Applied Energy 191 (2017) 492–501

Contents lists available at ScienceDirect

Applied Energy

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

Power capacity profile estimation for building heating and cooling in demand-side management

Juan A. Gomez *, Miguel F. Anjos

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

HIGHLIGHTS

- We present a new methodology to estimate power capacity profiles.
- We use a classification approach to estimate the capacity.
- Our methodology works with an existing demand-side management module.
- We take advantage of the structure of the problem.
- We report the performance of our approach on a real-world-based scenario.

ARTICLE INFO

Article history:
Received 29 September 2016
Received in revised form 21 January 2017
Accepted 27 January 2017
Available online 9 February 2017

Keywords:
Smart buildings
Power demand
Residential load sector
Least squares
Parameter estimation
Classification

ABSTRACT

This paper presents a new methodology for the estimation of power capacity profiles for smart buildings. The capacity profile can be used within a demand-side management system in order to guide the building temperature operation. It provides a trade-off between the quality of service perceived by the end user and the requirements from the grid in a demand-response context. We use a data-fitting approach and a multiclass classifier to compute the required profile to run a set of electric heating and cooling units via an admission control module. Simulation results validate the performance of the proposed methodology under various conditions, and we compare our approach with neural networks in a real-world-based scenario.

1. Introduction

In the context of power systems, reducing peaks and the fluctuation of consumption brings stability to the system and benefits to the players in the power supply network. In this respect, demand-response (DR) programs and demand-side management (DSM) systems encourage and facilitate the participation of the end users in the grid decisions. This participation is increasing with the development and implementation of smart buildings. DR programs have mostly been oriented to large consumers, but smart buildings can exploit the DR potential in residential and commercial buildings as well. These represent around 70% of the total energy demand in the United States [1]. In Canada, space heating is responsible for more than 60% of the total residential energy consumption, due to the cold climate [2]. Across the country, electric baseboards account for 27% of heating equipment, reaching 66% in the province of Quebec. On the other hand, the province of Ontario is typically a summer-peaking region due to the high temperatures during that season and the high penetration of air-conditioning systems [3,4].

Several authors have published DSM-related results. Normally their research motivation is oriented to load management, user behavior, cost performance, and curve shaping. Imposing a capacity constraint is a common idea among these approaches. Costanzo et al. [5] propose a multilayer architecture that provides a scheme for online operation and load control given a maximum consumption level. In the stochastic DSM program in [6], a DR aggregator imposes a capacity constraint. Bidding curves and price analyses are reported in order to guide end-users about increasing capacity. Rahim et al. [7] evaluate the performance of several heuristic-based controllers. They define the load management as a knapsack problem with preset power capacities for each time slot. In a similar way, [8] assumes a consumption limit that allows the

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

http://dx.doi.org/10.1016/j.apenergy.2017.01.064
0306-2619/

Notation

$h \in \{1, 2, \ldots, H\}$	set of time frames in horizon
$t \in \{1, 2, \ldots, S\}$	set of time steps in time frame h (same for every h)
$i \in \{1, 2, \ldots, I\}$	set of loads
N_h	number of requests received in time frame h
P_i	power level of load i (kW)
C_h	power capacity in time frame h (kW)
$r_{i,t}$	$\begin{cases} 1 & \text{if a request is created by load } i \text{ in time step } t \\ 0 & \text{otherwise} \end{cases}$
$x_{i,t}$	$\begin{cases} 1 & \text{if request from } i \text{ is accepted in time step } t \\ 0 & \text{otherwise} \end{cases}$
QoS_h	quality of service in time frame h
$\widehat{QoS}_h$	quality of service of the prediction model in time frame h
T	temperature (°C)
T^e_h	external temperature in time frame h (°C)
$\mathscr{P}$	power levels of the loads in each scenario
Ω	discrete set of capacities
$\omega \in \Omega$	capacity class

activation of only one load at a time. Li et al. [9] look for an optimal allocation of capacities based on a queueing strategy. The service provider determines the capacity to assign to each user from a set of renewable resources.

The idea of capacity subscription is explored in [10], where the individual consumer's demand is limited in a competitive market. On the other hand, the heuristic algorithm proposed in [11] aims to minimize the error between the actual power curve and the objective load curve by moving the shiftable loads. In this case the objective load curve can be seen as a soft constraint capacity profile.

A variation of the capacity limit is presented in [12], where each individual user has a predefined budget to maximize his/her satisfaction.

All the approaches mentioned represent the capacity as a given parameter, and some of them recognize the importance of using a forecasting tool to determine its value. Estimating the user consumption is a key step in the decision-making process for users and for higher levels in the power system. Relevant publications can be found in the load-forecasting literature. Suganthi and Samuel [13] give a comprehensive review of forecasting methods from classical time series to more sophisticated machine learning tools.

Load estimation methods are classified depending on the level of aggregation of the input data: they can be bottom-up or top-down [14]. Bottom-up models extrapolate the behavior of a larger system based on its inner elements. Top-down models make decisions from a global perspective and share them among all the subsystems.

Within these two categories different approaches have been used to estimate the energy demand. Ahmed et al. [15] compare artificial neural networks and the auto regressive integrated moving average, showing the effect on the scheduling of storage devices. Jain et al. [16] use support vector regression to evaluate the impact of the time and space granularity inside a multi-family unit. Al-Wakeel et al. [17] use a k-means-based load estimation method to compute future load profiles using complete and incomplete past information.

Logistic and Poisson regression are used in [18] to estimate energy demand in a large aggregated population. In a similar way, [19] presents a short-term forecasting method for aggregated loads, specifically in buildings with daily or seasonal patterns of consumption. Mohajeryami et al. [20] present an error analysis for different load estimation methods that are used in real-world operations. They highlight the importance of an accurate estimation for exploiting the DR potential.

On the other hand, when the prediction output belongs to a discrete set of categories the estimation can be defined as a classification problem. Some related energy problems are treated in this way: price forecasting in [21] and wind power ramp events in [22].

This paper proposes an approach for the estimation of a power capacity profile that works in combination with the admission controller (AC) module presented in [5]. This profile is used to ensure enough power to meet the demand for the next planning horizon (e.g., the next day in a day-ahead DR market). This novel approach takes advantage of the structure derived from the estimation problem to compute capacity profiles efficiently and reliably. Estimating the capacity that will be necessary allows us to define a relationship between the total expected demand and the level of service the user desires while providing DR. In this scenario the user will book a variable maximum power capacity per time frame over the planning horizon, ensuring a pre-established level of service. This approach could also include external factors such as peak control and pricing policies. The motivation is that a defined power *budget* limits the consumption and encourages load shifting. It also facilitates the integration of differential pricing for both energy and power.

This paper is structured as follows. We describe the proposed methodology in Section 2. We give simulation results for the real-world-based scenario in Section 3, and Section 4 presents our conclusions.

2. Power capacity profile

Fig. 1 shows the application of the AC module presented in [5]. The online algorithm in the AC has four stages. First, the space

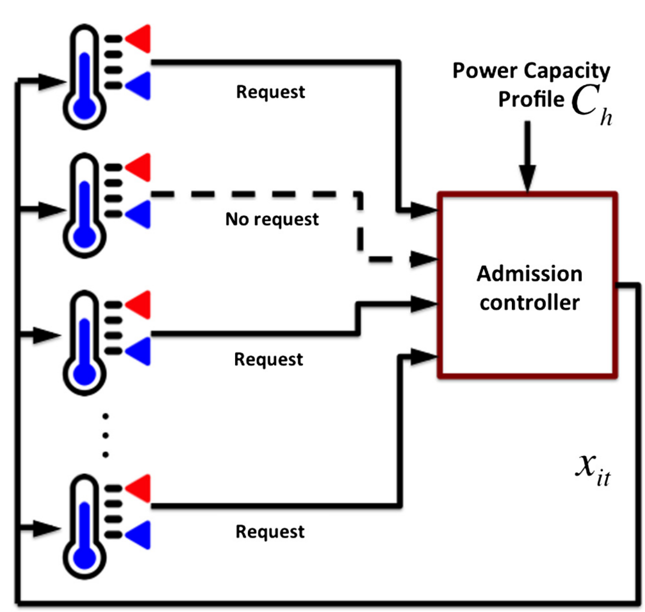

Fig. 1. Admission controller.