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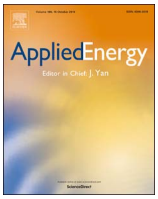

Optimal supply and demand bidding strategy for an aggregator of small prosumers

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HIGHLIGHTS

- Participation of an aggregator of small prosumers in the energy market.
- The aggregator exploits the flexibility of prosumers' appliances, in order to reduce market net costs.
- A two-stage stochastic optimization model to define demand and supply bids for the day-ahead energy market is presented.
- A model predictive control method to set the operation of flexible loads in real-time is presented.
- A case study of 1000 small prosumers from the Iberian market is used to compare the proposed methods to other benchmarks.

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ABSTRACT

This paper addresses the problem faced by an aggregator of small prosumers, when participating in the energy market. The aggregator exploits the flexibility of prosumers' appliances, in order to reduce its market net costs. Two optimization procedures are proposed. A two-stage stochastic optimization model to support the aggregator in the definition of demand and supply bids. The aim is to minimize the net cost of the aggregator buying and selling energy at day-ahead and real-time market stages. Scenario-based stochastic programing is used to deal with the uncertainty of electricity demand, end-users' behavior, outdoor temperature and renewable generation. The second optimization is a model predictive control method to set the operation of flexible loads in real-time. A case study of 1000 small prosumers from the Iberian market is used to compare four day-ahead bidding strategies and two real-time control strategies, as well as the performance of combined day-ahead and real-time strategies. The numerical results show that the proposed strategies allow the aggregator to reduce the net cost by 14% compared to a benchmark typically used by retailers (inflexible strategy).

1. Introduction

1.1. Motivation

Demand response is acknowledged as the inevitable solution to enhance the economic effectiveness of electricity markets, increase the integration of renewable energy resources and improve the operation of electric power systems [1]. Several countries have already established demand response programs that harness the largest and most energy intensive industrial and commercial clients through dynamic tariff schemes or direct use of load, as part of their system balancing activities [2]. According to the international energy agency, industrial users consume 32.1% of the total electricity demand in the developed countries, whereas commercial services and residential consumers account for 31.8% and 32.2%, respectively. Large consumers are already considered as a flexibility resource, while the major share of electricity consumption, small services and residential consumers, remain untapped. However, the recent advances in real deployment of smart home and grid technologies promise to leverage once and for all the active participation of small consumers in demand response programs [3,4]. The smart home technologies include automation solutions, such as home energy management systems (HEMS), photovoltaic (PV) systems and smart appliances with communication, monitoring and control functionalities. Therefore, the technical barriers of demand response are no longer on the side of the automation solutions. The main challenge is to transform these automation functionalities into products that can be traded by an aggregator in the electricity markets.

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Nomenclature

Abbreviations and Superscripts

AR/DE	arrival/departure of electric vehicles
DA	day-ahead
EV	electric vehicle
$HEMS$	home energy management system
INL	inflexible net load
MPC	model predictive control
PV	photovoltaic
RT	real-time
SL	shiftable load
TCL	thermostatically controlled load
$\wedge$	point forecast
$\underline{\vee}$,$\overline{\wedge}$	load, generation
$+$,$-$	positive, negative imbalances

Indices and Sets

$j \in S$	scenarios
$t,k,w \in H$	time interval
$v \in \{EV, TCL, SL, INL\}$	type of load
$i \in L^v$	loads
$H^v \subset H$	sub-set of time intervals
$O \subset H$	set of time intervals of active occupancy
	availability to start $\underline{H}^{SL}$ and complete $\overline{H}^{SL}$ a working cycle (sets)
$y \in N$	prosumers

Parameters

C	thermal capacitance (kWh/°C)
COP	coefficient of performance
CP	contracted power (kW)
D	number of time intervals of a working cycle
$\overline{E}$	maximum energy (kWh)
$\overline{P}$	maximum electric power (kW)
Pr	power profile (kW)
$\overline{SOC}$,$\underline{SOC}$	maximum, minimum state-of-charge (kWh)
R	thermal resistance (°C/kW)
λ	price (€/kWh)
π	probability of occurrence of the scenarios
η	efficiency
Δt,Δk	duration of time interval $t\,(1h)$,$k\,(0.25h)$
$\bar{\theta}$, $\underline{\theta}$	maximum, minimum temperature (°C)
θ^o	outdoor temperature (°C)

Variables

E	energy (kWh)
I	imbalance (kWh)
P	electric power (kW)
SOC	state-of-charge (kWh)
θ	temperature (°C)
ψ	sets the beginning of a working cycle (binary)
$\varnothing$	auxiliary (binary)

1.2. Related work

The participation of aggregators in the day-ahead (DA) energy market has been the focus of many recent studies. In the electric mobility context, Bessa et al. [5,6] proposed two deterministic optimization models to define demand bids, based on point forecasted information of electric vehicles (EV) mobility patterns and energy prices. Kristoffersen et al. [7] included battery wear costs in the DA optimization of EV charging. Vagropoulos and Bakirtzis [8] proposed a two-stage stochastic model to optimize demand bids, considering the uncertainty of EV mobility patterns and electricity prices through scenarios. Mohsenian-Rad [9] extended the aggregator portfolio to other shiftable loads (SL), such as dishwashers and washing machines. A time-coupled stochastic optimization problem was formulated to select price and demand bids to the DA market and demand bids to the real-time (RT) market. Ayón et al. [10] presented a deterministic model to optimize demand bids for the DA energy market, based on forecasted load flexibility. Under the assumption of direct control over thermostatically controlled loads (TCL), Chen et al. [11] proposed a stochastic model to define DA demand bids, based on scenarios of DA energy prices. Babar et al. [12] formulated an applied methodology for an agile demand response using micromodels. The objective is to optimize demand flexibility to be traded by an aggregator in the DA market. Saez-Gallego et al. [13] developed a billevel optimization model that uses price-consumption data to define demand bids that capture the price-response of consumers.

Another group of papers has presented strategies to control aggregated flexible resources, in order to comply with DA market commitments. Many of these studies are focused on TCL [14–17]. For example, Perfumo et al. [14] developed a model-based feedback control strategy for load management of large groups of TCL. Mathieu et al. [15] explored state estimation and control methods to manage RT energy imbalances. The authors also investigated how various levels of monitoring and communications infrastructure affect the aggregated control of TCL. Callaway [16] developed new methods to model and control aggregated TCL with the objective of delivering regulation services. Zhou et al. [17] proposed a two-level scheduling method to reduce imbalance costs through the control of aggregated TCL. This approach considers a model predictive control (MPC) optimization in the upper level to set the aggregated demand and a priority list strategy in the lower level to define ON/OFF set-points. Subramanian et al. [18] developed scheduling algorithms to coordinate populations of SL and storage devices, in order to minimize reserve deployment costs. Bessa et al. [5] proposed a management procedure based on deterministic optimization to set the operation of an EV fleet. In the topic of virtual power plants, Vasirani et al. [19] presented a MPC approach that uses the flexibility of EV to compensate the intermittent generation of wind farms.

1.3. Contributions

The expected transformation of consumers into prosumers in the coming years creates an opportunity for an aggregator to exploit distributed energy resources (i.e., loads and generators) as single products in the electricity market. This paper presents a framework to enable the participation of an aggregator of small prosumers on both sides of the energy market. The aggregator relies on the agility of the smart home appliances to provide flexibility and respond to fast market variations without compromising the energy needs and preferences of the prosumers. This load agility concept was proposed by Babar et al. in [12,20] and is known as agile demand response.

The contributions of this paper are two optimization models. The first contribution corresponds to a two-stage stochastic optimization model to support the aggregator in the definition of demand and supply bids to submit to the DA energy market. The aim is to minimize the net cost of the aggregator buying and selling energy in the DA and RT market stages. The bids result from the optimization of flexible and inflexible net load (INL). The flexible net load includes EV, TCL and SL.