Energy Conversion and Management 86 (2014) 1118–1127

Contents lists available at ScienceDirect

Energy Conversion and Management

journal homepage: www.elsevier.com/locate/enconman

Integrated scheduling of renewable generation and demand response programs in a microgrid

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ARTICLE INFO

Article history:
Received 12 March 2014
Accepted 24 June 2014

Keywords:
Microgrid
Demand response
Stochastic optimization
Renewable generation
Reserve

ABSTRACT

Wind and solar energy introduced significant operational challenges in a Microgrid (MG), especially when renewable generations vary from forecasts. In this paper, forecast errors of wind speed and solar irradiance are modeled by related probability distribution functions and then, by using the Latin hypercube sampling (LHS), the plausible scenarios of renewable generation for day-head energy and reserve scheduling are generated. A two-stage stochastic objective function aiming at minimizing the expected operational cost is implemented. In the proposed method, the reserve requirement for compensating renewable forecast errors is provided by both responsive loads and distributed generation units. All types of customers such as residential, commercial and industrial ones can participate in demand response programs which are considered in either energy or reserve scheduling. In order to validate the proposed methodology, the proposed approach is finally applied to a typical MG and simulation results are carried out.

1. Introduction

Increasing penetration of renewable energy generation in electric grid implies that system operators will need to manage the variable and uncertain nature of renewable resources like wind and solar in order to continuously maintain the electricity generation and consumption balance [1,2]. This requires operational changes and procurement of greater quantities of various ancillary services. Traditionally, many of these power system services have been provided exclusively by generators. However, over the past decade, alternative resources like demand response have become increasingly capable of providing a greater number and quantity of such electric grid services [3,4].

Microgrid (MG), as a small part of a power system, is a low voltage distribution network, comprising various Distributed Generators (DG), storage devices, and controllable loads, that faces with intermittent renewable power generation management [5]. Regarding the credibility of MGs, in recent years, there have been several research projects on the design, control, and operation of MGs throughout the world, such as the CERTS microgrid in USA [6,7], the smart poly-generation microgrid pilot project of the University of Genoa in Italy [8], and the energy integration test project carried out by NEDO in Japan [9]. As with all new technologies, the initial price of MGs is going to be expensive, but when they will built in scale and the cost of solar, wind, and other renewables will continue to fall, MGs will become increasingly cost-effective as well as efficient. Financial benefits of MGs may be observed as direct economic benefits, impacting both the capital and operating costs of the power system, or less directly, as service and environmental benefits [10,11].

However, the optimization of a MG has important differences from the case of a large power system and its conventional energy and reserve scheduling problem [12]. The control and scheduling of Distributed Energy Resources (DERs), including renewable generation in a MG, have been studied in many works [13–15]. A dynamic modeling and control strategy for a sustainable MG primarily supplied by wind and solar energy has been presented in [16]. The study considered both wind energy and solar irradiance changes in combination with load power variations.

Focusing on uncertainty of renewable sources, the wind speed and solar irradiance forecasting problem in a MG has been investigated in [17,18]. In [17], an artificial neural network has been used to forecast wind speed and optimal set points of DERs and storage devices have been determined based on the forecasted data in such a way that the total operation cost and the net emissions are simultaneously minimized. In [18], a day-ahead power forecasting module has been presented in order to provide the Photovoltaic

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http://dx.doi.org/10.1016/j.enconman.2014.06.078
0196-8904/

(PV) output data for DER scheduling in a MG. However, providing reserve for compensating wind and PV power fluctuations has not been taken into account within the day-ahead DER scheduling. A stochastic programming approach for reactive power scheduling of a MG, considering the uncertainty of wind power has been presented in [19]. Monte Carlo simulation enhanced by scenario reduction technique has been used to simulate plausible states of wind power and find an optimal operating strategy of DGs. In [20], MG intelligent energy management under cost and emission minimization has been investigated. Moreover, a fuzzy logic expert system has been implemented for battery scheduling. The proposed approach can handle uncertainties regarding the fuzzy environment of the overall MG operation and the uncertainty related to the forecasted parameters. The estimation model of spinning reserve requirement in a MG was proposed in [21]. In the proposed method, the uncertainty of wind and solar generation, as well as the unreliability of units and uncertainties caused by load demand, are considered. The approach aggregated various uncertainties in order to reduce the computational burden. The demand side reserve and load participation in energy markets was not considered in the model. In [22], a method for modeling the output powers of renewable DGs by using historical data has been presented. The method provides hourly generation and load profile considering the intermittent nature of renewable generation. The power dispatch problem of DGs for optimal operation of a MG has been proposed in [23]. The reserve has been scheduled for variations in load demand and the power outputs of non-dispatchable DGs while the objective function aims at minimizing the fuel cost during the grid-connected and islanded modes. In [24,25], wind speed, solar irradiance and load demand in each hour have been modeled by probability distribution functions (PDFs). Then, PDFs are truncated into a limited number of states; every scenario in each day-ahead period consists of a state derived from wind speed, solar irradiance and load demand discrete PDFs.

The concept and role of Demand Response (DR) in providing reserve in a MG is very important, especially in presence of renewable sources. DR programs are used by electric utilities to manage customer electricity consumption in response to supply conditions. A number of methods such as demand management in building [26,27], heat pumps and battery storage system management [28] have been used to address DR programs in MGs. A real-time pricing scheme for residential load management was proposed in [29,30]. These papers presented an automatic and optimal scheme for the operation of each appliance in households in presence of a real-time pricing tariff.

In addition to participate in energy scheduling, DR programs are being investigated for providing ancillary services such as primary frequency regulation [31,32], spinning reserve [33–35], real time voltage control [36] and system security improvements [37]. Basically, there are two typical approaches: indirect load control [38] and direct load control [39]. The potential of DR in balancing supply and demand on an hourly basis has been investigated in [40]. Results indicated that DR has the potential to improve overall power system operation, with production cost savings arising from both improved thermal power plant operation and increased wind production. Moreover, DR resources present a potentially important source of grid flexibility and can support intermittent renewable generation integration. The operation of an electrical demand side management system in a real solar house has been presented in [41]. Experimental results showed that a combination of DR and PV generation allows the use of local control techniques and achieves energy efficient levels.

However, analyses on renewable sources integration have not been explicitly incorporated as reserve capacity in the MG model.

In this paper, Latin hypercube sampling (LHS) is used in order to model plausible wind and PV generation scenarios. Using a stochastic method, energy and reserve scheduling is carried out by considering the generated scenarios. Moreover, the proposed method enables all type of residential, commercial and industrial loads to provide reserve capacity as well as load demand reduction in presence of a DR program.

The rest of this paper is organized as follows. In Section 2 and 3 DR programs and renewable generations' uncertainty are modeled, respectively. The method formulation is detailed in Section 4. Simulation results are presented in Section 5 while the paper is concluded in Section 6.

2. Demand response participants

Different types of electricity customers with different electricity consumption behavior and pattern are considered in the proposed method. The types of customers and their involvement in DR programs are described in this section:

2.1. Industrial customer

Industrial customers are usually characterized by heavy loads and have the largest load demand among residential and commercial customers. As every factory comprises more than one production line, the energy curtailment in each production line has a distinct price offer pertaining to its production. So, industrial customers offer their load curtailment as a multi steps package. The equations used for modeling the behavior of the ith industrial customer are the following ones from (1-4).

$$L^i_{Min} \leqslant l^i_1 \leqslant L^i_1 \tag{1}$$

$$0 \leqslant l^i_k \leqslant \left(L^i_{k+1} - L^i_k\right) \quad \forall\ k = 2, 3, \ldots, K \tag{2}$$

$$IC^E(i,t) = \sum_k l^i_k \tag{3}$$

$$IP^E(i,t) = \sum_k o^i_k \cdot l^i_k \tag{4}$$

where $i = 1, 2, \ldots, I$ represents an index used to identify industrial customers; index $k = 1, 2, \ldots, K$ represents the step of price-quantity offer package; l^i_k and o^i_k are the accepted load reduction and the offer price of industrial customer i in step k of price-quantity offer package; L^i_k is the maximum load reduction of industrial customer i in step k; L^i_{Min} is the minimum load reduction that an industrial customer can carry out; $IC^E(i,t)$ and $IP^E(i,t)$ are the total scheduled load reduction quantity and related cost prepared by the industrial customer i in period t.

At each hour, the sum of the scheduled energy reduction and reserve provided by each industrial load should not be greater than its maximum load reduction offer (L^i_{Max}). This means that the uncommitted load reduction capacity of each industrial customer's offer package in the energy scheduling can be scheduled for the reserve requirement. The reserve provided by each industrial customer is calculated as follows:

$$IC^E(i,t) + IC^R(i,t) \leqslant L^i_{Max} \tag{5}$$

$$IP^R(i,t) = IC^R(i,t) \times q^R_{i,t} \tag{6}$$

where t represents index of optimization period; $IC^R(i,t)$, $IP^R(i,t)$ represent the scheduled reserve and its cost provided by industrial customer i in period t, respectively; $q^R_{i,t}$ is price offer for providing reserve.