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/TIE.2018.2811403, IEEE Transactions on Industrial Electronics

Novel Incentive Mechanism for End-Users Enrolled in DLC-based Demand Response Programs within Stochastic Planning Context

Ozan Erdinc, *Senior Member, IEEE*, Akın Tascikaraoglu, *Member, IEEE*, Nikolaos G. Paterakis, *Member, IEEE*, and João P. S. Catalão, *Senior Member, IEEE*

***Abstract*--In this study, a novel direct load control (DLC) planning based on providing free energy credits to residential end-users for their heating, ventilation and air conditioning (HVAC) load during demand response (DR) events is proposed. The obtained credit can then be used by the end-users during relatively higher price periods free-of-cost to enable the end-users to lower their energy procurement costs. Furthermore, the resulting reduction in the total household energy consumption considerably decreases the critical load demands in power systems, which is of vital importance for load serving entities (LSEs) in maintaining the balance between supply and demand during peak load periods. In this regard, the aforementioned energy credits-based incentive mechanism is proposed for end-users enrolled in the DLC-based DR program, as a new contribution to existing literature, testing it in a stochastic day-ahead planning context.**

***Index Terms*--Demand response (DR); direct load control (DLC); energy credit; smart household; heating, ventilation and air conditioning (HVAC); thermostatically controllable loads (TCLs).**

NOMENCLATURE

The sets, parameters and decision variables that are used in this paper are alphabetically listed below. Other symbols and abbreviations are defined where they first appear.

A. Sets

h	Set of households.
i	Set of structural elements.
t	Set of time periods.
ω	Set of scenarios.

B. Parameters and Constants

$A_{i,h}$	Element area for household h [m^2].
c_a	Thermal capacity of the air [kJ/kg·K].
COP_h	HVAC coefficient-of-performance in household h.
$l_{i,h}$	Thickness value of element i for household h [m].
LX_h	Length, width and height of household h, where X = {1,2,3} [m].
M_h	Mass of air in household h [kg].
N	Sufficiently large positive constant.
P_h^{AC}	Rated HVAC power in household h [kW].
P_t^{des}	Desired reduction in power in period t of the DR event [kW].
$P_{h,t}^{load}$	Inflexible load demand of household h in period t [kW].
$P_{h,t,\omega}^{AC,ref}$	Reference HVAC power consumption of household h in period t in scenario ω [kW].
$R_{eq,h}$	Equivalent thermal resistance of household h [K/W].
$T_{t,\omega}^{a}$	Ambient temperature in period t in scenario ω [℃].
$T_{h,t}^{dec,max}$	Maximum allowed temperature set-point decrease from the desired level of household h during the DR event [℃].
$T_{h,t}^{des}$	Desired temperature level of household h in period t [℃].
T_h^{DB}	HVAC dead-band temperature of household h [℃].
$T_{h,t}^{inc,max}$	Maximum allowed temperature set-point increase from the desired level of household h during the DR period [℃].
t_1	DR event starting time.
t_2	DR event ending time.
t_3	Starting period of the peak price horizon.
t_4	Ending period of the peak price horizon.
V_h	Volume of household h [m^3].
ΔT	Time interval [h].
δ_{air}	Density of air [kg/m^3].
$\sigma_{i,h}$	Element i thermal coefficient for household h $[W/(m \cdot K)]$.
β_h	Roof angle of household h [deg].
λ_t	Electricity price in period t [€/kWh].
π_ω	Probability of occurrence of scenario ω.

C. Variables

$Cost_h$	Energy cost of household h [€].
$CV_{h,\omega}$	Comfort violation of household h in scenario ω [℃ · h].
$E_{h,\omega}^{credit}$	Energy credit earned by household h during the DR event in scenario ω [kWh].
$p_{h,t,\omega}^{AC}$	Actual HVAC power consumption of household h in period t in scenario ω [kW].
$P_{h,t,\omega}^{credit}$	Power credit earned by household h in period t during the DR event in scenario ω [kW].
$P_{h,t}^{F}$	The power that household h can use free-of-charge in period t [kW].
$T_{h,t,\omega}^{dn}$	Indoor temperature decrease with respect to the desired temperature for household h in period t in scenario ω [℃].
$T_{h,t,\omega}^{in}$	Indoor temperature of household h in period t in scenario ω [℃].

This work was supported by FEDER funds through COMPETE 2020 and by Portuguese funds through FCT, under Projects SAICT-PAC/0004/2015 - POCI-01-0145-FEDER-016434, POCI-01-0145-FEDER-006961, UID/EEA/50014/2013, UID/CEC/50021/2013, UID/EMS/00151/2013, SFRH/BPD/103744/2014 and 02/SAICT/2017 - 029803. Also, the research leading to these results has received funding from the EU Seventh Framework Programme FP7/2007-2013 under grant agreement no. 309048.

O. Erdinç is with the Department of Electrical Engineering, Yildiz Technical University, Istanbul, Turkey (e-mail: oerdinc@yildiz.edu.tr). O. Erdinç is also with INESC-ID, Instituto Superior Técnico, University of Lisbon, Lisbon 1049-001, Portugal.

A. Tascikaraoglu is with the Department of Electrical and Electronics Engineering, Mugla Sitki Kocman University, Mugla, Turkey (e-mail: akintascikaraoglu@mu.edu.tr).

N. G. Paterakis is with the Department of Electrical Engineering, Eindhoven University of Technology (TU/e), PO Box 513, 5600 MB Eindhoven, The Netherlands (e-mail: n.paterakis@tue.nl).

J.P.S. Catalão is with INESC TEC and the Faculty of Engineering of the University of Porto, Porto 4200-465, Portugal, also with C-MAST, University of Beira Interior, Covilhã 6201-001, Portugal, and also with INESC-ID, Instituto Superior Técnico, University of Lisbon, Lisbon 1049-001, Portugal (e-mail: catalao@ubi.pt).

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/TIE.2018.2811403, IEEE Transactions on Industrial Electronics

$T_{h,t,\omega}^{set}$ Thermostat set-point of household h in period t in scenario ω by LSE [℃].

$T_{h,t,\omega}^{up}$ Indoor temperature increase with respect to the desired temperature for household h in period t in scenario ω [℃].

$u_{h,t,\omega}^{ac}$ Binary variable showing the HVAC status in household h in period t in scenario ω (1=ON, 0=OFF)

I. Introduction

A. Motivation

IN alignment with the technological advances during the last decades, the structure of the traditional electric power system has evolved from a top-down and relatively static structure to an increasingly active one, driven by the integration of small-scale, non-dispatchable renewable energy systems (RES) and the identification of the capability of several types of load to be managed. In this context, the operation of the power system has become more complex and improved operational strategies have been proposed and implemented under the vision for a smarter grid aiming at enhancing the economic performance and the reliability of the power system [1], [2].

One of the pillars of the Smart Grid concept is the augmentation of the RES hosting capacity of the existing power system structure by exploiting the operational flexibility that may be procured from resources other than conventional generation, potentially located at the edges of the grid [3]. One example of such a source of flexibility is the deployment of energy storage units at different scales, which is a conceptually mature idea, albeit economically constrained by significant operational and investment costs [4]. An alternative to investing in energy storage is to exploit the flexibility embedded in various types of existing loads through the development of demand response (DR) strategies suitable for the engagement of different types of end-users [5], [6].

There are two main categories of DR mechanisms: indirect load control (ILC) and direct load control (DLC) [7]. On the one hand, ILC solutions depend on pricing mechanisms and are not generally demanding in terms of infrastructure investments. However, there are factors – mostly sociological – affecting the performance of such solutions with respect to the desired operational objectives, since the response of the end-users to the applied pricing mechanisms does not necessarily assert the assumption of economic rationality. On the other hand, DLC solutions provide the system operator (SO) with direct access to controlling specific loads or even managing the whole demand of an end-user, in return of incentives offered on the basis of being enrolled in the DLC oriented DR program. As a result, DLC is considered a more effective way of procuring ancillary services such as frequency regulation, peak clipping, valley filling, etc., during critical system conditions [7]-[9]. For this reason, the implementation of DLC-based DR programs addressed to residential end-users that are responsible for around 40% of electrical energy consumption worldwide has attracted significant interest.

Thermostatically controllable loads (TCLs) such as heating, ventilation and air conditioning (HVAC) units, electric water heaters (EWHs) and refrigerators in residential premises present a promising potential on the grounds of the advantage of thermal inertia, which allows interrupting their operation without having a direct impact on the comfort of end-users.

B. Literature Overview

There are several studies in the literature dealing with the use of TCLs in residential areas for DR purposes. The aggregate modeling and control of a collection of heterogeneous TCLs was studied in [10]. Similarly, an approach based on formal abstractions was presented in [11] in order to generate a dynamical stochastic model as an aggregation of the continuous temperature dynamics of a certain number of TCLs.

An energy management approach taking into account various criteria such as appliance power values, end-user preferences, electricity price and expected residential renewable power generation in the decision process was proposed in [12]. A two-layer distributed DLC method based on average consensus algorithm was introduced in [13] for large-scale residential DR implementations. Besides, various DR-enabled TCL models at the appliance level were proposed in [14] by considering the operational and physical characteristics of different loads.

In order to leverage the high thermal inertia of EWHs in residential implementations, several studies have focused on the use of this type of TCLs. For instance, a dual-element EWH model was presented in [7] and a DLC algorithm was proposed to aggregate the EWH load with the objective of providing regulation services. The potential benefits of these units at both premise and substation levels were investigated in a field experiment in [15]. Balancing services procurement in terms of managing EWH loads through bi-directional signals from load serving entities (LSE) was also discussed in [16]. The effectiveness of an analytical approach, which has been previously developed for making use of TCLs to provide sporadic reserve capacity, was examined in [17] for a large number of EWHs. The capabilities of aggregated EWHs for load shifting and balancing reserve at the presence of wind penetration were examined in [18].

The potential of refrigerators, which are another widely-used type of TCLs, was studied in [19] and [20] in terms of their benefits when used for frequency regulation services in power grids. Aunedi et al. [8] considered the same problem in the case of high wind power penetration and presented various results showing the environmental and the economic benefits of deploying refrigerators for frequency regulation. A switching-rate actuation strategy for managing the power consumption of a collection of refrigerators was presented in [21] in order to enable these loads to participate in large-scale DLC applications.

Among the different TCLs that are found in typical households, HVAC units have a relatively high energy consumption and are related to system stress conditions through their contribution to the summer peak load demand [22], [23]. With the objective of using in DR applications, the aggregated behavior of HVAC units was studied by modeling the HVAC dynamics in [23] and by assessing the importance of the distributions of different HVAC physical parameters in [22]. In order to provide primary reserves by taking advantage of the mentioned peculiarities of HVACs, a DLC approach that can be used for the control of these units was proposed in [24]. Again for supporting the provision regulation services with the use of HVACs, Zhang et al. [25] presented an approach based on a second-order equivalent thermal parameter model, Hao et al. [26] proposed a feedforward algorithm to control fans in HVAC units, and, Goddard et al. [27] put forward a HVAC model including a small number of parameters that are determined using system identification.

Controlling HVAC systems has been also widely used for different power system operations effectively in the literature. Their benefits for various services such as load balancing, load shifting and peak load shaving were evaluated in [28] and [29] where design considerations for a centralized HVAC controller were presented. In [30], a market-based control method was considered for TCLs under transactive control paradigm to participate in real-time retail electricity markets. Besides, in order to alleviate the non-renewable power induced demand variations, a Lyapunov optimization-based DR method that controls the HVAC on/off states was presented in [31]. Similarly, for the purpose of matching the aggregated HVAC load demand with the wind power generation, a sliding mode controller based on Lyapunov theory to design a sliding mode controller was proposed in [32], and a distributed pinning control method was presented to coordinate the operation of a population of HVAC units in [33].

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/TIE.2018.2811403, IEEE Transactions on Industrial Electronics

TABLE I. TAXONOMY OF THE PROPOSED CONCEPT COMPARED TO REPRESENTATIVE LITERATURE STUDIES CONSIDERING SPECIFICALLY THE ROLE OF TCLS FOR DEMAND SIDE FLEXIBILITY

Ref.	DR Strategy		Consideration of thermal comfort		End-user type			TCL type				Point of view	
	ILC	DLC	Simply by boundaries	Advanced by index definitions, etc.	Res.	Com.	Ind.	HVAC	EWH	Refrigerator	Other (heat pump, etc.)	LSE	End-user
[7]	-	√	√	-	√	√	-	-	√	-	-	√	-
[8]	-	√	-	-	√	-	-	-	-	√	-	√	-
[10]	-	√	√	-	√	-	-	√	-	-	-	√	-
[11]	-	√	-	-	√	-	-	√	-	-	-	√	-
[15]	-	√	-	-	√	-	-	-	√	-	-	√	-
[16]	-	√	√	-	√	-	-	√	-	-	-	√	-
[17]	-	√	√	√	√	-	-	-	√	-	-	√	-
[18]	√	√	√	-	√	-	-	-	√	-	-	√	-
[19]	-	√	-	-	√	-	-	-	-	√	-	√	-
[36]	-	√	√	√	√	-	-	√	√	-	√	√	-
[37]	-	√	√	√	√	-	-	√	-	-	-	√	-
[41]	√	-	√	√	-	√	-	√	-	-	-	-	√
[42]	√	-	√	-	√	-	-	-	√	-	√	-	√
[43]	-	√	√	-	√	-	-	√	-	-	-	√	-
[44]	-	√	√	-	√	-	-	-	-	√	-	√	-
[45]	-	√	-	-	-	√	-	-	-	-	-	√	-
[46]	-	√	√	√	√	-	-	-	-	-	√	√	-
[47]	-	√	-	-	√	-	-	-	-	√	-	√	-
This paper	√	√	√	√	√	-	-	√	-	-	-	√	√

*Res.=Residential, Com.=Commercial, Ind.=Industrial

Regardless of its applications in power systems, several studies in the literature have focused on developing new control approaches that can be used for HVAC units. A stochastic method was proposed in [34] for controlling the aggregated power consumption of a high number of HVACs in a decentralized manner. Also, in order to take advantage of two widely-used direct HVAC demand control methods, namely the direct compressor control mechanism (DCCM) and the thermostat set-point control mechanism (TSCM), a combined control approach was presented in [35].

The literature studies that are discussed above have generally considered the DR problem from the perspective of LSEs and aggregators; however, the effectiveness of all the residential-based DR programs depends on the willingness of the end-users to a great extent and therefore, the concerns of the end-users and the potential benefits to be provided to them should be also taken into account for achieving the desired objectives in the applications at residential levels. With such an objective, Koutitas et al. [36] introduced the fairness concept between the end-users in a DLC program in terms of economic benefits; however, the fairness in the consumer comfort violation was not considered in this study. Erdinc et al. [37] developed a fairness-oriented approach to improve the satisfaction of the comfort level of end-users enrolled in a HVAC aggregation DLC program.

Besides, a robust optimization algorithm was presented in [38] to schedule the HVAC consumption for decreasing the electricity costs while taking into account the electricity price and the number of deviations from the comfortable temperature zone. A response fatigue index was introduced in [39] and this index was used in a stochastic model for the purpose of minimizing the electricity costs of consumers while maintaining their comfort level. In a recent study, Erdinc et al. [40] proposed the concept of offering energy credits to residential end-users while neglecting the impacts of different levels of desired peak load reduction ratios on the benefits of enrolled end-users in the DR program. However in [40], the scalability of the proposed energy credit approach was not discussed. There are also many studies considering the role of TCLs for providing demand side flexibility and a few of them can be found in [41]-[47].

C. Content and Contributions

The comprehensive review on the most recent literature shows that the majority of studies on DLC-based DR programs generally focus on the modelling of TCLs and/or employing these models for improved power system operations. These studies, however, have also reported that the potential benefits of DLC-based DR programs are substantially influenced by the number of end-users enrolled in DR programs and thus by their willingness to participate in these programs.

Considering this fact, a novel incentive mechanism is proposed in this paper in order to motivate the owners of residential HVAC units to engage in DLC DR programs. The proposed mechanism relies on providing energy credits to the end-users on the basis of their contribution during a DR event, which in turn can be used in periods outside the time span of a DR event in order to reduce their energy procurement cost.

The contributions of the study are as follows:

- An energy credit-based incentive structure is proposed for DLC applications for the purpose of providing the end-users with the opportunity of managing the trade-off between decreasing their energy costs and maintaining their comfort level.
- The proposed approach is tested in a stochastic day-ahead planning context by taking the uncertainty of the ambient temperature variations into account.
- The benefits of the end-user from the proposed incentive structure are analyzed in terms of operational cost reduction.
- The scalability of the approach and the impact of different demand side load reduction levels have been investigated via case studies.

The taxonomy of the proposed concept compared to representative studies on similar topics is given in Table I from which it can be seen that the current study clearly differs from the existing literature, especially by considering both DLC approach and consumer side ILC approach in a cause-effect relation taking both LSE and consumer sides into account.

D. Organization of the paper

The remainder of this paper is organized as follows: the proposed methodology is described in detail in Section II. The results are presented and extensively discussed in Section III. Finally, the conclusions and possible directions for future studies are summarized in Section IV.

II. METHODOLOGY

The concept proposed in this study is visualized in Fig. 1. It is assumed that the SO has the capability of communicating with the households and controlling their HVAC units during contracted DR events. The main objective of the SO is to reduce the peak load by limiting the use of residential HVAC units that have accepted to react during the DR event. It is to be noted that all the residential HVACs are considered to be available for the DR events in this study; nevertheless, this case can be easily extended to account for uncertainty in the availability of HVACs, e.g., due to communication failure or for consumer opt-out options.

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/TIE.2018.2811403, IEEE Transactions on Industrial Electronics

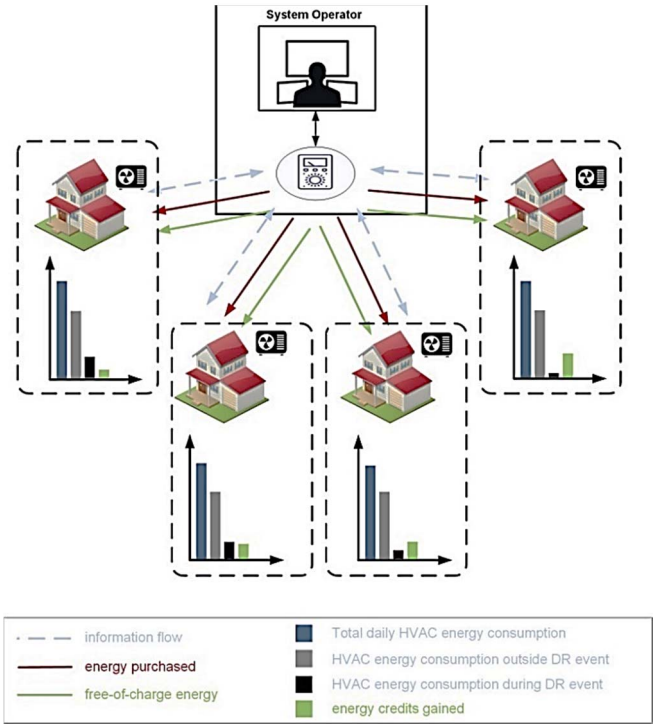


Figure 1. Overview of the proposed credit-based incentive mechanism.

During the DR periods, the end-users gain energy credits according to the reduction level in their HVAC units. In other words, the higher the reduction in the HVAC energy consumption, the more credits the end-users will obtain, as shown in Fig. 1. The credits, therefore, can be used in the periods with higher energy prices to induce cost savings.

A. Optimal procurement of HVAC load reduction during DR

The optimization problem that must be solved by the LSE in order to determine the optimal procurement of HVAC load reductions is represented by (1)-(12).

$$Minimize\ \text{Total Credit} = \sum_{\omega} \pi_{\omega} \cdot \sum_{h} E_{h,\omega}^{credit} \tag{1}$$

subject to:

$$T_{h,t}^{des} - T_{h,t}^{dec,max} \le T_{h,t,\omega}^{set} \le T_{h,t}^{des} + T_{h,t}^{inc,max}, \quad \forall h, t \in [t_1, t_2], \omega \tag{2}$$

$$T_{h,t,\omega}^{set} - T_h^{DB} \le T_{h,t,\omega}^{in} \le T_{h,t,\omega}^{set} + T_h^{DB}, \forall h, t, \omega \tag{3}$$

$$T_{h,t,\omega}^{in} = T_{h,t}^{des} + T_{h,t,\omega}^{up} - T_{h,t,\omega}^{dn}, \forall h, t, \omega \tag{4}$$

$$T_{h,t,\omega}^{up} \le N \cdot u_{h,t,\omega}^{ac}, \forall h, t, \omega \tag{5}$$

$$T_{h,t,\omega}^{dn} \le N \cdot \left(1 - u_{h,t,\omega}^{ac}\right), \forall h, t, \omega \tag{6}$$

$$T_{h,t,\omega}^{in} = \left(1 - \frac{\Delta T}{1000 \cdot M_h \cdot c_a \cdot R_{eq,h}}\right) \cdot T_{h,(t-1),\omega}^{in} + \frac{\Delta T}{1000 \cdot M_h \cdot c_a \cdot R_{eq,h}} \cdot T_{t-1,\omega}^{a} - \frac{COP_h \cdot P_h^{AC} \cdot \Delta T}{0.000277 \cdot M_h \cdot c_a} \cdot u_{h,t,\omega}^{ac}, \quad \forall h, t > 1, \omega \tag{7}$$

$$p_{h,t,\omega}^{AC} = P_h^{AC} \cdot u_{h,t,\omega}^{ac}, \forall h, t, \omega \tag{8}$$

$$P_{h,t,\omega}^{credit} = P_{h,t,\omega}^{AC,ref} - p_{h,t,\omega}^{AC}, \forall h, t \in [t_1, t_2], \omega \tag{9}$$

$$p_t^{des} \le \sum_{h} P_{h,t,\omega}^{credit}, \forall t \in [t_1, t_2], \omega, \quad if \sum_{h} P_{h,t,\omega}^{AC,ref} \ne 0 \tag{10}$$

$$p_{h,t,\omega}^{AC} = 0, \forall h, t \in [t_1, t_2], \omega\ if\ P_{h,t,\omega}^{AC,ref} = 0 \tag{11}$$

$$E_{h,\omega}^{credit} = \sum_{\tau=t_1}^{t_2} P_{h,t,\omega}^{credit} \cdot \Delta T\ , \forall h, \omega \tag{12}$$

The objective function stands for the minimization of the expected total free-of-cost energy credits awarded to the consumers over the horizon, on the basis of the load reductions procured through the DLC DR program. In this study, the TSCM is adopted, considering that the LSE directly manipulates the thermostat temperature set-point $T_{h,t,\omega}^{set}$. Thus, the main decision variable for the operation of the proposed methodology is $T_{h,t,\omega}^{set}$. This approach is considered more suitable for peak load reduction compared to DCCM. The temperature set-point $T_{h,t,\omega}^{set}$ can be changed during DR event horizon within the limits defined in the contract between the end-user and the LSE as expressed by (2).

The indoor temperature limits are defined by (3), where T_h^{DB} stands for the dead-band control parameter. In order to estimate the end-users' comfort violation the indoor temperature is decomposed based on (4), while (5) and (6) enforce the fact that an upward and a downward temperature deviation with respect to the user's desired temperature set-point cannot have non-zero values simultaneously. Regarding the indoor temperature, a model based on the equivalent thermal resistance of the household is used in this study, as represented by (7) considering solely the cooling operation, while the model for heating mode can also be trivially derived. Considering a rectangular geometry and an inclination of the roof of β°, the equivalent thermal resistance of the houses and the air mass inside them can be calculated using (13)-(15).

$$R_{eq,h} = \frac{1}{N^e} \sum_{i} \frac{l_{i,h}}{\sigma_{i,h} \cdot A_{i,h}}, \forall i, h \tag{13}$$

$$V_h = L1_h \cdot L2_h \cdot L3_h + tan(\beta_h) \cdot L1_h \cdot L2_h, \forall h \tag{14}$$

$$M_h = V_h \cdot \delta_{air}, \forall h \tag{15}$$

It should be noted that the interaction of air mass and building envelop mass, the influence of solar radiation, and natural air exchange are not taken into account in the study. Moreover, without loss of generality, the HVAC system is acting as an air conditioning unit in the proposed formulation.

The HVAC power consumption of each household h in period t in scenario ω follows (8). The reduced power value for each household compared to reference HVAC operation pattern that will be added as a credit to each household during the DR event is calculated by (9). The stochasticity in the reference HVAC operating pattern is related to the uncertainty of the ambient temperature variations during the DR event apart from the physical structure of the households. The total of the power values added to household credits should be equal or greater than the desired load reduction by LSE if the total of the reference HVAC consumption patterns of households is non-zero as in (10).

The household HVAC power is restricted to be zero by (11) if the reference HVAC power consumption pattern of this household is already zero in period t in scenario ω. Besides, the baseline of HVAC load is calculated based on the power that would have been consumed if a DR event had not taken place. The total obtained energy credit per household during the DR event to be further used in the subsequent periods to achieve economic benefits is calculated by (12). To clarify the concept behind the proposed approach, first of all, it should be noted that high prices for the residential end-users regardless of the type of varying pricing scheme (Time-of-Use pricing, dynamic pricing, etc.) coincide with peak demand periods of residential end-users (generally between 6 pm and 10 pm). However in reality, the system peak in most countries occurs around the noon on hot summer days. Therefore, many real-life DR programs, including residential end-user load aggregation oriented programs, target noon hours of very hot summer days to incentivize end-users to aid reducing the overall system peak loading conditions. As it can also be followed from the practical evidence (e.g., see the residential DR practice in Australia given in Ref. [41]), the residential end-users are incentivized for their energy reduction in noon times which are generally off-peak hours for residential premises.

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/TIE.2018.2811403, IEEE Transactions on Industrial Electronics

Therefore, a different way incentivizing the residential end-users rather than flat payments is offered in this study to gain more, proportionally to the discomfort they are subjected to. Thus, the incentivized time from the LSE side and normal benefit time from end-user side are not contradictory, and the concept proposed in this study shows a structure compatible with the way of implementing DR in real-world applications.

It is worth mentioning that the LSE aims at maintaining the supply and demand balance by reducing the demand. However, the LSE should not be willing to maximize the credit to be given to the end-users. On the contrary, as the satisfaction of the reduction of required levels of power compared to the reference conditions provided by scenarios is already ensured by constraint (10), the LSE would be willing to give minimum credits to the end-users in case of a DR event. Besides, the objective function requests that the minimum amount of credits is given such that the required load reduction is achieved. Giving more credits after having satisfied the load reduction is not economically beneficial for the LSE as these extra credits will unnecessarily lower the income of the LSE in peak price periods. Therefore, the ultimate purpose of the LSE is the minimization of credit costs that are required to level supply and demand by demand side power reduction via the applied DR program. The comfort violation of household h in scenario ω is calculated in ${}^{0}C.h$ using (16), in which the upward and downward deviations from the desired temperature set-point is considered.

$$CV_{h,\omega} = \sum_{\tau=t_1}^{t_2} \left(T_{h,t,\omega}^{up} + T_{h,t,\omega}^{dn}\right) \cdot \Delta T \,, \forall h, \omega \qquad (16)$$

It should be noted that the comfort of end-users depends on many physical factors such as the occupancy of a room, their activities, the type of clothing, etc. rather than solely on the indoor temperature. However, modeling these factors is complex, while an attempt of SOs to gather such information could violate the privacy of the end-users. On the contrary, this study is based on the assumption that the end-users have already conveyed their preferences by limiting the maximum and minimum permitted indoor temperature values to the SO. Regarding the output (see Section III.A), the model gives the optimal schedule for each household's HVAC unit in each scenario and the corresponding credits the household owners gain proportionally to the comfort violation they experience during the DR event.

B. Evaluation of Performance

To evaluate the performance of the proposed DLC-DR scheme, the impacts on the daily operational cost and the extent of end-users' comfort violation during the DR event are considered. First, the maximum energy procurement cost reduction for each household is calculated by solving the optimization problem described by (17)-(19). Equality (17) stands for the minimization of the energy cost. As regards the utilization of the free-of-cost energy credits, they can only be used once the DR event is over, as expressed by (18). Finally, (19) constrains the activation of credits to the amount earned during the DR event.

$$Minimize\ Cost_h = \sum_{t} \left[\left(P_{h,t}^{load} - P_{h,t}^{F}\right) \cdot \Delta T \cdot \lambda_t\right], \forall h \qquad (17)$$

subject to:

$$\sum_{\tau=t_3}^{T} \left(P_{h,t}^{F} \cdot \Delta T\right) \le \sum_{\omega} \pi_\omega \cdot E_h^{credit}, \forall h, t \in [t_3, t_4] \qquad (18)$$

$$P_{h,t}^{F} \le P_{h,t}^{load}, \forall h, t \in [t_3, t_4] \qquad (19)$$

III. Tests And Results

A. Input Data

In order to demonstrate the use of the proposed concept, 40 identical households having the structural parameters shown in Table II are considered for simplicity while discussing the results, as in [37].

The air density and thermal capacity are considered constant and equal to $\delta_{air} = 1.225\ kg/m^3$ and $c_a = 1.01\ kJ/kg{\cdot}K$ for standard conditions. Besides, it is assumed that all the households have identical HVAC units with a power rating of 3 kW and a coefficient-of-performance of 2. Besides, a peak-reduction DR event is assumed to be activated between 1 pm and 3 pm on the considered day. The initial room temperatures of households are randomly allocated between 19.1^0C and 20.9^0C.

Other temperature related parameters for households are provided in Table III. Moreover, 10 equiprobable scenarios for the ambient temperature variation during the considered DR event period are randomly generated considering a variation band around the real measured temperature data.

The scenarios are shown in Fig. 2. A time granularity of 5 min (0.0833h) is adopted in the model and GAMS 24.0.2 with the solver CPLEX 12 is used for solving the optimization problem.

B. Simulation and Results

The desired load reduction during an actual DR event when the reference HVAC power is non-zero is initially assumed to be 12 kW from the total of the 40 households, which is 10% of maximum dispatchable total HVAC power for the considered households with the given HVAC rated power values. It should be noted that if the reference HVAC power is zero, the constraint for $P_{des,t}$ is the not enforced for these intra-hour periods since no actual reduction from zero is possible.

Figures 3-5 depict the actual reference HVAC power and the HVAC power consumption for Scenarios 1-3. It is clear that for all non-zero reference HVAC power periods, the system deploys sufficient HVAC units to reduce the HVAC load demand by the desired amount. As the methodology should satisfy the desired load reduction in all scenarios, results regarding the other scenarios are not provided here.

The comfort violation index value for individual households during DR event is presented in Fig. 6. For the sake of simplicity, the mean value of the comfort violation index values among the scenarios is portrayed for each household. The individual comfort violation among the enrolled end-users varies considerably; however, as the households gain more free-of-cost energy credits when their comfort violation increases, no more constraints regarding fairly allocation of comfort violation among the enrolled end-users as in [37] are enforced in this study.

The mean free-of-cost energy credit values are shown in Fig. 7. Similar to Fig. 6, the mean value of energy credit values is given for each household. The free-of-cost energy credit value generally increases with the increase of comfort violation as can be observed by comparing Figs. 6 and 7, thus the individual end-users facing more discomfort during the DR event will generally have more chance to reduce their electricity costs with the use of the obtained free-of-cost energy credits.

The impacts of increasing the desired load reduction during non-zero HVAC reference power periods from 12 kW to 24 kW (20% of the dispatchable total contracted HVAC loads) are shown in Figs. 8 and 9 in terms of comfort violation and free-of-cost energy credits.

TABLE II. PHYSICAL PARAMETERS OF THE HOUSEHOLDS

Parameter	*Value*	*Unit*	*Parameter*	*Value*	*Unit*
House length (L_1)	30	m	Area of windows	1	m^2
House width (L_2)	10	m	Wall thermal coefficient	0.038	$W/(m \cdot K)$
House height (L_3)	4	m	Window thermal coefficient	0.781	$W/(m \cdot K)$
Roof angle (β)	40	deg	Windows thickness	0.05	m
Window numbers	6	-	Wall thickness	0.15	m

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/TIE.2018.2811403, IEEE Transactions on Industrial Electronics

The increase in the desired load reduction value increases the comfort violation as the SO should intervene with the use of more HVAC loads via manipulating the temperature set-points. However, as a result, the free-of-cost energy credit values increase as well as the comfort violation among the contracted end-users.

TABLE III. TEMPERATURE-RELATED PARAMETERS OF THE HOUSEHOLDS

Parameter	*Value*	*Unit*
$T_{des,h}$	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

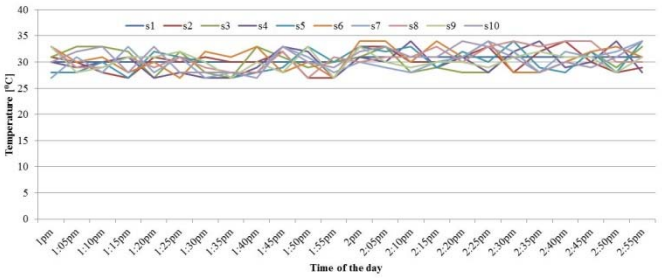


Figure 2. Scenarios for ambient temperature variation.

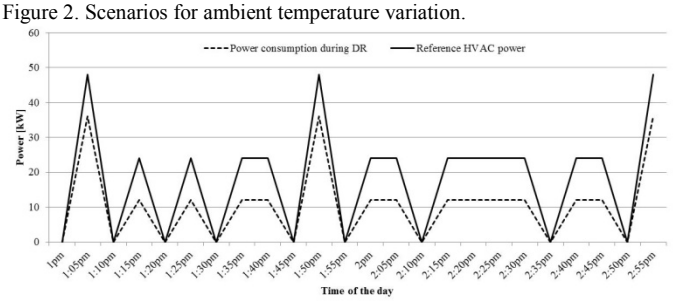


Figure 3. HVAC power consumption during the DR event for Scenario 1.

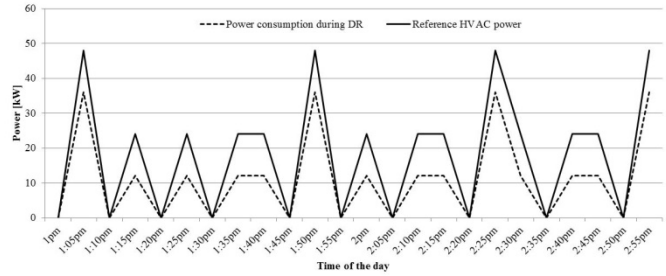


Figure 4. HVAC power consumption during the DR event for Scenario 2.

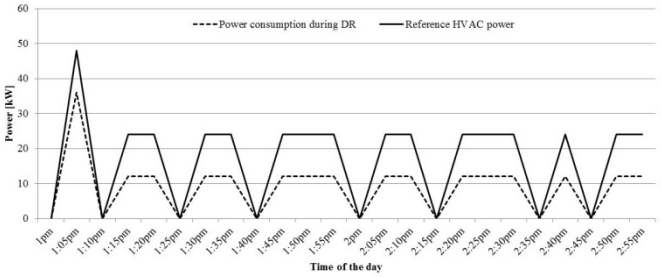


Figure 5. HVAC power consumption during the DR event for Scenario 3.

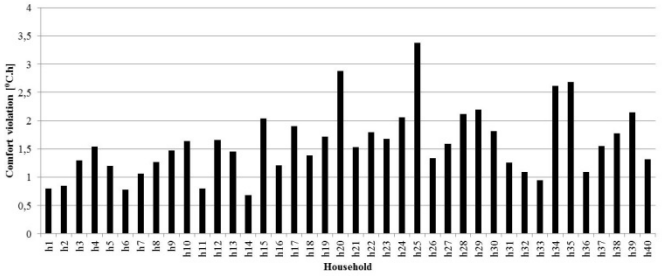


Figure 6. The comfort violation index value of end-users experienced during DR event.

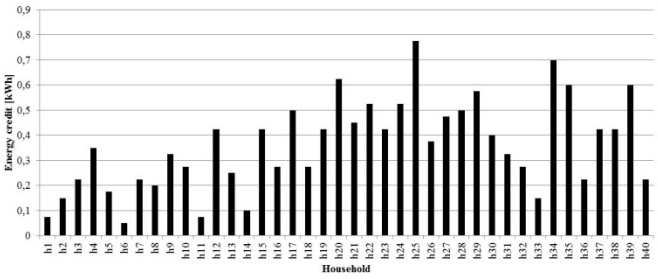


Figure 7. The free-of-cost energy value of end-users gained during DR event.

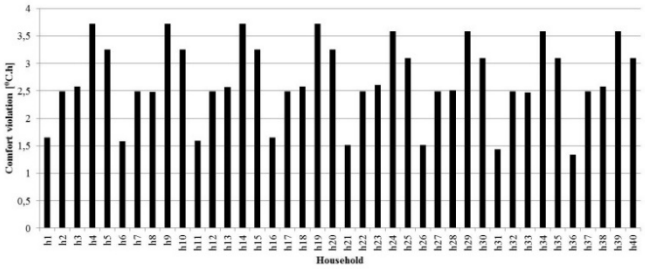


Figure 8. The comfort violation index value of end-users experienced during DR event if the desired power reduction is increased to 24 kW.

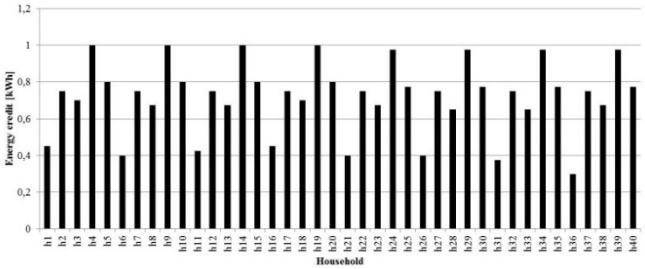


Figure 9. The free-of-cost energy value of end-users gained during DR event if the desired power reduction is increased to 24 kW.

Results regarding the load reduction performance of the proposed concept if the desired power reduction is increased to 24 kW are shown in Figs. 10-12. The increased load reduction requirement is still satisfied for non-zero HVAC power reference periods. In order to present the economic benefits of the end-users from the obtained energy credits, a test case is provided for selected households that gained 0.7747 kWh and 0.9996 kWh free-of-cost energy credits during the DR cases of 12 kW and 24 kW desired load reduction levels, respectively.

This energy credit can be used by the end-user during the peak price period between 6 pm and 9 pm of the price variation shown in Fig. 13 [30]. The inflexible power demand of a 4-member household including several loads is presented in Fig. 14 [12] for the mentioned peak-price period. The cost reduction oriented residential household energy management system allocates a free-of-cost power variation from the grid as shown in Figs. 15 and 16 for 0.7747 kWh and 0.9996 kWh free-of-cost energy credit values, respectively. As it can be seen, the free-of-cost power variation that is limited by the energy credit of the household is scheduled for the highest price period to enable purchasing less energy with cost for reducing the daily operational costs.

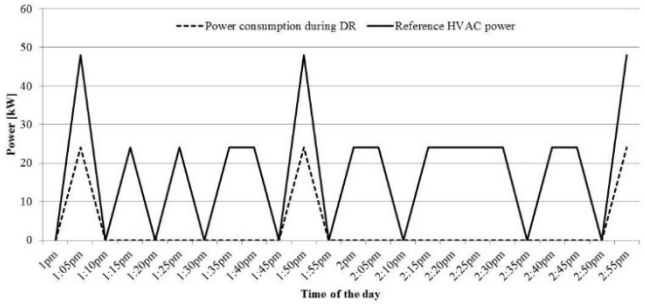


Figure 10. The HVAC power consumption during the DR event for Scenario-1 if the desired power reduction is increased to 24 kW.

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/TIE.2018.2811403, IEEE Transactions on Industrial Electronics

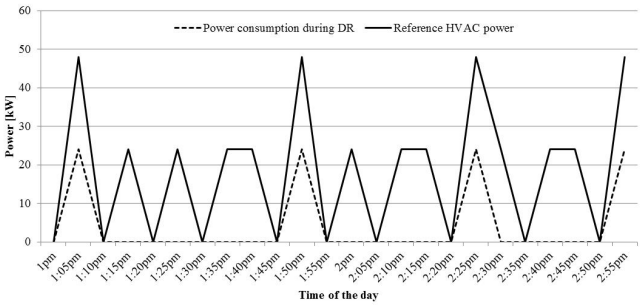


Figure 11. The HVAC power consumption during the DR event for Scenario-2 if the desired power reduction is increased to 24 kW.

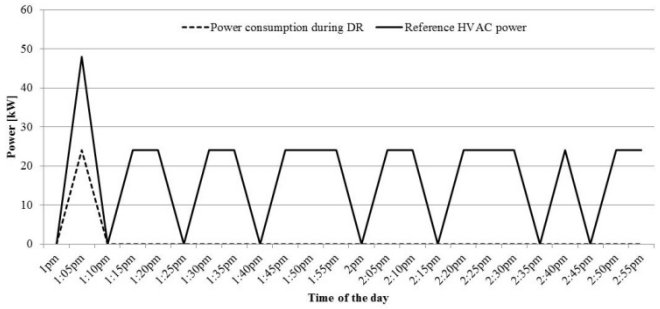


Figure 12. The HVCA power consumption during the DR event for Scenario-3 if the desired power reduction is increased to 24 kW.

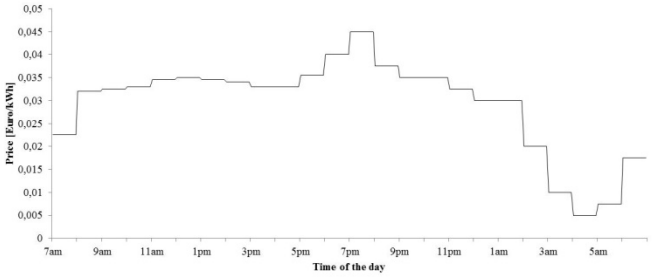


Figure 13. The daily dynamic pricing signal.

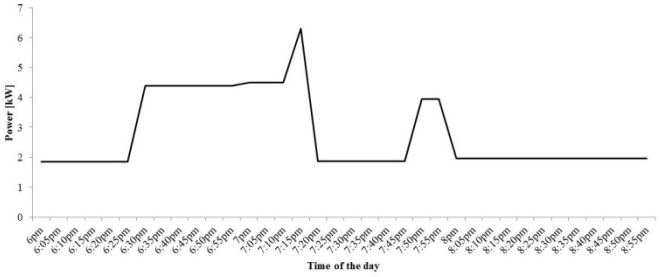


Figure 14. The power demand of the household during peak-price period.

The relevant results for the total operational costs during the peak price period with and without energy credits are summarized in Table IV. The proposed energy credits-based strategy enables around 10% of total cost reduction, which is a considerable benefit for the enrollment of the end-users for such DR programs.

In order to analyze the scalability of the proposed approach, the same concept is applied to a collection of 250 households with the identical physical structure given above in Table II. In addition, the desired temperature levels of households are varied between 18^0C and 22^0C to enhance the complexity of the analysis from end-users' preferences point of view. It is assumed in this analysis that the LSE requests a 50 kW of reduction during the DR event. The relevant results for HVAC power consumption for first three scenarios of 250 households are depicted in Figs. 17-19. As it can be observed, the required levels of load reduction are obtained in all scenarios from the LSE point of view. As the number of flexible resources increases compared to the case of 40 households, the LSE requests less amount of average comfort violation from the households, and in turn gives fewer amounts of average credits.

Here, as an example, house 7 gains a credit that lowers the household consumption cost by 2% by its allowed comfort violation based HVAC operation. Here, it should be noted that the computational burden of increasing the scale of the problem is negligible (less than 1 second), therefore depicting the scalability of the approach.

It should be mentioned that the uncertainty regarding the operation of the HVAC is not only related to the ambient temperature; however, dealing specifically with the uncertainty resources in HVAC operation was the subject of several studies in the literature (e.g. [48]), while the proposed concept can be readily extended by increasing the number of uncertainty sources in the stochastic formulation.

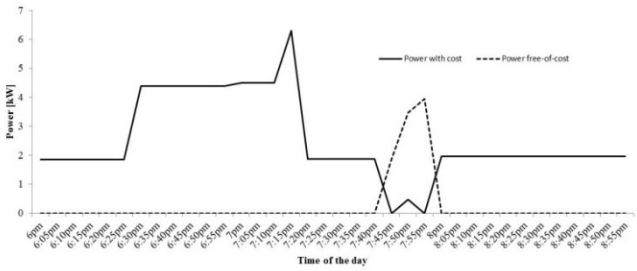


Figure 15. The power decomposition for free-of-cost energy credit value of 0.7747 kWh.

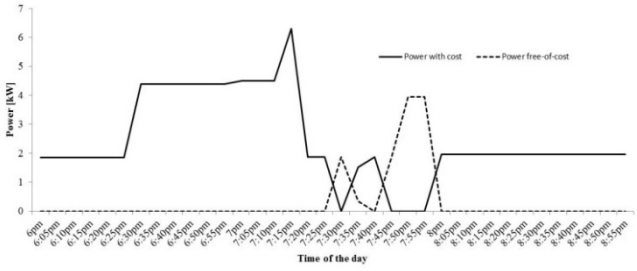


Figure 16. The power decomposition for free-of-cost energy credit value of 0.9996 kWh.

TABLE IV. COMPARISON OF TOTAL COSTS WITH AND WITHOUT ENERGY CREDITS

Energy credit value [kWh]	*Total cost during peak price period [Euro]*	
	Without energy credit	*With energy credit*
0.7747	0.344	0.309
0.9996		0.299

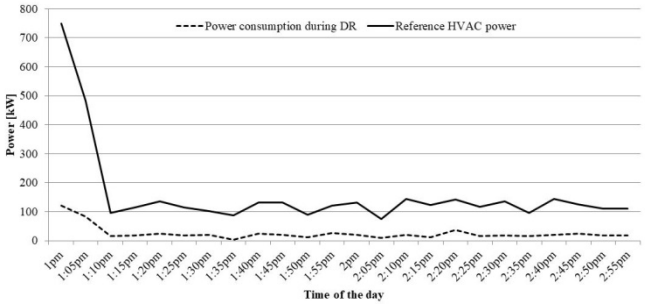


Figure 17. HVAC power consumption during the DR event for Scenario 1 of 250 households.

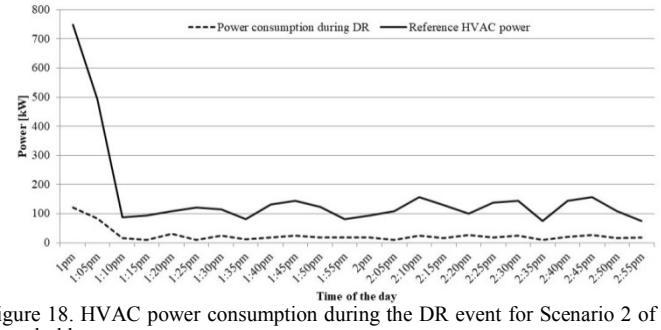


Figure 18. HVAC power consumption during the DR event for Scenario 2 of 250 households.

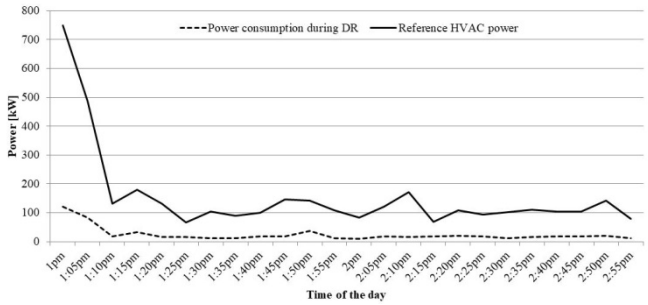


Figure 19. HVAC power consumption during the DR event for Scenario 3 of 250 households.

IV. Conclusions and Future Research

In this study, a novel DLC approach based on allocating energy credits was proposed in order to present end-users with an opportunity for reducing their electricity costs. With the objective of realizing this commitment without radically affecting the comfort level of end-users, free energy credits were provided to residential end-users enrolled in the DR program on the condition that intervention to their HVAC units during predefined DR events was allowed. The end-users can then use these credits during the periods with high energy prices for considerable cost savings. The effectiveness of the energy credits-based incentive strategy was thoroughly examined in a day-ahead planning context in terms of operational cost reduction, regarding also the uncertainty of ambient temperature variations, and the results showed that the proposed strategy accomplished a total cost reduction of around 10%, which is very significant and can be pointed out as a decisive factor for increasing the participation ratio of end-users into the DR programs.

The future directions of the study can be listed as follows:

- The detailed investigation of the benefits of such reductions from the perspective of LSEs, including their contribution to the operational power system procedures such as peak load leveling and frequency regulation.
- The implementation of the proposed credit-based strategy for different TCLs such as EWH and refrigerators, and also on the households with energy storage systems.
- In this context, instead of individual storage systems, shared energy storage systems can be considered as these systems provide higher energy storage capacities with lower costs to each end-user, also taking into account the fairness in the allocation of these capacities.
- The impact of other physical factors such as the number of users, their activities, their clothes, etc. rather than solely the indoor temperature variation on the comfort of end-users.
- The power flow is neglected in this study as the considered area is considerably smaller (a common LV bus of a distribution system) that can be managed by a distributed approach e.g. by an aggregator rather than a centralized approach e.g. by a distribution system operator. If a wider area of the power network was considered, it would be vital to also consider multiple load aggregation areas and therefore the interaction of different system buses by network constraints.
- The evaluation of the benefits of the proposed approach based on a robust optimization algorithm might decrease the unfavorable effects of the uncertainties that can appear in the system (e.g. by adding end-user opt-out preferences, by including different system components with stochastic characteristics, etc.).

V. References

[1] P. He, M. Li, l. Zhao, B. Venkatesh, and H. Li, "Water-filling exact solutions for load balancing of smart power grid systems," *IEEE Trans. Smart Grid*, 2017, article in press.

[2] Y. Gong, Y. Cai, Y. Guo, and Y. Fang, "A privacy-preserving scheme for incentive-based demand response in the smart grid," *IEEE Trans. Smart Grid*, vol. 7, pp. 1304-1313, May 2016.

[3] N. G. Paterakis, O. Erdinc, A. G. Bakirtzis, and J. P. S. Catalao, "Load-following reserves procurement considering flexible demand-side resources under high wind power penetration," *IEEE Trans. Power Systems*, vol. 30, pp. 1137-1350, May 2015.

[4] W. Tushar, B. Chai, C. Yuen, S. Huang, D. B. Smith, H. V. Poor, and Z. Yang, "Energy storage sharing in smart grid: A modified auction-based approach," *IEEE Trans. Smart Grid*, vol. 7, pp. 1462-1475, May 2016.

[5] A. Gholian, H. Mohsenian-Rad, and Y. Hua, "Optimal industrial load control in smart grid," *IEEE Trans. Smart Grid*, vol. 7, pp. 2305-2316, Sep. 2016.

[6] A. Safdarian, M. Fotuhi-Firuzabad, and M. Lehtonen, "Optimal residential load management in smart grids: A decentralized framework," *IEEE Trans. Smart Grid*, vol. 7, pp. 1836-1845, July 2016.

[7] 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.

[8] 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.

[9] I. Tinnirello, G. Neglia, L. Giarre, G. Di Bella, A. Jean-Marie, and M. Ippolito, "Large scale control of deferrable domestic loads in smart grids," *IEEE Trans. Smart Grid*, 2017, *in press*.

[10] J. Hu, J. Cao, M. Z. Q. Chen, J. Yu, J. Yao, S. Yang, and T. Yong, "Load following of multiple heterogeneous TCL aggregators by centralized control," *IEEE Trans. Power Systems*, 2017, *in press*.

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

[12] O. Elma, A. Taşcıkaraoğlu, A. T. İnce, and U. S. Selamoğulları, "Implementation of a dynamic energy management system using real time pricing and local renewable energy generation forecasts," *Energy*, vol. 134, pp. 206-220, 2017.

[13] C. Chen, J. Wang, and S. Kishore, "A Distributed Direct Load Control Approach for Large-Scale Residential Demand Response," *IEEE Trans. on Power Systems*, vol. 29, no. 5, pp. 2219-2228, Sept. 2014.

[14] 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.

[15] 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.

[16] 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.

[17] A. Abiri-Jahromi, and F. Bouffard, "Contingency-Type Reserve Leveraged Through Aggregated Thermostatically-Controlled Loads—Part II: Case Studies," *IEEE Trans. Power Systems*, vol. 31, no. 3, pp. 1981-1989, May 2016.

[18] 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.

[19] 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.

[20] V. Lakshmanan, M. Marinelli, J. Hu, and H. W. Bindner, "Provision of secondary frequency control via demand response activation on thermostatically controlled loads: Solutions and experiences from Denmark," *Appl Energy*, vol. 173, no. 1, pp 470-480, July 2016.

[21] L. C. Totu, R. Wisniewski, and J. Leth, "Demand response of a TCL population using switching-rate actuation," *IEEE Trans. Control Systems Technology*, 2017, *in press*.

[22] 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.

[23] 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.

[24] H. Hao, B. M. Sanandaji, K. Poolla, and T. L. Vincent, "Aggregate Flexibility of Thermostatically Controlled Loads," *IEEE Trans. Power Systems*, vol. 30, no. 1, pp. 189-198, Jan. 2015.

[25] 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.

[26] 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.

[27] 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.

[28] 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.

[29] 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.

[30] S. Behboodi, D. P. Chassin, N. Djilali, and C. Crawford, "Transactive control of fast-acting demand response based on thermostatic loads in real-time retail electricity markets," *Applied Energy*, 2017, *in press*.

[31] 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.

[32] 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.

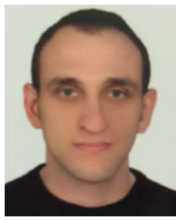
[33] J. Hu, J. Cao, T. Yong, J. M. Guerrero, M. Z. Q. Chen, and Y. Li, "Demand response load following of source and load systems," *IEEE Trans. Control Systems Technology*, 2017, *in press*.

[34] 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.
[35] 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.
[36] G. Koutitas, "Control of flexible smart devices in the smart grid," *IEEE Trans. Smart Grid*, vol. 3, pp. 1333-1343, Sep. 2012.
[37] O. Erdinc, A. Tascikaraoglu, N. Paterakis, Y. Eren, and J. P. S. Catalao, "End-user comfort oriented day-ahead planning for responsive residential HVAC demand aggregation considering weather forecasts," *IEEE Trans. Smart Grid*, vol. 7, pp. 362-372, Jan. 2017.
[38] Y. Du, L. Jiang, C. Duan, Y. Li, and J. S. Smith, "Energy Consumption Scheduling of HVAC Considering Weather Forecast Error through Distributionally Robust Approach," *IEEE Trans. Industrial Informatics*, 2017, in press.
[39] M. Shafie-khah and P. Siano, "A Stochastic Home Energy Management System considering Satisfaction Cost and Response Fatigue," *IEEE Trans. Industrial Informatics*, 2017, in press.
[40] O. Erdinc, A. Tascikaraoglu, N. G. Paterakis, J. P. S. Catalao, "An Energy Credit Based Incentive Mechanism for the Direct Load Control of Residential HVAC Systems Incorporation in Day-Ahead Planning," *IEEE PowerTech Conference*, Manchester, UK, 18-22 June 2017.
[41] Y. J. Kim, "Optimal Price-Based Demand Response of HVAC Systems in Multi-Zone Office Buildings Considering Thermal Preferences of Individual Occupants," *IEEE Trans. Industrial Informatics*, 2018, in press.
[42] F. Ruelens, B. J. Claessens, S. Vandael, B. De Schutter, R. Babuska, and R. Belmans, "Residential Demand Response of Thermostatically Controlled Loads Using Batch Reinforcement Learning," *IEEE Trans. Smart Grid*, vol. 8, pp. 2149-2159, Sept. 2017.
[43] J. Hu, J. Cao, T. Yong, J. M. Guerrero, M. Z. Q. Chen, and Y. Li, "Demand Response Load Following of Source and Load Systems," *IEEE Trans. Control System Technology*, vol. 25, pp. 1586-1598, Sept. 2017.
[44] L. C. Totu, R. Wisniewski, and J. Leth, "Demand Response of a TCL Population Using Swithcing-Rate Actuation," *IEEE Trans. Control System Technology*, vol. 25, pp. 1537-1551, Sept. 2017.
[45] 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.
[46] N. Good, E. Karangelos, A. N. Espinosa, and P. Mancarella, "Optimization Under Uncertainty of Thermal Storage-Based Flexible Demand Response With Quantification of Residential Users' Discomfort," *IEEE Trans. Smart Grid*, vol. 6, pp. 2333-2342, Sept. 2015.
[47] E. C. Kara, M. Berges, and G. Hug, "Impact of Disturbances on Modeling of Thermostatically Controlled Loads for Demand Response," *IEEE Trans. Smart Grid*, vol. 6, pp. 2560-2568, Sept. 2015.
[48] 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.

BIOGRAPHIES

Ozan Erdinc (M'14-SM'16) received the B.Sc., M.Sc., and Ph.D. degrees from Yildiz Technical University (YTU), Istanbul, Turkey, in 2007, 2009, and 2012, respectively. Until May 2013, he worked in the private sector in different positions including electrical installations, renewable energy investments and as procurement expert. In June 2013, he became a Postdoctoral Fellow with the University of Beira Interior, Covilhã, Portugal, under the EU-FP7 funded Project "Smart and Sustainable Insular Electricity Grids Under Large-Scale Renewable Integration". Later, he joined the Department of Electrical Engineering, YTU, Istanbul, where in April 2016 he obtained the title of *Doçent Dr.* (Associate Prof. Dr.). He is currently also a Researcher with the INESC-ID, Lisbon, Portugal.

Prof. Erdinc is an Editor of the IEEE TRANSACTIONS ON SUSTAINABLE ENERGY since February 2018. His research interests are hybrid renewable energy systems, electric vehicles, power system operation, and smart grid technologies.



Akın Tascikaraoglu (S'12-M'14) received the B.Sc., M.Sc., and Ph.D. degrees from Yildiz Technical University, Istanbul, Turkey, in 2006, 2008, and 2013, respectively. From February 2012 to October 2017 he was a researcher in the Department of Electrical Engineering, Yildiz Technical University, Istanbul. Also, he was a Postdoctoral Scholar at the University of California, Berkeley from April 2013 to April 2014. He is currently an Assistant Professor with the Department of Electrical and Electronics Engineering, Mugla Sitki Kocman University, Mugla. His research interests include among others forecasting, renewable energy, power system operation, smart grid, and demand response.

Nikolaos G. Paterakis (S'14-M'15) received the Dipl. Eng. degree from the Department of Electrical and Computer Engineering, Aristotle University of Thessaloniki, Thessaloniki, Greece in 2013 and the Ph.D. degree from the University of Beira Interior, Covilhã, Portugal in 2015. From October 2015 to March 2017 he was a Post-Doctoral Fellow with the Department of Electrical Eng ineering, Eindhoven University of Technology, Eindhoven, The Netherlands, where he is currently an Assistant Professor. His research interests include power systems operation and planning, renewable energy integration, ancillary services, demand response and smart grid applications.

João P. S. Catalão (M'04-SM'12) received the M.Sc. degree from the Instituto Superior Técnico (IST), Lisbon, Portugal, in 2003, and the Ph.D. degree and Habilitation for Full Professor ("Agregação") from the University of Beira Interior (UBI), Covilha, Portugal, in 2007 and 2013, respectively.

Currently, he is a Professor at the Faculty of Engineering of the University of Porto (FEUP), Porto, Portugal, and Researcher at INESC TEC, INESC-ID/IST-UL, and C-MAST/UBI. He was the Primary Coordinator of the EU-funded FP7 project SiNGULAR ("Smart and Sustainable Insular Electricity Grids Under Large-Scale Renewable Integration"), a 5.2-million-euro project involving 11 industry partners. He has authored or coauthored more than 600 publications, including 215 journal papers (more than 60 IEEE Transactions/Journal papers), 335 conference proceedings papers, 2 books, 34 book chapters, and 14 technical reports, with an *h*-index of 35, an *i10*-index of 135, and over 5500 citations (according to Google Scholar), having supervised more than 50 post-docs, Ph.D. and M.Sc. students. He is the Editor of the books entitled *Electric Power Systems: Advanced Forecasting Techniques and Optimal Generation Scheduling* and *Smart and Sustainable Power Systems: Operations, Planning and Economics of Insular Electricity Grids* (Boca Raton, FL, USA: CRC Press, 2012 and 2015, respectively). His research interests include power system operations and planning, hydro and thermal scheduling, wind and price forecasting, distributed renewable generation, demand response and smart grids.

Prof. Catalão is an Editor of the IEEE TRANSACTIONS ON SMART GRID, an Editor of the IEEE TRANSACTIONS ON POWER SYSTEMS, and an Associate Editor of the *IET Renewable Power Generation*. From 2011 till 2018 (seven years) he was an Editor of the IEEE TRANSACTIONS ON SUSTAINABLE ENERGY. He was the Guest Editor-in-Chief for the Special Section on "Real-Time Demand Response" of the IEEE TRANSACTIONS ON SMART GRID, published in December 2012, and the Guest Editor-in-Chief for the Special Section on "Reserve and Flexibility for Handling Variability and Uncertainty of Renewable Generation" of the IEEE TRANSACTIONS ON SUSTAINABLE ENERGY, published in April 2016. Since May 2017, he is the Corresponding Guest Editor for the Special Section on "Industrial and Commercial Demand Response" of the IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS. He was the recipient of the 2011 Scientific Merit Award UBI-FE/Santander Universities, the 2012 Scientific Award UTL/Santander Totta, the 2016 FEUP Diploma of Scientific Recognition, and the Best INESC-ID Researcher 2017 Award, in addition to an Honorable Mention in the 2017 Scientific Awards ULisboa/Santander Universities. Moreover, he has won 4 Best Paper Awards at IEEE Conferences.