Applied Energy 156 (2015) 642–654

Contents lists available at ScienceDirect

Applied Energy

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

Demand side management in a day-ahead wholesale market: A comparison of industrial & social welfare approaches

Bo Jiang [a,*], Amro M. Farid [b,a], Kamal Youcef-Toumi [a]

[a] Mechanical Engineering, Massachusetts Institute of Technology, Cambridge, MA 02139, USA
[b] Thayer School of Engineering Dartmouth College Hannover, New Hampshire 03755, USA

HIGHLIGHTS

- We compare two demand side management in a day-ahead electricity wholesale market.
- We develop and reconcile social welfare & industrial DSM mathematical models.
- We show the industrial netload has an additional forecast quantity of baseline.
- We analytically and numerically show the model equivalence with accurate baseline.
- We numerically demonstrate the baseline errors lead to higher and costlier dispatch.

ARTICLE INFO

Article history:
Received 3 February 2015
Received in revised form 16 June 2015
Accepted 4 July 2015

Keywords:
Social welfare maximization
Industrial demand side management (DSM) implementation
Electricity consumption baseline

ABSTRACT

The intermittent nature of renewable energy has been discussed in the context of the operational challenges that it brings to electrical grid reliability. Demand side management (DSM) with its ability to allow customers to adjust electricity consumption in response to market signals has often been recognized as an efficient way to mitigate the variable effects of renewable energy as well as to increase system efficiency and reduce system costs. However, the academic & industrial literature have taken divergent approaches to DSM implementation. While the popular approach among academia adopts a social welfare maximization formulation, the industrial practice compensates customers according to their load reduction from a predefined electricity consumption baseline that would have occurred without DSM. This paper rigorously compares these two different approaches in a day-ahead wholesale market context analytically and in a test case using the same system configuration and mathematical formalism. The comparison of the two models showed that a proper reconciliation of the two models might make them mitigate the stochastic netload in fundamentally the same way, but only under very specific conditions which are rarely met in practice. While the social welfare model uses a stochastic net load composed of two terms, the industrial DSM model uses a stochastic net load composed of three terms including the additional baseline term. DSM participants are likely to manipulate the baseline in order to receive greater financial compensation. An artificially inflated baseline is shown to result in a different resources dispatch, high system costs, and unachievable social welfare, and likely requires more control activity in subsequent layers of enterprise control.

1. Introduction

1.1. Motivation

The intermittent nature of renewable energy has been discussed in the context of the operational challenges that it brings to electrical grid reliability [1–3]. The fast fluctuations in renewable energy generation require high ramping capability which must be met by dispatchable energy resources. Additionally, a sudden loss of renewable generation can threaten grid reliability in the absence of adequate generation reserves.

In contrast, demand side management (DSM) with its ability to allow customers to adjust electricity consumption in response to market signals has often been recognized as an efficient way to shave load peaks [4–7] and mitigate the variable effects of renewable energy [8–10]. This work focuses on DSM where end users can change their consumption in response to dynamic changes in electricity price signals [11], rather than static energy

* Corresponding author.
E-mail addresses: bojiang@mit.edu (B. Jiang), amfarid@mit.edu (A.M. Farid), youcef@mit.edu (K. Youcef-Toumi).

http://dx.doi.org/10.1016/j.apenergy.2015.07.014
0306-2619/© 2015 Published by Elsevier Ltd.

Nomenclature

GC	subscript for dispatchable (controllable) generators (e.g. thermal plants)
GS	subscript for stochastic generators (e.g. wind, solar photo-voltaic)
DC	subscript for dispatchable (controllable) demand units (i.e. participating in DSM)
DS	subscript for stochastic demand units (i.e. conventional load)
i	index of dispatchable generators
j	index of dispatchable demand unit
k	index of stochastic generators
l	index of stochastic demand unit
t	index of unit commitment time intervals
N_{GC}	number of dispatchable generators
N_{DC}	number of dispatchable demand units
N_{GS}	number of stochastic generators
N_{DS}	number of stochastic demand units
T	number of unit commitment time intervals
$\mathcal{W}$	social welfare
P_{GCit}	dispatched power generation at the ith dispachable generator in the tth time interval
P_{DCjt}	dispatched power consumption at the jth dispatchable demand unit in the tth time interval
$\hat{P}_{DCjt}$	forecasted power consumption of the jth dispatchable demand unit in the tth time interval
$\tilde{P}_{DCjt}$	baseline power consumption of the jth dispatchable demand unit in the tth time interval
$\hat{P}_{GSkt}$	forecasted power generation at the kth stochastic generator in the tth time interval
$\hat{P}_{DSlt}$	forecasted power consumption of the lth stochastic demand unit in the tth time interval
$\underline{P_{GCi}}$	min. capacity of the ith dispatchable generator
$\underline{P_{DCj}}$	min. capacity of the jth dispatchable demand unit
$\underline{R_{GCi}}$	min. ramping capability of the ith dispatchable generator
$\underline{R_{DCj}}$	min. ramping capability of the jth dispatchable demand unit
$\overline{P_{GCi}}$	max. capacity of the ith dispatchable generator
$\overline{P_{DCj}}$	max. capacity of the jth dispatchable demand unit
$\overline{R_{GCi}}$	max. ramping capability of the ith dispatchable generator
$\overline{R_{DCj}}$	max. ramping capability of the jth dispatchable demand unit
$\mathcal{C}_{GCi}$	cost of the ith dispatchable generator
$\mathcal{S}_{GCi}$	startup cost of the ith dispatchable generator
$\mathcal{D}_{GCi}$	shutdown cost of the ith dispatchable generator
$\mathcal{R}_{GCit}$	running cost of the ith dispatchable generator in the tth time interval
A_{GCi}	quadratic cost function coefficient of the ith dispatchable generator
B_{GCi}	linear cost function coefficient of the ith dispatchable generator
ζ_{GCj}	cost function constant of the ith dispatchable generator
$\mathcal{U}_{DCj}$	demand utility of the jth dispatchable demand unit
$\mathcal{S}_{DCj}$	startup utility of the jth dispatchable demand unit
$\mathcal{D}_{DCj}$	shutdown utility of the jth dispatchable demand unit
$\mathcal{R}_{DCjt}$	running utility of the jth dispatchable demand unit in the tth time interval
A_{DCj}	quadratic utility function coefficient of the jth dispatchable demand unit
B_{DCj}	linear utility function coefficient of the jth dispatchable demand unit
ζ_{DCj}	utility function constant of the jth dispatchable demand unit
$\mathcal{C}_{DCj}$	cost of the jth virtual generator
$\mathcal{S}_{DCj}$	startup cost of the jth virtual generator
$\mathcal{D}_{DCj}$	shutdown cost of the jth virtual generator
$\mathcal{R}_{DCjt}$	running cost of the jth virtual generator in the tth time interval
$\mathcal{A}_{DCj}$	quadratic cost function coefficient of the jth virtual generation
$\mathcal{B}_{DCj}$	linear cost function coefficient of the jth virtual generation
ξ_j	cost function constant of the jth virtual generation
w_{GCit}	binary variable for the state of the ith dispatchable generator in the tth time interval
u_{GCit}	binary variable for the startup state of the ith dispatchable generator in the tth time interval
v_{GCit}	binary variable for the shutdown state of the ith generator in the tth time interval
w_{DCjt}	binary variable for the state of the ith dispatchable demand unit in the tth time interval
u_{DCjt}	binary variable for the startup state of the jth dispatchable demand unit in the tth time interval
v_{DCjt}	binary variable for the shutdown state of the jth dispatchable demand unit in the tth time interval
ω_{DCjt}	binary variable for the state of the jth virtual generation in the tth time interval
μ_{DCjt}	binary variable for the startup state of the jth virtual generation at the beginning of the tth time interval
ν_{DCjt}	binary variable for the shutdown state of the jth virtual generation at the beginning of the tth time interval

efficiency techniques. It increases the bulk electric system flexibility [12,13] and reliability [7,13–15] by providing additional dispatchable resources which can potentially offset imbalances caused by renewable energy [16,17]. DSM has also been advocated for its ability to increase system efficiency and reduce system costs [18,19]. By encouraging customers to adjust their electricity consumption in response to market signals, DSM reduces the need for more expensive generators with high ramping capability. Meanwhile, DSM increases the utilization of generating capacities that would have been otherwise idle during off-peak hours, thus reducing the real cost of renewable integration [20]. The electricity supply side, load-reducing customers and non-load-reducing customers all benefit economically from load reductions [21–23].

The deregulation of electricity markets [24–28], along with the advances in information and communication technologies [12,29–31], has motivated more active DSM programs. As a result, Independent System Operators (ISOs) and Reliability Transmission Organizations (RTOs) have been implementing DSM for its potential to lower market prices, reduce price volatility, improve customer options, and increase the elasticity from wholesale to retail market [32]. Researches on DSM have addressed the minimization of energy consumption, maximization of customer utility, the minimization of customer discomfort, the stabilization of electricity prices, and multi-objective optimizations from the customer side [33–40]. In addition, there have also been studies on the integration of DSM and renewable uncertainty [41], centralized or distributed demand control algorithms [14,30,42–46], demand-side storage [47,48], models of customer behavior [49], and prediction of DSM participation potential [50–52].

Despite its recognized importance [53–55], the industrial and academic literature seem to have taken divergent approaches to