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Stochastic interval-based optimal offering model for residential energy management systems by household owners

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A R T I C L E I N F O

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A B S T R A C T

This paper proposes an optimal bidding strategy for autonomous residential energy management systems. This strategy enables the system to manage its domestic energy production and consumption autonomously, and trade energy with the local market through a novel hybrid interval-stochastic optimization method. This work poses a residential energy management problem which consists of two stages: day-ahead and real-time. The uncertainty in electricity price and PV power generation is modeled by interval-based and stochastic scenarios in the day-ahead and real-time transactions between the smart home and local electricity market. Moreover, the implementation of a battery included to provide energy flexibility in the residential system. In this paper, the smart home acts as a price-taker agent in the local market, and it submits its optimal offering and bidding curves to the local market based on the uncertainties of the system. Finally, the performance of the proposed residential energy management system is evaluated according to the impacts of interval optimistic and flexibility coefficients, optimal bidding strategy, and uncertainty modeling. The evaluation has shown that the proposed optimal offering model is effective in making the home system robust and achieves optimal energy transaction. Thus, the results prove that the proposed optimal offering model for the domestic energy management system is more robust than its non-optimal offering model. Moreover, battery flexibility has a positive effect on the system's total expected profit. With regarding to the bidding strategy, it is not able to impact the smart home's behavior (as a consumer or producer) in the day-ahead local electricity market.

1. Introduction

1.1. Aims and approaches

Customers are going to play a key role in the prospective power systems [1]. This will be possible because power will no longer be generated at centralized facilities, instead different technologies will be used to generate energy locally, this is called distributed generation. The infrastructure of smart grid makes this transition possible [1]. Thus, in power distribution systems' demand-side players – e.g. smart homes – will manage their own electrical energy according to the real and fair price [2]. Besides, current electricity markets are not able to satisfy customers' strategic behavior based on their autonomous decision-makings [3]. Hence, decentralized electricity markets are capable of adapting to the flexible behavior of electrical customers. In this way, smart homes are active agents and play a critical role in the bottom layer of the power systems. Smart homes are prosumers, this means they can be both producers and consumers. Hence, smart homes need energy management systems in order to make optimum decisions related to the management of energy inside the home, such as the choice of the best strategies when trading energy with other players (e.g. aggregators, retailers, local market operator, other consumers) in the distribution power network. In this way, distribution power networks are defined as complex ecosystems consisting of machines, networks, procedures, operators, and players which are organized hierarchically in the bottom layer of power systems in order to deliver electric power to end-users [34]. Different studies have considered distinct aspects of Residential Energy Management Systems (REMSs), e.g. residential electrical appliances [7], the main purposes of residential scheduling [8,15], decision-making under uncertainty [2], the implementation of

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Nomenclatures

Indices

t	index of time periods
j	index of electrical loads
ω	index of real-time scenarios

Objective function variables

EP	expected profit ($)

Day-ahead variables

$\lambda^{da}(t)$	day-ahead electricity price at time period t (€/kW h)
$C^{da}(t)$	day-ahead state of the charge of the battery at time period t (kW h)
$EL^{da}(t)$	day-ahead home energy consumption at time period t (kW h)
$k(t)$	day-ahead Dispatched status of PV power system at time period t
$P^{da}_{ch}(t)$	day-ahead battery energy charged at time period t (kW h)
$P^{da}_{dis}(t)$	day-ahead energy discharged from the battery at time period t (kW h)
$P^{da}_{dis,in}(t)$	day-ahead discharged energy of the battery that is injected to the smart home at time period t (kW h)
$P^{da}_{dis,out}(t)$	day-ahead energy discharged from the battery that is injected into the power grid at time period t (kW h)
$P^{da}_{pv,in}(t)$	day-ahead PV energy generation that is injected to the smart home at time period t (kW h)
$P^{da}_{pv,out}(t)$	day-ahead PV energy generation that is injected into the power grid at time period t (€/kW h)
$P^{da}_{pv,p}(t)$	day-ahead PV energy generation at time period t (kW h)
$P^{da}_{net}(t)$	day-ahead energy purchased from the local market at time period t (kW h)
$P^{da}_{sold}(t)$	day-ahead energy sold from home to the local market at at time period t (kW h)
$u^{da}(t)$	day-ahead discharging commitment binary variable for the battery at time period t
$v^{da}(t)$	day-ahead transacted energy status at time period t (kW h)

Real-time variables

$\Delta P^{rt}_{sold}(t,\omega)$	real-time sold energy from home to the local market in scenario ω and at time period t (kW h)
$\Delta P^{rt}_{net}(t,\omega)$	real-time energy purchased from the local market in scenario ω and at time period t (kW h)
$\theta^{in}(t,\omega)$	indoor temperature in scenario ω and at time period t (°C)
$C^{rt}(t,\omega)$	real-time state of charge of the battery in scenario ω and at time period t (kW h)
$EL^{rt}(t,\omega)$	real-time home energy consumption in scenario ω and at time period t (kW h)
$EL^{rt}_{j}(t,\omega)$	real-time energy consumption of load j in scenario ω and at time period t (kW h)
$EL^{rt}_{mrs}(t,\omega)$	real-time energy consumed by the must-run services in scenario ω and at time period t (kW h)
$EL^{rt}_{pp}(t,\omega)$	real-time energy consumed by the pool pump in scenario ω and at time period t (kW h)
$EL^{rt}_{sh}(t,\omega)$	real-time energy consumed by the space heater in scenario ω and at time period t (kW h)
$EL^{rt}_{swh}(t,\omega)$	real-time energy consumed by the storage water heater in scenario ω and at time period t (kW h)
$ES^{rt}(t,\omega)$	load shedding of home in scenario ω and at time period t (kW h)
$ES^{rt}_{j}(t,\omega)$	shedding of load j in scenario ω and at time period t (kW h)
$ES^{rt}_{mrs}(t,\omega)$	load shedding of the must-run services in scenario ω and at time period t (kW h)
$ES^{rt}_{pp}(t,\omega)$	load shedding of the pool pump in scenario ω and at time period t (kW h)
$ES^{rt}_{sh}(t,\omega)$	load shedding of the space heater in scenario ω and at time period t (kW h)
$ES^{rt}_{swh}(t,\omega)$	load shedding of the storage water heater in scenario ω and at time period t (kW h)
$L^{rt}_{mrs}(t,\omega)$	real-time load of the must-run services in scenario ω and at time period t (kW)
$L^{rt}_{pp}(t,\omega)$	real-time load of the pool pump in scenario ω and at time period t (kW)
$L^{rt}_{sh}(t,\omega)$	real-time load of the space heater in scenario ω and at time period t (kW)
$L^{rt}_{swh}(t,\omega)$	real-time load of the storage water heater in scenario ω and at time period t (kW)
$P^{rt}_{ch}(t,\omega)$	real-time battery energy charged in scenario ω and at time period t (kW h)
$P^{rt}_{dis}(t,\omega)$	real-time energy discharged from the battery in scenario ω and at time period t (kW h)
$P^{rt}_{dis,in}(t,\omega)$	real-time energy discharged from the battery that is injected into the smart home in scenario ω and at time period t (kW h)
$P^{rt}_{dis,out}(t,\omega)$	real-time energy discharged from the battery that is injected into the power grid in scenario ω and at time period t (kW h)
$P^{rt}_{pv}(t,\omega)$	real-time PV energy generation in scenario ω and at time period t (kW h)
$P^{rt}_{pv,in}(t,\omega)$	real-time PV energy generation that is injected into the smart home in scenario ω and at time period t (kW h)
$P^{rt}_{pv,out}(t,\omega)$	real-time PV energy generation that is injected into the power grid at scenario ω and at time period t (kW h)
$S^{PV}(t,\omega)$	energy spilled from PV in scenario ω and at time period t (kW h)
$u^{rt}(t,\omega)$	real-time discharging commitment binary variable for the battery in scenario ω and at time period t
$v^{rt}(t,\omega)$	day-ahead transacted energy status at scenario ω and at time period t
$z(t,\omega)$	operation status of the pool pump in scenario ω and at time period t

Parameters

α_{price}	optimistic coefficient of price
α_{pv}	optimistic coefficient of PV energy generation
$\sigma^{dn}_{price}(t)$	lower bound predicted price error at time period t (€/kW h)
$\sigma^{up}_{price}(t)$	upper bound predicted price error at time period t (€/kW h)
$\sigma^{dn}_{pv}(t)$	lower bound predicted error for PV energy generation at time period t (kW h)
$\sigma^{up}_{pv}(t)$	upper bound predicted error for PV energy generation at time period t (kW h)
$\lambda^{da}(t)$	day-ahead electricity price at time period t (€/kW h)
$\lambda^{pred}(t)$	day-ahead price prediction at time period t (€/kW h)
$\lambda^{rt}_{net}(t,\omega)$	price of the electrical energy purchased from the real-time local market in scenario ω and at time period t (€/kW h)
$\lambda^{rt}_{sold}(t,\omega)$	price of the electrical energy sold to the real-time local market in scenario ω and at time period t (€/kW h)
η_{B2H}	discharging efficiency of the battery
η_{H2B}	charging efficiency of the battery
γ	flexibility coefficient
π_{ω}	probability of real-time scenarios in scenario ω
θ^{in}_{des}	desired indoor temperature (°C)
θ^{in}_{i}	initial indoor temperature (°C)
$\theta^{out,pred}(t,\omega)$	predicted outdoor temperature in scenario ω and at time period t (°C)