Applied Energy 225 (2018) 1205–1218

Contents lists available at ScienceDirect

Applied Energy

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

Stochastic operation of home energy management systems including battery cycling

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HIGHLIGHTS

- We propose a stochastic model for scheduling of resources of smart homes.
- Battery cycling aging is considered by a Lagrangian relaxation based algorithm.
- A Competitive Swarm Optimizer decomposes and solves the problem.
- The Value of the Stochastic Solution demonstrates the advantages of the model.

ARTICLE INFO

Keywords:
Microgrids
Energy storage
Stochastic optimization
Uncertainties
Battery cycling
Flexibility

ABSTRACT

The present work proposes a stochastic approach for Day-Ahead operation of Home Energy Management Systems when batteries, solar photovoltaic resources and Electric Water Heaters are considered. The optimization problem minimizes the operation costs formed by energy procurement in the wholesale market and the equivalent cycling aging cost of the batteries, and also includes the uncertainty of the PV production and the load. The complete two-stage stochastic formulation results in a Mixed-Integer Nonlinear Programming problem that is decomposed using a Competitive Swarm Optimizer to handle the calculation of the battery cycling aging cost. A Storage Disaggregation Algorithm based on Lagrangian relaxation is used to reduce the problem size and to allocate individual State of Charge for the batteries. In addition, the advantages of considering a stochastic approach are shown by means of the Value of the Stochastic Solution. This methodology has been developed in the context of the Horizon 2020 project SENSIBLE as part of the tasks related to a use case that considers an aggregator that participates in the electricity market with a portfolio of prosumers with active demand capability.

1. Introduction

The increasing penetration of decentralized renewable generation in the medium- and low-voltage grid is motivating development of new tools in order to face the challenges imposed by this new paradigm. These trends push even further, reaching the building and home level, and leading to the development of concepts such as Home Energy Management Systems (HEMS) [1]. In the smartgrid context, the flexibility features of renewables, storage technologies, demand response (DR) and interaction with the grid [2], can be exploited by different market agents to minimize operation costs. In the concrete case of the present work, the aim is to analyze the interaction between thermal and electric storage for an aggregation of smart homes including uncertainties in load and PV production, and also considering battery aging. .

1.1. Current research

1.1.1. Battery cycling in smart home applications

The aging of storage devices is a complex process that depends on chemical reactions with electrode interfaces, and the degradation of materials caused by cycling and aging of non-active components [3,4]. This process can be analyzed and modeled by tracking the cycling patterns, the respective Depth of Discharge (DOD) and the rate at which this process occurs [5].

Some research has been published in recent years that includes this process in the HEMS operation. For example, [6] evaluates the impacts of peak shaving by means of active demand and different storage technologies in a single household. To include cycling of the storage device, a set of values of the energy that can be cycled are predefined and analyzed.

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https://doi.org/10.1016/j.apenergy.2018.04.130
Received 1 February 2018; Received in revised form 27 April 2018; Accepted 28 April 2018
0306-2619/

Nomenclature

Abbreviations

BESS	Battery Energy Storage System
CSO	Competitive Swarm Optimizer
DOD	Depth of Discharge
DR	Demand Response
EWH	Electric Water Heater
HEMS	Home Energy Management System
HEV	Hybrid Electric Vehicle
MPC	Model Predictive Control
PCC	Point of Common Coupling
PV	Photovoltaic
RCA	Rainflow Counting Algorithm
RES	Renewable Energy Sources
SDA	Storage Dissaggregation Algorithm
SOC	State of Charge
SRB	Smart Residential Building
TES	Thermal Energy Storage
VSS	Value of Stochastic Solution

Indices

h	index for household, $h = 1,2,...,N$
j	index for depths of discharge found with the rainflow counting algorithm and associated with a certain SOC, $j \in \Omega$
s	index for scenario, $s = 1,2,...,S$
t	index for time step, $t = 1,2,...,T$

Parameters

$\overline{H}_h$	TES device maximum power [kW]
$\overline{P}_h^{\mathrm{ch}}$	battery's maximum charging power [kW]
$\overline{P}_h^{\mathrm{dch}}$	Battery's maximum discharging power [kW]
$\overline{X}_h$	battery's maximum SOC [kWh]
$\overline{Y}_h$	TES device maximum SOC [kWh]
η^c	battery's charging efficiency
η^d	battery's discharging efficiency
μ_t^+	positive imbalance price [EUR/kWh]
μ_t^-	negative imbalance price [EUR/kWh]
π_t	spot price [EUR/kWh]
$\underline{X}_h$	battery's minimum SOC [kWh]
$\underline{Y}_h$	TES device minimum SOC [kWh]
C_h	thermal capacitance of TES device
P_h^{max}	maximum contracted power for house h
P_h^{min}	minimum contracted power for house h
p_s	probability of scenario s
$Q_{t,h,s}$	thermal load
R_h	thermal resistance of TES device

Variables

$\lambda_{t,s}^{agg}$	Lagrange multiplier associated with each constraint (19)
$\mathbf{X}_{h,s}$	vector $[X_{1,h,s},...,X_{T,h,s}]^T$
$\mathbf{X}_{t,s}^{agg}$	Aggregated SOC
$H_{t,h,s}$	EWH input [kW]
$I_{t,s}^+$	positive imbalance [kWh]
$I_{t,s}^-$	negative imbalance [kWh]
P_h^{ct}	customer's contracted power[kW]
$P_{t,h,s}^{\mathrm{ch}}$	battery charging power [kW]
$P_{t,h,s}^{\mathrm{dch}}$	battery discharging power
$P_{t,h,s}^{\mathrm{net}}$	customer's net power [kW]
P_t^g	day-ahead energy commitment in the wholesale market
$u_{t,h,s}$	binary variable. Equals “1” if battery is charging, “0” otherwise
$v_{t,h,s}$	binary variable. Equals “1” if battery is discharging, “0” otherwise
$X_{t,h,s}$	battery SOC [kWh]
$Y_{t,h,s}$	SOC of TES device [kWh]

In [7], a degradation model is used to optimize the operation of an off-grid system with a single PV and battery. The proposed linear model identifies lower and higher State of Charge (SOC) and charging/discharging cycles, and assigns a linear cost.

The work in [8] presents a model for a smart energy community in which storage depreciation is calculated based on a predefined lifespan of 10 years and 3000 cycles for a li-ion Battery Energy Storage System (BESS). The model then calculates a proportional cost with the net energy input. This calculation method disregards partial cycling of the BESS, and thus can lead to an underestimation of the actual depreciation cost. A model considering voltages and currents produced by different levels of DOD is analyzed in [9], for serving the purpose of managing resources in a residential microgeneration system composed of a single house with a PV-battery array.

A more detailed [10] electro-thermal battery model is used for determining savings in the secondary reserve market for a system-operator owned BESS. This model includes a variable dispatch cost for batteries through parameter-fitting analysis, including terminal voltage, currents, temperature and SOC. Although this is a more detailed model of the internal interactions in the BESS, this approach would require parametrization for each storage unit analyzed.

1.1.2. Battery cycling in other power systems applications

The authors of [11] develop a short-term cost model for a utility-scale BESS, in order to solve a 24 h resource-scheduling problem. The number of cycles and the DOD for a given time horizon are explicitly included in the optimization problem. Given that the relation of DOD and life cycles is nonlinear, the operation costs of the BESS are based on linearization by segments, and by assigning a charging cycle variable and constant cost. In this case, the resulting Mixed-Integer Linear Programming (MILP) is solved using a commercial solver. A Similar linearization-based modeling is used in [12] by approximating the slope of battery life as a function of the number of cycles but excluding the effects of DOD and solving the resulting MILP with a commercial solver. Paper [13] includes a vehicle battery degradation model consisting on piecewise linear approximation and including the effects of DOD. This research also uses a MILP solver to perform the optimization.

Following the same logic as the previous work, the research [14] presents an explicit cost function that models battery degradation, which is used to implement a Model Predictive Control (MPC) peak shaving algorithm including a 1 MW BESS. The authors achieve the explicit formulation of the degradation costs by detecting transitions between charging/discharging and idle mode by state representation. In this way, they identify a quadratic cost function that captures cycling stress in terms of power, DOD and SOC. One advantage of this approach is the possibility of embedding a quadratic-approximated aging model into an optimization problem, without adding major complexity in terms of non-linear equations.

In [15], authors propose a model for wind-based network planning, and analyze the economic impacts of changing initial SOC and the non-linear inverse relation of DOD and life-cycles. Another interesting model which considers explicit cycling by counting state transition in the case of Hybrid Electric Vehicles (HEV), is presented in [16]. Quadratic explicit modeling is proposed in [17] to calculate battery