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

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***Abstract*—This paper investigates 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 methodology. The thermal models form the base to determine the flexibility present in these houses with respect to cooling requirements. The linear models are shown to be reasonably accurate when used to predict indoor temperature changes. Furthermore, the resulting prediction errors can be largely attributed to human behavior. The considered thermal models are integrated in a planning-based demand-side management methodology while accounting for such prediction errors. The resulting methodology 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. 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 intermittent renewable resources are being introduced at all levels of the electricity supply chain, not just at the transmission grid where traditional large scale power plants are situated. Furthermore, their intermittent nature requires costly backup generation to account for fluctuations in both supply and demand. These trends cause an increasing amount of stress on our electricity supply chain with costly investments projected to be required in the future [2].

Both of the aforementioned issues can in part be alleviated by exploiting flexibility on the consumer side, shaping the load profile to better fit the projected production profile of renewable resources while accounting for grid constraints. Using the flexibility on the demand side of the electricity supply chain is called demand-side management (DSM). Several applications of DSM already exist, specifically for larger, more predictable consumers. However, with the increasing penetration of both larger flexible loads (e.g., electric vehicles) and local production (e.g., rooftop photovoltaic), the potential benefit of DSM on the residential side is increasing [3]–[5].

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Traditional large electrical loads present in hot climates are heating, ventilation and air conditioning (HVAC) systems [6], [7]. These systems can offer flexibility to the electricity supply chain by reducing or increasing electricity consumption of the compressor, thereby slightly varying the indoor temperature. However, to ensure user comfort, the operation of the HVAC system must be such that the temperature is kept between bounds around a given set point. The flexibility offered by multiple houses can be aggregated to achieve a greater effect on the neighborhood load profile. In this work we investigate the potential for a DSM methodology to use flexibility provided by HVAC systems present in a residential neighborhood.

Specifically, we consider a planning-based DSM methodology called *profile steering* consisting of three steps; prediction, planning, and real-time control [8]. To integrate HVAC systems in our methodology, we first require thermal models of residential houses to assess the available flexibility. For this we study a linear model previously used in a similar setting [9]. The linearity of the model ensures scalability and tractability of our methodology for a larger number of houses. We investigate the capability of the model to predict indoor temperature changes and show that we can implement the model in our methodology even in the presence of significant prediction errors.

The rest of the paper is organized as follows. In Section II we briefly introduce the considered demand-side management methodology. Then, in Section III we describe the thermal model used and analyze its predictive capability. Next, in Section IV we discuss the integration of the thermal models in our approach. Section V shows results of a simulation study to assess the potential of the considered houses. Finally, in Section VI we present some conclusions.

II. Profile steering

In this section we introduce the profile steering DSM methodology and discuss how we can incorporate HVAC systems within this methodology. Profile steering has previously been shown to have great potential for the reduction of peak consumption in the presence of a large number of electric vehicles [8]. The methodology first makes a prediction of the relevant influence factors, e.g., the non-controllable load profile and outdoor temperature. Then a plan is made for the controllable devices, balancing loads and generation in the direction of a predetermined desired profile. This is done in an iterative fashion using a rolling horizon. Finally, the plan is realized in the real-time control step, accounting for prediction errors.

In the considered implementation a neighborhood controller communicates with the home energy management systems (HEMS) to coordinate the use of the HVAC system in each of the homes. For the details on this coordination we refer the reader to [8]. The HEMS aims to minimize the euclidean distance between the house profile and the desired profile p received from the neighborhood controller. Thus the HEMS attempts to schedule the flexible loads in the home, in our case the HVAC system, to minimize

$$\sum_t (x_t - p_t)^2, \tag{1}$$

where x_t is the load for the house and p_t is the desired load, for time step t. We assume that only the HVAC system offers flexibility, hence we can assume that x_t is the load profile of the HVAC system for time step t instead and the remaining load of the house has already been compensated for in the desired profile p_t. It should be noted that the approach is more general as it is not limited to the control of a single appliance per house, but allows the inclusion of additional flexible loads such as swimming pool pumps or water heating systems.

Focusing on the HVAC system, the HEMS needs to decide on a HVAC load value x_t within the system's range:

$$0 \leq x_t \leq X_{max}, \tag{2}$$

with X_{max} the system's rated power. Furthermore, thermal comfort inside the house needs to be maintained;

$$\overline{T_t} - dev_t \leq T_t \leq \overline{T_t} + dev_t, \tag{3}$$

where T_t is the indoor temperature inside the house, $\overline{T_t}$ is the set point of the thermostat and dev_t is the maximum permitted deviation from the set point, each for time step t. In the next section, we discuss how we determine: the parameters $\overline{T_t}$ and dev_t, and the temperature profile T_t in order to determine feasible schedules for the load profile of the HVAC system.

III. Thermal model

In order to determine the flexibility provided by a household when it comes to the HVAC system two things are required. First, we need to know the comfort limits of the system, given by $\overline{T_t}$ and dev_t. Second, we need a thermal model to determine bounds on the operation of the HVAC system imposed by the comfort limits. We assume the former can be extracted by the HEMS from the thermostat. To determine the latter we develop and validate a thermal model in the remainder of this section.

A. Model determination

For our thermal model, we consider a discrete time linear model. This agrees with the time steps in our DSM methodology and has been shown to work for small sized HVAC systems [9]. Furthermore, a linear model ensures scalability and tractability of our system for a larger number of houses. To determine the flexibility of the system given by (3), we determine the indoor temperature T_{t+1} for the next time interval using the indoor temperature T_t, HVAC average power consumption x_t and outdoor temperature O_t of the current time interval:

$$T_{t+1} = aT_t + bx_t + cO_t + d_t, \tag{4}$$

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. This is similar to a model used for residential HVAC systems in [10]. To determine the constant d_t from historic data, we assume that it is invariant for the same period on different days, i.e., $d_t = d_{t+96}$ if we use fifteen minute time steps.

Note that we can assume that the indoor temperature does not change if the HVAC system is unused, the indoor and outdoor temperature are equal, and the other thermal gains/losses are zero (i.e. $x_t = d_t = 0$ and $T_{t+1} = T_t = O_t$). Thus we can assume that:

$$T_t = aT_t + cT_t,$$

from which we can conclude that $a + c = 1$. This allows us to rewrite (4) to

$$T_{t+1} - T_t = bx_t + c(O_t - T_t) + d_t, \tag{5}$$

relating the indoor temperature *change* between consecutive time intervals to the HVAC system power consumption, the difference between indoor and outdoor temperature, and other thermal gains and losses.

To obtain the coefficients of the thermal model given in (4), we use data from the Pecan Street Inc. dataset [11], 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 [12]. As the focus of this work is on cooling, we consider only data obtained in the summer of 2015, between the 1st of June and the 31st of September. A total of ten households have been identified for which we could obtain the required data. For each of these houses the model given in (4) was fitted using linear regression.

B. Model verification

To verify the validity of the fitted model, we are mainly interested in the predictive power of the model. To this end we split the data of each house into two sets. The first set, the training set, consists of the odd numbered days. We used this set to fit the model coefficients. The second set consisting of the even numbered days, the validation set, we used for model verification. In particular, we use data from the validation set to predict indoor temperatures and compare them to the measurements in the set.

TABLE I
STATISTICS ON THE PREDICTION CAPABILITY OF THE THERMAL MODEL

House	Mean (°C)	Standard deviation (°C)	Auto-correlation	MAPE daily HVAC use (%)
1	5.67×10^{-5}	0.17	-0.07	7.1
2	-2.80×10^{-3}	0.15	-0.28	15.6
3	1.06×10^{-4}	0.11	-0.38	8.4
4	1.38×10^{-3}	0.31	0.17	31.8
5	3.65×10^{-3}	0.17	0.26	25.1
6	-4.21×10^{-3}	0.22	-0.21	14.3
7	9.22×10^{-4}	0.12	-0.27	17.4
8	5.62×10^{-4}	0.11	-0.18	13.2
9	7.98×10^{-4}	0.38	-0.03	312.6
10	-3.92×10^{-3}	0.23	-0.31	21.0

The mean and standard deviation of the differences between the predicted values and measured values in the validation set for each house are given in Table I. The average error made by the model when predicting indoor temperature changes is nearly 0. However, the standard deviation varies from house to house and indicates that the errors can be quite large. However, this is not surprising, as human behavior can be a large factor in the thermal gains and losses of a household [9], [13]. Furthermore, human behavior is in general hard to predict on the household level. Therefore, we believe it is not realistic to pursue a model capable of accurately deducing the thermal gains and losses due to spontaneous variations in human behavior. Hence reliable DSM methodologies that plan and predict the usage of HVAC systems must be able to account for these errors through other means. In the next section we show how we can deal with these errors within the real-time control step of the profile steering approach.

To ensure that the model is suitable for use in our DSM methodology, we investigate if the model gives reasonable HVAC power consumption prediction values compared to measured data. Using data from our validation set and (5) we could estimate the expected required power consumption of the HVAC system for every time interval. As could be expected, due to the, sometimes large, errors made by the model, this sometimes leads to inaccurate or even infeasible values. However, as the average error made by the model is nearly zero, we consider an entire day instead, i.e., in the case of fifteen minute intervals we estimate the HVAC energy consumption for 96 intervals. Summing (5) over 96 intervals and rewriting it results in:

$$\sum_{i=t}^{t+96} x_i = \sum_{i=t}^{t+96} \frac{T_{i+1} - T_i - c(O_i - T_i) - d_i}{b}. \qquad (6)$$

We use data from our validation set and (6) to estimate the HVAC power consumption for complete days and compare this estimate to the measured values. The mean absolute prediction error (MAPE) between the predicted consumption and the measured consumption for each day in the validation set is given in column 5 of Table I. The very large value for house 9 is due to the fact that the HVAC system only runs sporadically. Furthermore, the daily HVAC power consumption does not vary much over the 2 months of data in the validation set, indicating that the HVAC system is mainly used to compensate for thermal gains caused by other factors than outside temperature. As these are not explicitly modeled in our thermal model, it is not surprising that the model does not do very well in predicting the HVAC usage.

Based on the large standard deviation found for the distribution of the errors made by the models of houses 4 and 9, we deemed these models unfit and excluded them from the simulation study detailed below. As mentioned before, for house 9 this is believed to be due to outdoor temperatures having very little effect on the indoor temperature. Furthermore, while the model of house 5 seemed to be a decent fit, it turned out that the HVAC system in this house has to run almost constantly to keep the building at a desirable temperature. This indicates that the system itself is undersized for its actual use and hence offers nearly no flexibility for a DSM methodology. Hence we also excluded this house from our simulation study.

Finally, we determined if a correlation between the various model parameters and the error made by the model exists. Hereby, no significant correlation was found. Also, we determined the auto correlation between the time series of errors made by the models for each of the houses. The auto correlation with a lag of a single time step is also given in Table I. As this value is negative for each of the houses for which we deemed the model decent fits, it follows that we expect a (large) positive error to cause the error for the next time step to be negative.

IV. IMPLEMENTATION WITH PREDICTION ERRORS

The thermal model, given by (4), can be used to determine the flexibility for our profile steering approach. Note that (3) is a linear set of constraints after substitution of our thermal model. Since the objective of the profile steering, given in (1), is convex quadratic, it follows that the problem can be solved by, e.g., a convex solver.

However, as shown, the predicted indoor temperature can be inaccurate. In an actual implementation this can be accounted for by allowing the HEMS to update the schedule for the HVAC system in case the measured indoor temperature deviates too far from the predicted value. In particular, in profile steering this could be done for every time step, resulting in an approach similar to model model predictive control. However, this is not an option in a simulation study, as the errors made cannot be observed. In this section we discuss how we can still incorporate the prediction errors in our models for a simulation study and construct a base case to be used as comparison for the profile steering approach.

A. Prediction errors in profile steering

An efficient approach for simulation is to use the obtained differences between the predicted indoor temperature and the measured value from the validation part of the dataset. That is, we can modify the indoor temperature change during a time interval by adding an error term to it, sampled from the set of errors between the predicted and measured temperatures for the validation part of the dataset. Note that we showed before that there is a negative auto correlation in the time series of these errors. Thus, independent sampling causes the error to deviate on average further from the model output than is actually the case. We assume that this deviation is not large enough, so that independent sampling approximates the differences between the model output and the actual system performance well enough. This approach promises appropriate control compared with an implementation measuring the errors made by the thermal model or using complex, computationally intensive models.

This approach accounts for the incorporated errors by updating the schedule in every time step. Since letting the neighborhood controller negotiate with every HEMS is a computationally costly operation, we only update the schedule locally, using the last received requested profile by the HEMS (see Section II). As we only account for the errors in indoor temperature change after each time step, we set the allowed range of the temperature variation to be stricter for our approach, such that the temperature stays within the desired bounds unless a rather large disturbance is added.

B. Base case

We have argued above that we can integrate HVAC systems in profile steering and simulate the load profile of a neighborhood. However, to assess the gains of such an implementation we require a base case for comparison. Unfortunately, the indoor temperature in the dataset does not appear to follow an easy-to-determine set point and, more importantly, does not have clearly defined bounds between which it needs to be maintained. Hence, it is difficult to compare our profile steering approach to the measurement data, as it is hard to determine what the actual flexibility is.

Most residential HVAC systems are equipped with a thermostat with deadband controller [10], [13]. The thermostat turns the HVAC system on when the temperature reaches the upper limit and off once it reaches the lower limit. We implemented such a system within the simulation. However, the granularity of 15 minutes time steps is not sufficient to capture the dynamics of the system, as the actual controller might switch on or off in the middle of a time step. To this end we calculate T_{t+1} using (4) and add the sampled error term. If T_{t+1} lies outside the thermal comfort range, we use linear interpolation to determine at what point during the 15 minute interval the HVAC would have switched on. For example, if $T_{t+1} > \overline{T_{t+1}} + dev_{t+1}$ we calculate τ using:

$$T_t + \tau(T_{t+1} - T_t) = \overline{T_{t+1}} + dev_{t+1}. \qquad (7)$$

The resulting value of τ gives the portion of the time interval after which the HVAC system is turned on. The actual power consumption of the HVAC system can now be set as $(1 - \tau) \times X_{max}$ (recall that X_{max} is the rated power of the HVAC system). This value can be used in (4) to obtain the adjusted indoor temperature. A similar procedure is used to account for the HVAC system turning off when the lower limit of the deadband is reached. Note that it is possible that the resulting indoor temperature is still outside the deadband, particularly if we add a large disturbance term.

V. Simulation study

In this section we compare the results of a simulation study using the profile steering methodology to those of a simulation with deadband control. Furthermore, we investigate the potential of profile steering if the errors made by our thermal model are assumed to be known a priori, i.e., we consider profile steering where we assume the thermal model gives perfect predictions.

In our simulation study profile steering is applied to the seven households for which we obtained reasonable thermal models in Section III. Results are given in Fig 1 a) for the case when the errors made by the models are either known or unknown during the planning phase of the methodology. Furthermore, results are given for the case when the deadband control is applied in each house. For each case we used a desired temperature of 23° C with a maximum allowed deviation of 0.5° C. Note that the load curve is sorted non-decreasingly to accentuate the difference between the cases. The results show a significant improvement in 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. However, perfect predictions would help the houses to attain 100% self-consumption of electricity generated by PV.

In Fig 1 b) and c) the results are shown for the cases when either fourteen or twenty-one houses are considered. We created this scenario by using the same thermal model for two or three houses respectively while using data for the other loads from a different summer week. The results show that our methodology is able to significantly level the aggregated profile of the houses. However, in both cases the peak reduction can be improved upon significantly if a perfect thermal model is present. We believe the discrepancy between the cases is caused by the fact that the major peaks in the case of seven houses are large but short, allowing the HVAC system to compensate, even in the case of significant errors in the thermal models. These results indicate that improvements in the thermal model combined with good human behavior forecasting techniques can further increase the potential of DSM with residential HVAC systems.

Finally, we varied the allowed maximum deviation in the case of seven houses. The results can be seen in Figure 1 d). Only the deadband load duration curve for an allowed deviation of 0.5° C is shown (i.e., $dev^h_t \equiv 0.5$), as the load duration curves for other allowed deviations are nearly identical. The results show that increasing the allowed deviation improves the ability for the system to level the load duration curve. However, the improvement achieved from increasing the allowed deviations appears to be only limited.

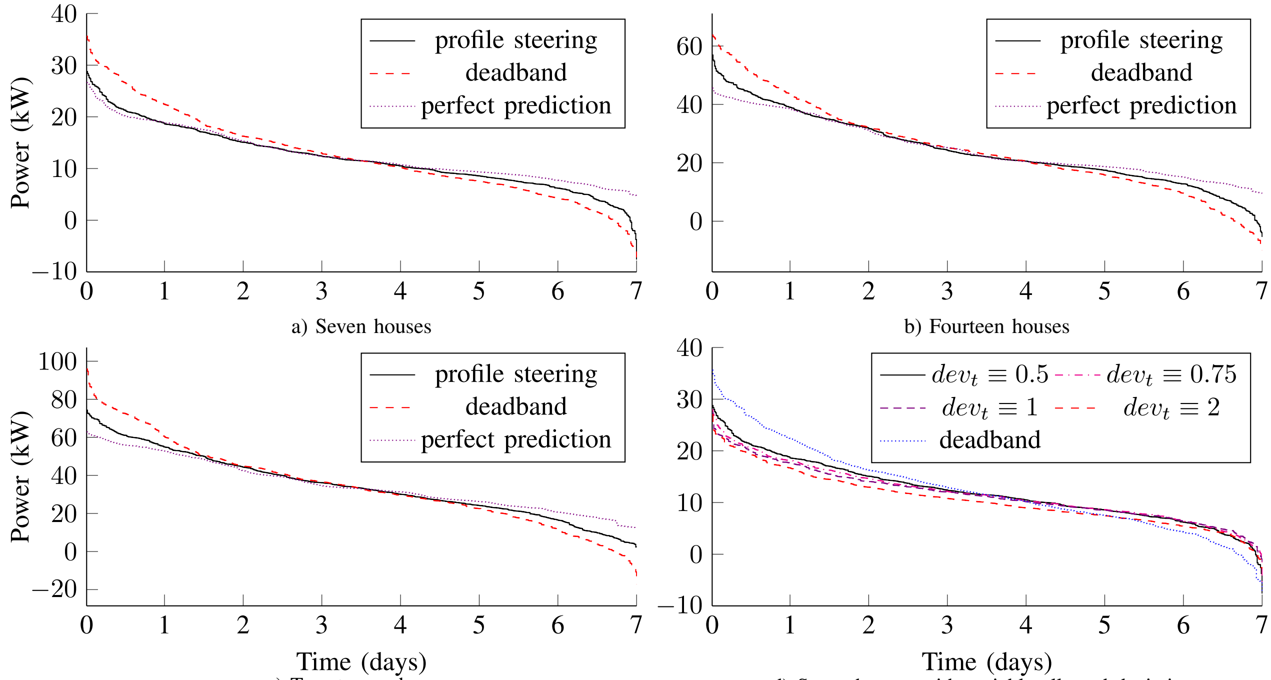

Fig. 1. The load duration curve resulting from the simulation studies.

VI. Conclusion & Outlook

In this paper we developed a residential thermal model to determine the potential flexibility that can be provided by HVAC systems for DSM. We showed that a basic thermal model, while giving a decent fit, makes significant errors in predicting the indoor temperature over time. As these errors are most likely caused by human behavior, we adopted the considered DSM methodology to account for these prediction errors made by the thermal model.

Furthermore, we integrated the developed thermal models in the considered DSM methodology and carried out a simulation study. In this study we showed that, while the proposed models allow an important degree of leveling of the load profile of a group of residential houses, there is still room for improvement compared to the situation where thermal gains and losses can be predicted perfectly. Development of a system that makes better predictions, thus incorporating more flexibility in the system, is left as future work. For the considered group of houses we were also able to show that increasing the allowed deviation from the thermostat setpoint yields diminishing returns on the ability to flatten the load profile. This leads us to question the economic viability of grid operators offering incentives to increase the allowed deviations from thermostat setpoints when the grid is operating under normal conditions.

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