Applied Energy 88 (2011) 4700–4712

Contents lists available at ScienceDirect

Applied Energy

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

Modeling storage and demand management in power distribution grids

Andreas Schroeder [*]

German Institute for Economic Research, Mohrenstr. 58, 10117 Berlin, Germany

ARTICLE INFO

Article history:
Received 30 March 2011
Received in revised form 2 June 2011
Accepted 4 June 2011
Available online 29 June 2011

Keywords:
Storage
Demand management
Stochastic optimization
Benders Decomposition

ABSTRACT

Storage devices and demand control may constitute beneficial tools to optimize electricity generation with a large share of intermittent resources through inter-temporal substitution of load. This paper quantifies the related cost reductions in a simulation model of a simplified stylized medium-voltage grid (10 kV) under uncertain demand and wind output. Benders Decomposition Method is applied to create a two-stage stochastic optimization program. The model informs an optimal investment sizing decision as regards specific 'smart' applications such as storage facilities and meters enabling load control. Model results indicate that central storage facilities are a more promising option for generation cost reductions as compared to demand management. Grid extensions are not appropriate in any of the scenarios. A sensitivity analysis is applied with respect to the market penetration of uncoordinated Plug-In Electric Vehicles which are found to strongly encourage investment into load control equipment for 'smart' charging and slightly improve the case for central storage devices.

1. Introduction

Since electricity demand and the availability of output from Renewable Energy Sources (RES) are intermittent by nature, system operators have to resort to relatively costly measures such as reserve energy to maintain system stability. Back-up capacities are set to become more relevant with increasing shares of RES penetration. In this context, storage devices serve to store excessive electricity generation and feed-in missing energy in times of need. An alternative concept of better aligning demand and supply of electricity through two-way digital communication technology is commonly referred to as 'smart metering'. Measures to manage demand with the help of smart meters include demand response and direct load control. Recent legislation obliges German grid operators and utilities to install smart metering systems in new and refurbished dwellings. While legislative pressure spurs investment in smart metering, it may imply a negative effect on investment incentives in storage.

This paper scrutinizes load control and storage facilities as potential concurrent options targeting at electricity generation cost reductions and it quantifies possible substitution effects. Because of their common purpose, direct load control and centralised storage are two competing or possibly complementary solutions from the perspective of a vertically integrated power distribution system operator and utility. Moreover, it is tested whether storage and load control could alleviate the need for grid reinforcements by avoiding capacity shortages. The idea is that avoided shortage adds value to storage or DSM devices because of capacity upgrade deferral and added electricity sales [1]. Additionally to these issues, a methodological purpose of this paper is to demonstrate how stochastic optimization and Benders Decomposition Method can be sensibly applied to analyze and compare investment options in a power distribution system setting. The focus lies on short-term uncertainties and their impact on investment decisions.

There exists a broad range of literature dealing with storage sizing decisions. Refs. [2–6] perform numerical optimizations in a deterministic setting. Applications of stochastic patterns of generation and demand can be found in [7–10]. Tan et al. [10] present a stochastic optimization model of battery sizing for demand management with emphasis on outage probabilities which is not dealt with in this paper. Roy et al. [11] apply stochastic wind generation patterns to a wind-battery system sizing model with deterministic demand. Ref. [12] do likewise with Plug-in Electric Vehicles (EV) as storage facilities.

The combination of intermittency of renewable resources and demand-side-management (DSM) is addressed in [13,14]. Concerning demand-side management (DSM), numerous research publications were found on investment decisions into DSM. Ki Lee et al. [15] assess investment into demand management systems for heating in a national case study for Korea. Paulus and Borggrefe [16] adopt a system-wide perspective of investment in DSM in a case study for Germany with focus on industrial consumers. Manfren et al. [17] deal with distributed generation planning, but avoid making any investment analysis. Neenan and Hemphill [18] investigate investment from a societal perspective while

---

[*] Tel.: +49 30 89789692; fax: +49 30 89789200.
E-mail address: aschroeder@diw.de

0306-2619/$ - see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.apenergy.2011.06.008

Nomenclature

Set

n	node with subset *nn* (1–5)
l	line (1–4)
t	hour (1–24)
s	technology (wind, solar, pv, chp, biomass, hydro, nuclear, hardcoal, lignite, gas)
sc	scenario (1–50)
$iter$	iteration (unlimited)

Variable

$D(n, t, sc)$	demand shifting (kW h)
$S_{in}(n, t, sc)$	storage inflow (kW h)
$S_{out}(n, t, sc)$	storage outflow (kW h)
$G(n, t, sc, s)$	generation (kW h)
$I_s(n)$	investment in storage (both kW and kW h)
$I_d(n)$	investment in a DSM system (absolute number)
$P(l, t, sc)$	phases angle difference (–)

Parameter

$q(n, t, sc)$	consumer demand (kW h)
$g_{max}(n, t, sc, s)$	maximum generation capacity (kW h)
$c_g(s)$	variable generation cost (EUR/kW h)
c_s	levelized investment cost for storage (EUR/kW h and EUR/kW)
c_d	levelized investment cost for DSM (EUR/kW h)
e	storage efficiency (%)
$d_{pos}(t,n)$	positive load shift capacity (kW)
$d_{neg}(t,n)$	negative load shift capacity (kW)
$lf(l,t,sc)$	electricity flow (kW)
$x(l)$	line reactance (Ohm)
$b(n,n)$	network susceptance matrix (–)
$h(l,n)$	weighted network matrix (–)
$lm(l,n)$	incidence matrix (–)
$lf_{max}(l)$	maximal capacity for line flow (kW)
$slack(n)$	slack variable (–)
$p(sc)$	probability (%)
λ_s	dual of fixing storage investment in subproblem (EUR/kW h and EUR/kW)
λ_d	dual of fixing DSM investment in subproblem (EUR per dwelling)
$\alpha(iter)$	sub-problem objective (EUR)
$I_{sMasterProblem}(n)$	investment in storage from master problem (both kW and kW h)
$I_{dMasterProblem}(n)$	investment in a DSM system from master problem (absolute number)
w	wind speed (meter/s)
k	Weibull scale parameter (–)
m	Weibull shape parameter (–)
r	random number with uniform distribution (0–1)

[19,20] find that investment into DSM appliances might not be all that profitable in general. It is intended to further investigate this claim in the present analysis.

This paper's contribution is unique in that no study explicitly compares the cost saving potential of storage and DSM in a comprehensive model including grid representation, endogenous investment and factors of uncertainty. Whilst an 11 kV distribution network representation in combination with a benefit analysis for storage and demand response measures can be found in [21], the present work complements their analysis by adding endogeneity to the investment into storage devices and DSM appliances as well as uncertainty of demand and wind generation. A further contribution consists in the application of Benders Decomposition Method to the stochastic program. Decomposition methods can be applied to numerous bi-level optimization problems in the energy sector, such as unit-commitment or capacity expansion. To the author's best knowledge, an application to evaluating storage and DSM infrastructure investment is unprecedented.

The article is divided into a descriptive part, including the methodology and model description, an explanation of parameters and scenarios applied. Subsequently, results are outlined, discussed and final conclusions are drawn.

2. Model description

A basic direct current (DC) load flow model [22] is adapted to a situation with DSM and storage management. The model is designed as linear program under a cost minimization regime with hourly time resolution of two exemplary holidays (winter/summer). It is coded in General Algebraic Modeling System (GAMS) and can be solved with the solver CPLEX [23]. A vertically integrated system operator and utility is considered as the cost minimizing agent. As explicated before, the aim of the operator is to reduce generation cost by performing load management through storage and DSM. The agent can decide on whether to invest in storage and DSM technology as well as how to operate it. Still, the operator is able to shift the vertical demand curve left and rightwards through direct load control. The extensive-form cost-minimisation objective reads as follows:

$$\text{Objective(extensive form)} \quad \min_{\substack{I_d, I_s,\\ G, D,\\ S_{in}, S_{out}, P}} \sum^{SC} prob(SC) \cdot \sum^{N}\sum^{T}\left[\sum^{S} C_g(S)\cdot G(n,t,sc,s) + I_d(n)\cdot C_d + I_s(n)\cdot C_s\right] \tag{1}$$

The agent minimizes generation cost ($c_g \cdot G$) of each technology s as well as investment cost of DSM ($I_d \cdot c_d$) and storage ($I_s \cdot c_s$). Besides generation and investment, the agent can manipulate storage in – and outflow (S_{in} and S_{out}), shed or induce consumption (D) and transfer electricity from one node to another (P), subject to constraints detailed below. All variables are positive.

On the demand side, consumers are aggregated at each of the 10 kV/0.4 kV sub-station nodes n. Thus, a diurnal pattern of consumer demand (without DSM and storage), denoted by q, can be approximated using standard averaged load profiles weighted by the number of customers at the respective node. A perfectly inelastic, hence vertical demand function is assumed. This is a fundamentally different approach to demand response studies [24,25] and suitable here, since the focus lies on the producer side. There is no demand response. The consumer demand q is supplemented by contributions from DSM and charging of a battery. Note that demand is treated as stochastic parameter and it thus depends on the set *sc*.

Demand, supply and network flows constitute the energy balance constraint per node (2). It incorporates the simultaneity of generation and consumption as well as the first Kirchhoff rule