs against possible variations in renewable power generation without having to pay a high robustness cost. To be more specific, the total cost of the DDRO model is about 10% lower than that of its deterministic counterpart. Comparing the performance of different uncertainty sets shows that the RKDE-based set outperforms the polyhedral set especially when the reliability level increases. This indicates that the RKDE-based set more effectively handles the uncertainty of renewable power generation in MGs and makes a reasonable trade-off between system robustness and economic performance. Therefore, the RKDE-based set is more appropriate for risk-averse decision-makers who want to enhance the robust performance of MGs with a smaller increment of the total system cost. There are a number of future research directions that can be considered. First, the robust performance of MGs can be improved by hedging against the abrupt outage of power generation caused by extreme weather conditions. Second, the proposed DDRO model could be integrated with principal component analysis (PCA) as a dimension reduction method to handle high-dimensional uncertainty more efficiently. Third, the robust energy management models can be solved in a distributed manner to protect the privacy of MGs.

References

[1] Wang H, Huang J. Incentivizing energy trading for interconnected microgrids. IEEE Transactions on Smart Grid. 2016;9:2647-57.
[2] Querini PL, Chiotti O, Fernádez E. Cooperative energy management system for networked microgrids. Sustainable Energy, Grids and Networks. 2020;23:100371.
[3] Mohseni S, Pishvaee MS, Dashti R. Privacy-preserving energy trading management in networked microgrids via data-driven robust optimization assisted by machine learning. Sustainable Energy, Grids and Networks. 2023:101011.
[4] Islam M, Yang F, Amin M. Control and optimisation of networked microgrids: A review. IET Renewable Power Generation. 2021;15:1133-48.
[5] Zou H, Mao S, Wang Y, Zhang F, Chen X, Cheng L. A survey of energy management in interconnected multi-microgrids. IEEE Access. 2019;7:72158-69.
[6] Bazmohammadi N, Tahsiri A, Anvari-Moghaddam A, Guerrero JM. A hierarchical energy management strategy for interconnected microgrids considering uncertainty. International Journal of Electrical Power & Energy Systems. 2019;109:597-608.
[7] Mohseni S, Pishvaee MS. A robust programming approach towards design and optimization of microalgae-based biofuel supply chain. Computers & Industrial Engineering. 2016;100:58-71.
[8] Aghdam FH, Kalantari NT, Mohammadi-Ivatloo B. A stochastic optimal scheduling of multi-microgrid systems considering emissions: A chance constrained model. Journal of Cleaner Production. 2020;275:122965.
[9] Pishvaee MS, Mohseni S, Bairamzadeh S. Biomass to Biofuel Supply Chain Design and Planning Under Uncertainty: Concepts and Quantitative Methods. 2020.
[10] Ning C, You F. Optimization under uncertainty in the era of big data and deep learning: When machine learning meets mathematical programming. Computers & Chemical Engineering. 2019;125:434-48.
[11] Ning C, You F. Data-driven adaptive nested robust optimization: general modeling framework and efficient computational algorithm for decision making under uncertainty. AIChE Journal. 2017;63:3790-817.
[12] Mohseni S, Pishvaee MS. Data-driven robust optimization for wastewater sludge-to-biodiesel supply chain design. Computers & Industrial Engineering. 2020;139:105944.
[13] Liu Y, Guo L, Wang C. A robust operation-based scheduling optimization for smart distribution networks with multi-microgrids. Applied Energy. 2018;228:130-40.
[14] Fu Y, Zhang Z, Li Z, Mi Y. Energy Management for Hybrid AC/DC Distribution System With Microgrid Clusters Using Non-Cooperative Game Theory and Robust Optimization. IEEE Transactions on Smart Grid. 2020;11:1510-25.
[15] Zhang B, Li Q, Wang L, Feng W. Robust optimization for energy transactions in multi-microgrids under uncertainty. Applied Energy. 2018;217:346-60.
[16] Gazijahani FS, Salehi J. Reliability constrained two-stage optimization of multiple renewable-based microgrids incorporating critical energy peak pricing demand response program using robust optimization approach. Energy. 2018;161:999-1015.
[17] Li L, Cao X, Wang P. Optimal coordination strategy for multiple distributed energy systems considering supply, demand, and price uncertainties. Energy. 2021;227:120460.
[18] Wang B, Zhang C, Li C, Yang G, Dong ZY. Transactive Energy Sharing in a Microgrid via an Enhanced Distributed Adaptive Robust Optimization Approach. IEEE Transactions on Smart Grid. 2022;13:2279-93.
[19] AlDavood MS, Mehbodniya A, Webber JL, Ensaf M, Azimian M. Robust Optimization-Based Optimal Operation of Islanded Microgrid Considering Demand Response. Sustainability. 2022;14:14194.

[20] Wu J, Liu Y, Chen X, Wang C, Li W. Data-driven adjustable robust Day-ahead economic dispatch strategy considering uncertainties of wind power generation and electric vehicles. International Journal of Electrical Power & Energy Systems. 2022;138:107898.
[21] Li Y, Han M, Shahidehpour M, Li J, Long C. Data-driven distributionally robust scheduling of community integrated energy systems with uncertain renewable generations considering integrated demand response. Applied Energy. 2023;335:120749.
[22] Li X, Liu Y, Guo L, Li X, Wang C. A data-driven based uncertainty set modelling method for microgrid robust optimization with correlated wind power. CSEE Journal of Power and Energy Systems. 2022.
[23] Zhou Y, Wei Z, Shahidehpour M, Chen S. Distributionally robust resilient operation of integrated energy systems using moment and wasserstein metric for contingencies. IEEE Transactions on Power Systems. 2021;36:3574-84.
[24] Wang L, Jiang C, Gong K, Si R, Shao H, Liu W. Data-driven distributionally robust economic dispatch for distribution network with multiple microgrids. IET Generation, Transmission & Distribution. 2020;14:5712-9.
[25] Li J, Khodayar ME, Wang J, Zhou B. Data-Driven Distributionally Robust Co-Optimization of P2P Energy Trading and Network Operation for Interconnected Microgrids. IEEE Transactions on Smart Grid. 2021;12:5172-84.
[26] Ning C, You F. A data-driven multistage adaptive robust optimization framework for planning and scheduling under uncertainty. AIChE Journal. 2017;63:4343-69.
[27] Kim J, Scott CD. Robust kernel density estimation. The Journal of Machine Learning Research. 2012;13:2529-65.
[28] Ning C, You F. Data-driven decision making under uncertainty integrating robust optimization with principal component analysis and kernel smoothing methods. Computers & Chemical Engineering. 2018;112:190-210.
[29] Wang D, Qiu J, Reedman L, Meng K, Lai LL. Two-stage energy management for networked microgrids with high renewable penetration. Applied Energy. 2018;226:39-48.
[30] Liu Z, Wang L, Ma L. A transactive energy framework for coordinated energy management of networked microgrids with distributionally robust optimization. IEEE Transactions on Power Systems. 2019;35:395-404.
[31] Bertsimas D, Sim M. The price of robustness. Operations research. 2004;52:35-53.
[32] Mohseni S, Pishvaee MS, Sahebi H. Robust design and planning of microalgae biomass-to-biodiesel supply chain: A case study in Iran. Energy. 2016;111:736-55.