This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2556619, IEEE Transactions on Smart Grid

End-User Comfort Oriented Day-Ahead Planning for Responsive Residential HVAC Demand Aggregation Considering Weather Forecasts

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Abstract—**There is a remarkable potential for implementing demand response (DR) strategies for several purposes such as peak load reduction, frequency regulation, etc. by using thermostatically-controllable appliances (TCAs). In this study, an end-user comfort violation minimization oriented DR strategy for residential heating, ventilation and air conditioning (HVAC) units is proposed. The proposed approach manipulates the temperature set-point of HVAC thermostats aiming to minimize the average discomfort among end-users enrolled in a DR program, while satisfying the DR event related requirements of the load serving entity. Besides, the fairness for the allocation of the comfort violation among enrolled end-users is also taken into account. Moreover, maintaining the load factor during the contracted DR period compared to a base case in order to reduce the load rebound effect due to shifting the use of HVAC units is also provided with the proposed strategy. Last but not least, the heat index considering the impact of humidity is utilized instead of using ambient dry-bulb temperature through a spatio-temporal forecasting approach.**

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

I. Nomenclature

The main nomenclature used throughout the paper is listed in Tables I-IV.

II. Introduction

A. Motivation and Background

THE electric power demand may vary significantly during the day, season and year and this issue is one of the main concerns of System Operators. In this regard, the production facilities should be suitably dispatched in all time periods in order to satisfy the varying load demand.

The demand side has been traditionally considered relatively inelastic and therefore, the generation side should be adapted in order to fully supply it. However, a series of drivers have motivated efforts aiming to enable the active participation of the demand side in the power system operational procedures.

The activities through which the activation of the demand side is attempted are commonly referred to as demand side management (DSM). Among the different DSM solutions, demand response (DR) strategies are gaining more attention in power system operations recently, driven by the increasing interest in implementing the smart grid concept with several DR programs offered by load serving entities (LSEs) around the world.

There are two main DR strategy types: direct load control (DLC) and indirect load control (via various price-based programs) [1]. Although price-based methods are considered to be less demanding in terms of the required communication and control infrastructure, DLC programs aiming at peak load shaving during critical periods or at providing regulation services (e.g. frequency regulation to handle renewable energy volatility) are tools that are already being actively and effectively used by LSEs [1]-[3].

The participants in DR programs get paid for providing demand response capacity [4]. Thus, the DR capacity can be defined as "the potential for flexible response from end-use appliances across the commercial, industrial, and residential sectors" [5]. The demand response capacity can be acquired from many types of end-user appliances as well as end-user types.

TABLE I. ABBREVIATIONS

DCCM	direct compressor control mechanism.
DLC	direct load control.
DR	demand response.
DSM	demand side management.
EWH	electric water heater.
HI	heat index.
HVAC	heating, ventilation and air conditioning
LSE	load serving entity.
TCA	thermostatically-controllable appliance.
TSCM	thermostat set-point control mechanism.
WBGT	Wet-bulb globe temperature.

TABLE II. SETS

h	set of households.
t	set of time periods.

This work was supported by FEDER funds through COMPETE and by Portuguese funds through FCT, under FCOMP-01-0124-FEDER-020282 (Ref. PTDC/EEA-EEL/118519/2010), UID/CEC/50021/2013 and SFRH/BPD/103744/2014, and by The Scientific and Technological Research Council of Turkey (TUBITAK) under Project Grant Number 115E215. Also, the research leading to these results has received funding from the EU Seventh Framework Programme FP7/2007-2013 under grant agreement no. 309048 (project SiNGULAR).

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This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2556619, IEEE Transactions on Smart Grid

TABLE III. PARAMETERS

$A_{i,h}$	element area for 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	model order.
N	sufficiently large positive constant.
N_{com}	ratio between minimum and maximum comfort violation values for all households in order to ensure fairness for comfort violation.
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·°C/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·°C].
β_h	roof angle of household h [deg].

However, the telemetry requirements have limited the DLC based DR programs to be almost exclusively addressed to large industrial and commercial customers. As the required communication and control infrastructure is expected to be enabled by smart grid deployment for all types of end-users, residential or small industrial customers also have been in the center of the design of such programs [1], [6].

TABLE IV. VARIABLES

com_vio_h	comfort violation of household h [°C · h].
com_vio_{max}	maximum comfort violation value for all households [°C · h].
com_vio_{min}	minimum comfort violation value for all households [°C · h].
$p_{AC,h,t}$	actual power consumption of the HVAC unit of household h in period t [kW].
$T_{down,h,t}$	decrease in the ambient dry-bulb temperature from desired comfort temperature for household h in period t [°C].
$T_{in,h,t}$	ambient dry-bulb 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 ambient dry-bulb 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 ambient dry-bulb temperature of household h in period t is above desired comfort temperature, else 0.

This would give access to a large portion of the total demand, given that 20-40% of the electricity in developed countries is consumed by residential end-users [7]. For instance, in the Electricity Reliability Council of Texas (ERCOT) jurisdiction area, the residential demand was around 6 GWh, which stands for 20% of the overall electricity consumption in March 2010. However, the hot weather in August 2010 induced a residential load of 35.3 GWh that was 52% of total load [8].

Among many appliances within residential end-user areas, thermostatically-controllable appliances (TCAs) including Heating, Ventilation and Air Conditioning (HVAC) units, electric water heaters (EWHs), refrigerators, 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 [6], [9]. HVAC units are considered as the most suitable candidates among TCAs in order to implement DR solutions, mainly due to their larger energy consumption throughout the day, especially in the summertime during which LSEs face a greater challenge in comparison with other periods of the year [10].

B. Literature Overview

A considerable number of studies in the literature were dedicated to the use of different kinds of TCAs in order to obtain demand side flexibility during critical periods. Heffner et al. [11] 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 are also discussed in [12]. Furthermore, the provision of load shifting and renewable energy based volatility suppression was studied in [13].

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Angeli and Kountouriotis [14] 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 [15]. 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 [16] and Zhang and Lu in [17]. HVAC response capability to mitigate the renewable energy volatility was the scope of the studies conducted by Bashash and Fathy in [18] and Zheng and Cai in [19]. The use of building scale HVAC units for regulation services regarding high frequency power mismatches was discussed by Hao et al. [20] and Goddard et al. [21]. Additionally, the impacts of uncertainty regarding HVAC physical parameters were analyzed in [10]. The study presented in [22] compared two 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 in [23]. The idea of maintaining fairness for the enrolled consumers while exercising DLC was introduced by Koutitas [24]. However, [24] 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 TCA type to aggregate a population of TCAs for load balancing services was conducted by Soudjani and Abate [25]. Besides, the verified TCA models were presented by Shao et al. in [26].

C. *Content and Contributions*

In this study, a day-ahead residential HVAC load aggregation scheduling, considering the minimization of the average consumer comfort violation among the enrolled end-users is presented. One of the major barriers to the wider implementation of residential DR is the insufficient social acceptance of them, which has a direct connection to the unwillingness of the end-user to incur a compromise of its comfort level during a DR event. Therefore, the end-user comfort violation is a major issue that can affect the wider penetration of such strategies.

Nowadays, there is an increasing trend in the relevant industry for enabling “behavioral DR” [27]. This concept aims to clearly show to the end-users willing to participate in DR programs what their gains are, in order to motivate them to become part of such programs. Typically, simple interfaces embedded in smart phone applications or personal computers present the daily economic savings, the contribution to environmental sustainability, etc. Embedding the proposed strategy in this framework will use a similar infrastructure to engage people in participating in DR programs. Through their smart devices, the occupants will be able to monitor how their comfort violation is minimized through comparisons with a reference case and by providing brief explanations on how they should perceive the results.

Thus, through simple and effective interfaces, suitably designed to be used by non-experts, and with dynamic information updates by the load serving entities, the occupants can be more easily aware of their benefits by participating in such DR programs.

The contribution of this study is three-fold:

- Implementation of a consumer comfort violation minimization oriented approach that has not been considered in the relevant literature, aiming to increase the social acceptance of DR in residential premises.
- Consideration of the fairness in the allocation of comfort violation among the enrolled consumers and the constraint of the load factor during contracted DR period in order to improve the end-users’ satisfaction and reduce load rebound effect.
- Consideration of the impact of humidity on ambient dry-bulb temperature, which provides a more realistic estimation in comparison with the utilization of the ambient dry-bulb temperature in the model, where the weather forecasts are performed using a *spatio-temporal* approach.

D. *Organization of the paper*

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

III. 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 ambient dry-bulb temperature with respect to the end-user’s predefined value, which is measured in ℃·h. For example 10 ℃·h may stand for a decrease/increase of 1℃ for 10 hours or 2℃ for 5 hours, etc. The objective function is expressed by (1).

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

The division by $\mathrm{N_h}$ in (1) is performed in order to obtain the average comfort violation among the enrolled end-users. Normally for the proposed methodology it can be eliminated without changing the optimal solution. However in order to compare individual comfort violation value of each end-user with the average comfort violation among the enrolled end-users, this division term is needed. Also, if $\mathrm{N_h}$ is defined as a time dependent parameter, then a varying number of households can be considered in different periods.

The ambient dry-bulb temperature depends on several factors such as the thermal properties of air, the heat exchange between the house and the 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 [28], [29].

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

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 $\beta°$ [30].

$$R_{eq,h} = \frac{1}{N} \sum_i \frac{l_{i,h}}{\sigma_{i,h} A_{i,h}} \quad (3)$$

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

$$M_{a,h} = V_h \cdot \delta_{air} \quad (5)$$

In each time interval t the ambient dry-bulb temperature of household h is decomposed as in (6).

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

The desired temperature is determined by the end-user. This value can be either specified in the DR enrollment contract or it can be dynamically set before each DR event. Alternatively, a range of temperatures can be provided. This requirement can be trivially considered by altering (1) and (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.

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

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

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 [22].

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).

$$T_{des,h} - T_{dec_{allowed},h} \leq T_{set,h,t} \leq T_{des,h} + T_{inc_{allowed},h}, \quad \forall t \in [t_1, t_2] \quad (9)$$

The decision variable for the operation of the proposed methodology is $T_{set,h,t}$.

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

The ambient dry-bulb temperature limits are defined by (10).

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

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

$$p_{AC,h,t} = P_{AC,h} \cdot u_{AC,h,t}, \forall t \quad (11)$$

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).

$$P_{des,t} \leq P_{total\_ref,t} - \sum_h p_{AC,h,t}, \forall t \in [t_3, t_4] \quad (12)$$

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 also load increase requirements in certain periods.

The comfort violation per household is calculated using (13) considering both the upward and downward deviations with respect to the desired temperature:

$$com\_vio_h = \sum_{t=t_1}^{t=t_2} (T_{up,h,t} + T_{down,h,t}) \Delta T, \forall t \in [t_1, t_2] \quad (13)$$

Although the main objective is to minimize the average comfort violation among enrolled consumers, it is also necessary to ensure the fairness of the allocation of this comfort violation among the consumers.

Therefore (14)-(15) are used to obtain a fair allocation constrained by a percentage between the minimum and maximum values of the comfort violation:

$$com\_vio_{min} \leq com\_vio_h \leq com\_vio_{max}, \forall t \in [t_1, t_2] \quad (14)$$

$$com\_vio_{max} \leq N_{com} \cdot com\_vio_{min}, \forall t \in [t_1, t_2] \quad (15)$$

Constraints (14)-(15) ensure that the maximum comfort violation among the enrolled consumers will not exceed N_{com} times the minimum comfort violation value. It should be noted that specifying a smaller N_{com} value will lead to a more fair distribution of the comfort violation among the enrolled end-users but will also increase the chance of facing infeasibility. On the other hand, larger N_{com} value will lead to an undesired unfair operation of the proposed methodology.

It is very likely that reducing the power consumption in some specific periods will lead to a load recovery or load rebound effect that is caused by the aggregation of total HVAC load before or after the actual DR event.

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This effect will lead to a sharp peak just after or before the actual DR event that is undesired by the LSE and should be prevented. In this regard, an additional constraint is also inserted to maintain the load factor of the case of DR event equal or greater than the load factor of $P_{total\_ref,t}$. Here the mentioned load factor related constraint is decomposed into two constraints as follows:

$$\sum_{h} p_{AC,h,t} \leq max(P_{total\_ref,t}), \forall t \in [t_1, t_2] \tag{16}$$

$$avg\left(\sum_{h} p_{AC,h,t}\right) \geq avg(P_{total\_ref,t}), \forall t \in [t_1, t_2] \tag{17}$$

where max and avg notations represent the maximum and average values of the relevant variables and parameters within the defined time horizon. Constraints (16) and (17) limit the load factor to be equal to or greater than the reference condition. Since the load factor is defined as the ratio of average power to the maximum power within a predefined time horizon, (16) tends to increase the nominator of load factor formulation while (17) tends to decrease the denominator compared to the reference case. Thus, (16) and (17) constrain the load factor in the DR program at least to be equal to the reference case.

B. *Perceived 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 end-users due to three main reasons: (i) relative humidity, which causes air temperature to be felt warmer than its actual value since high humidity reduces the evaporation of perspiration from the body and thereby, results in a feeling of being overheated, (ii) wind speed, which generally makes oneself to feel colder and, (iii) direct insolation which causes us to feel increased temperature if we are exposed to it, compared to shaded areas. Other factors influencing how an individual feels temperature are subjective, i.e., they vary from person to person.

The air temperature given by the standard thermometers is the measure of the temperature recorded in an area protected from exogenous weather variables such as humidity, sunshine and wind. Therefore, it cannot indicate the temperature that end-users feel. Hence, new temperature definitions were recommended to determine the temperature more accurately. For example, Wet Bulb Globe Temperature (WBGT) defines the perception of temperature depending on solar radiation, humidity, temperature and wind speed. However, WBGT is not frequently used in the literature of ambient dry-bulb temperature forecasting due to its location-specific structure. Besides, in the residential buildings, the humidity can be indicated as the only factor that affects the measured temperature due to the very limited effects of wind speed and radiation on the temperature that an individual feels because of walls, windows, etc. Therefore, another 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 indoor conditions. Considering the significant effect of humidity on the perceived temperature and therefore, on the control of HVAC units, the HI is used in this study in order to estimate the human-perceived equivalent temperature.

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.

B.1. Forecasting Model

The efficiency of the proposed day-ahead planning approach is mainly based on the accurate hourly temperature information of the following day. Therefore, a spatio-temporal approach, which accounts for the temperature data collected from both the site of interest and other weather stations on its surrounding area, is used for the daily forecasts of temperature. It is assumed that the promising results accomplished with spatio-temporal methods in the recent studies on wind forecasting [31]-[35] and solar forecasting [36]-[39], which are due to their efficiency in exploiting all the available data and to their relatively lower computational cost, these methods might be also used effectively for the forecasts of other meteorological quantities including temperature.

In order to alleviate the requirement of a time-consuming data selection process, the proposed algorithm uses all the available temperature data from 43 meteorological stations in the training stage but in forecasting stage only the data that have the potential to benefit the predictions are included [40]. The contribution of the data from different meteorological stations to the output of target station is determined considering the correlations between the target station and its neighbor stations for each prediction horizon (i.e. 24 h). The proposed approach can be defined as follows (18)-(22).

$$\boldsymbol{y} = A_1\boldsymbol{x_1} + A_2\boldsymbol{x_2} + \cdots + A_K\boldsymbol{x_K} = \sum_{i=1}^{K} A_i\boldsymbol{x_i} \tag{18}$$

where

$$\boldsymbol{y} = \begin{bmatrix} y_{n+1}^{h^*} \\ y_{n+2}^{h^*} \\ \vdots \\ y_{n+M}^{h^*} \end{bmatrix} \tag{19}$$

$$A = [T_{Mn}^{1} \quad \cdots \quad T_{Mn}^{H}] \tag{20}$$

$$\boldsymbol{x} = \begin{bmatrix} x_1^1 \\ \vdots \\ x_n^1 \\ \vdots \\ \vdots \\ x_1^H \\ \vdots \\ x_n^H \end{bmatrix} \tag{21}$$

The matrix T_{Mn}^{h} is an M x n Toeplitz matrix given by (22).

$$\boldsymbol{T_{Mn}} = \begin{pmatrix} y_n & \cdots & y_1 \\ y_{n+1} & \ddots & \vdots \\ \vdots & \ddots & \vdots \\ y_{n+M-1} & \cdots & y_M \end{pmatrix} \tag{22}$$

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In (18)-(22), $\boldsymbol{y}$ denotes the output vector (i.e., temperature values of target house in this study) and $\boldsymbol{x}$ is a coefficient matrix associated with the i-th time lag, in which the vector elements are calculated with the least-squares method. Also, n is the model order and $n+M$ represents the training data size. Besides, y_t^h is the temperature value at the h-th house at sample time t $(t = 1,2,\ldots,M+n)$, y^{h^*} is the target variable and H is the number of houses $(h = 1,2,\ldots,H)$.

B.2. Heat Index

The HI equation (18), which is obtained by multiple regression analysis, is used in this study [41].

$$\begin{aligned} HI_t = & -42.379 + (2.04901523 \times T_{a,t}) \\ & + (10.14333127 \times RH_t) \\ & - (0.22475541 \times T_{a,t} \times RH_t) \\ & - (6.83783 \times 10^{-3} \times {T_{a,t}}^2) \\ & - (5.481717 \times 10^{-2} \times RH_t^2) \\ & + (1.22874 \times 10^{-3} \times {T_{a,t}}^2 \\ & \times RH_t) \\ & + (8.5282 \times 10^{-4} \times T_{a,t} \\ & \times RH_t^2) \\ & - (1.99 \times 10^{-6} \times {T_{a,t}}^2 \\ & \times RH_t^2) \end{aligned} \quad (23)$$

with $T_{a,t}$ being ambient dry-bulb temperature and RH_t being relative humidity at time t. The HI cannot be measured by using an instrument. Instead, various equations are provided in the literature in order to approximate this value using the ambient dry-bulb temperature, which is easily measured with common thermometers, and humidity. Note that since this "perceived temperature" also depends on the subjective parameters such as the state of human body and the heat resistance of clothes, a mean value is generally used instead of extreme values.

IV. Tests And Results

A. Input Data

Hourly temperature and relative humidity data from Meteorological Terminal Aviation Routine (METAR) weather reports of 43 weather stations located in USA are used [42]. 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 set from June 2 to June 15 and, (ii) an one-week test set from June 16 to June 23.

The forecasts of the perceived temperature are carried out with a two-stage process. In the first stage, daily ambient dry-bulb temperature is forecasted with the proposed spatio-temporal method and the temperature forecasts obtained are converted to the perceived temperature forecasts in the second stage by using the HI equation given in (18). For the ambient dry-bulb temperature forecasts, first, the data from all the 43 weather stations are applied to the forecasting model, as an alternative approach to the use of various methods for the purpose of determining the best subset of weather stations [43,44].

A coefficient vector $\boldsymbol{x}$, as shown in (20), is then calculated in the training phase. Lastly, the forecasted values are calculated using the $\boldsymbol{x}$ vector and the matrix A that includes the recent measurements. The $\boldsymbol{x}$ vector is recalculated every prediction horizon. Also, a recursive approach is followed in the forecasts, i.e., the temperature forecasts at time t are included in the matrix A for the forecasting of the temperature value at time $t+1$ and so on. Once the forecasts are completed for the corresponding time horizon, the matrix A is updated with the new values measured during the previous prediction horizon and a new prediction process begins for the next horizon. This algorithm helps the model always present the latest temperature trend, resulting in a higher accuracy. Fig. 1 presents the results of the ambient dry-bulb temperature forecasting compared to the real values, where it may be noticed that the two time series present sufficient similarity.

With the objective of better measuring the effectiveness of the proposed daily forecasting approach, various performance metrics for this method as well as three different time series methods are shown in Table V. The metrics given in Table V, namely, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Normalized Root Mean Squared Error (NRMSE), are negatively oriented error metrics, which means that the lower these metrics are, the higher the forecast accuracy is. Basically, a permanent deviation between the measurements and forecasts indicates a higher MAE while large error values observed generally in peak times cause a higher RMSE value. NRMSE provides a scale-independent error measure that allows comparing the forecasting accuracy obtained in the case of different data sets.

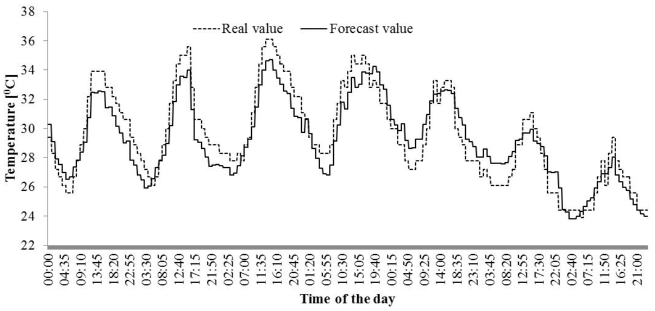

Figure 1. The comparison of real and forecasted values for ambient dry-bulb temperature.

TABLE V. Comparison of Statistical Error Measures for Different Approaches

Forecasting Model	*MAE [°C]*	*RMSE [°C]*	*NRMSE [%]*
Persistence	2.15	2.71	22.17
Autoregressive	1.42	1.79	14.70
WT-ANN	1.21	1.45	11.85
Proposed model	1.04	1.14	9.33

As it can be seen in Table V, the persistence model, which simply uses the last measured value as forecast during the prediction time, gives relatively poor forecasts. Despite its inefficiency in such a long prediction horizon, the results of this model are included in the comparisons since it is the most commonly used benchmark method in the literature of forecasting for a wide range of prediction horizons [45].

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2016.2556619, IEEE Transactions on Smart Grid

More reasonable forecasts are achieved by including a number of recent data in addition to the last measured value in the Autoregressive (AR) model. Furthermore, a compound model that integrates Artificial Neural Networks (ANN) and Wavelet Transform (WT) is employed for the comparisons due especially to its high efficiency on the modelling of the daily cycles embedded in time series [46]. Compared to the error metrics of benchmark models given in Table V, its significantly lower metrics show the effectiveness of the proposed model for daily temperature forecasts.

The impact of the humidity on the perceived temperature is not negligible as mentioned before. Thus, the ambient dry-bulb temperature forecasts, together with the humidity data, are applied to ambient dry-bulb temperature-to-HI formulation given in (18) in order to calculate the anticipated perceived temperature. The comparison of the ambient dry-bulb temperature and the HI is presented in Fig. 2. As it may be noticed, there are significant differences between the HI and the ambient dry-bulb temperature, which can affect the day ahead planning significantly and it is therefore more valid to use the actual HI the households will face. As the HI index is considered to imply the relevant changes in outdoor dry-bulb temperature regarding the humidity and all the enrolled households are considered to be imposed to similar outdoor conditions, the individual household indoor temperature variations regarding outdoor temperature changes are just affected by the physical household parameters.

For the sake of simplicity and clarity while discussing the results, 40 identical households (such as a site of flats constructed by the same company identically in a field) with the structural parameters shown in Table VI are considered. As stated in [47], a specification of household types can be realized between relatively uninsulated (Type 1) to well-insulated (Type 7) household structures and some specific physical parameters for house types 1 to 7 are given in the relevant literature [48]. However, dealing with the uncertainty of such parameters can be realized via various estimation techniques etc.

Generally, the density of the air and its thermal capacity depend on its thermodynamic properties (temperature, pressure, etc.). In this study, they are considered constant and utilized standard values $\delta_{\text{air}} = 1.225$ kg/m^3 and $c_a = 1.01$ kJ/kg°C. 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. Besides, the HI variation during the considered period is shown in Fig. 3 (June 16, 2013). Moreover, the temperature based parameters for households are also presented in Table VII. It should be noted that the same value is assigned to all end-users in terms of desired temperature for the sake of simplicity and of showing comparatively how the temperature varies among the enrolled end-users starting from the same point and for the same necessities imposed by the end-users. However, the desired temperature can also be diversified by the proposed methodology as $T_{des,h}$ is a parameter related to each end-user's preferences. However, as the proposed methodology is not mainly targeting the $T_{des,h}$ setting -in fact $T_{up,h,t}$ and $T_{down,h,t}$ variables specifying how much $T_{in,h,t}$ diverges from the desired comfort settings are the primary factors affecting the comfort violation-, the performance is not largely dependent on the defined $T_{des,h}$ value.

The time granularity used in the optimization is 5 min (0.0833h). The Mixed-Integer Linear Programming (MILP) model has been coded in GAMS 24.0.2 and has been solved by the commercial solver CPLEX 12. For the DR contract, the households are assumed to accept being involved in DR events during summer times between 12pm-6pm.

Besides, it is also assumed for the considered sample day that a peak-reduction DR event is activated between 2pm-4pm. It should also be noted that the initial ambient dry-bulb temperature values of households are randomly allocated between 19.1^{0}C and 20.9^{0}C.

B. Simulation and Results

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 power consumption pattern ($P_{total\_ref,t}$) as shown in Figs. 4-6.

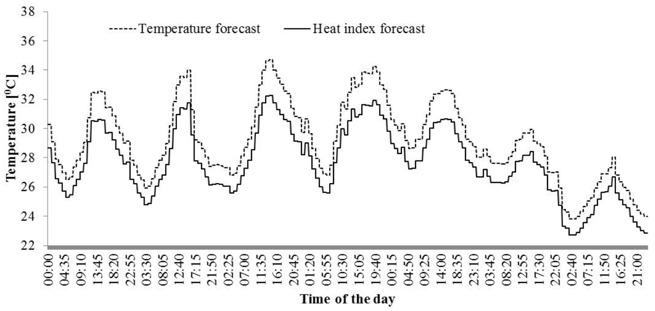

Figure 2. The comparison of forecasted temperature and HI.

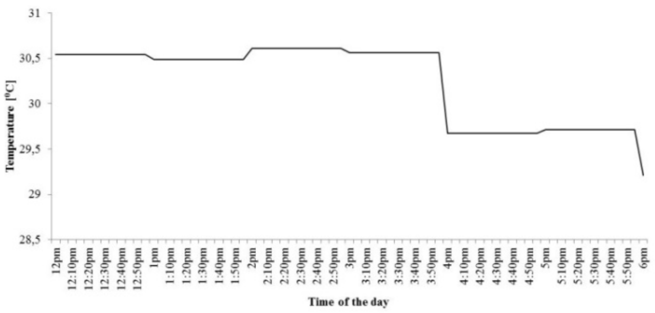

Figure 3. The HI variation during the DR event.

TABLE VI. 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· °C
House height (L_3)	4	m	Window thermal coefficient	2808	J/h·m· °C
Roof angle (β)	40	*deg*	Thickness of windows	0.05	m
Number of windows	6	-	Thickness of walls	0.15	m

TABLE VII. 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

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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 2pm and 4pm, 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. Three case studies are provided as follows:

- Case 1: Consideration of only the average comfort violation neglecting constraints (14)-(17).
- Case 2: Consideration of the fair allocation of comfort violation among enrolled end-users neglecting the load factor constraints (16)-(17).
- Case 3: Consideration of both the fair allocation of comfort violation and load factor constraints.

The power consumption during the contracted DR period and the reference power for all case studies are depicted in Figs. 4-6.

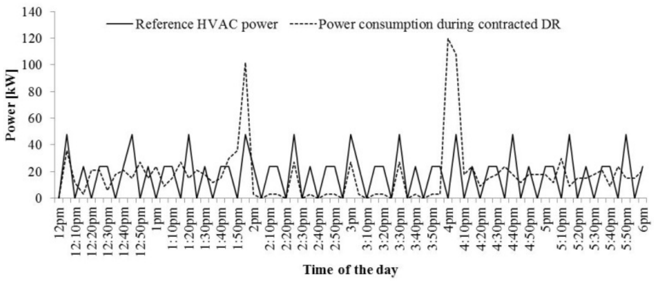

Figure 4. The power consumption by HVAC during the DR event for Case-1.

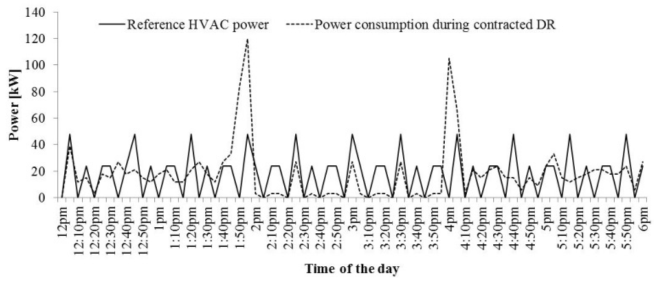

Figure 5. The power consumption by HVAC during the DR event for Case-2.

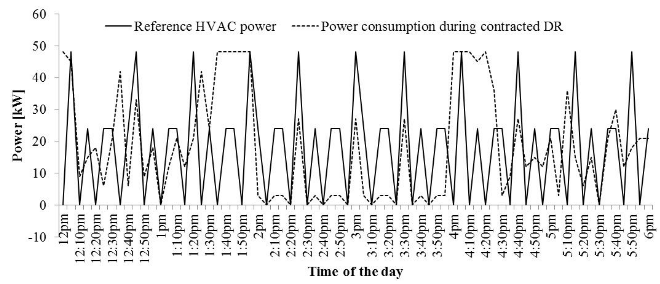

Figure 6. The power consumption by HVAC during the DR event for Case-3.

Firstly, it is evident that the proposed limitation on satisfying at least the level of desired reduction during the actual DR event between 2pm and 4pm is satisfied by the proposed approach in each case. Besides, implementing such strategies is known to be accompanied by the load-rebound effect due to shifting consumption before or after the DR event. This issue can be observed in Figs. 4 and 5 for Case-1 and Case-2 where the constraints related to load factor are neglected. The temperature set-points of HVAC units are set to higher values than the corresponding the ambient dry-bulb 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. Then when the actual DR event period ends, the households thermostat temperature set-points are set to values around the desired level in order to minimize the comfort violation that provides an additional peak load demand after the DR event.

In order to tackle with this problematic issue for LSEs, constraining the load factor reduces these additional peaks before or after the actual DR event within the contracted DR period as seen in Fig. 6.

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. The results regarding the ambient dry-bulb temperature of households for all cases can be seen in Figs. 7-9.

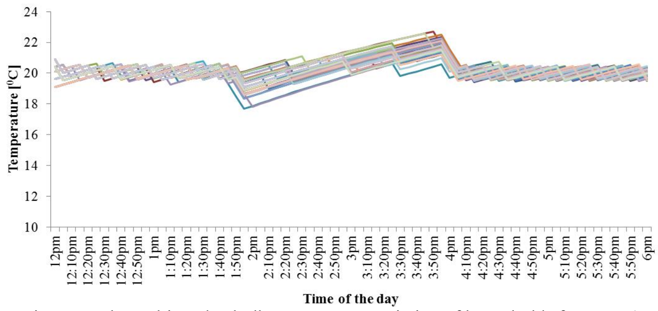

Figure 7. The ambient dry-bulb temperature variation of households for Case-1.

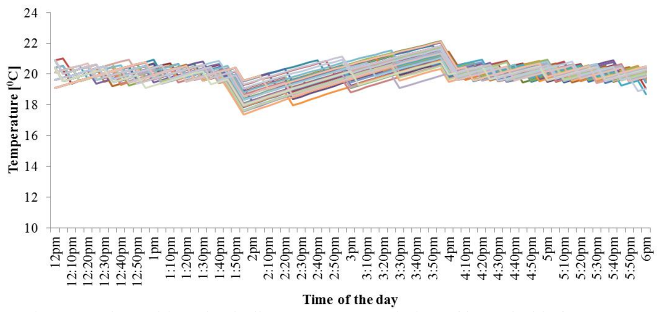

Figure 8. The ambient dry-bulb temperature variation of households for Case-2.

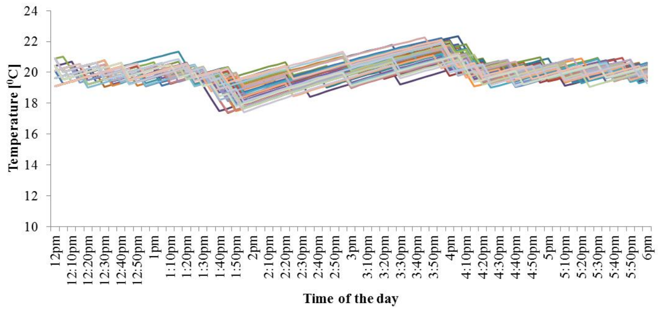

Figure 9. The ambient dry-bulb temperature variation of households for Case-3.

It can be noticed that most households follow a similar pattern of temperature, 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. 10. Besides, the relevant results together with the load factor values for each case are summarized in Table VIII.

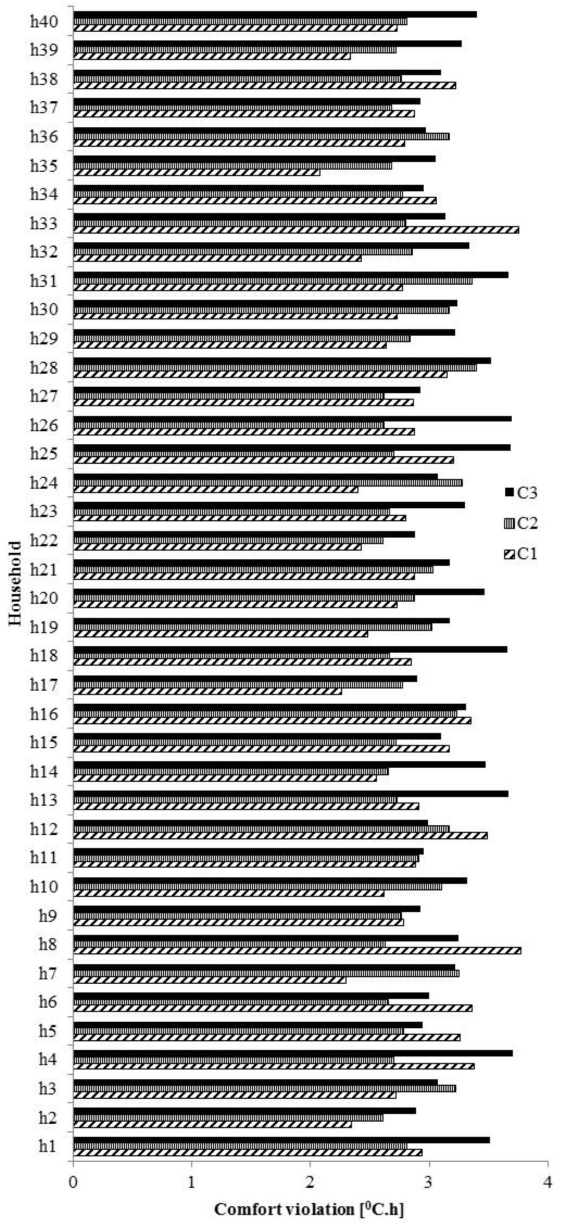

Figure 10. The comfort violation index value of end-users for all cases.

TABLE VIII. GENERAL OVERVIEW OF THE OBTAINED RESULTS

Case	*Minimum Com. Vio. [°C · h]*	*Maximum Com. Vio. [°C · h]*	*Average Com. Vio. [°C · h]*	*Load Factor*
Base Case	1.5132	1.6636	1.5718	0.3698
Case-1	2.0773	3.7758	2.8562	0.1438
Case-2	2.6127	3.3956	2.8724	0.1465
Case-3	2.8802	3.7011	3.2263	0.3792

It should be noted that for Case-2 and Case-3, N_{com} parameter is set to 1.3 in order to limit the maximum comfort violation among the enrolled end-users in the DR event to be less than 30% more of minimum comfort violation. This extra constraint on fairness slightly increases the average comfort violation while providing a more homogenous distribution of the comfort violation among the end-users when the results given in Fig. 10 and Table VIII are examined for Case-1 and Case-2. In order to sustain the load factor more than the base case, Case-3 can be expected to cause more comfort violation among the end-users. This issue can be observed from the results in Fig. 10 and Table VIII. Together with sustaining the ratio of 1.3 times between maximum and minimum comfort violations, the average comfort violation increases significantly in Case-3 on behalf of providing a higher load factor. This clearly indicates that it is a trade-off for the LSE to find the right balance between minimizing the comfort violation and sustaining an acceptable level of load factor during the DR events.

V. CONCLUSIONS

In this study, an end-user average comfort violation minimization oriented HVAC load aggregation strategy was proposed based on MILP. The aim of the proposed approach was to minimize the average deviation of household temperature values of a group of contracted residential end-users during a DR event, while satisfying load reduction targets of the LSE. A TSCM approach was employed to manipulate the end-users' HVAC temperature settings in order to aggregate the mentioned reduction of the total HVAC load. Besides, the fairness among the end-users in terms of comfort violation allocation was considered together with constraining load factor during contracted DR period in order to reduce possible load rebound effect. Moreover, the HI was utilized instead of the ambient dry-bulb temperature, also supported by a spatio-temporal forecasting method. Based on the simulations conducted, the strategy proved to have a decrement in violation of end-user comfort level while effectively satisfying the requirement of LSE in terms of load demand reduction. Besides, the constraints related to comfort violation fairness and load factor improved the fair distribution among contracted end-users and load rebound effect as shown in relevant comparisons. There are numerous areas to which this study can be extended. Although this study aims at residential end-users and specifically HVAC units, the proposed formulation is extendible to a variety of appliance types by additional specifications on comfort violation because of the participation in DR programs. Thus, the diversification of demand response capacity offered by each end-user type and more specifically by each end-user appliance can be considered in a future study aiming at more different DR enabling appliance scheduling. Investigating the relationship between HVAC power consumption and humidity especially for indoor dynamics by specifically focusing on this issue can be also considered in a future study. Other future studies could also consider a DCCM approach using decentralized solutions by TCL aggregators instead of a centralized solution, the implementation of a stochastic approach considering the uncertainty related to the acceptance of the contracted end-users to participate in the actual DR event, the definition of an economic incentive index related to the each end-user's comfort violation, and finally considering end-users with multiple TCLs and other appliances convenient for DR purpose (e.g. electric vehicles).

VI. References

[1] J. Kondoh, N. Lu, and D. J. Hammerstrom, "An evaluation of the water heater load potential for providing regulation service," *IEEE Trans. Power Systems*, vol. 26, pp. 1309-1316, Aug. 2011.

[2] M. Aunedi, P. A. Kountouriotis, J. E. O. Calderon, D. Angeli, and G. Strbac, "Economic and environmental benefits of dynamic demand in providing frequency regulation," *IEEE Trans. Smart Grid*, vol. 4, pp. 2036-2048, Dec. 2013.

[3] M. Alizadeh, Y. Xiao, A. Scaglione, and M. V. D. Schaar, "Dynamic incentive design for direct load scheduling programs," *IEEE Journal of Selected Topics in Signal Processing*, vol. 8, pp. 1111-1126, Dec. 2014.

[4] Enernoc Co. – What is demand response? [Online]. Available: http://www.enernoc.com/our-resources/term-pages/what-is-demand-response.

[5] V. M. Shiljkut, and N. Lj. Rajakovic, "Demand response capacity estimation in various supply areas," *Energy*, vol. 92, pp. 476-486, December 2015.

[6] C. Vivekananthan, and Y. Mishra, "Stochastic ranking method for thermostatically controllable appliances to provide regulation services," *IEEE Trans. Power Systems*, vol. 30, pp. 1987-1996, July 2015.

[7] A. M. Garcia, M. Kessler, J. A. Fuentes, and E. G. Lazaro, "Probabilistic characterization of thermostatically controlled loads to model the impact of demand response programs," *IEEE Trans. Power Systems*, vol. 26, pp. 241-251, Feb. 2011.

[8] P. Wattles, "*ERCOT demand response overview & status report*," AMIT-DSWG workshop AMI's next frontier: demand response, http://www.ercot.com/content/meetings/dswg/keydocs/2011/0830/3_ERCOT_presentation_workshop_083011.pdf.

[9] C. Perfumo, J. H. Braslavsky, and J. K. Ward, "Model-based estimation of energy savings in load control events for thermostatically controlled loads," *IEEE Trans. Smart Grid*, vol. 5, pp. 1410-1420, May 2014.

[10] Y. Sun, M. Elizondo, S. Lu, and J. C. Fuller, "The impact of uncertain parameters on HVAC demand response," *IEEE Trans. Smart Grid*, vol. 5, pp. 916-923, Mar. 2014.

[11] G. C. Heffner, C. A. Goldman, and M. M. Moezzi, "Innovative approaches to verifying demand response of water heater load control", *IEEE Trans. Power Delivery*, vol. 21, pp. 388-397, Jan. 2006.

[12] N. Lu, "An evaluation of the HVAC load potential for providing load balancing services," *IEEE Trans. Smart Grid*, vol. 3, pp. 1263-1270, Sep. 2012.

[13] S. A. Pourmousavi, S. N. Patrick, and N. H. Nehrir, "Real-time demand response through aggregate electric water heaters for load shifting and balancing wind generation," *IEEE Trans. Smart Grid*, vol. 5, pp. 769-778, Mar. 2014.

[14] D. Angeli, and P. A. Kountouriotis, "A stochastic approach to dynamic-demand refrigerator control," *IEEE Trans. Control Systems Technology*, vol. 20, pp. 581-592, May 2012.

[15] W. Zhang, J. Lian, C. Y. Chang, K. Kalsi, "Aggregated modeling and control of air conditioning loads for demand response," *IEEE Trans. Power Systems*, vol. 28, pp. 4655-4664, Nov. 2013.

[16] N. Lu, and Y. Zhang, "Design considerations of a centralized load controller using thermostatically controlled appliances for continuous regulation reserves," *IEEE Trans. Smart Grid*, vol. 4, pp. 914-921, June 2013.

[17] Y. Zhang, and N. Lu, "Parameter selection for a centralized thermostatically controlled appliances load controller used for intra-hour load balancing," *IEEE Trans. Smart Grid*, vol. 4, pp. 2100-2108, Dec. 2013.

[18] S. Bashash, and H. K. Fathy, "Modeling and control of aggregate air conditioning loads for robust renewable power management," *IEEE Trans. Control Systems Technology*, vol. 21, pp. 1318-1327, July 2013.

[19] L. Zheng, and L. Cai, "A distributed demand response control strategy using Lyapunov optimization," *IEEE Trans. Smart Grid*, vol. 5, pp. 2075-2083, July 2014.

[20] H. Hao, Y. Lin, A. S. Kowli, P. Barooah, and S. Meyn, "Ancillary service to the grid through control of fans in commercial building HVAC systems," *IEEE Trans. Smart Grid*, vol. 5, pp. 2066-2074, July 2014.

[21] G. Goddard, J. Klose, and S. Backhaus, "Model development and identification for fast demand response in commercial HVAC systems," *IEEE Trans. Smart Grid*, vol. 5, pp. 2084-2092, July 2014.

[22] C. H. Wai, M. Beaudin, H. Zareipour, A. Schellenberg, and N. Lu, "Cooling devices in demand response: A comparison of control methods," *IEEE Trans. Smart Grid*, vol. 6, pp. 249-260, Jan. 2015.

[23] S. H. Tindemans, V. Trovato, and G. Strbac, "Decentralized control of thermostatic loads for flexible demand response," *IEEE Trans. Control Systems Technology*, vol. 23, pp. 1685-1700, Sept. 2015.

[24] G. Koutitas, "Control of flexible smart devices in the smart grid," *IEEE Trans. Smart Grid*, vol. 3, pp. 1333-1343, Sep. 2012.

[25] S. E. Z. Soudjani, and A. Abate, "Aggregation and control of populations of thermostatically controlled loads by formal abstraction," *IEEE Trans. Control Systems Technology*, vol. 23, pp. 975-990, May 2015.

[26] S. Shao, M. Pipattanasomporn, and S. Rahman, "Development of physical-based demand response-enabled residential load models," *IEEE Trans. Power Systems*, vol. 28, pp. 607-614, May 2013.

[27] Intelen Co. – DiG solution [Online]. Available: http://intelen.com/us/solutions/how-it-works.html.

[28] H. Wang, K. Meng, F. Luo, Z. Y. Dong, G. Verbic, Z. Xu, and K.P. Wong, "Demand response through smart home energy management using thermal inertia," *in Proc.* 2013 Australasian Universities Power Engineering Conference , pp. 1-6.

[29] N. G. Paterakis, O. Erdinc, A. G. Bakirtzis, and J. P. S. Catalao, "Optimal household appliances scheduling under day-ahead pricing and load-shaping demand response strategies," *IEEE Trans. Industrial Informatics*, article in press.

[30] F. de Angelis, M. Boaro, S. Squartini, F. Piazza, and Q. Wei, "Optimal home energy management under dynamic electrical and thermal constraints," *IEEE Trans. Industrial Informatics*, vol. 9, pp. 1518-1527, Aug. 2013.

[31] J. Tastu, P. Pinson, P. J. Trombe, and H. Madsen. "Probabilistic forecasts of wind power generation accounting for geographically dispersed information," IEEE Trans Smart Grid, vol. 5, pp. 480-489, Jan. 2014.

[32] L. Xie, Y. Gu, X. Zhu, and M. G. Genton. "Short-term spatio-temporal wind power forecast in robust look-ahead power system dispatch," IEEE Trans Smart Grid, vol. 5, pp. 511–520, Jan. 2014.

[33] J. Dowell, and P. Pinson, "Very-short-term probabilistic wind power forecasts by sparse vector autoregression," IEEE Trans Smart Grid, in press.

[34] A. Tascikaraoglu, B. M. Sanandaji, K. Poolla, and P. Varaiya, "Exploiting sparsity of interconnections in spatio-temporal wind speed forecasting using Wavelet Transform," Appl Energ, vol. 165, pp. 735-747, Mar. 2016.

[35] M. He, L. Yang, J. Zhang, and V. Vittal. "A spatio-temporal analysis approach for short-term forecast of wind farm generation," IEEE Trans Power Syst, vol. 29, pp. 1611-1622, Jul. 2014.

[36] R. Bessa, A. Trindade, and V. Miranda, "Spatial-temporal solar power forecasting for smart grids," IEEE Trans. Industr Inform, vol. 11, pp. 232–241, Feb. 2015.

[37] C. Yang, A. Thatte, L. Xie, "Multitime-scale data-driven spatiotemporal forecast of photovoltaic generation," IEEE Trans Sust Energy, vol. 6, pp. 104–112, Jan. 2015.

[38] A. Zagouras, H. T. Pedro, and C. F. Coimbra, "On the role of lagged exogenous variables and spatio–temporal correlations in improving the accuracy of solar forecasting methods," Renew Energ, vol. 78, pp. 203–218, June 2015.

[39] A. W. Aryaputera, D. Yang, L. Zhao, and W. M. Walsh, "Very short-term irradiance forecasting at unobserved locations using spatio-temporal kriging," Solar Energ, vol. 122, pp. 1266–1278, Dec. 2015.

[40] B. M. Sanandaji, A. Tascikaraoglu, K. Poolla, and P. Varaiya, "Low-dimensional Models in Spatio-Temporal Wind Speed Forecasting," in Proc. *2015 American Control Conference (ACC)* , pp. 4485-4490.

[41] L. P. Rothfusz, "The heat index equation," National Weather Service Technical Attachment (SR 90–23), 1990.

[42] Iowa Environmental Mesonet, "ASOS historical data," 2014. [Online]. Available: http://mesonet.agron.iastate.edu/ASOS/.

[43] T. Hong, P. Wang, and L. White, "Weather station selection for electric load forecasting", *Int J Forecasting*, vol. 31, pp. 286-295, June 2015.

[44] J. Xie, and T. Hong, "GEFCom2014 Probabilistic electric load forecasting: An integrated solution with forecast combination and residual simulation", *Int J Forecasting*, in press.

[45] A. Tascikaraoglu, and M. Uzunoglu. "A review of combined approaches for prediction of short-term wind speed and power," *Renew Sust Energ Rev*, vol. 34, pp. 243-254, June 2014.

[46] A. Tascikaraoglu, A. R. Boynuegri, M. Uzunoglu. "A demand side management strategy based on forecasting of residential renewable sources: A smart home system in Turkey," *Energ Buildings*, vol. 30, pp. 309-320, Sep. 2014.

[47] Y. Sun, M. Elizondo, S. Lu, and J. C. Fuller, "The impact of uncertain physical parameters on HVAC demand response," *IEEE Trans. Smart Grid*, vol. 5, pp. 916-923, March 2014.

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[48] J. C. Fuller, N. P. Kumar, and C. A. Bonebrake, "Evaluation of representative smart grid project technologies: Demand response," Pacific Northwest National Laboratory, Richland, WA, USA, Tech. Rep. PNNL-20772, Jan. 2012 [Online]. Available: http://www.pnnl.gov/main/publications/external/technical_reports/PNNL-20772.pdf

BIOGRAPHIES

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