Load shedding optimization via data-driven modelling of HVAC

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1 Introduction

The internal mass of a building can provide flexibility capacities which can contribute to maintain the grid stability, to reduce peak demand, to avoid investments in grid infrastructure reinforcement and construction of costly power plants [1], [2]. In this context we investigate optimal control of the HVAC system (Heating Ventilation and Air Conditioning) for integration in DR (Demand Response) programs that encourage consumers energy flexibility.
Many complex modelling approaches exist in the literature, requiring a lot of building data. In order to design a scalable and easily implemetable solution, we propose a method that relies on data from commonly available sensors and is designed to achieve load control by day-ahead optimal scheduling of temperature setpoints.

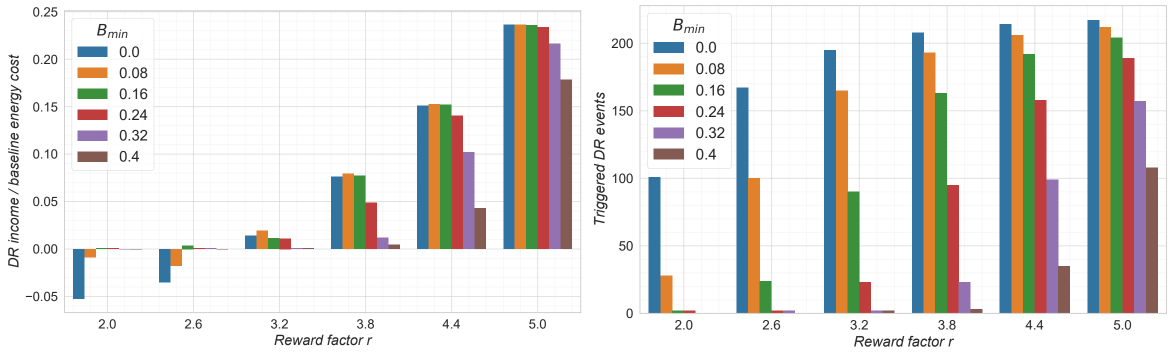
2 Problem statement

For the sake of clarity we focus on the winter/heating season, although the approach can be applied without loss of generality to the summer/cooling season. We assume a DR market model where cost incentives for load reduction are sent for the following day. Load control is performed by modifying the nominal temperature setpoints, i.e. preheating the building and using thermal inertia to achieve load reduction. The objective is to determine optimal temperature setpoint modifications in a pre-defined comfort tunnel $[T^{sp}_{min}, T^{sp}_{max}]$, to be applied in a uniform manner throughout all zones. The study is based on simulation data using IDA-ICE - an advanced dynamic multi-zone building simulation tool.

3 DR participation income

The critical issue in the problem described above is to estimate precisely the HVAC load with respect to the controlled temperature setpoints. The proposed approach consists in the design of a ML (Machine Learning) predictive model (here XGBoost [3] regression model) that approximates a static map between the target - HVAC load, and the features - comfort setpoints, exterior temperature, hour, and direct solar irradiance. The learning data set is augmented with mean averaging windows versions of the default sampled data set. This reinforces the dependency between the predictive variables and the target, therefore improving the model's precision. For a given DR event, the predictive model is used to estimate the preheating energy, i.e. overconsumption due to a setpoint increase ΔT^{sp}_{min}, and the shedded energy due to the setpoint reset to its nominal value. Optimization is thus performed by selecting among a set of preheating scenarios the one resulting in the greatest net benefit. Given r, a reward factor for DR participation with respect to the baseline energy cost, the net benefit for a given DR event is estimated based on the difference between the resulting participation reward and the preheating cost. Participation to the event is triggered if the maximum estimated net benefit, relative to the baseline energy consumption, is greater than a certain threshold B_{min}.

Hereby we illustrate the possible income for a limited set of DR events and optimization parameters/variables. Fig. 1a illustrates, for different reward factors r and participation thresholds B_{min}, the ratio between DR income and total baseline energy consumption. Fig. 1b illustrates the corresponding total number of triggered DR participations.



(a) DR income estimations.

(b) Number of triggered events

FIG. 1 – An example of DR participation for different reward factors r and participation thresholds B_{min}. The set of scenarios is defined by 2 DR events per day, in the morning and early evening. The decision variables set is limitted as follows : the pre-heating duration is 1 hour, the shedding duration is 1 hour, the possible ΔT^{sp}_{min} are 1, 2 or 3 °C.

4 Conclusion

The proposed approach applies for flexibility optimization of HVAC systems in a DR framework. The design of a predictive ML model for power consumption estimation is emphasized, which relies on a restrictive set of variables accessible in real-life situations. The method is scalable and can be replicated if more detailed information about the building is available, for example power consumptions for separate zones. By using the proposed method, the flexibility leverage allows non negligeable incomes based on realistic DR remunerations. For a relative reward $r = 5$, the illustrated example shows an income from DR participation representing 2.87 % of the total energy cost for the considered winter season. This estimation is based though on a restrictive set of DR scenarios, durations and setpoint modifications. The study is being continued in order to set up a proper optimization framework in which the set of DR events, decision variables and income estimations will be refined and explored in detail.

Références

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