Electrical Power and Energy Systems 104 (2019) 664–672

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

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

Optimization-based estimation of power capacity profiles for activity-based residential loads

Juan A. Gomez-Herrera*, Miguel F. Anjos

GERAD and Department of Mathematics and Industrial Engineering, Polytechnique Montreal, C.P. 6079, Succ. Centre-Ville, Montreal, QC H3C 3A7, Canada

ARTICLE INFO

Keywords:
Smart buildings
Power demand
Residential load sector
User behavior
Activity-based loads
Stochastic optimization

ABSTRACT

This paper proposes a framework to determine capacity profiles in smart buildings. In this scheme the users choose a level of power capacity to account for their stochastic demand while paying the corresponding electricity prices through a flexible time-and-level-of-use pricing policy. We formulate a two-stage stochastic optimization model that minimizes the total cost of booking a power capacity level and meeting the energy demand for the planning horizon. We present two approaches to select the scenarios for the stochastic optimization. In the first approach, we assume that the probability distributions of the start times of the loads are known, and the scenarios are generated using those distributions. In the second approach, we assume that only historical consumption data is available and we propose a new algorithm to build the scenarios using this data. Our simulation experiments validate the performance of both approaches and report cost savings of up to 16%.

1. Introduction

The increasing development of smart grids (SGs) creates potential benefits and challenges for utilities, consumers, and society in general. A SG allows information flow among all the participants [1], supporting decisions that ensure the stability, reliability, and economic viability of the system.

In this context, the consumers (end-users) can become decision-makers and participate in grid's decisions through demand response (DR) programs [2]. DR programs are designed to encourage end-users to change their consumption preferences in a way that is beneficial for the grid, normally in exchange for compensation.

DR programs can be classified in two groups: incentive-based programs and pricing programs. In incentive-based programs the consumer commits to reducing consumption over a determined period of time under prespecified conditions.

In pricing DR programs, the utility offers a variable tariff, expecting that the user will react by shifting load to cheaper time frames. If the users do not shift they pay more to meet their energy requirements. These pricing policies normally reflect the aggregated peak of demand and therefore the utility's generation costs. They are mostly oriented to customers in residential and commercial sectors and have particular potential in smart buildings [3], where the end-users can seek to benefit while meeting the grid requirements.

The residential and commercial sectors have specific characteristics that must be taken into account. First, the demand is driven by a large number of end-users with low individual consumption. Second, the consumption is triggered by the user behavior, which may be (highly) stochastic.

There are various models that consider user behavior. Some approaches seek to predict the future user consumption based on historical data. The review presented by [4] contains some of the most common bottom-up approaches to load forecasting. The model presented in [5] determines consumption profiles based on the aggregation of individual loads, the number of people in the housing unit, and their activity profiles. In a similar way, [6] uses a Markov-chain Monte-Carlo model to compute the activity profiles in order to estimate realistic load profiles for a wide variety of housing units. The approach presented in [7] uses logistic and Poisson regression to model the correlational and consistency elements of the shared activities of multiple inhabitants in a household. Poisson regression accounts for the activities that can occur multiple times during the day, and logistic regression estimates the probability for each event.

The characterization framework in [8] analyzes the controllable demand and its potential savings for users participating in an energy management system. Similarly, the approach in [9] estimates consumption profiles by fitting probability density distributions over a historical set for single and multiple housing units.

The importance of a consumption-aware user is discussed in [10]. This survey includes elements such as potential energy savings,

* Corresponding author.
E-mail address: juan.gomez@polymtl.ca (J.A. Gomez-Herrera).

https://doi.org/10.1016/j.ijepes.2018.07.023
Received 22 November 2017; Received in revised form 10 March 2018; Accepted 16 July 2018

Electrical Power and Energy Systems 104 (2019) 664–672

Notation

Sets

$t \in T$	Set of time frames in horizon
$m \in M$	Set of loads
$i \in S$	Set of scenarios
$j \in Q^L$	Set of intervals of the cost step function for the lower tariff
$q \in Q^H$	Set of intervals of the cost step function for the higher tariff

Optimization Parameters

K_t^0	Time of use tariff in time frame t (¢/kWh)
K_{jt}^L	Lower tariff in interval j in time frame t (¢/kWh)
K_{qt}^H	Higher tariff in interval q in time frame t (¢/kWh)
K_t^F	Booking cost in time frame t (¢/kWh)
C_{jt}^L	Capacity lower bound in interval j in time frame t for the lower tariff (kW)
C_{qt}^H	Capacity lower bound in interval q in time frame t for the higher tariff (kW)
π_{it}	Probability of scenario i in time frame t
D_{it}	Demand for scenario i in time frame t

Optimization Variables

x_{ijt}^L	Electricity consumption at lower tariff in scenario i, time frame t, and interval j (kWh)
x_{iqt}^H	Electricity consumption at higher tariff in scenario i, time frame t, and interval q (kWh)
c_{jt}	Booked capacity in time frame t and interval j (kW)
$\bar{c}_{qt}$	Auxiliary variable to identify the higher tariff interval q in time frame t
ϕ_{jt}	$\begin{cases} 1 & \text{Capacity in time frame } t \text{ belongs to interval } j \text{ for the lower tariff} \\ 0 & \text{Otherwise} \end{cases}$
δ_{qt}	$\begin{cases} 1 & \text{Capacity in time frame } t \text{ belongs to interval } q \text{ for the higher tariff} \\ 0 & \text{Otherwise} \end{cases}$

Scenario Generation from Distributions (SfD)

P_m	Power consumption of load m (kW)
L_m	Duration of load m (h)
$\widetilde{X}_{mt}$	$\begin{cases} 1 & \text{Load } m \text{ is active in time frame } t \\ 0 & \text{Otherwise} \end{cases}$
σ	Standard deviation for the loads arrival time
ρ	Significance threshold for scenario elimination

Scenario Generation from Historical Data (SfH)

N	Number of days in Γ
$\Gamma \in \mathbb{R}^{N \times \|T\|}$	Historical load consumption
G	Number of time segments
$\overline{G}(n)$	Number of time segments in iteration n
α	Number of iterations with a constant $\overline{G}(n)$
β	Stopping criterion

activities with higher potential impact, and the availability of information and automation in the building.

Besides estimating load and understanding user behavior, there are various strategies for integrating the consumers into the grid decisions. The authors in [11] present a comprehensive review of optimization-based approaches for demand-side management (DSM). They compare the system granularity, the time scale and the type of demand (deterministic or stochastic). DSM normally deals with user's costs and demand satisfaction. In [12–14], the user preferences are typically hard constraints and are met while optimizing the energy consumption or peak reduction.

In a similar way, the mixed integer linear optimization model in [15] minimizes the cost for the user in a day-ahead context. This approach considers priorities for the operation of a set of dispatchable appliances. The mixed integer nonlinear model in [16] maximizes the difference between a utility and a cost function while determining the operation time and the power consumption level of each device. On the other hand, multi-objective optimization is used to trade-off energy costs and comfort in [17,18].

As previously mentioned, user participation can be encouraged by DR pricing programs. A pricing policy that considers user behavior facilitates the user's integration into the SG decisions. Different pricing policies are assessed in [19,20] to explore the effect on user participation and grid performance. Declining block rates are analyzed in [21] to achieve a balance between electricity cost and user comfort. The role of electricity tariffs in solar panel penetration and the benefit for residential users are explored in [22]. In other cases there is a negotiation process. The user behavior is considered during the process of setting prices in [23]. In this case a bilevel optimization approach is used to find a trade-off between the revenue obtained by the energy provider and the user dissatisfaction.

In this article we propose a novel framework that integrates features of user behavior models, user participation through DSM, and DR pricing programs in order to provide residential and commercial users, and utilities with a tool to support decisions within a SG.

The proposed framework determines power capacity profiles that account for the stochastic demand generated by the user behavior. The user selects a capacity and its corresponding energy prices in a novel flexible time-and-level-of-use (TLOU) pricing context. This goes beyond a forecasting approach, since it determines how to respond to the expected demand (i.e., the forecast) in a way that ensures user satisfaction, and considers the user cost and the grid requirements.

We propose a two-stage stochastic optimization model that minimizes the cost of booking power capacity and satisfying energy demand. We introduce two approaches to generate the consumption scenarios. In the first approach, we generate the scenarios from the distributions of the start times of the loads. In the second approach, we use a novel algorithm that builds the scenarios from historical consumption data.

The use of capacity profiles offers savings for the users and provides the grid with more information about the operation of the system. One of the main features of this work is that the users do not manage their consumption to follow a fixed cost profile; instead, they can select the electricity prices from a group of tariffs that adjust to their preferences while considering the grid requirements.

This article is structured as follows: the proposed approaches are described in Section 2, the experimental results and analysis are presented in Section 3, and the conclusion is given in Section 4.

2. Proposed framework

Our framework is based on the concept of a capacity profile. A power capacity profile allows us to establish a trade-off between user energy requirements and peak-oriented grid decisions. The framework uses a two-stage stochastic optimization model to estimate capacity profiles considering the user behavior and a dynamic cost scheme. The consumer books a maximum level of consumption per time frame, providing the grid with information in advance and receiving energy below that level at a discounted price. The utility uses this information for planning purposes and is able to charge a higher price if the user exceeds the specified level.

This paradigm facilitates the integration of renewable resources