An Energy Credit Based Incentive Mechanism for the Direct Load Control of Residential HVAC Systems Incorporation in Day-Ahead Planning

Ozan Erdinç and Akın Taşcıkaraoğlu,
Department of Electrical Engineering
Yildiz Technical University,
Istanbul, Turkey
oerdinc@yildiz.edu.tr;
atasci@yildiz.edu.tr

Nikolaos G. Paterakis
Department of Electrical Engineering
Eindhoven University of Technology
Eindhoven,
The Netherlands
n.paterakis@tue.nl

João P. S. Catalão
INESC TEC and FEUP, Porto,
C-MAST/UBI, Covilha, and
INESC-ID/IST-UL, Lisbon,
Portugal
catalao@ubi.pt

***Abstract*—The increasing operational complexity of power systems considering the higher renewable energy penetration and changing load characteristics, together with the recent developments in the ICT field have led to more research and implementation efforts related to the activation of the demand side. In this manner, different direct load control (DLC) and indirect load control concepts have been developed and DLC strategies are considered as an effective tool for load serving entities (LSEs) with several real-world application examples. In this study, a new DLC strategy tailored for residential air-conditioners (ACs) participating in the day-ahead planning, based on offering energy credits to the enrolled end-users is proposed. The mentioned energy credits are then used by residential end-users to lower their energy procurement costs during peak-price periods. The strategy is formulated as a stochastic mixed-integer linear programming (MILP) model considering uncertainties related to weather conditions. The outcomes regarding the end-user comfort level and economic benefits are also analyzed.**

***Index Terms*—demand response; direct load control; energy credit; thermostatically controllable appliances.**

NOMENCLATURE

The sets, parameters and decision variables that are used in this paper are alphabetically listed below.

A. Sets

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

B. Parameters and Constants

$A_{i,h}$	Area for household h [m^2].
c_a	Air thermal capacity [kJ/kg·°C].
COP_h	AC unit performance coefficient in household h.
$l_{i,h}$	Thickness value of element i for household h[m].
Lx_h	Length, width and height of house h, where $x = \{1,2,3\}$ [m].
M_h	Air mass in household h [kg].
N	Sufficiently large positive constant.
P_h^{AC}	Rated power of AC unit in household h [kW].
P_t^{des}	Desired reduction in power for the DR event in period t [kW].
$P_{h,t}^{load}$	Inflexible load demand of household h in period t [kW].
$P_{h,t,\omega}^{AC,ref}$	Reference AC based power consumption of household h in period t in scenario ω [kW].
$R_{eq,h}$	Resistance regarding the thermal characteristics of household h [h·°C/J].
$T_{t,\omega}^{a}$	Ambient temperature in period t in scenario ω [°C].
$T_{h,t}^{dec,max}$	Maximum permitted decrease in temperature set-point for the DR event with respect to the temperature set by household h [°C].
$T_{h,t}^{des}$	Desired temperature of household h in period t to guarantee comfort [°C].
T_h^{DB}	Operational limits around the temperature set-point for AC unit of household h [°C].
$T_{h,t}^{inc,max}$	Maximum permitted increase in temperature set-point with respect to the temperature set by household h during the DR event [°C].
t_1	Period in which the DR event starts.
t_2	Period in which of the DR event ends.
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 period duration [h].
δ_{air}	Air density [kg/m^3].

$\sigma_{i,h}$	Thermal coefficient of the i-th element of household h [J/h·m·°C].
β_h	Angle of the roof 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 [°C · 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 AC unit 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 [°C].
$T_{h,t,\omega}^{in}$	Indoor temperature of household h in period t in scenario ω [°C].
$T_{h,t,\omega}^{set}$	Thermostat set-point for household h in period t in scenario ω [°C].
$T_{h,t,\omega}^{up}$	Indoor temperature increase with respect to the desired temperature for household h in period t in scenario ω [°C].
$u_{h,t,\omega}^{ac}$	Binary variable for the AC unit status of household h in period t in scenario ω (1=ON, 0=OFF)

I. INTRODUCTION

The complexity in the operation of electric power systems has increased gradually over the last decades, originating from the higher penetration of non-dispatchable renewable energy systems and the introduction of new types of electrical loads with different characteristics, e.g., electric vehicles during charging. The mentioned challenges together with the developments in the ICT area have stimulated research on the development of different concepts for operating the electric power system from the load serving entities' (LSEs) point of view. All these activities are generally covered by the smart grid vision that aims to enable higher penetration of renewable energy systems together with increased flexibility in power system operations [1].

The demand side, which was formerly considered to be inflexible, is nowadays emerging as a flexibility resource. The flexibility of the demand is exploited in terms of demand response (DR). DR strategies can be categorized as indirect load control (ILC) and direct load control (DLC) approaches.

ILC solutions are generally based on pricing mechanisms, aiming to change the demand pattern of end-users by assigning different prices to different periods of the day. The most well-known application of ILC strategies is the time-of-use (ToU) pricing. Although the ILC strategies are less demanding from the perspective of the communications and control infrastructure that needs to be installed, these strategies do not guarantee that the relevant end-users will react to the pricing schemes as expected, which depends on complex sociological factors. On the contrary, DLC strategies are viewed as a more effective tool for LSEs especially for the provision of several ancillary services including frequency regulation, peak load reduction in critical periods, etc. [2], [3].

Several DLC implementations have been adopted by different LSEs and a detailed overview of practical evidence can be found in [4]. DLC implementations can be considered more mature for applications engaging industrial end-users; however, the implementation of such strategies for residential end-users is also an area of intensive research and real-world applications [5]. In this regard, thermostatically controllable appliances (TCAs) including heating, ventilation and air-conditioning (HVAC) units or more often called air-conditioners (ACs), electric water heaters (EWHs) and refrigerators are given specific importance [6], [7].

There are several studies in the literature dealing with DLC involving residential TCAs. Heffner et al. [8] discussed the potential of EWHs to provide DR, where both the substation level and the end-user premises are examined. Kondoh et al. [2] analyzed the provision of regulation services by EWHs using two-way signals to establish a DLC strategy. Angeli and Kountouriotis [9] considered the possibility of using refrigerator units to provide frequency regulation services. Frequency regulation supported by refrigerators was also discussed by Aunedi et al. considering economic and environmental perspectives in a system with significant wind power generation penetration [3]. Garcia et al. [7] provided the AC loads aggregation using various approaches to analyze the AC dynamics. The services regarding reduction in peak load and regulation of frequency by managing the AC loads were considered in [10]. Moreover, the load balancing services by means of bi-directional LSE signals for increase requirements or power reduction through AC loads were the main topic of the studies presented by Lu and Zhang [11] and Zhang and Lu [12]. The study in [13] analyzed two different approaches, namely, the direct compressor control mechanism (DCCM) and the thermostat set-point control mechanism (TSCM) for AC load aggregation. The issue of exercising DLC fairly was investigated by Koutitas [14]. In this study fairness is approached in terms of the economic benefits received by the different consumers, yet fairness in terms of violating the comfort of the enrolled consumers was not considered. Erdinc et al. [15] proposed a fairness oriented approach to improve the satisfaction of the comfort level of end-users enrolled in a AC aggregation DLC program. A literature survey dedicated on the utilization of TCAs for DR can also be found in [4].

This study proposes a new incentive mechanism in order to motivate owners of AC units to engage in DLC DR programs. The proposed concept relies on providing free energy credits to the end-users on the basis of their performance during a DR event, which then can be used in periods outside the time span of a DR event for reducing the cost of procuring energy. Moreover, the proposed approach is evaluated in a stochastic day-ahead planning context.

The contributions of this study are as follows:

- An energy credits-based incentive structure for DLC programs is proposed.
- The stochasticity regarding ambient temperature is considered.
- The benefits for the end-users from the proposed incentive structure are analyzed in terms of operational cost reduction.

The rest of the study is structured as follows: the methodology is presented in Section II. The obtained results are analyzed in Section III. Finally, the concluding remarks as well as the possible future extensions are discussed in Section IV.

II. METHODOLOGY

For the concept proposed in this study, it is assumed that the LSE has the capability of communicating directly with the households and controlling their ACs during the contracted DR events. The main objective of the LSE is to obtain reduction in peak demand by limiting the use of residential ACs that have accepted to react during the DR event. It is to be noted that all the residential ACs 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 ACs, e.g., due to communication failure or for consumer opt-out options.

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

A. Optimal Procurement of ACs based load reduction during DR events

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

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

subject to:

$$T^{des}_{h,t} - T^{dec,max}_{h,t} \leq T^{set}_{h,t,\omega} \leq T^{des}_{h,t} + T^{inc,max}_{h,t}, \quad \forall \mathrm{h}, \mathrm{t} \in [\mathrm{t}_1, \mathrm{t}_2], \omega \tag{2}$$

$$T^{set}_{h,t,\omega} - T^{DB}_{h} \leq T^{in}_{h,t,\omega} \leq T^{set}_{h,t,\omega} + T^{DB}_{h}, \forall h, t, \omega \tag{3}$$

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

$$T^{up}_{h,t,\omega} \leq N \cdot u^{ac}_{h,t,\omega}, \forall h, t, \omega \tag{5}$$

$$T^{dn}_{h,t,\omega} \leq N \cdot \left(1 - u^{ac}_{h,t,\omega}\right), \forall h, t, \omega \tag{6}$$

$$\begin{aligned} T^{in}_{h,t,\omega} = {} & \left(1 - \frac{\Delta T}{1000 \cdot M_h \cdot c_a \cdot R_{eq,h}}\right) \cdot T^{in}_{h,(t-1),\omega} \\ & + \frac{\Delta T}{1000 \cdot M_h \cdot c_a \cdot R_{eq,h}} \cdot T^{a}_{t-1,\omega} \\ & - \frac{COP_h \cdot P^{AC}_{h} \cdot \Delta T}{0.000277 \cdot M_h \cdot c_a} \cdot u^{ac}_{h,t,\omega}, \\ & \forall h, t > 1, \omega \end{aligned} \tag{7}$$

$$p^{AC}_{h,t,\omega} = P^{AC}_{h} \cdot u^{ac}_{h,t,\omega}, \forall h, t, \omega \tag{8}$$

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

$$p^{des}_{t} \leq \sum_{h} P^{credit}_{h,t,\omega}, \forall t \in [t_1, t_2], \omega, \quad if \sum_{h} P^{AC,ref}_{h,t,\omega} \neq 0 \tag{10}$$

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

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

In this study, the TSCM approach is adopted, which implies that the LSE manipulates the thermostat temperature set-point $T^{set}_{h,t,\omega}$ in a direct way. This approach is more applicable to peak demand reduction, while DCCM is considered more appropriate for the provision of regulation services. The thermostat set-point $T^{set}_{h,t,\omega}$ can be altered within the DR period considering the lower and upper 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^{DB}_{h} stands for the dead-band control parameter. For estimating the comfort violation of end-users, the indoor temperature is decomposed based on (4), while (5) and (6) enforce the fact that an upward and a downward temperature deviation regarding the user's desired temperature set-point cannot have non-zero values simultaneously.

The indoor temperature varies depending on various parameters such as the specifications of the air, the thermodynamic properties of the building, and the heat exchange between ambient and house. The thermal modeling of the houses, which is based on the equivalent resistance regarding structure's thermal characteristics, is represented by (7) for cooling operational concept. The calculations based on the equivalent resistance regarding the buildings' thermal characteristics and the air mass within the house can be carried out using equations (13)-(15), assuming simply a rectangular household geometry.

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

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

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

The ACs based power consumption for each household h in period t in scenario ω follows (8). The reduced power value for each household compared to reference ACs 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 operating pattern of the ACs 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 ACs based consumption patterns of households is non-zero as in (10). The household ACs based power is restricted to be zero by (11) if the reference ACs based power consumption pattern of this household is already zero in period t in scenario ω. Besides, the baseline of AC 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). The comfort violation of household h in scenario ω is calculated in $^{0}C.h$ using (16), taking into account both directions of temperature deviation with respect to the user specified temperature set-point.

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

B. Evaluation of Performance

To examine 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.

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

subject to:

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

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

III. TEST AND RESULTS

A. Input Data

In order to illustrate the developed approach, 40 identical households ware considered [15]. Their structural parameters are shown in Table I. In general, the density and the thermal capacity of the air inside a building are not constant and depend on thermodynamic properties such as pressure and temperature. However in this study, they are assumed constant and equal to $\delta_{air} = 1.225$ kg/m^3 and $c_a = 1.01$ kJ/kg°C for standard conditions. Moreover, it is assumed that an AC unit of 3kW with a coefficient-of-performance (COP) of 2 is identically placed in all the households.

A DR event aiming reduction in peak demand that is triggered between 1 pm and 3 pm of the considered day is studied. The initial indoors temperature values of households are randomly selected in the range between 19.1 ^{0}C and 20.9 ^{0}C. The relevant parameters are presented in Table II. 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. 1. The time step is considered as 5 min (0.0833h). GAMS 24.0.2 with CPLEX 12 solver has been used for the computer implementation of model.

B. Simulation and Results

The total load reduction that is requested from the households with an AC that is operating during the DR event is 24 kW. This reduction stands for the 20% of the maximum dispatchable AC power that can be harnessed by the considered pool of households. It is to be noted that the constraint for $P_{des,t}$ is enforced only for the relevant periods of non-zero AC reference power, due to the fact a reduction in power is not possible.

Figures 2 and 3 depict the ACs based actual reference power and the ACs based power consumption for Scenarios 1 and 2. It is clear that for all non-zero reference ACs based power periods, the system manages sufficient amount of AC units to reduce the ACs based load demand by the desired amount. The methodology should satisfy the desired load reduction under all scenarios and for the sake of brevity, results regarding the other scenarios are not provided here.

TABLE I. HOUSEHOLD STRUCTURAL PARAMETERS

Parameter	Value	Units	Parameter	Value	Units
Length of house (L_1)	30	m	Area of windows	1	m^2
Width of house (L_2)	10	m	Wall thermal coefficient	136.8	J/h·m·℃
Heigth of house (L_3)	4	m	Thermal coefficient of window	2808	J/h·m·℃
Angle of roof (β)	40	deg	Window thickness	0.05	m
Number of windows	6	-	Wall thickness	0.15	m

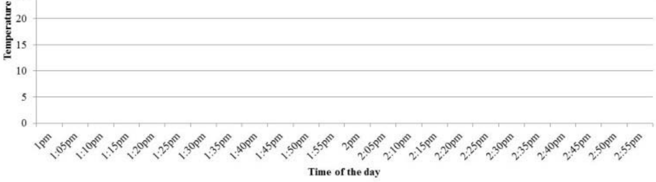

Figure 1. Scenarios for ambient temperature variation.

TABLE II. TEMPERATURE-RELATED PARAMETERS OF HOUSEHOLDS

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

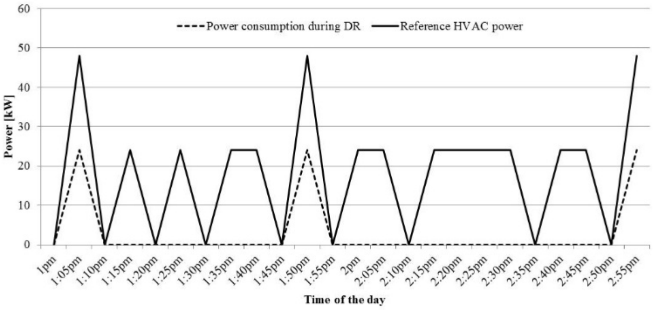

Figure 2. The AC power variation for the DR event period in Scenario-1.

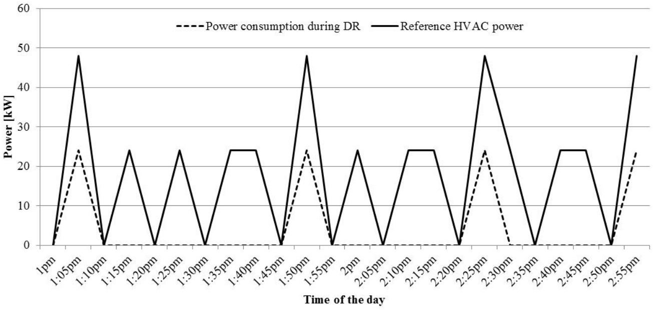

Figure 3. The AC power variation for the DR event period in Scenario-2.

The comfort violation index value for individual households during DR event is presented in Fig. 4. 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 for allocating the comfort violation in a fairly manner for the contracted end-users as in [15] are enforced in this study. The mean free-of-cost energy credit values are shown in Fig. 5. Similar to Fig. 4, 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. 4 and 5, 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.

To investigate the end-users' economic benefits from the obtained energy credits, a test case is provided for selected households that gained 0.9996 kWh free-of-cost energy credits during the DR case of 20% desired load reduction level. 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. 6 [16]. The inflexible power demand of a 4-member household including several loads is presented in Fig. 7 [17] for the mentioned peak-price period.

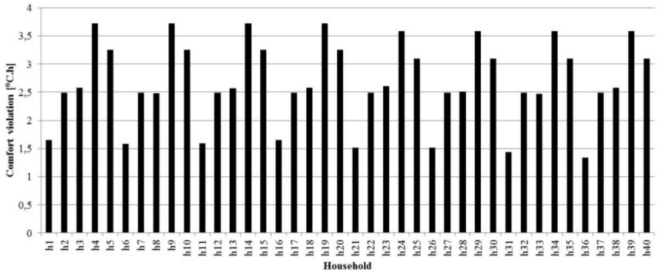

Figure 4. The comfort violation index value of end-users experienced during DR event.

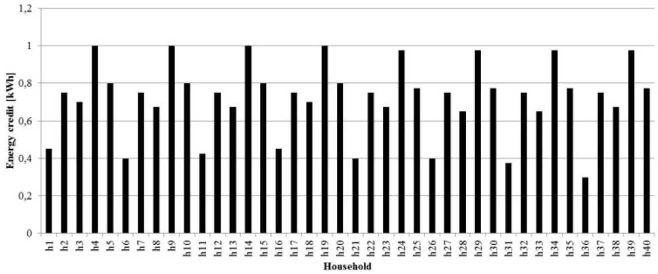

Figure 5. The free-of-cost energy value of end-users gained during DR event.

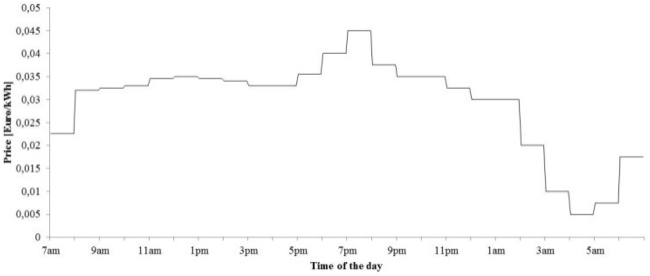

Figure 6. The daily dynamic pricing signal.

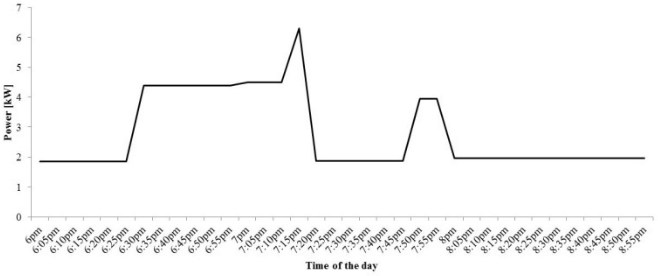

Figure 7. The power demand of the household during peak-price period.

The cost reduction oriented residential household energy management system allocates a free-of-cost power variation from the grid as shown in Fig. 8 for 0.9996 kWh free-of-cost energy credit value. 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. The relevant results for the total operational costs during the peak price period with and without energy credits are summarized in Table III. The proposed energy credits-based strategy enables more than 10% of total cost reduction, which is a considerable benefit for the enrollment of the end-users for such DR programs.

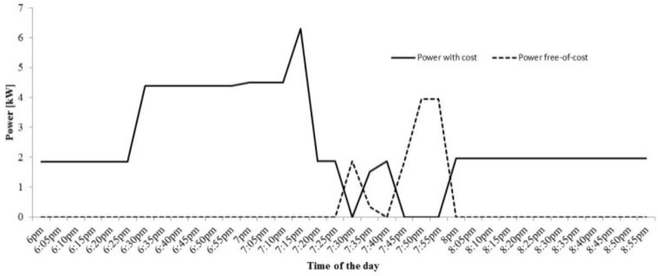

Figure 8. The power decomposition for free-of-cost energy credit value of 0.9996 kWh.

TABLE III. 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***
0.9996	0.344	0.299

IV. CONCLUSIONS

In this study, a new DLC strategy incentivizing the enrolled end-users with energy credits to reduce their electricity costs during peak price periods was proposed. The mentioned free energy credits were provided to the end-users on the condition that intervention to their AC units during predefined DR events was allowed. The effectiveness of the energy credits-based incentive strategy was examined in a day-ahead planning context in terms of operational cost reduction, regarding also the uncertainty of the ambient temperature variations, and the results showed that the proposed strategy accomplished a total cost reduction of more than 10%, which can be pointed out as a decisive factor for increasing the participation ratio of end-users into DR programs. The comfort violation of end-users, which is also an important factor for the commitment of end-users for such programs, was also analyzed in this study. The study can further be enhanced by employing the DCCM for AC unit control, enlarging the study to cover a higher number of households with different AC consumption profiles and more of the end-user appliances including other types of TCAs as well as other new type loads such as electric vehicles, using also real validated data sets available in the literature.

ACKNOWLEDGMENT

This work was supported by The Scientific and Technological Research Council of Turkey (TUBITAK) under Project Grant Number 116E115, 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 and SFRH/BPD/103744/2014. Also, the funding from the EU Seventh Framework Programme FP7/2007-2013 under grant agreement no. 309048 for the research leading to these results is also acknowledged.

REFERENCES

[1] A. Tascikaraoglu, B. M. Sanandaji, “Short-term residential electric load forecasting: A compressive spatio-temporal approach,” *Energy and Buildings*, vol. 111, no. 1, pp. 380-392, Jan. 2016.

[2] 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.

[3] 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.

[4] N.G. Paterakis, O. Erdinc, and J.P.S. Catalão, "An overview of demand response: key-elements and international experience", *Renewable and Sustainable Energy Reviews*, vol. 69, pp. 871-891, March 2017.

[5] 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”, *Energy and Buildings*, vol. 80, pp. 309-320, Sept. 2014.

[6] 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.

[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] 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.

[9] 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.

[10] 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.

[11] 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.

[12] 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.

[13] 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.

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

[15] O. Erdinc, A. Tascikaraoglu, N.G. Paterakis, Y. Eren, and J.P.S. Catalão, “End-user comfort oriented day-ahead planning for responsive residential HVAC demand aggregation considering weather forecasts”, *IEEE Trans. Smart Grid*, vol. 8, pp. 362-372, Jan. 2017.

[16] N. G. Paterakis, O. Erdinc, A. Bakirtzis, and J. P. S. Catalao, “Optimal Household Appliances Scheduling Under Day-Ahead Pricing and Load-Shaping Demand Response Strategies,” *IEEE Trans. Industrial Informatics*, vol. 11, pp. 1509-1519, Dec. 2015.

[17] N. G. Paterakis, A. Taşcıkaraoğlu, O. Erdinç, A. G. Bakirtzis, and J. P. S. Catalão, "Assessment of Demand-Response-Driven Load Pattern Elasticity Using a Combined Approach for Smart Households," *IEEE Trans. Industrial Informatics*, vol. 12, no. 4, pp. 1529-1539, Aug. 2016.