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A robust optimization approach for energy generation scheduling in microgrids

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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 combined heat and power (CHP) generators. In such systems, the fluctuant net demands (i.e., the electricity demands not balanced by renewable energies) and heat demands impose unprecedented challenges. To cope with the uncertainty nature of net demand and heat demand, a new flexible uncertainty model is developed. Specifically, we introduce reference distributions according to predictions and field measurements and then define uncertainty sets to confine net and heat demands. The model allows the net demand and heat demand distributions to fluctuate around their reference distributions. Another difficulty existing in this problem is the indeterminate electricity market prices. We develop chance constraint approximations and robust optimization approaches to firstly transform and then solve the prime problem. Numerical results based on real-world data evaluate the impacts of different parameters. It is shown that our energy generation scheduling strategy performs well and the integration of combined heat and power (CHP) generators effectively reduces the system expenditure. Our research also helps shed some illuminations on the investment policy making for microgrids.

1. Introduction

The electricity grid is being restructured to allow high penetration of distributed generators to become more environment friendly and cost effective [1]. The growth and evolution of the power grids is expected to come with the plug-and-play of the basic structure called microgrid. Microgrids can operate in grid-connected mode, in which they are allowed to import power from the electricity grid, or in islanded mode, where they are isolated from the upstream power grid and use their local generators as the source of power supply when needed. There are world-wide deployments of pilot microgrids, especially in Europe, e.g., those reported in [2,3].

Energy generation scheduling to achieve robust and economic power supply is an essential component in microgrids. Two features of microgrids are the integration of large-scale renewable sources and the use of combined heat and power (CHP) generators. Such features, however, impose significant difficulties on the design of intelligent control strategies for microgrids. Traditional generation scheduling schemes are typically based on perfect prediction of future demands [4], which is hardly the case in the microgrids since small-scale demands are hard to predict and renewable energies are highly volatile. Furthermore, although the integration of CHP generators can bring great economic benefits to microgrids by simultaneous production of useful heat and electricity outputs, thereby increasing the overall efficiency and bringing environmental benefits, it brings new uncertainties to the scheduling problem: the heat demand exhibits a new stochastic pattern and makes it more difficult to predict the overall energy demands. On top of these, the real-time pricing in electricity market yields another uncertainty dimension to the scheduling problem. The microgrid has to make a proper strategic decision on the amount of power to be imported so as to cope with the financial risks brought by price uncertainty. Because of these unique challenges, it remains an open issue to design robust and cost-effective energy generation scheduling strategies for microgrids.

1.1. Related work

Energy generation scheduling is the process of effectively scheduling different energy sources (local generators, central grid, renewable energy generations, etc.) to meet the energy requests at the minimum cost subject to various physical constraints of the

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power systems. It is a classic problem in electricity system which is composed of two aspects, namely unit commitment (UC) [5] and economic dispatch (ED) [6], respectively. The UC problem involves determining the start-up and shut-down schedules for generator units to be used to meet forecast demand over a short time in future. It is a complex optimization problem with both integer and continuous variables and has been shown to be NP-complete in general. The basic UC methods reported in literature include priority listing [7], dynamic programming [8], Lagrangian relaxation [9], and integer programming method [10,11], etc. Once the UC problem has determined the start-up and shut-down schedules, the ED problem seeks to find the optimal allocation of electric power outputs from various available generators without alternating their on/off status. Readers can refer to comprehensive surveys on UC [12] and ED [13] for more details.

Conventional energy generation scheduling is typically conducted 24 h in advance (day ahead) and based on the fact that the system load can be forecast with reasonably good accuracy one day in advance. In microgrids, however, this is no longer the case due to the fact that accurate predictions of small-scale electricity and heat demands, renewable energy supplies and electricity market prices are very difficult, as we stated earlier. Some recent literature has investigated energy generation scheduling of microgrids [14–18]. In [14], a multi-objective optimization of economic load dispatch for a microgrid is investigated using evolutionary computation. The paper aims at minimizing the emission of the thermal generators and minimizing the total operating cost. In [15], a generalized formulation for intelligent energy management of microgrid is proposed using artificial intelligence techniques jointly with linear-programming-based multi-objective optimization. Similarly, in [16], an intelligent energy management system is proposed for optimal operation of a CHP-based microgrid over a 24-h time interval. Authors of [17,18] also propose different energy management strategies based on different assumptions. The limitation of these results, however, is that they all assume that the energy demands and supplies are known ahead of time, which is rarely the case in practice.

There also exist some studies considering demand and supply uncertainties when scheduling the energy generation. Such work can be categorized into two groups: the stochastic optimization based approaches [19–25] and robust optimization based approaches [26–30]. In [19], a stochastic programming approach is adopted in the development of the proposed bidding strategies for microgrid producers and loads. In [20], the authors develop a solution method for scheduling units of a power-generating system to produce electricity by taking into consideration the stochastic nature of the hourly load and its correlation structure. In [21], a stochastic model for the long-term solution of security-constrained unit commitment is proposed. A more complicated scenario can be found in [22], in which an efficient stochastic framework is developed to investigate the effect of uncertainty on the operation management of microgrids. The proposed stochastic framework considers the uncertainties of load forecast error, wind turbine generation, photovoltaic generation and market price concurrently. Authors of [23] examine the impact of the stochastic nature of wind on planning and dispatch of a system. Similarly, authors of [24] compare stochastic and reserve methods and evaluate the benefits of a combined approach for the efficient management of uncertainty in the unit commitment problem. In [25], a two-stage stochastic objective function aiming at minimizing the expected operational cost is implemented. Note that the stochastic optimization approach 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 practical limitations. First, it may be difficult and costly to obtain an accurate probability distribution of uncertainty. Second, the solution only provides probabilistic guarantees to the system reliability. To obtain a highly reliable guarantee requires a huge number of samples, which poses substantial computational challenges.

In recent literature, robust optimization has received growing attentions as a modeling framework for optimization under uncertainty. In [26], a two-stage adaptive robust unit commitment model is proposed for the security constrained unit commitment problem in the presence of nodal net injection uncertainty. In [27], a robust optimization approach is proposed to accommodate wind output uncertainty, with the objective of providing a robust unit commitment schedule for the thermal generators in the day-ahead market. In [28], a power scheduling approach is proposed based on robust optimization to address the intrinsically stochastic availability of renewable energy sources. References [29,30] also present robust optimization based approaches for optimal microgrid management considering wind power or energy consumption uncertainties. Instead of postulating explicit probability distribution, robust optimization confines the random variable in a predefined uncertainty set containing the worst-case scenario. For instance, in [26–28,31,32,29,30], uncertainties in price prediction or renewable energy generation are presented as interval values with deterministic lower and upper bounds, and the framework developed in [33,34] is incorporated to solve the problem. Without requiring an explicit probability distribution, the uncertainty can be characterized more flexibly. In addition, the conservativeness of the solution can easily be controlled and the problem is always computationally tractable both practically and theoretically even for large scale problems.

In our study, the robust optimization concept is also applied to tackle the uncertainties in energy generation scheduling problem of microgrids. Different from the previous robust optimization works [26–28,31,32,29,30] which confine the uncertainty within a lower and upper bounds, in our work, we propose a new uncertainty model to characterize the renewable energy and user demand uncertainties, which can provide more statistical details in describing the underlying uncertainty. Moreover, the proposed uncertainty model is also flexible enough that we can incorporate more information into the uncertainty model when such information is available.

1.2. Main contributions

In this paper, we consider a robust optimization based energy generation scheduling problem in a CHP-microgrid scenario considering the net demand (the electricity demand not balanced by renewable energy) uncertainty, heat demand uncertainty and electricity price uncertainty. The main contributions of this paper can be briefly summarized as follows:

- We propose a new flexible uncertainty model to capture the fluctuant nature of the net demand and heat demand. Specifically we extract reference distributions as useful references and allow the actual distributions of net demand and heat demand to vary around their references. To the best of our knowledge, this is the first time that distribution uncertainty model is adopted to depict the indeterminacy nature of net demand and heat demand.
- We develop chance constraint approximation and robust optimization approaches based on our uncertainty model to transform the constraints with random variables into typical linear constraints. Then an iterative algorithm is designed to solve the problem.
- Price uncertainty is addressed by adopting robust optimization techniques, which allows the degree of conservatism to be controlled easily. We finally transform the prime problem into