Applied Energy 159 (2015) 391–400

Contents lists available at ScienceDirect

Applied Energy

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

Self-balancing robust scheduling with flexible batch loads for energy intensive corporate microgrid

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HIGHLIGHTS

- Two-stage and multi-level robust self-balancing scheduling model is built.
- Load following capability of corporate microgrid is analyzed.
- The multi-level model is converted to the single-level model with a set of constraints.
- The computational efficiency can be improved by using the proposed solving method.

ARTICLE INFO

Article history:
Received 2 May 2015
Received in revised form 25 August 2015
Accepted 3 September 2015

Keywords:
Self-balance
Batch load uncertainty
Robust optimization
Load management

ABSTRACT

With the development of microgrid technology, for an energy intensive corporate such as an iron and steel plant energy consumptions and costs can be saved significantly by achieving the balance between self-generation and consumption. In this paper, we present a self-balancing and robust scheduling model with flexible batch loads for an energy intensive corporate. The model is a multi-level optimization model with the objective to minimize the unbalance cost in the worst case. Load following properties are given to determine whether the uncertain loads can be followed or not, and the self-balancing capability of an energy intensive corporate is analyzed. The problem is equivalently converted from the multi-level model to a single-level optimization model with a set of constraints. In this way, the iteration between the outer and inner level can be avoided. Case study based on an energy intensive corporate microgrid is tested and the results show that the unbalance cost can be significantly reduced by using the robust self-balancing model. In addition, compared the approach method with iterative solving method, computational efficiency can be improved and local optimum can be avoided.

1. Introduction

In an energy intensive corporate, such as an iron and steel company, self-generation power plant (SGPP) is often built to make the best use of the by-product energy such as furnace gas generated in production processes [1–7]. In many cases if the self-scheduled SGPP cannot balance the corporate loads which have significant fluctuations in the production processes, there would be extra energy costs paid to the power grid. For example, Shanghai Baosteel Corporation, a typical energy intensive corporate, must pay for the burst load following capability, reserve and other services [8,9] due to its load fluctuations. Therefore, it is very important and desirable for the SGPP to balance the corporate loads.

With the development of the smart grid, one potential way of overcoming this unbalance would be to alter the self-generation in such a way that self-generation more closely follows the electricity load. This self-balance can be achieved by demand side management (DSM).

DSM is an effective means to solve the power demand – supply contradiction, improve energy efficiency, and enhance the sustainable development of economy [10]. DSM activities could be classified into energy efficiency and demand response and are popular due to technological advances in smart grid and electricity market deregulation [11]. The literatures on DSM are abundant and cover various aspects. In [12], in order to sufficiently explore solar energy and to benefit customers at demand side, optimal energy management for a grid-connected photovoltaic-battery hybrid system was proposed. In [13] modeled the DSM problem as two non-cooperative games to solve the possibility of existing more than one supplier in the smart grid. Considering two industrial

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http://dx.doi.org/10.1016/j.apenergy.2015.09.014
0306-2619/

Nomenclature

Indices

k	index of time periods running from 1 to K
q	index of equipment, running from 1 to Q
m	index of virtual equipment, running from 1 to QM_q
i	index of virtual equipment's batches running from 1 to $MI_{q,m}$

Constants

τ_q^{off}	minimum down time of the qth equipment
$T_{q,m,i}$	the total duration of the mth virtual equipment of the qth equipment for the ith batch
λ_k^{in}	price of negative unbalance incurred in time period k ($/MW h)
λ_k^{out}	price of positive unbalance incurred in time period k ($/MW h)
$p^{\min}$	minimum output of generator
$p^{\max}$	maximum output of generator
Δ^u	ramp-up rate limit of generator
Δ^d	ramp-down rate limit of generator

Variables

L_k^{FL}	flexible load in kth time period
L_k^{NFL}	non-flexible load in kth time period
$W_{q,m,i,d}$	load of the mth virtual equipment of the qth equipment for the ith batch in the dth period
$\tau_{q,m,i}^{on}$	starting time of the mth virtual equipment of the qth equipment for the ith batch
$\Upsilon_{q,k}$	initial state of the qth equipment in kth time period
$I_{q,m,i,k}$	initial state of the mth virtual equipment of the qth equipment for the ith batch in kth time period
$\mu_{q,m,i,k}$	state of the mth virtual equipment of the qth equipment for the ith batch in kth time period
$U_{q,k}$	state of the qth equipment in kth time period
p_k	output of generator in kth time period
L_k	load in kth time period
$\underline{x}$, $\bar{x}$	the minimum and the maximum of variable x

electricity consumers, the potential for implementation of price based demand response by an industrial consumer was analyzed in [14]. For efficient DSM implementation, based on integer genetic algorithm, a multi-objective DSM solution was present in [15] to benefit both utilities and consumers. For the industry, the electricity load is due to production process and is complex. In order to manage industrial energy, Lampret et al. [16] presented the energy-flow rate, exergy-flow rate and cost-flow rate diagrams. Industrial production loads were modeled in [17] and load scheduling algorithms were developed for achieving a near optimal schedule [17]. In addition, Ashok and Banerjee [18], Ashok [19] and Babu and Ashok [20] presented load models, which incorporated the characteristics of batch-type loads common to any type of process industry and the optimization models were solved by mixed integer programming.

For an iron and steel enterprise, the gateway energy balance was defined as the difference between the self-generation and the load, and a balance model was formulated in [8]. To maintain the self-generation balance more effectively, the electrical load tracking problem integrated with both flexible load adjustment and self-generation was analyzed in [7]. The self-balancing problems with deterministic loads were solved and good results were obtained in [2,7,8]. As is known to all, during the production process, there are many uncertainties. And then how to achieve the self-balance with uncertain loads is very challenging.

In recent years, robust optimization methods were developed to solve the stochastic optimization problems for the worst case with a bounded uncertain set [21–25]. These two-stage or multi-stage optimization models were usually solved by Benders decomposition approach that needed the iterations between the outer level and inner level and significant computational cost. For these methods, sometimes the calculating time is huge or the optimal solution possible is local optimum. Then how to solve the robust optimization problem efficiently is still difficult and challenging.

In this paper, we present a self-balancing robust scheduling framework with flexible batch loads for an energy intensive corporate considering uncertain operating batch loads. The objective in this multi-level optimization problem is to minimize the unbalance cost in the worst case. The decision process is a two-stage process: the first-stage decision process is to optimize the production unit operating states that are here-and-now variables; the second-stage decision process is to optimize the generation outputs in every period that are wait-and-see variables. The second-stage decision process consists of two parts: finding the worst case in the kth period for any possible case and minimizing the unbalance cost for the given loads in the kth period. The production unit states are robust since any possible unbalance cost would be less than the optimal cost. The features of the method presented in this paper can be summarized as follows:

(1) The uncertainties in loads are taken into account and the multi-level self-balancing problem to minimize the unbalance cost by optimizing both generators and the flexible loads is formulated explicitly. The self-balancing model under uncertainties provides an effective way to decrease the electricity cost for corporate microgrid.
(2) Load following capability is evaluated to determine whether the uncertain loads can be followed so that we can analyze the self-balancing capability of an energy intensive corporate.
(3) The multi-level model is equivalently converted to the single level one with a set of constraints. Compared with the iterative solution method, the approach to solve the problem in the paper avoids the iterations between the outer and inner level with improved computational efficiency and avoids local optimum.

The rest of this paper is organized as follows. The robust self-balancing model is formulated in Section 2. Section 3 analyzes the self-balancing capability of the energy intensive corporate. The robust solution approach is proposed to solve the model in Section 4. Section 5 shows the simulation results. Finally, conclusions are drawn in Section 6.

2. Robust self-balancing model

In energy intensive corporates, the electricity load consists of flexible load (FLD) and non-flexible load (NFLD). FLDs are the production unit running loads with flexible starting time and the NFLD can be called basic load. For the diversity of the working condition, both FLD and NFLD are uncertain and can change freely in