Assessing the Potential of Residential HVAC Systems for Demand-Side Management

Thijs van der Klauw, Gerwin Hoogsteen,
Marco E. T. Gerards and Johann L. Hurink
Department of Electrical Engineering, Mathematics and Computer Science
University of Twente, Enschede, The Netherlands

Xianyong Feng and
Robert E. Hebner
Center for Electromechanics
University of Texas, Austin, USA

***Abstract*—We investigate the potential of residential heating, ventilation and air conditioning systems to contribute to dynamic demand-side management. Thermal models for seven houses in Austin, Texas are developed with the goal of using them in a planning-based demand-side management approach. The thermal models form the base to determine the flexibility present in these houses with respect to cooling requirements. The derived thermal models are shown to be reasonably accurate when used to predict indoor temperature changes. They are integrated in the planning-based demand-side management approach profile steering, which accounts for prediction errors. Simulations show that the approach is capable of flattening the load profile of the considered houses considerably.**

***Index Terms*—Demand-side management, HVAC systems, Residential control.**

I. Introduction

Our energy supply chain is undergoing rapid changes caused by the energy transition. Amongst others, there is a drive towards electrification of our energy use (e.g., e-mobility) and the use of intermittent, renewable resources (e.g., photovoltaics) [1]. These changes are causing a loss of flexibility on the supply side of our electricity grids. This in turn causes problems concerning the reliability of our grids. However, the potential flexibility on the demand side is increasing. This flexibility can be exploited by a demand-side management (DSM) approach to ensure the energy transition towards a carbon-free society can become reality.

Traditional large electrical loads present in residential settings in hot climates are heating, ventilation and air conditioning (HVAC) systems [2], [3]. Their prevalence means that these systems can be used *now* to provide flexibility in the energy consumption of residential customers. Therefore, we investigate how we can incorporate such systems in an existing DSM approach called *profile steering* [4]. As this DSM approach is based on discrete time scheduling, as well as many other approaches, we need to determine how much flexibility is available in the system for each of the time intervals for which a schedule is to be made. In other words, a model is required that determines how an energy consumption schedule of the HVAC system relates to indoor temperatures over the scheduling horizon.

II. Flexibility of HVAC systems

To determine the flexibility provided by HVAC systems, we need to determine how the operation of these systems affects the indoor temperature, as this temperature generally needs to be kept between user defined bounds. As profile steering uses discrete time intervals, we also assume that for each HVAC system an indoor temperature set point $\overline{T_t}$ and an allowed deviation dev_t are known for each time interval t. The actual indoor temperature T_t, which depends on the use of the HVAC system, must satisfy the constraint:

$$\overline{T_t} - dev_t \leq T_t \leq \overline{T_t} + dev_t. \tag{1}$$

To model the relation between energy consumed by the HVAC system and T_t we use a linear model that has been shown to work in a similar setting [5]. The use of a linear model ensures scalability and tractability of our system for a large number of HVAC systems. In the model, we determine the indoor temperature T_{t+1} for the next time interval using the indoor temperature T_t, the HVAC system's average power consumption x_t, and the outdoor temperature O_t of the current time interval, by:

$$T_{t+1} = aT_t + bx_t + cO_t + d_t, \tag{2}$$

where $a, b, c,$ and d_t are parameters of the model. Note that parameter d_t varies over time and can be used to model thermal gains and losses not captured by the other parts of the model, e.g., thermal gains from solar radiation and human occupancy/behavior. Our model is similar to a model used for residential HVAC systems in [6]. To determine d_t from historic data, we assume that it is invariant for the same time interval on different days, i.e., $d_t = d_{t+96}$ if we use fifteen minute time steps.

To obtain the coefficients of the thermal model (2), we use data for the summer of 2015 from the Pecan Street Inc. dataset [7], which contains detailed electricity consumption data for a large body of houses predominantly in Austin, Texas. We combine this data with openly accessible weather data from Austin, Texas [8]. We identified a total of ten households in the dataset for which we could obtain the required data (including indoor temperature measurements). For each of these houses the model (2) was fitted using linear regression.

Based on various indicators we determined for which of the houses the fitted model gives reasonable results. We concluded seven of the ten houses are modelled accurately enough and used these in a simulation study to show the potential of the considered systems.

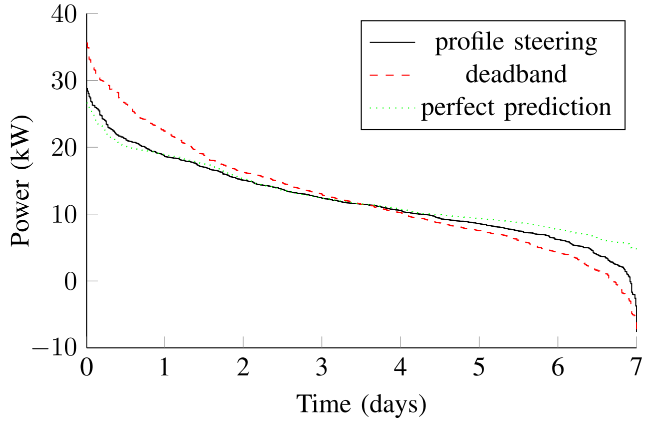

Fig. 1. Load duration curve for seven houses with the thermal model and either profile steering, deadband control or profile steering with perfect predictions implemented.

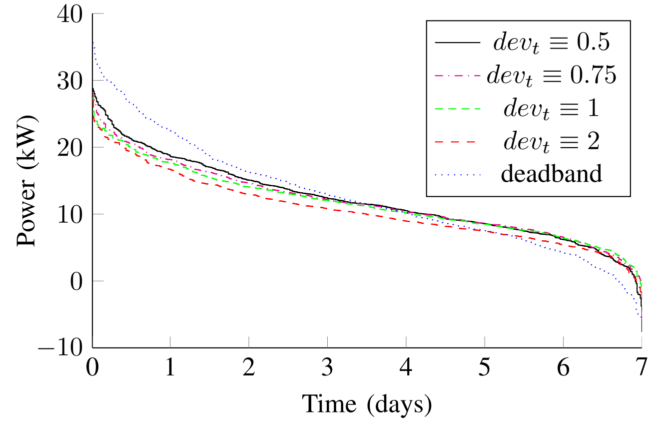

Fig. 2. Load duration curve for seven houses with the thermal model comparing deadband control to profile steering with different allowed deviations from the setpoint.

III. Simulation Study

To show the effectiveness of profile steering when controlling HVAC systems we setup a simulation study. In this study we compare the obtained results to the results for a scenario with a traditional control approach. This traditional approach is deadband control, whereby the HVAC system switches on when the indoor temperature reaches the (user defined) upper bound and switches off when it reaches the lower bound. Furthermore, we investigate how much potential of the system is lost due to the errors made by our thermal model in predicting the effect of the energy consumption of the HVAC system on the indoor temperature. We do this by comparing the results of a simulation with our thermal model, which makes prediction errors, with a simulation using perfect predictions. Note that in case prediction errors are present, the profile steering approach adapts the energy consumption of the HVAC systems to ensure user comfort is met.

Results for the simulation with the selected seven houses are given in Figure 1. In this figure also results are given for the case when deadband control is applied in each house. For each case we used $T_t \equiv 23°\text{C}$ and $dev_t \equiv 0.5°\text{C}$. Note that the load curve is sorted non-decreasingly to accentuate the difference between the cases. The results show a significant flattening of the load profile of the considered houses when profile steering is used. Furthermore, the results show that a perfect thermal model does not significantly increase the ability of profile steering to flatten the load profile during peak hours.

In another series of simulations we varied the allowed maximum deviation of the indoor temperature to determine if even more flexibility can be obtained in this way. The results are depicted in Figure 2. When simulating deadband control with different allowed deviations from the setpoint the resulting load duration curves were nearly identical, so we only depict one in Figure 2. The results show that increasing the allowed deviation improves the ability for the system to level the load duration curve. However, the improvement for increased allowed deviations appears to be limited.

IV. Conclusion

HVAC systems, currently prevalent in the residential sector in hotter climates, can aid in significantly flattening the load profile of a neighborhood of houses. This indicates that the system can aid in realizing the energy transition. To unlock the potential of these systems we showed that a linear thermal model can sufficiently predict the available flexibility in HVAC systems. Combining the thermal model with profile steering gives a robust approach that is capable of handling the prediction errors. Furthermore, diminishing returns in the increase in obtained flexibility were observed when we increased the allowed deviation from the set point temperature.

References

[1] S. Vandael, B. Claessens, M. Hommelberg, T. Holvoet, and G. Deconinck, “A scalable three-step approach for demand side management of plug-in hybrid vehicles,” *Smart Grid, IEEE Transactions on*, vol. 4, no. 2, pp. 720–728, June 2013.

[2] W. J. Cole, J. D. Rhodes, W. Gorman, K. X. Perez, M. E. Webber, and T. F. Edgar, “Community-scale residential air conditioning control for effective grid management,” *Applied Energy*, vol. 130, pp. 428 – 436, 2014.

[3] S. Bashash and H. Fathy, “Modeling and control insights into demand-side energy management through setpoint control of thermostatic loads,” in *American Control Conference (ACC), 2011*, June 2011, pp. 4546–4553.

[4] M. Gerards, H. Toersche, G. Hoogsteen, T. van der Klauw, J. Hurink, and G. Smit, “Demand side management using profile steering,” in *PowerTech, 2015 IEEE Eindhoven*, June 2015, pp. 1–6.

[5] A. Aswani, N. Master, J. Taneja, D. Culler, and C. Tomlin, “Reducing transient and steady state electricity consumption in hvac using learning-based model-predictive control,” *Proceedings of the IEEE*, vol. 100, no. 1, pp. 240–253, Jan 2012.

[6] W. J. Cole, K. M. Powell, E. T. Hale, and T. F. Edgar, “Reduced-order residential home modeling for model predictive control,” *Energy and Buildings*, vol. 74, pp. 69 – 77, 2014.

[7] “Pecan street inc. dataport 2016.” [Online]. Available: https://dataport.pecanstreet.org

[8] “wunderground,” last Accessed on 6-Jan-2016. [Online]. Available: http://www.wunderground.com/