The Role of Residential HVAC Units in Demand Side Flexibility Considering End-User Comfort

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***Abstract*—There are several services such as peak load reduction and frequency regulation that can be provided by exploiting the thermostatically-controllable appliances (TCAs) demand response (DR) potential. To stimulate the adoption of DR strategies, preserving the end-user comfort level is a crucial issue. In this regard, as a novel contribution to the existing literature, this study proposes a DR strategy for residential heating, ventilation and air conditioning (HVAC) units aiming to minimize average end-user comfort violation, while satisfying the requirements of the load serving entity. The proposed approach manipulates the temperature set-point of HVAC thermostats of the enrolled end-users. Besides, a spatio-temporal to obtain weather forecasts is developed.**

***Index Terms*--Demand response; direct load control; heating, ventilation and air conditioning (HVAC) units; thermostatically controllable appliances; weather forecasting.**

NOMENCLATURE

The main nomenclature used throughout the paper is stated below.

A. Sets

h	set of households.
t	set of time periods.

B. Parameters

$A_{i,h}$	element area of household h [m^2].
c_a	thermal capacity of air [kJ/kg·°C].
COP	coefficient of performance.
HI_t	heat index in period t [°C].
$l_{i,h}$	element thickness value for household h [m].
$L_{1,h}$	length of household h [m].
$L_{2,h}$	width of household h [m].
$L_{3,h}$	height of household h [m].
$M_{a,h}$	mass of air for household h [kg].
N	sufficiently large positive constant.
N_h	number of households enrolled to the DR program.
$P_{AC,h}$	HVAC rated power of household h [kW].
$P_{des,t}$	desired power reduction in period t of the DR event [kW].
$P_{total\_ref,t}$	reference total HVAC power consumption in period t [kW].
$R_{eq,h}$	equivalent thermal resistance of household h [h·ºC/J].
RH_t	relative humidity in period t.
$T_{a,t}$	ambient dry-bulb temperature in period t [°C].
$T_{dec\_allowed,h}$	maximum allowed temperature set-point decrease from the desired comfort temperature level of household h during the DR event [°C].
$T_{des,h}$	desired comfort temperature level of household h [°C].
T_h^d	HVAC dead-band based operational deviation from the HVAC temperature set-point to the down side for HVAC of household h [°C].
T_h^u	HVAC dead-band based operational deviation from the HVAC temperature set-point to the upper side for HVAC of household h [°C].
$T_{inc\_allowed,h}$	maximum allowed temperature set-point increase from the desired comfort temperature level of household h during contracted DR period [°C].
t_1	starting period of the contracted DR period.
t_2	ending period of contracted DR period.
t_3	starting period of the actual DR event.
t_4	ending period of the actual DR event.
V_h	volume of household h [m^3].
ΔT	time granularity [h].
δ_{air}	air density [kg/m^3].
$\sigma_{i,h}$	element thermal coefficient for household h [J/h·m·ºC].
β_h	roof angle of household h [deg].

C. Variables

$p_{AC,h,t}$	actual power consumption of the HVAC unit of household h in period t [kW].
$T_{down,h,t}$	decrease in the indoors temperature from desired comfort temperature for household h in period t [°C].
$T_{in,h,t}$	indoors temperature of household h in period t [°C].
$T_{set,h,t}$	thermostat temperature set-point of household h in period t by LSE [°C].
$T_{up,h,t}$	increase in the indoors temperature from desired comfort temperature for household h in period t [°C].

$u_{AC,h,t}$	binary variable for the status of the HVAC unit of household h in period t (1=ON, 0=OFF)
$u_{1,h,t}$	binary variable – 1 if the indoors temperature of household h in period t is above desired comfort temperature, else 0.

I. INTRODUCTION

A. Motivation and Background

The relatively inelastic electric load demand generally presents significant variations throughout the day, season and year and traditionally generating units are dispatched in a suitable manner to satisfy the demand. However, the possibility of enabling an active participation of the demand side has proven to provide flexibility to System Operators. The concept of activating the demand side is generally referred to as demand response (DR). A significantly increasing number of DR solutions are offered by several load serving entities (LSEs) around the world.

The DR strategies can be generally categorized in direct load control (DLC) and indirect load control (ILC) (via various price-based programs) [1]. The main advantage of ILC solutions is their relatively lower dependence on communication and control infrastructure investments. However, the performance of ILC solutions in terms of supplying the requirements of LSEs mainly depends on the response of the end-users to the applied pricing schemes, which involves complex sociological aspects. Therefore, for specific requirements of LSEs such as peak load shaving during critical periods or the provision of regulation services (e.g. frequency regulation to handle renewable energy volatility), DLC solutions are considered as a more effective tool on the grounds that the required response is already under the control of the LSE, in contrast with the uncertain and asymmetrical response of consumers under price-based programs [1]-[3].

The DLC-based DR programs have been mainly addressed to large industrial and commercial customers due to the limitations imposed by telemetry requirements. On the other hand, it is expected that such strategies will increase also for residential end-users that are responsible for 20-40% of electricity consumption in developed countries, supported by the deployment of smart grid technologies (smart meters and relevant communication infrastructure) within residential end-user premises.

There are many appliances in residential end-user premises that can be manipulated by DLC-based DR programs. Among them, thermostatically-controllable appliances (TCAs) including Heating, Ventilation and Air Conditioning (HVAC) units, electric water heaters (EWHs), refrigerators, heat pumps, etc. represent a considerable potential for DLC-based DR programs due to their rapid response and the fact that thermal inertia allows for a sustained interruption of their service without compromising the comfort of the end-user [4], [5]. HVAC units are considered the most suitable candidates among TCAs in order to implement DR solutions effectively, mainly due to their continuous and larger energy consumption throughout the day, especially in the summertime, during which LSEs face a greater challenges in comparison with other periods of the year [6],[7].

B. Literature Overview

An increasing number of literature studies have recently been dedicated to the use of different kinds of TCAs in order to obtain demand side flexibility during critical periods. Heffner et al. [8] considered the DR potential of residential EWHs on a pilot test study, examining both the end-user premises and the substation levels. Kondoh et al. [1] also investigated the potential of EWHs providing regulation services through a DLC approach using bi-directional signals for power decrease and increase requirements. EWHs load based balancing services through bi-directional LSE signals were also discussed in [9]. Furthermore, the provision of load shifting and renewable energy based volatility suppression was studied in [10].

Angeli and Kountouriotis [11] studied the potential of refrigerators providing frequency regulation services. Frequency regulation by refrigerators for a power system with high wind power penetration was analyzed by Aunedi et al. both from the environmental and the economic benefit perspectives [2].

Garcia et al. [7] assayed the aggregation of HVAC loads considering three different techniques to model the HVAC dynamics. Frequency regulation and peak load reduction services provision by HVAC were discussed in [12]. Furthermore, the potential of HVAC offering load balancing services through bi-directional LSE signals for power reduction or increase requirements was analyzed by Lu and Zhang in [13] and Zhang and Lu in [14]. HVAC response capability to mitigate the renewable energy volatility was the scope of the studies conducted by Bashash and Fathy in [15] and Zheng and Cai in [16]. The use of building scale HVAC units for regulation services regarding high frequency power mismatches was discussed by Hao et al. [17] and Goddard et al. [18]. Additionally, the impacts of uncertainty regarding HVAC physical parameters were analyzed in detail in [6]. The study presented in [19] compared two different methods, namely the thermostat set-point control mechanism (TSCM) and the direct compressor control mechanism (DCCM) for HVAC load aggregation. Stochastic switching based control of a population of HVAC loads was also proposed by Tindemans et al. [20]. The idea of maintaining fairness before the enrolled consumers for while exercising DLC was introduced by Koutitas [21]. However, [21] defined fairness from the perspective of the economic benefits of the different end-users, while the fairness in violating the consumer comfort constraints was neglected. A generic study regardless of the TCA type aiming to aggregate a population of TCAs for load balancing services was conducted by Soudjani and Abate [22]. Besides, the verified TCA models were presented by Shao et al. in [23].

C. Content and Contributions

In this study, the role of residential HVAC units in demand side flexibility is analyzed considering also the end-user comfort preservation constraints, which is a novel point compared to the existing literature. A day ahead HVAC load aggregation planning is provided, aiming at the minimization of the average consumer comfort violation among the enrolled end-users, which is a vital point for the wider social acceptance of such DR strategies. Besides, a *spatio-temporal* approach is used for weather forecasts considering the impact of humidity on ambient temperature, which has been ignored in the relevant literature studies.

D. Organization

The remainder paper is organized as follows: Section II describes the employed methodology. Afterwards, Section III presents and discusses the results of the numerical simulations. Finally, conclusions are drawn in Section IV.

II. METHODOLOGY

A. HVAC Load Aggregation Model

The objective function to be minimized is the average comfort violation of each household which is related to the increase or decrease in the indoors temperature with respect to the end-user's predefined value, which is measured in ℃ · h. For example, 10 ℃ · h may mean a decrease/increase of 1℃ for 10 hours or 2℃ for 5 hours, etc.).

The objective function is expressed by (1).

$$min \sum_{h} \sum_{t=t_1}^{t=t_2} \frac{\left(T_{up,h,t} + T_{down,h,t}\right)\Delta T}{N_h} \tag{1}$$

The indoors temperature depends on several factors such as the thermal properties of air, the heat exchange between the house and ambient, as well as the thermodynamic properties of the building structure. In this study, a model based on the equivalent thermal resistance of the building is developed and is represented by (2). Naturally, this model is based on differential equations that under several plausible assumptions may be linearized [24], [25].

$$\begin{aligned} T_{in,h,t} = {} & \left(1 - \frac{\Delta T}{1000 \cdot M_{a,h} c_a R_{eq,h}}\right) \cdot T_{in,h,t-1} \\ & + \frac{\Delta T}{1000 \cdot M_{a,h} c_a R_{eq,h}} \cdot HI_{t-1} \\ & - u_{AC,h,t-1} \frac{COP_h \cdot P_{AC,h} \cdot \Delta T}{0.000277 \cdot M_{a,h} c_a}, \forall t > 1 \end{aligned} \tag{2}$$

It should be noted that (2) considers only the cooling operation of the HVAC. A similar expression can be trivially derived for the heating mode of the HVAC as well. Here, the calculations regarding the equivalent thermal resistance of the houses as well as the mass of air inside the building structure may be performed using equations (3)-(5), considering for simplicity a rectangular geometry and an inclination of the roof of β° [26].

$$R_{eq,h} = \frac{1}{N} \sum_{i} \frac{l_{i,h}}{\sigma_{i,h} A_{i,h}} \tag{3}$$

$$V_h = L_{1,h} \cdot L_{2,h} \cdot L_{3,h} + tan(\beta_h) \cdot L_{1,h} \cdot L_{2,h} \tag{4}$$

$$M_{a,h} = V_h \cdot \delta_{air} \tag{5}$$

In each time interval t the indoors temperature of each household h can be decomposed as in (6).

$$T_{in,h,t} = T_{des,h} + T_{up,h,t} - T_{down,h,t}, \forall t \tag{6}$$

In order to prevent $T_{up,h,t}$ and $T_{down,h,t}$ from receiving values simultaneously, the binary variable u_1 is employed as in (7) and (8), in which N is a sufficiently large constant.

$$T_{up,h,t} \leq N \cdot u_{1,h,t}, \forall t \tag{7}$$

$$T_{down,h,t} \leq N \cdot \left(1 - u_{1,h,t}\right), \forall t \tag{8}$$

In this study, the TSCM will be followed considering that the LSE will directly manipulate the thermostat temperature set-point $T_{set,h,t}$. This is considered to be more suitable in the literature for peak load reduction, while DCCM in which LSE directly turns the HVAC "on" or "off" is considered to be more suitable for fast regulation services [19].

The temperature set-point $T_{set,h,t}$ can be changed during the DR horizon within the upper and lower limits by LSE in order not to exceed the contracted allowed minimum comfort violation limits of the end-user as expressed by (9).

$$\begin{aligned} T_{des,h} - T_{dec_{allowed},h} \leq T_{set,h,t} \leq T_{des,h} + T_{inc_{allowed},h}, \\ \forall t \in [t_1, t_2] \end{aligned} \tag{9}$$

Here, $T_{set,h,t}$ manipulation between the given limits will allow LSE to investigate different strategies like cooling down the household below the comfort temperature within the DR horizon (e.g. 12 pm - 6 pm) but before actual DR event (e.g., 2-4 pm). This will give LSE considerable flexibility. Furthermore, these strategies can be strictly categorized (e.g., pre-cooling strategy, temperature increment strategy, etc.), forcing the LSE to select one of the possible strategies for each household. The indoors temperature limits are defined by (10).

$$T_{set,h,t} - T_h^d \leq T_{in,h,t} \leq T_{set,h,t} + T_h^u, \forall t \tag{10}$$

The power consumption of HVAC of each household h at each time t follows (11).

$$p_{AC,h,t} = P_{AC,h} \cdot u_{AC,h,t}, \forall t \tag{11}$$

The total desired load reduction from the HVAC units of the households enrolled in the DR program during a DR event is obtained by (12).

$$P_{des,t} \leq P_{total\_ref,t} - \sum_{h} p_{AC,h,t}, \forall t \in [t_3, t_4] \tag{12}$$

The total HVAC consumption during the actual DR event, between t_3 and t_4, should be reduced at least by the level of $P_{des,t}$ with respect to $P_{total\_ref,t}$. A similar approach can be applied to consider load increase requirements in certain periods.

B. Apparent Temperature Forecast

Residential HVAC units are generally controlled by setting a desired temperature value and the operation of the unit is interrupted once the set value is reached. However, the temperature measured by the thermostats of HVAC or an ordinary thermometer is mostly different from the temperature which affects the comfort of the end-users. Therefore, a different metric, called Heat Index (HI), which measures the effect of humidity on the ambient dry-bulb temperature is more widely used to describe the perception of temperature for indoors conditions. Thus, in order to calculate the required HI values, first, the ambient dry-bulb temperature data are forecasted and the HI are then calculated with a temperature-to-HI formulation given in [27]:

$$\begin{aligned} HI_t = -42.379 &+ \left(2.04901523 \times T_{a,t}\right) \\ &+ \left(10.14333127 \times RH_t\right) \\ &- \left(0.22475541 \times T_{a,t} \times RH_t\right) \\ &- \left(6.83783 \times 10^{-3} \times {T_{a,t}}^{2}\right) \\ &- \left(5.481717 \times 10^{-2} \times RH_t^2\right) \\ &+ \left(1.22874 \times 10^{-3} \times {T_{a,t}}^{2} \right. \\ &\left. \times RH_t\right) \\ &+ \left(8.5282 \times 10^{-4} \times T_{a,t} \right. \\ &\left. \times RH_t^2\right) \\ &- \left(1.99 \times 10^{-6} \times {T_{a,t}}^{2} \times RH_t^2\right) \end{aligned} \tag{13}$$

with $T_{a,t}$ being ambient dry-bulb temperature and RH_t being relative humidity at time t.

For the forecast of ambient dry-bulb temperature, a spatio-temporal approach [28], which accounts for both spatial and temporal data with the objective of making use of the high correlations between the weather characteristics of adjacent locations, is used. Detailed information on the application of a similar approach for is given in [29], [30].

III. TEST AND RESULTS

Hourly temperature and relative humidity data from Meteorological Terminal Aviation Routine (METAR) weather reports of 43 weather stations located in USA are used [31]. A time period spanning from June 2, 2013 to June 23, 2013, which presents high and unsteady temperature characteristics, is considered in the simulations. The data is divided into two subsets: (i) a two-week training and model parameter selection set from June 2 to June 15 and, (ii) a one-week test set from June 16 to June 23.

The forecasts of the felt temperature are carried out with a two-stage process: daily ambient temperature forecasts with a spatio-temporal method and conversion to the corresponding felt temperature forecasts using equation (13). Figure 1 presents the results of the dry ambient temperature forecasting compared to the real values, where it may be noticed that the two time series present sufficient similarity. The impact of humidity on the felt temperature is not negligible as mentioned before. Therefore, the comparison of the dry temperature and the HI is presented in Fig. 2. As it may be noticed, there are significant differences between the HI and the dry temperature, which can affect the day ahead planning significantly and it is therefore more valid to use the actual HI the households will face.

For the sake of simplicity, 40 identical households with the structural parameters shown in Table I are considered. Generally, the density of the air and its thermal capacity depend on its thermodynamic properties (temperature, pressure, etc.). In this study, for the sake of simplicity, these parameters are considered constant and utilized standard values $\delta_{\text{air}} = 1.225$ kg/m^3 and $\text{c}_\text{a} = 1.01$ kJ/kg℃. Furthermore, all the households are assumed to have identical HVAC units with a rated power of 3kW and the coefficient-of-performance (COP) of 2. The temperature based parameters for households are also presented in Table II. Moreover, the HI variation during the considered period is shown in Fig. 3.

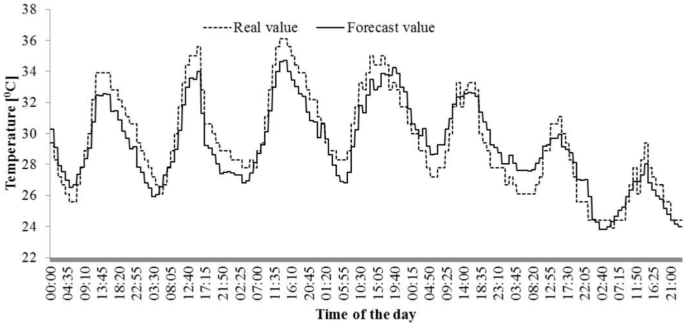

Figure 1. The comparison of real and forecasted values for dry temperature.

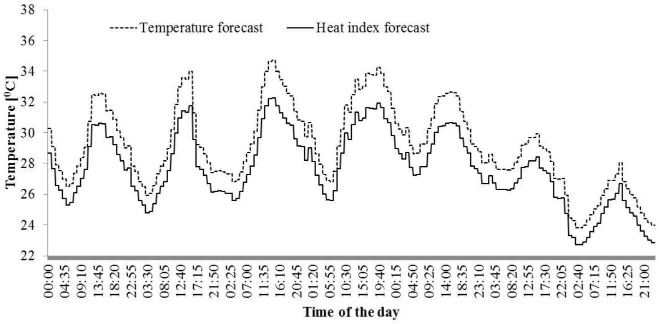

Figure 2. The comparison of forecasted temperature and heat index.

TABLE I. STRUCTURAL PARAMETERS OF THE HOUSEHOLDS

Parameter	Value	Units	Parameter	Value	Units
House length (L_1)	30	m	Area of windows	1	m^2
House width (L_2)	10	m	Wall thermal coefficient	136.8	J/h·m· ℃
House height (L_3)	4	m	Window thermal coefficient	2808	J/h·m· ℃
Roof angle (β)	40	deg	Thickness of windows	0.05	m
Number of windows	6	-	Thickness of walls	0.15	m

TABLE II. TEMPERATURE-BASED PARAMETERS OF THE HOUSEHOLDS

Parameter	Value	Units
$T_{des,h}$	20	^{0}C
$T_{dec\_allowed,h}$	4	^{0}C
$T_{inc\_allowed,h}$	4	^{0}C
T_h^d	1	^{0}C
T_h^u	1	^{0}C

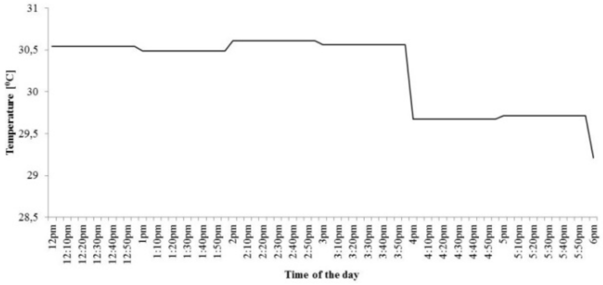

Figure 3. The heat index variation during the DR event.

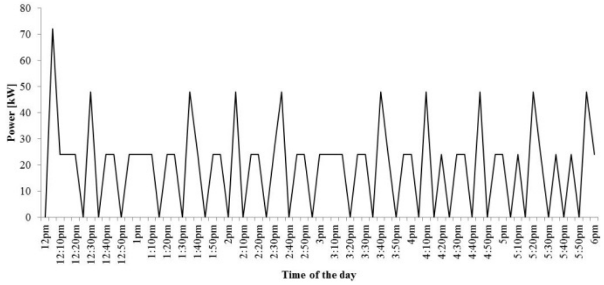

Figure 4. The reference total HVAC power consumption.

The time granularity used in the optimization is 5 min (0.0833h). For the DR contract, the households are assumed to accept being involved in DR events during summer times between 12 pm-6 pm. Besides, it is also assumed for the considered sample day that a peak-reduction DR event is activated between 2 pm-4 pm.

The model is initially run by defining $T_{set,h,t} = T_{des,h}$, while implementing no constraint for the desired power reduction in order to obtain the reference HVAC based power consumption pattern ($P_{total\_ref,t}$) as shown in Fig. 4. Subsequently, the proposed strategy is evaluated in order to assess its impacts on consumer satisfaction in terms of the average comfort maximization while taking into account the constraint of $P_{des,t}$. It should be noted that during the actual DR event between 2 pm and 4 pm, if the $P_{total\_ref,t}$ is zero then the constraint for $P_{des,t}$ is not implemented for these intra-hour periods, since no actual reduction from zero is possible.

The desired load reduction when the reference HVAC power is non-zero during an actual DR event is assumed to be 20 kW from the total of the 40 households. Figure 5 portrays the obtained reduction and the reference HVAC power during the actual DR event between 2 pm and 4 pm. Evidently, the proposed limitation on satisfying at least the level of desired reduction is satisfied by the proposed approach.

Implementing such strategies is known to be accompanied by the load-rebound effect due to shifting consumption before or after the DR event. This can be observed in Fig. 6. The temperature set-points of HVAC units are set to higher values than the corresponding indoors temperature just before the actual DR event by the employed strategy in order to cool down the households that will be called during the actual event. Implementing a generic strategy without focusing on end-user comfort, only with the limitation of satisfying a load reduction target, is likely to cause more discomfort for end-users.

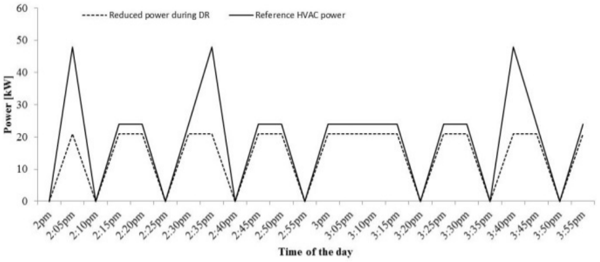

Figure 5. The reduced HVAC power during the actual DR event.

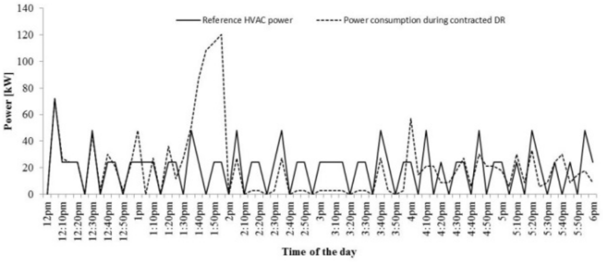

Figure 6. The power consumption by HVAC during the DR event.

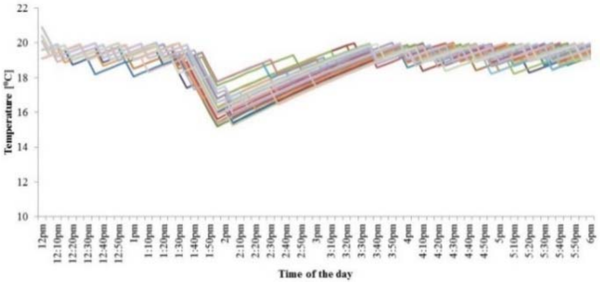

Figure 7. The indoors temperature variation of households.

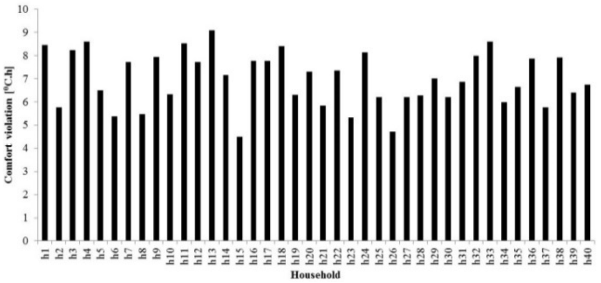

Figure 8. The comfort violation index value of end-users.

The results regarding the indoors temperature of households can be seen in Fig. 7. It should be noted that the initial indoors temperature values of households are randomly allocated between 19.1 ^{0}C and 20.9 ^{0}C. It can be noticed that most households follow a similar temperature pattern, while the proposed approach allocated their HVAC operation considering load reduction targets during the DR event periods. As the proposed study aims to minimize the comfort violation of end-users, the results related to each consumer in terms of the proposed comfort violation index are presented in Fig. 8. The average comfort index violation value during contracted DR period between 12 pm and 6 pm is 6.96 ℃ · h. However, as it can be seen in Fig. 8, there are differences between comfort violation of the individual end-users. In this regard, further care should be taken in order to fairly allocate the violation of end-users comfort.

The model has been coded in GAMS 24.0.2 and has been solved using the commercial solver CPLEX 12. The average solution time is 13 sec on a desktop computer (i5 at 3.2GHz, 4GB of RAM, 64bit Windows). As the computational capabilities of embedded systems increase, it appears that such algorithms will be practically applicable even for significantly larger scale systems. As a result, the model presented in this study may indeed be employed in real-life, real-time applications.

IV. CONCLUSIONS

The role of residential HVAC loads on increasing the demand side flexibility was analyzed in this study. A new point of view was explored, considering the minimization of end-user comfort violation as a prior point while satisfying the LSE requirements. A TSCM approach for HVAC load control was implemented. Based on the simulations conducted, the strategy proves to have a decrement in violation of end-user comfort level while effectively satisfying the requirement of LSE in terms of load demand reduction. The study can be extended by applying also a DCCM approach or considering different loads for the DLC strategy to increase the diversity in end-user types having different load types with different characteristics (such as electric vehicles, shiftable appliances, etc.).

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