Energy Generation Scheduling in Microgrids Involving Temporal-Correlated Renewable Energy

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***Abstract*—In this paper, a cost minimization problem is formulated to intelligently schedule energy generations for microgrids equipped with unstable renewable sources and energy storages. In such systems, the uncertain renewable energy will impose unprecedented scheduling challenges. To cope with the fluctuate nature of the renewable energy, an uncertainty model based on renewable energies' moment statistics is developed. Specifically, we obtain the mean vector and second-order moment matrix according to predictions and field measurements and then define uncertainty set to confine the renewable energy generation. The uncertainty model allows the renewable energy generation distributions to fluctuate within the uncertainty set. We develop chance constraint approximations and robust optimization approaches based on a Chebyshev inequality framework to firstly transform and then solve the scheduling problem. Numerical results based on real-world data traces evaluate the performance bounds of the proposed scheduling scheme. It is shown that the temporal-correlation information of the renewable energy within a proper time span can effectively reduce the conservativeness of the solution. Moreover, detailed studies on the impacts of different factors on the proposed scheme provide some interesting insights which shall be useful for the policy making for the future microgrids.**

I. Introduction

The power grid is being restructured to allow high penetration of distributed generators to become more environmental friendly and cost effective. The growth and evolution of the future electricity grids is expected to come with the plug-and-play of the basic structure named microgrid. Microgrids can operate in grid-connected mode, where they are allowed to import power from the electricity grid, or in islanded mode, in which they are isolated from the upstream power grid and utilize their local generators as the source of power supply when needed. There are world-wide deployments of pilot microgrids, such as those reported in [1] and [2].

Energy generation scheduling to achieve reliable and economic power supply is an essential component in microgrids. Two features of microgrids are the integrations of large-scale renewable sources and energy storage systems. Such features, however, impose significant challenges on the design of intelligent control strategies for microgrids. Traditional generation scheduling schemes are typically based on perfect predictability of energy generation, which is hardly the case in the microgrids as the renewable energies are highly volatile and hard to predict. Although the integration of energy storages may to a certain extent alleviate the uncertainty problem caused by the fluctuations of renewable energies, it further complicates the scheduling process of the system operation. Because of these unique challenges, it remains an open issue to design robust and cost-effective energy generation scheduling schemes for microgrids.

A. *Related Work*

There exists some literature taking into account renewable energy uncertainties when scheduling the energy generation in microgrids. Such work can be mainly classified into two categories: the stochastic optimization based approaches [3]–[6] and robust optimization based approaches [7]–[10]. the stochastic optimization approaches explicitly incorporate a probability distribution function of the uncertainty, and they often rely on enumerating discrete scenarios of the uncertainty realizations. Such approaches mainly have two limitations. First, it may be difficult and costly to obtain an accurate probability distribution of uncertainty. Second, the solution may only provide probabilistic guarantees to the system reliability. To obtain a highly reliable guarantee requires a large number of samples, which poses substantial computational challenges.

In some recent studies, robust optimization has received growing attention as a modeling framework for optimization under uncertainties. Instead of postulating explicit probability distribution, robust optimization confines the random variable in a pre-defined uncertainty set containing the worst-case scenario. For instance, in [7]–[10], uncertainties in renewable energy generation are presented as interval values with deterministic lower and upper bounds, and the framework developed in [11] is incorporated to solve the problem. With no requirement for an explicit probability distribution, uncertainty can be characterized more flexibly. The conservativeness of the solution can also be easily controlled and the problem is computationally tractable both practically and theoretically even for large scale problems.

In our study, the robust optimization concept is also applied to tackle the renewable energy uncertainties in energy generation scheduling problem of microgrids. Different from the previous robust optimization works [7]–[10] which usually confine the uncertainty within a pre-defined lower and upper bounds, in this paper, we adopt first- and second-order moment statistics to characterize the renewable energy uncertainties, which can provide more details in describing the underlying uncertainty. Moreover, moment statistics are very easy to obtain in practice.

B. Main Contributions

In this paper, by extending our previous work [12], [13], we consider a robust optimization-based energy generation scheduling problem in a microgrid scenario considering the uncertainty of renewable energy and integration of energy storages. The main contributions of this paper can be briefly summarized as follows:

- We adopt the moment statistic model to capture the fluctuant nature of the renewable energy. To the best of our knowledge, this is the first time that moment statistics are utilized to model and analyze the properties of renewable energy generation. In addition, moment statistics are easy to obtain in practical applications. Compared with the distribution uncertainty model proposed in our previous work [12], [13], the microgrid systems do not need to analyze a large amount of historical data by adopting the moment statistic model.
- The energy generation scheduling problem is formulated into a cost minimization problem with random variables in the constraints. We develop chance constraint approximations and robust optimization approaches to transform the problem into a solvable form.
- To the best of our knowledge, this work is the first to investigate how the temporal-correlation information of renewable energy impacts the energy generation scheduling in microgrids.
- Numerical results based on real-world data evaluate the impacts of different parameters and performance bounds of the proposed scheduling scheme. A novel observation is that the temporal-correlation information of the renewable energy can help to effectively reduce the conservativeness of the problem solving and improve the performance of the proposed generation scheduling scheme.

The rest of this paper is organized as follows. Section II introduces the particulars of the system operation. In Section III, we introduce the mathematical depiction of the energy generation scheduling problem and the moment statistic model of renewable energies. Section IV presents the chance constraint approximation and robust optimization approach for handling the demand balancing and renewable energy uncertainties. The simulation results and discussions are shown in Section V. The parameters and calibration data are drawn from real-world statistics. Finally, we conclude our paper and discuss the future work directions in Section VI.

II. System Model

We consider a microgrid comprising a number of homogeneous conventional power units, a renewable energy generation system (e.g., solar panels) and an energy storage system.

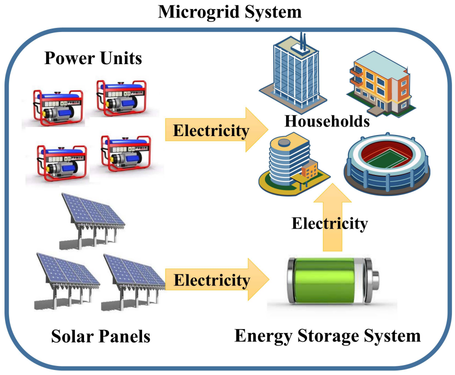

Fig. 1: The architecture of a typical microgrid system.

Currently the microgrid is operated in the islanded mode. The illustration of the microgrid system is shown in Fig. 1. The particulars of the system operation are explained in the followings.

We divide time into discrete time slots with an equal length. Let $\mathcal{A}$ denote the set of conventional power generators. Further denote the start up cost for turning on a generator a as c_a^s, the sunk cost of maintaining the generator a in active mode for one unit of time as c_a^b, and the marginal cost for the generator a to produce one unit of electricity as c_a^m. Adopting a general power unit model, we define the energy generation scheduling vector $\mathbf{x_a}$ and state vector $\mathbf{y_a}$ as follows:

$$\mathbf{x_a} = [x_a^1, x_a^2, ..., x_a^H] \text{ and } \mathbf{y_a} = [y_a^1, y_a^2, ..., y_a^H], \tag{1}$$

where $H \geq 1$ is the scheduling horizon which indicates the number of time slots ahead that are taken into account for decision making in the energy generation scheduling. For each coming time slot $h \in \mathcal{H} = [1, 2, ..., H]$, we use a binary variable $y_a^h = 0/1$ to denote the state of generator a (off/on) and a variable x_a^h to denote the dispatched load to power unit a. For each unit a with a maximum power output capacity E_a^{max} and a minimum stable output E_a^{min}, we have

$$y_a^h \cdot E_a^{min} \leq x_a^h \leq y_a^h \cdot E_a^{max}. \tag{2}$$

In our model, we assume that the renewable energy harvested from solar panels will be first saved into energy storage devices for future use, i.e., a solar-plus-battery system is considered. The household can obtain electricity from energy storages in an on-demand manner. Denote the household demand and energy obtained from energy storages at time h as D^h and V^h, respectively. A central requirement of the microgrid is to set the energy source power such that the electricity could meet the demand at all time slots. This statement can be described as

$$\sum_{h=1}^{H} x_a^h + V^h = D^h, \ \forall h \in \mathcal{H}. \tag{3}$$

Let B^h denote the amount of energy stored in the battery. To ensure that there is always backup power for emergency use, we require the battery to be maintained at or above its initial level at the end of the scheduling horizon:

$$\sum_{h=1}^{H} V^h - \sum_{h=1}^{H} \xi^h \leq 0, \tag{4}$$

where $\xi^h \in [0, \xi^{max}]$ is the random variable representing the amount of energy harvested from renewable energy devices (e.g., solar panels), and ξ^{max} denotes the maximum generation capacity of the renewable energy generators. A battery's level can never go beyond the maximum capacity or drop below 0. Therefore we have that

$$0 \leq B^h \leq B^{max}, \tag{5}$$

where B^{max} represents the maximum capacity of the energy storage devices. Last, the battery level varies over time as

$$B^{h+1} = B^h + \xi^h - V^h. \tag{6}$$

In this paper, we assume that the energy storage device is of a large size. Under such case, constraints (5) and (6) can be relaxed when scheduling the energy generation in microgrids [14].

III. Problem Formulation

A. Cost Minimization Formulation

The microgrid aims to minimize the operation cost of the whole system over the entire time horizon. The cost minimization formulation is defined as follows

$$\begin{aligned} \min_{\mathbf{X},\mathbf{Y},\mathbf{V}} \quad & \sum_{h=1}^{H} \sum_{a\in\mathcal{A}} \left[c_a^m \cdot x_a^h + c_a^b \cdot y_a^h + c_a^s \cdot (y_a^h - y_a^{h-1})^+ \right] \\ \text{s.t.} \quad & (2)-(4),\ y_a^h \in \{0,1\} \\ & x_a^h, V^h \in \mathbb{R}_0^+, h \in \mathcal{H}, a \in \mathcal{A}, \end{aligned} \tag{7}$$

where $\mathbf{X} = [\mathbf{x_1}, \mathbf{x_2}, ..., \mathbf{x_a}, ...]^{\mathrm{T}}$ and $\mathbf{Y} = [\mathbf{y_1}, \mathbf{y_2}, ..., \mathbf{y_a}, ...]^{\mathrm{T}}$ are matrices of decision vectors $\mathbf{x_a}$ and $\mathbf{y_a}$ for $a \in \mathcal{A}$, respectively; $\mathbf{V} = [V^1, V^2, ..., V^h, ...]$ is the vector of decision variables V^h for $h \in \mathcal{H}$; $(\cdot)^+$ is a function where $(x)^+ = \max(0, x)$. The cost function comprises the operation and start-up costs of conventional power generators for the entire time horizon H.

A difficulty in solving this problem lies in the correlation term $(y_a^h - y_a^{h-1})^+$. By introducing an auxiliary variable z_a^h into the problem formulation, an equivalent expression can be obtained as

$$\begin{aligned} \min_{\mathbf{X},\mathbf{Y},\mathbf{Z},\mathbf{V}} \quad & \sum_{h=1}^{H} \sum_{a\in\mathcal{A}} \left[c_a^m \cdot x_a^h + c_a^b \cdot y_a^h + c_a^s \cdot z_a^h \right] \\ \text{s.t.} \quad & z_a^h \geq 0,\ z_a^h \geq y_a^h - y_a^{h-1} \\ & (2)-(4),\ y_a^h, z_a^h \in \{0,1\} \\ & x_a^h, V^h \in \mathbb{R}_0^+, h \in \mathcal{H}, a \in \mathcal{A}, \end{aligned} \tag{8}$$

where $\mathbf{Z}_{|\mathcal{A}|\times H}$ is the matrix of auxiliary variable z_a^h for $a \in \mathcal{A}$, $h \in \mathcal{H}$. The objective for introducing an auxiliary variable z_a^h into problem formulation (7) is to have an equivalent, solvable problem without the correlation term $(y_a^h - y_a^{h-1})^+$.

Another difficulty in solving problem (7) is the indeterminacy of renewable energy generations ξ^h existing in (4). Note that to optimize over the space defined by (4) amounts to solving an optimization problem with potentially large or even infinite number of constraints. Obviously, this realization of uncertainties is intractable. Next, we adopt the moment statistic model to capture the uncertainties of ξ^h.

B. Moment Statistic Model

It is generally difficult to characterize the renewable energy generation. However, we may measure the variability of renewable energy generation using its mean and second-order moments, which are quite easy to obtain from field measurements. Mathematically, we may assume that renewable energy generation $\xi = [\xi^1, ..., \xi^H]$ is confined by the following uncertainty set:

$$\begin{aligned} \mathcal{P}(\mu, S) = \Big\{ \mathbb{P}_\xi \in \mathcal{P}_\infty : & \int_{\mathbb{R}^n} \xi \cdot \mathbb{P}(\mathrm{d}\xi) = \mu, \\ & \int_{\mathbb{R}^n} \xi\xi^T \mathbb{P}(\mathrm{d}\xi) = S \Big\}, \end{aligned} \tag{9}$$

where $\mu \in \mathbb{R}^H$ and $S \in \mathbb{S}^H$, $\mathbb{S}^H$ is the set of symmetric matrixes with dimension H, while $\mathcal{P}_\infty$ represents the set of all distributions on $\mathbb{R}^H$. Thus, $\mathcal{P}(\mu, S)$ contains all distributions that share the same mean μ and second-order moment matrix S. The temporal-correlated information of renewable energy generation is included in S, e.g., the two lines above and below the diagonal of S indicate the correlation within one time slot. With this moment statistic model, we are now ready to transform the constraint (4) to allow efficient solution of (8).

IV. Optimization Algorithm

A. Robust Approach for Constraint (4)

As shown in (4), the energy storage balance can be expressed as: $\sum_{h=1}^{H} V^h - \sum_{h=1}^{H} \xi^h \leq 0$. In practice, a decision criterion is to properly set decision vector $\mathbf{V}$ to allow good confidence that (4) is satisfied. To achieve that, we may introduce a small value ϵ to control the degree of conservativeness and change the above expression into a chance constraint

$$\mathbf{P}\Big(\sum_{h=1}^{H} \xi^h < \sum_{h=1}^{H} V^h\Big) \leq \epsilon, \tag{10}$$

where ϵ is the fault tolerance limit of the microgrid, representing the acceptable probability that the desirable power supply is not attained. Then we can have the robust expression that

$$\sup_{\mathbb{P}_\xi \in \mathcal{P}(\mu,S)} \mathbf{P}\Big(\sum_{h=1}^{H} \xi^h < \sum_{h=1}^{H} V^h\Big) \leq \epsilon. \tag{11}$$

Theorem 1: Solving the left part of inequality (11) is equivalent to solving the following semidefinite programming problem (SDP):

$$
\begin{aligned}
\max \quad & \sum_{i=1}^{k} \lambda_i & (12)\\
\text{s.t.} \quad & z_i \in \mathbb{R}^H, Z_i \in \mathbb{S}^H, \lambda_i \in \mathbb{R} \quad \forall i = 1, 2, ..., k \\
& a_i^T z_i \geq b_i \lambda_i \quad \forall i = 1, 2, ..., k \\
& \sum_{i=1}^{k} \begin{pmatrix} Z_i & z_i \\ z_i^T & \lambda_i \end{pmatrix} \preceq \begin{pmatrix} S & \mu \\ \mu^T & 1 \end{pmatrix} \\
& \begin{pmatrix} Z_i & z_i \\ z_i^T & \lambda_i \end{pmatrix} \succeq 0 \quad \forall i = 1, 2, ..., k
\end{aligned}
$$

where $a_{1_{H\times 1}} = -1 \cdot [1, 1, ..., 1]^T$; $[a_2, ..., a_{H+1}] = -1 \cdot \mathbf{I}_H$; $[a_{H+2}, ..., a_{2H+1}] = \mathbf{I}_H$, and $\mathbf{I}_H$ is the identity matrix with dimension H; $b_1 = \sum_{h=1}^{H} V^h$; $[b_2, ..., b_{H+1}] = [0, .., 0]^T$; $[b_{H+2}, ..., b_{2H+1}] = \xi^{max} \cdot [1, 1, ..., 1]^T$, and obviously $k = 2H + 1$.

The SDP reformulation (12) can be obtained through the generalized Chebyshev inequality bounds. Detailed proof of **Theorem 1** is lengthy and omitted here due to limited space. Readers may refer to reference [15] for more detailed descriptions. Defining $b_1 = \sum_{h=1}^{H} V^h$ as the robust electricity acquisition (EA) decision, which equals the amount of electricity obtained from energy storage systems during the whole time horizon. Further define $K_\xi(b_1) = \sup_{\mathbb{P}_\xi \in \mathcal{P}(\mu, S)} \mathbf{P}(\sum_{h=1}^{H} \xi^h < \sum_{h=1}^{H} V^h)$ as the worst-case fault probability. We can then get a worst-case mapping $\mathcal{M}_{wc}$ which maps the robust EA decision b_1 to $K_\xi(b_1)$:

$$
\mathcal{M}_{wc}: \quad b_1 \longrightarrow K_\xi(b_1). \tag{13}
$$

B. Determine the Robust EA Decision Threshold

Since there exist random variables in the constraint (4), we cannot solve energy generation scheduling problem (8) directly. As mentioned before, we adopt chance constraint approximations and robust approaches to transform the constraint (4). The goal of such transformation is to determine the maximum robust EA decision b_1^* (i.e., robust EA decision threshold) so that the constraint (4) can be transformed into a solvable form.

Theorem 2: The worst-case fault probability $K_\xi(b_1)$ is non-decreasing with respect to the robust EA decision b_1.

It is straightforward to derive **Theorem 2** since $\mathrm{d}K_\xi(b_1)/\mathrm{d}b_1 = f_\xi(b_1) \geq 0$, where f_ξ is the probability density function of random variable $\sum_{h=1}^{H} \xi^h$. Though directly obtaining the robust decision threshold is not practical, the monotonicity of $K_\xi(b_1)$ enlightens us a bisection method to search for the solution for $K_\xi(b_1^*) = \epsilon$. The main idea is to perform the search within an interval of $[0, \rho]$, where ρ is an empirical constant such that $K_\xi(\rho) > \epsilon$.

Details of the algorithm for searching the robust EA decision threshold are presented in Algorithm 1. Note that, in the 5th line of the algorithm, we use interior point method to solve the SDP problem in **Theorem 1** and obtain the worst-case probability with fixed robust EA decision. Then we compare the worst-case fault probability at $b_{1\_}$ and b_1^{-} with the fault tolerance limit ϵ, respectively. The comparison results help shrink the search region as shown in lines 6-9.

Algorithm 1 Search for robust EA decision threshold b_1^*

Input: Mean vector μ; Second-order moment matrix S
Search radius ρ; Battery balance fault tolerant limit ϵ;
Computational accuracy tolerance ε.
Output: Robust EA decision threshold such that $K_\xi(b_1^*) = \epsilon$;
1: **Begin**
2: **initialize** $b_{1\_} = 0$, $b_1^{-} = \rho$
3: **while** $|b_{1\_} - b_1^{-}| > \varepsilon$
4: **set** $\bar{b}_1 = \frac{b_{1\_} + b_1^{-}}{2}$
5: **compute** $K_\xi(\bar{b}_1)$ by solving the SDP problem (12)
6: **if** $\left(K_\xi(\bar{b}_1) - \epsilon\right)\left(K_\xi(b_1^{-}) - \epsilon\right) < 0$
7: **then** set $b_{1\_} = \bar{b}_1$
8: **else** set $b_1^{-} = \bar{b}_1$ **end if**
9: **if** $|K_\xi(\bar{b}_1) - \epsilon| < \varepsilon$ **break end if**
10: **end while**
11: **set** $b_1^{*} = \bar{b}_1$
12: **End**

Once the robust EA decision threshold b_1^* for the constraint (4) is obtained, we can approximate (4) with the following constraint:

$$
\sum_{h=1}^{H} V^h = b_1^*. \tag{14}
$$

Now we can tackle the following optimization problem rather than the original formulation (8)

$$
\begin{aligned}
\min_{\mathbf{X},\mathbf{Y},\mathbf{Z},\mathbf{V}} \quad & \sum_{h=1}^{H} \sum_{a\in\mathcal{A}} \left[c_a^m \cdot x_a^h + c_a^b \cdot y_a^h + c_a^s \cdot z_a^h\right] & (15)\\
\text{s.t.} \quad & z_a^h \geq 0, \; z_a^h \geq y_a^h - y_a^{h-1} \\
& (2)\ (3)\ (14), \; y_a^h, z_a^h \in \{0, 1\} \\
& x_a^h, V^h \in \mathbb{R}_0^+, h \in \mathcal{H}, a \in \mathcal{A}.
\end{aligned}
$$

Note that constraint (4) with random variables in the initial formulation (8) is approximated and replaced by (14) with no random variable. This problem is a mixed integer programming (MILP) problem, which can be solved effectively by cutting plane method, branch and bounded method, etc.

V. Performance Evaluation and Analysis

In this section, we present numerical results based on real world traces to assess the performance bounds of the proposed energy generation scheduling scheme and evaluate the effects of different parameters.

A. Parameters and Settings

We assume there are solar panels in the microgrid system. The area of solar panels in this microgrid system is set to be 1.5×10^4 m^2. The energy conversion efficiency is 0.4. The monthly clearness index time series are from 10 meteorological stations in Singapore. These stations are designed

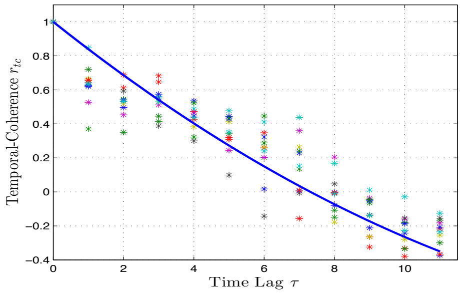

Fig. 2: Temporal correlation fitting using first two weeks' radiation data of November 2012. Nonlinear least square method is adopted to get the fitted curve $r_{tc} = 1 - 0.1644\tau + 0.0.0038\tau^2$.

to perform monitoring of solar radiation. Silicon sensors are employed at each station, with some also having pyranometers that measure diffuse and global irradiance. The silicon sensors are calibrated by the Fraunhofer Institute for Solar Energy Systems to achieve an uncertainty under 2%. The data used in this work is hourly data collected by these 10 stations in November 2012 [16], [17].

We obtain the electricity demand statistics from [18]. We focus on a college at Forecasting Climate Zone (FCZ) 09. This trace contains hourly electricity demand of the college in year 2002. The parameters of conventional power generators are set based on the statistics in [19]. The maximum output of a power unit is $E_a^{max} = 3.5$ MWh and the minimum stable output is $E_a^{min} = 1.5$ MWh. The marginal cost for producing one unit of electricity is $c_a^m = 0.051$ \$/KWh, which is obtained using the fuel price and the energy conversion efficiency. The sunk cost for a generator keeping in active mode is $c_a^b = 110$ \$/h, which includes the operation cost, capital cost, and maintenance cost. The start up cost is set to be $c_a^s = 560$ \$. Finally, unless otherwise stated, it is assumed there are 10 power units in this microgird system, the duration of a time slot is 1 h and the time horizon is 12 h. The MILP problem is solved using Mosek optimization toolbox 7.0 on an Intel workstation with 6 processors clocking at 3.2 GHZ and 16 GB of RAM.

B. Results and Discussions

We first investigate the statistical properties of solar energy generation in the time domain. In particular, we adopt solar irradiance data for the first two weeks in November 2012. Nonlinear least square method is used to obtain the fitted line. The results concerning the temporal coherence of solar energy generation with respect to time lag is depicted in Fig. 2. Note that the colored dots show the coherence of solar energy generations in 10 stations, and the blue curve is the fitted function $r_{tc} = 1 - 0.1644\tau + 0.0.0038\tau^2$, where τ is the time lag and r_{tc} is the coherence. As we observe in the figure, solar energy generations show near-linear correlation in the time domain, and such observations help us analyze the performance bounds of the proposed energy generation scheduling scheme in the following contents.

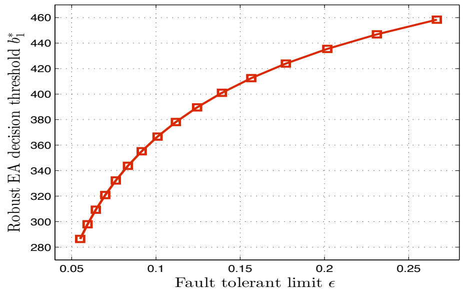

Fig. 3: Robust EA decision threshold b_1^* with respect to the fault tolerant limit ϵ.

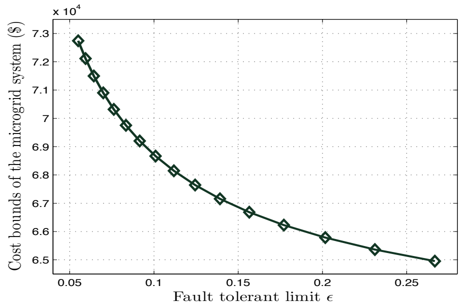

Fig. 4: Cost bounds of the microgrid system with respect to the fault tolerant limit ϵ.

Next, we investigate how the robust EA decision threshold b_1^* varies when the fault tolerant limit ϵ increases. Figure 3 plots the mapping from fault tolerance limit ϵ to robust EA decision threshold b_1^*. It is shown from the figure that the robust EA decision threshold b_1^* grows when ϵ increases. In other words, a larger fault tolerant limit ϵ permits a higher reliance on the solar energy (a larger robust EA decision threshold), which is straightforward to understand. Note that the robust EA decision threshold function is monotone, therefore it is justified to adopt the bisection method as presented in Algorithm 1 to search for the robust EA decision threshold. We also observe that the incremental rate of the robust EA decision threshold slows down when ϵ increases.

In Fig. 4, we vary the values of fault tolerance limit ϵ and study how system cost bound changes with respect to ϵ. Note that the cost bound represents the operation cost of the microgrid system under the worst-case condition of solar energy generation. Apparently, the cost bound decreases when ϵ increases. The reason is that when ϵ increases, the protection level for the robust solution will decrease, the scheduling strategies of the microgrid hence become less conservative, leading to the decline of the operation cost. Also note that the cost bound is less sensitive when the fault tolerance limit ϵ is at a higher level.

In Fig. 5, we evaluate how the fault probability $K_{\xi}(b_1)$ varies with respect to the amount of temporal-correlation information utilized under different values of robust EA decision b_1. Specifically, we conduct a set of experiments. In the first

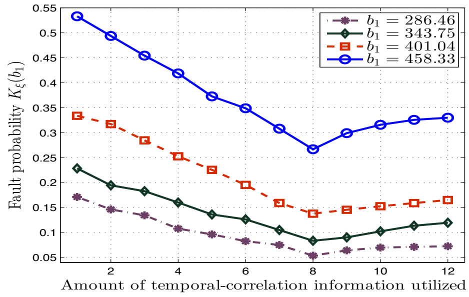

Fig. 5: Fault probability $K_\xi(b_1)$ with respect to the amount of temporal-correlation information utilized under different value of robust EA decision b_1.

step, we only utilize the mean and variance information of renewable energy generation to define μ vector and S matrix, i.e., the elements in S is set to 0 except for those on the diagonal; At the second step, we add the temporal-correlation information within 1-hour time lag, i.e., only the diagonal, and the lines above and below it have values in the second-order moment matrix S. Then, at each time step n, $n \geq 2$, the temporal-correlation information within time lag 0 and time lag $n-1$ is utilized for the decision making. We repeat such process until time step 12. At each step of the experiment, we compute the fault probability under different values of robust EA decision and plot Fig. 5. As depicted in this figure, when we expand the time lag window to utilize more temporal-correlation information, the fault probability will decrease first and then increase. This result indicates that the temporal-correlation information of solar energy generation within a proper time span is of benefit for reducing the conservativeness of the robust solution, whereas the correlation information outside a time lag (8 hours) window is useless, even harmful for the decision making. Thus, we may suggest that the microgrid should only utilize the temporal-correlation information within 8 hours for developing the scheduling strategies.

VI. Conclusion

In this paper, we investigated the energy generation scheduling problem in a microgrid system equipped with renewable energy resources and energy storage devices. The aim of the scheduling is to minimize the system operation cost while maintaining the system reliability. To cope with the indeterminacy nature of renewable energy generation, we adopted a moment statistic model to confine the fluctuations. Such model allows convenient handling of volatile renewable energies as long as the generations are not too intensely different from the predictions or empirical knowledge. Chance constraint approximations and robust optimization approaches based on generalized Chebyshev bounds are developed to first transform and then solve the scheduling problem. Numerical results based on real-world statistics evaluate the cost bounds of the proposed scheduling scheme. The impact of different parameters has been carefully studied. Moreover, we investigated the temporal-correlation properties of the solar energy. It is shown that the temporal-correlation information of solar energy generation within a proper time lag is beneficial for reducing the conservativeness of the robust solution, whereas the correlation information of longer time span may be harmful for the decision making. These results, as we believe, shall provide useful insights helping the microgrid system operators to develop rational scheduling strategies.

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