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Robust optimization for day-ahead market participation of smart-home aggregators

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HIGHLIGHTS

- Day-ahead energy market participation of smart homes is proposed.
- Robust optimization is used to include uncertainties in PV, price and demand.
- Non-linear battery cycling aging is included in the optimization model.
- Best solutions are selected with Pareto optimality theory.

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ABSTRACT

This paper proposes an optimization model to participate in day-ahead energy markets when PV generation, thermal and electro-chemical storage devices are aggregated at the residential level. The model includes uncertainty in energy prices, PV and load; and adjustable robust optimization is used to determine a tractable counterpart of the problem. By means of robust control parameters, solutions with different levels of conservatism can be found and analyzed. In addition, the presented model includes explicit representation of battery degradation by means of special ordered sets. This equivalent cycling aging calculation takes into account the non-linear relation between depth of discharge and total life cycles of the battery by piecewise linearization. Performance analysis shows the advantage of the proposed approach when compared to the deterministic solution in terms of average cost and risk. For the analyzed real-life test system, the robust formulation achieves cost reduction of up to 5.7% and standard deviation decreases as much as 36.4%.

1. Introduction

Increasing penetration of decentralized renewable generation into medium- and low-voltage grids is motivating the development of new tools to overcome the challenges imposed by this new paradigm. These trends have extended even further to reach the building and home level, 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 energy prices, load and PV production, and also considering battery aging.

1.1. Current research

Regarding management models for joint thermal and electric storage technologies at the residential level, approaches include that presented in [3], which proposes a residential microgrid in which thermal and electric storage make it possible to shave the demand peak and enhance the system's self-sufficiency. The approach in [4] presents a methodology for intraday management of PV and Electric Water Heaters (EWH) in an LV network, with the EWH acting as a flexible load rather than a storage device.

Ref. [5] presents an optimization problem for the day-ahead market that minimizes retailer costs represented by imports/exports, and gas costs, along with expected balancing costs in real-time operation. The model does not include Battery Energy Storage Systems (BESS), but does include thermal load and electro-thermal storage. Sizing and operation of storage devices in smart buildings is presented in [6],

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Nomenclature

ARO	Adjustable Robust Optimization
BESS	Battery Energy Storage System
BESS	Battery Energy Storage Systems
DoD	Depth of Discharge
DR	Demand Response
DSO	Distribution System Operator
EV	Electric Vehicle
EWH	Electric Water Heater
HEMS	Home Energy Management System
LV	Low Voltage
MG	Microgrid
MPC	Model Predictive Control
MV	Medium Voltage
PCC	Point of Common Coupling
PDF	Probability Density Function
PV	Photovoltaic
RES	Renewable Energy Sources
RO	Robust Optimization
SO	Stochastic Optimization
SOC	State of Charge
SRB	Smart Residential Building
TES	Thermal Energy Storage

Indices

$\wedge$	marker to identify central forecasts
h	index for household, $h = 1, 2, ..., N$
s	index for segment, $s = 1, 2, ..., S$
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
Γ	robustness parameter
π_t	spot price [EUR/kWh]
$\underline{X}_h$	battery's minimum SOC [kWh]
$\underline{Y}_h$	TES device minimum SOC [kWh]
$a_{h,s}$, $b_{h,s}$	parameters of piecewise cost functions
C_h	thermal capacitance of TES device
$D_{t,h}$	electrical load
$D_{t,h}^{q\%}$	q-th quantile Electrical load
$Q_{t,h,s}$	EWH load [kW]
R_h	thermal resistance of TES device

Variables

$H_{t,h}$	EWH input [kW]
$l_{t,h,s}$	binary variable to detect active segment
$P_{t,h}^{\mathrm{c}}$	battery charging power [kW]
$P_{t,h}^{\mathrm{d}}$	battery discharging power [kW]
$P_{t,h}^{\mathrm{pcc}}$	maximum allowed power at the PCC [kW]
P_t^E	day-ahead energy commitment in the wholesale market [kWh]
$u_{t,h}$	binary variable. Equals "1" if battery is charging, "0" otherwise
$X_{t,h}^D$	battery DoD at the beginning of a charging cycle [p.u.]
$X_{t,h}$	battery SOC [kWh]
$x_{t,h}$	binary variable to detect beginning of a charging cycle
$X_{t,h,s}^{Ds}$	battery DoD at the beginning of a charging cycle in segment s [p.u.]
$Y_{t,h}$	SOC of TES device
z, q, y	dual and auxiliary variables of the robust counterpart

including electrical and thermal storage, but disregarding cycling effects.

Ref. [7] presents a cooperative scheme of Smart Residential Buildings (SRB), considering batteries, thermal storage and electric vehicles. Although cycling is not taken into account, this study constitutes an interesting benchmark given that different network configurations and interactions are presented.

A multi-energy microgrid was recently proposed in [8], in which thermal and electrical storage and heat sources are used to reduce operation costs and alleviate network capacity issues at the Point of Common Coupling (PCC). Although this paper does not account for either battery cycling or uncertainties, it does present a thorough modeling of different energy sources and their interactions, and is tested on a system comprising 300 households.

In this smart grid context, uncertainty plays an important role in the decision-making process. One common practice to facilitate these optimization processes is Stochastic Optimization (SO), which typically aims to determine the optimal solution among a number of expected predefined scenarios [9]. However, drawbacks of SO include factors such as the requirements for probabilistic information of uncertain variables, the implementation of specialized scenario generation/reduction techniques, and the computational burden related to large number of scenarios.

An alternative approach which has gained substantial attention in recent years is Robust Optimization (RO) [10], which is an interval-based optimization method. RO does not require knowledge of the Probability Density Function (PDF) of uncertain variables, but rather requires moderate information, i.e. an uncertainty set for each uncertain variable. RO provides a robust optimal solution that is feasible (immunized) within the confidence interval.

RO has been successfully used to tackle uncertainty, mainly in large-scale power systems problems with a variety of objectives. For instance, it has been used to capture load and wind uncertainty in Unit Commitment (UC) [11]. In the case of large-size battery participation in energy and ancillary markets, RO was used in [12] to capture uncertainty in prices. In transmission expansion planning, this methodology has been used to cope with demand and renewable generation uncertainty [13]. In [14], strategic bidding for a wind farm and battery was achieved by including price and wind power uncertainty. Stand-alone wind systems for market participation have also included RO analysis [15].

Although most RO applications are related to large power systems, the growing interest in decentralized and distributed energy has pushed the research community to explore this approach.

Although little research has been done on exploiting RO capabilities in residential storage-based energy systems, some work has been published in recent years, specifically related to medium-size DG/microgrid management. For instance [16], presents a model for strategic bidding in energy and ancillary markets for a microgrid consisting of RES, a microturbine (MT) and a battery, in which RO is used to include RES uncertainty and SO is used to tackle price uncertainty. For bidding purposes in day-ahead and real-time markets, Ref. [17] proposes a hybrid stochastic/robust approach, in which RO captures uncertainty in real-time prices, while stochastic optimization is used to include wind and PV scenarios. Both approaches ([16,17]) assume deterministic demand.