Applied Energy 225 (2018) 611–621

Contents lists available at ScienceDirect

Applied Energy

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

Optimal sizing of energy storage systems under uncertain demand and generation

Martina Bucciarelli*, Simone Paoletti, Antonio Vicino

Dipartimento di Ingegneria dell'Informazione e Scienze Matematiche, Università di Siena, via Roma 56, Siena 53100, Italy

HIGHLIGHTS

- A practical problem tackled mathematically with focus on computational aspects.
- Sizing of energy storage systems installed in a distribution network.
- Uncertainty taken into account via a stochastic programming formulation.
- A computationally hard scenario-based problem solved via a decomposition approach.
- A metric for scenario reduction exploiting the problem structure proposed.

ARTICLE INFO

Keywords:
Energy storage sizing
Distribution network
Optimal power flow
Scenario reduction
Two-stage stochastic programming

ABSTRACT

Energy storage systems have been recently recognized as an effective solution to tackle power imbalances and voltage violations faced by distribution system operators due to the increasing penetration of low carbon technologies. To fully exploit their benefits, optimal sizing of these devices is a key problem at the planning stage. This paper considers the sizing problem of the energy storage systems installed in a distribution network with the aim, e.g., of preventing over- and undervoltages. In order to accommodate uncertainty on future realizations of demand and generation, the optimal sizing problem is formulated in a two-stage stochastic framework, where the first stage decision involves the storage sizes, while the second stage problem provides the optimal storage control policy for given demand and generation profiles. By taking a scenario-based approach, the two-stage problem is approximated in the form of a single multi-scenario, multi-period optimal power flow, whose size, however, becomes computationally intractable as the number of scenarios grows. To overcome this issue, the paper presents a procedure to compute upper- and lower bounds to the optimal cost of the approximate problem. Moreover, when the objective is to minimize the total installed storage capacity, an iterative algorithm based on scenario reduction is proposed, which converges to the optimal solution of the approximate problem. The whole procedure is tested on the topology of the IEEE 37-bus test network, considering scenarios of demand and generation which feature over- and undervoltages in the absence of storage devices.

1. Introduction

The ever growing penetration of low carbon technologies, such as distributed generation (e.g., wind and photovoltaic), electric vehicles and heat pumps, is a matter of concern for distribution system operators (DSOs), which have to guarantee a predefined level of quality of electricity supply. For instance, modifications of typical power flows in distribution networks may cause abnormal fluctuations of the voltage magnitude, which are not tolerated beyond specified limits around the nominal value. In this respect, energy storage systems (ESSs) represent an effective solution for DSOs to tackle voltage problems in distribution feeders [1], alternative to other solutions, such as traditional grid reinforcement, on-load tap changers at secondary substations [2,3], soft-open points [4], and reactive power control of distributed generation (DG) [5]. ESSs are storage devices interfaced with the grid through a power electronic converter. In this way, they can be controlled to act as loads in case of overvoltages, and as generators in case of undervoltages. This adds to a number of other benefits that ESSs bring to the whole electricity system, and to different stakeholders [6–8].

To fully exploit the benefits of storage devices, the problem of their optimal allocation must be addressed at the planning stage. The ESS allocation decision problem consists of defining the type and the

* Corresponding author.
E-mail addresses: bucciarelli@diism.unisi.it (M. Bucciarelli), paoletti@diism.unisi.it (S. Paoletti), vicino@diism.unisi.it (A. Vicino).

https://doi.org/10.1016/j.apenergy.2018.03.153
Received 21 November 2017; Received in revised form 19 March 2018; Accepted 30 March 2018

Nomenclature

Acronyms

AC	alternating current
DC	direct current
DG	distributed generation
DSO	distribution system operator
ESS	energy storage system
LV	low voltage
MV	medium voltage
OPF	optimal power flow
PF	power flow
SDP	semidefinite programming

Parameters

ΔT	time step
T	number of time steps per day
η_s^c, η_s^d	charging/discharging efficiency of storage at bus s
Γ_s, Υ_s, Ξ_s	column vectors of the polygonal approximation of the capability curve of storage at bus s
ρ_s	power-to-energy ratio of storage at bus s
$\underline{E}_s$	lower limit of the energy level of storage at bus s
$\overline{S}_{ij}$	upper bound to the apparent power through line (i,j)
$\overline{v}_i$	upper bound to the voltage magnitude at bus i
$\underline{v}_i$	lower bound to the voltage magnitude at bus i
p_d	scenario of demand and generation
π_d	probability of scenario p_d
Y_{ij}	(i,j)-entry of the network admittance matrix Y
y_{ij}	line admittance between buses i and j

Sets

$\mathscr{D}$	index set of scenarios
$\mathscr{E}$	set of lines
$\mathscr{L}$	set of load buses
$\mathscr{N}$	set of buses
$\mathscr{P}$	set of scenarios
$\mathscr{S}$	set of buses equipped with storage
$\mathscr{T}$	set of time indexes
$\mathscr{X}$	feasible solution set of the first-stage problem
$\mathscr{Y}$	feasible solution set of the second-stage problem

Variables

E_s	energy capacity of storage at bus s
$r_s(t)$	active power exchanged by storage at bus s and time t
$b_s(t)$	reactive power exchanged by storage at bus s and time t
$e_s(t)$	energy level of storage at bus s and time t
$P_i^D(t)$	active power demanded at bus i and time t
$P_i^G(t)$	active power generated at bus i and time t
$Q_i^D(t)$	reactive power demanded at bus i and time t
$Q_i^G(t)$	reactive power generated at bus i and time t
$S_i(t)$	net complex power injection into bus i at time t
$V_i(t)$	complex voltage at bus i and time t
x	decision variables of the first-stage problem
y_d	decision variables of the second-stage problem for scenario p_d

number of devices to be deployed, their locations (siting), and sizes (sizing) [9]. The interested reader is referred to the survey paper [10] for a literature review on ESS allocation techniques, classified according to both the ESS application and the methodology used to find a solution. In most cases, optimal ESS siting and sizing are carried out simultaneously, either through a cost-benefit analysis [11,12], or formulating a single optimization problem [13–15]. In other cases, the two problems are dealt with separately. A heuristic method is proposed in [16] to detect the sensitive buses of the grid under a wide range of contingencies. Voltage magnitudes and angles under the contingencies are forecast by exploiting complex-valued neural networks and time domain power flow. In [17], the ESS siting problem is tackled via a different heuristic approach, which returns the most suitable ESS locations in the grid based on voltage sensitivity analysis. In some applications, ESS locations may also be decided a priori, and the ESS allocation problem boils down to determine only the size of each ESS.

For given ESS type, number and locations, a quite general approach is to formulate the ESS sizing problem in an optimal power flow (OPF) framework, where a suitable cost function (typically including storage installation and operation costs, as well as power losses and generation costs) is optimized, subject to storage dynamics, power flow and network constraints. Linearization of power flow constraints via DC approximation is often adopted when dealing with transmission networks, where line resistances are typically negligible compared to line reactances [18–20]. When such an assumption is not valid, like in distribution networks, a full or approximated AC OPF is considered. Branch flow equations are used to model the power network in [13,14,21]. A bi-level optimization model, where the second-level problem is a linear program minimizing the daily coincident peak demand, is proposed in [15]. In [22], linear approximations of voltage, branch flow, and network power losses are presented, leading to a linearized OPF. A simplified power balance model of the network is adopted in [23], while in [24] the distribution network is modelled through a continuous tree with linearized DistFlow model. These simplified models are defined to cope with the computational burden of (multi-period) AC OPF problems, due to nonconvexity of AC power flow equations, and time-coupling constraints introduced by ESS dynamics. Other solution strategies proposed in the literature for the same purpose, rely on semi-definite convex relaxations of the OPF problem [25–27], second-order cone programming [13,21], and alternating direction method of multipliers [14].

In deterministic OPF problems, net power injected at load buses is assumed to be given, but unfortunately future realizations of demand and DG are unknown at the planning stage. This calls for a formulation of the optimal ESS sizing problem which takes uncertainty sources explicitly into account. Stochastic optimization paradigms are suitable to this aim [28]. Probability density functions of wind power generation and demand are considered in [20,29] within probabilistic OPF formulations. A two-stage programming formulation of the optimal ESS sizing problem is proposed in [23], including chance constraints to model wind forecast errors. Chance constraints accounting for wind power and demand forecast errors, are also considered in [30]. Since stochastic optimization problems are typically intractable, they are often tackled by defining a large number of scenarios, which are expected to represent the original stochastic information. Suitable scenario generation techniques based on time-series and regression models [31], as well as copula models [32], can be used to this aim. Then, an approximate reformulation of the optimization problem is derived by replicating power flow variables and constraints for each scenario [13,14,23]. In order to keep the problem size affordable, scenario-based approaches are often coupled with techniques to downsize the scenario set. To this aim, clustering algorithms, such as K-means and centroid-linkage clustering, are adopted [13,23]. Another possibility is to apply scenario reduction techniques based on the notion of probability distance [33]. However, as shown in [34], all these techniques may fail in preserving the useful information contained in the original scenario set.