A New Perspective for Sizing of Distributed Generation and Energy Storage for Smart Households under Demand Response

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Abstract

As a recently increasing trend among different applications of smart grid vision, smart households as a new implementation area of demand response (DR) strategies have drawn more attention both in research and in engineering practice. On the other hand, optimum sizing of renewable energy based small scale hybrid systems is also a topic that is widely covered by the existing literature. In this study, the sizing of additional distributed generation (DG) and energy storage systems (ESSs) to be applied in smart households, that due to DR activities have a different daily demand profile compared with normal household profiles, is investigated. To the best knowledge of the Authors this is the first attempt in the literature to investigate this issue, also including step-wise decreasing cost functions for DG and ESS, varying load and DG production profiles seasonally, and weekday-weekend horizons for a long-term analysis period. The study is conducted using a mixed-integer linear programming (MILP) framework for home energy management system (HEM) modeling and techno-economical sizing. Also, different sensitivity analyses considering the impacts of variation of economic inputs on the provided model are realized.

Keywords: Distributed Generation; Energy Storage; Smart Households; Demand Response; Home Energy Management.

Nomenclature

A. Abbreviations

BCR benefit-to-cost ratio.
DPP discounted payback period.
DR demand response.
ESS energy storage system.
EV electric vehicle.
PV photovoltaics.
TC total cost.
$TNPV$ total net present value.

B. Indices

n index of years in total project horizon
t period of the day index in time units [h or min].

C. Parameters

$C_{cap,ESS}$ ESS unit overnight capital cost [$/kWh].

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$C_{cap,PV}$ PV unit overnight capital cost [$/kW].
$C_{main,ESS}$ ESS unit annual maintenance cost [$/kWh-y].
$C_{main,PV}$ PV unit annual maintenance cost [$/kW-y].
$C_{rep,ESS}$ ESS unit replacement cost [$/kWh].
$C_{rep,PV}$ PV unit replacement cost [$/kW].
CE_{ESS} charging efficiency of the ESS.
CE_{EV} charging efficiency of the EV.
CR_{ESS} charging rate of the ESS [kW per time interval].
CR_{EV} charging rate of the EV [kW per time interval].
d real discount rate.
DE_{ESS} discharging efficiency of the ESS.
DE_{EV} discharging efficiency of the EV.
DR_{ESS} discharging rate of the ESS [kW per time interval].
DR_{EV} discharging rate of the EV [kW per time interval].
$ESS^{n}_{rep,flag}$ ESS replacement flag throughout project horizon.
K_T number of time intervals in one hour.
$n_{ESS,max}$ maximum multiplication coefficient for ESS sizing considering base size (1 kWh in this study).
N_P project horizon [years].
$n_{PV,max}$ maximum multiplication coefficient for PV sizing considering base size (1 kW in this study).
N_1, N_2 modeling constants for ESS.
N_3 maximum power that can be drawn from the grid [kW].
N_4 maximum power that can be sold back to the grid [kW].
P_t^{other} household power demand [kW].
$P_t^{PV,pro}$ power produced by the PV [kW].
$PV^{n}_{rep,flag}$ PV replacement flag throughout project horizon.
$SOE^{ESS,ini}$ initial state-of-energy of the ESS [kWh].
$SOE^{ESS,max}$ maximum allowed state-of-energy of the ESS [kWh].
$SOE^{ESS,min}$ minimum allowed state-of-energy of the ESS [kWh].
$SOE^{EV,ini}$ initial state-of-energy of the EV [kWh].
$SOE^{EV,max}$ maximum allowed state-of-energy of the EV [kWh].
$SOE^{EV,min}$ minimum allowed state-of-energy of the EV [kWh].
T^a arrival time of EV to household.
T^d departure time of EV from household.
TC_{base} total cost for the base case [$].
λ_t^{buy} price of energy bought from the grid [cents/kWh].
λ_t^{sell} price of energy sold back to the grid [cents/kWh].

D. Variables

$C_{cap,tot}$ total overnight capital investment cost [$].
$C_{main,tot}$ total annual maintenance cost [$].
$C_{rep,tot}$ total replacement cost [$].
n_{ESS} optimum size of ESS to be installed [kWh].
n_{PV} optimum size of PV to be installed [kW].
$P_t^{ESS,ch}$ ESS charging power [kW].
$P_t^{ESS,dis}$ ESS discharging power [kW].
$P_t^{ESS,sold}$ power injected to grid from the ESS [kW].
$P_t^{ESS,used}$ power used to satisfy household load from the ESS [kW].
$P_t^{EV,ch}$ EV charging power [kW].
$P_t^{EV,dis}$ EV discharging power [kW].
$P_t^{EV,sold}$ power injected to grid from the EV [kW].
$P_t^{EV,used}$ power used to satisfy household load from the EV [kW].
P_t^{grid} power supplied by the grid [kW].
$P_t^{PV,sold}$ power injected to grid from the PV [kW].
$P_t^{PV,used}$ power used to satisfy household load from the PV [kW].
P_t^{sold} total power injected to the grid [kW].

SOE_t^{ESS} state-of-energy of the ESS [kWh].
SOE_t^{EV} state-of-energy of the EV [kWh].
TC_{com} total cost for compared case [$].
TCR total cost reduction [$].
TPV_{inc} total present value of the income [$].
TPV_{out} total present value of the outflow [$].
u_t^{ESS} binary variable. 1 if ESS is charging during period t, 0 else.
u_t^{EV} binary variable. 1 if EV is charging during period t, 0 else.
u_t^{grid} binary variable. 1 if grid is supplying power during period t, 0 else.

1. Introduction

1.1. Motivation and background

Smart grid vision is one of the primary concerns of recent investments in electricity industry that is promoted by the short-term and long-term plans of leading country governments. As the smart grid idea is mainly based on accommodating all types of generation and storage options and especially enabling active participation of consumer side of the generation/consumption balance, activities related to the demand side of the power system are gaining more importance [1]. Among these activities, demand response (DR) strategies play the major role in promoting the smart grid implementations [2].

The US Department of Energy (DOE) defines DR as "*changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized*". DR comprises incentive based programs and price based programs (time-of-use, critical peak pricing, dynamic pricing, etc.) [3,4]. DR can be considered mature for industrial consumers, but is a new concept for residential units responsible for nearly 40% of the global energy consumption [5]. The application of DR in such residential units calls for the definition of smart households that can monitor their use of electricity in real-time and act in order to lower their electricity bills [5,6].

DR activities for smart households surely result in a small or significant change in their daily power consumption pattern. The home energy management (HEM) systems of smart households are likely to shift most of the possible consumption from peak price periods to off-peak price periods (that is usually after midnight) in order to reduce the corresponding daily electricity consumption cost [7]. Such shifting actions in DR based smart households are the main reason for the aforementioned changes in daily power consumption profile. These changes raise concerns and points that require reconsideration such as the impact of having new peaks in formerly off-peak hours etc. In this regard, sizing approaches for the evaluation of investments of small-scale generation and storage units at the end-users premises, considering only normal load patterns, should be reconsidered. DR strategies and their impact on the load profile are likely to affect the technically and economically optimal results related to such investments. This is a topic that requires attention since effective investments determine the development of distributed generation, a core element of the future smart grid.

1.2. Literature overview

There is a rich literature on sizing of different hybrid distributed generation system structures for applying both in grid-connected and stand-alone modes of operation. As an example for sizing of stand-alone systems, Kolhe [8] provided the optimum sizing of a stand-alone PV-battery hybrid system using levelized energy cost computation. Katsigiannis et al. [9] applied a mixed simulated annealing-tabu search based optimization methodology for component sizing of a small autonomous power system including wind turbine, PV, biodiesel, conventional diesel, fuel cell and battery systems. Hong and Lian [10] employed a Markov-based genetic algorithm in order to techno-economically size the components of a stand-alone wind/PV/diesel hybrid structure. A pattern search- based optimization method combined with a sequential Monte Carlo simulation approach was proposed by Arabali et al. [11] for the stochastic performance assessment and sizing of a hybrid power system including wind, PV and ESS units. A new perspective also considering the aging-based performance degradation impacts on sizing results was presented by Erdinc and Uzunoglu in [12].

The sizing of renewable energy systems and ESS units in a grid-connected mode of operation has also been well-covered in the existing literature. In this concept, Alsayed et al. [13] realized the optimum sizing of a grid-connected wind-PV hybrid system adopting different multicriteria decision analysis optimization approaches. Bahramirad et al. [14] specifically focused on ESS sizing for a microgrid with consideration of reliability constraints in mixed-integer linear programming (MILP) framework. The same topic of ESS sizing in a MILP framework for a microgrid was also the topic of Chen et al. [15] from a different perspective based on cost-benefit analysis for both islanded and grid-connected modes of operation. A significantly detailed literature survey on different methods, several considerations, etc. applied for sizing of renewable energy based hybrid systems was given in [16-20].

There are also many recent studies dealing with DR strategies for the optimum appliance operation of smart households. Chen et al. [21] and Tsui and Chan [22] developed an optimization strategy for the effective operation of a household with a price signal based DR. Li and Hong [23] proposed a “user-expected price” based DR strategy for a smart household also including a battery based ESS aiming at lowering the total electricity cost by charging and discharging the ESS at off-peak and peak price periods, respectively. However, the impact of including an additional EV load that can also be helpful for peak clipping in certain periods when EV is at home and the possibility of an own production facility are not evaluated in Ref. [23]. Zhao et al. [24] considered the HEM strategy based control of a smart household including photovoltaic (PV) based production facilities, the availability of the EV and an ESS. However, V2H and further possible V2G operating modes of EV are not taken into account in Ref. [24]. Restegar et al. [25] developed a smart home load commitment strategy considering all the possible operating modes of EV and ESS, yet neglecting the impact of an extra peak power limiting strategy that is probable to be imposed by a LSE. This is an important fact that is also disregarded in [21]-[24].

Pipattanasomporn et al. [26] and Kuzlu et al. [27] presented a HEM strategy considering peak power limiting DR strategy for a smart household, including both smart appliances and EV charging. Shao et al. [28] also investigated EV for DR based load shaping of a distribution transformer serving a neighborhood. Refs. [26]-[28] did not provide an optimum operating strategy considering price variability with the aim of obtaining the lowest daily cost apart from just limiting the peak power drawn from the grid by household in certain periods. Matalanas et al. [29] applied an HEM system based on neural networks with experimental results for a household including PV and ESS. However, the impacts of varying price as well as other types of DR strategies are not evaluated in Ref. [29]. Angelis et al. [30] performed the evaluation of a HEM strategy considering the electrical and thermal constraints imposed by the overall power balance and consumer preferences. Chen et al. [31] provided an appliance scheduling in a smart home considering dynamic prices and appliance usage patterns of consumer. Missaoui et al. [5] also provided a smart building energy management strategy based on price variations and external conditions as well as comfort requirements. The pricing data based energy management is also suggested by Hu and Li [32] together with a hardware demonstration.

Besides, in a recent study, Erdinc [7] considered the possible operating conditions within a smart household including EV, ESS and PV under different DR strategies of price-based and peak-power limiting, where constant sizing of PV and ESS were considered and the sensitivity of total cost of daily operation of the household to PV and ESS sizes was considered manually without an optimization perspective.

These papers together with many other studies not referred here have provided valuable contributions to the application of economical investments for small-scale renewable energy systems in general and smart grid concepts in household areas. However, to the best knowledge of the authors none of the studies in the literature considered the sizing of extra renewable energy system investments considering the changing load profile imposed by the price responsive DR activities within the concept of smart households. One exception which can be considered the most similar area of research is the study of Kahrobaee et al. [33], where the influence of demand side activities related to price variation were implemented within the sizing purpose of a wind turbine and battery-based small own generation and ESS system for a smart household. However, in the proposed strategy of Ref. [33], there were different steps where the optimum operating strategy of smart household appliances, ESS, etc. was decided and the sensitivity of total daily operation cost of the household was evaluated in an optimization framework. However, the combination of these different steps under a single step by a proper formulation can be considered more effective to analyse the intercorrelated impacts of sizing and DR activities. Besides, only a single day operation was considered in Ref. [33], where the impacts of seasonal, weekday-weekend impacts on load profiles as well as the variability of DG based power production throughout the year were neglected, which is the core of all sizing studies by providing at least 1 year of system analysis.

1.3. Contribution of the study

The novel point of this study is the provision of a single step methodology to size additional PV and ESS for a smart household, the load profile of which is affected by the decisions of a HEM system that operates under dynamic pricing based DR.

Under a mixed-integer linear programming (MILP) modeling framework, the HEM structure and thus the daily operation of the smart household is associated with the sizing procedure, pertaining a long-term horizon. The HEM structure considers a small-scale distributed renewable energy generation system (PV), an electric vehicle (EV) capable of operating in vehicle-to-home (V2H) mode, together with an ESS.

Sizing of the PV and the ESS affects the smart household operation, while the load pattern induced by the DR scheme affects the sizing results. To reveal the relation of the aforementioned components, different case studies, as well as sensitivity analyses are presented. Besides, a step-wise decreasing unit capital cost function for PV and ESS is used to consider the cost advantage that arises with increased capacity, which is neither considered in many studies on sizing issue nor in the most similar study in the literature given in Ref. [33]. Moreover, the seasonal and weekday-weekend load variability is also taken into account together with EV availability variation for different household owner profiles.

1.4. Paper organization

The remainder of this paper is organized as follows: Section 2 gives the methodology employed in the study. Section 3 includes the case studies and sensitivity analyses for the evaluation of the sizing results for a smart-household participating in a DR initiative. Finally, concluding remarks are presented in Section 4.

2. System description and methodology

The objective is to minimize the total net present value (TNPV) of the cash flows:

$$Min. \qquad TNPV = TPV_{out} - TPV_{inc} \tag{1}$$

which in turn aims maximizing the "Benefit-to-Cost Ratio (BCR)" expressed by (2) by trying to simultaneously maximizing TPV_{inc} and minimizing TPV_{out} in (1):

$$BCR = \frac{TPV_{inc}}{TPV_{out}} \tag{2}$$

In (1) and (2), TPV_{out} stands for the total present value of the outflows related to the total capital investment, replacement and maintenance costs of the additional PV based distributed generation (DG) and battery based ESS equipments for the total project lifetime and is calculated by:

$$TPV_{out} = C_{cap,tot} + C_{rep,tot} + C_{main,tot} \tag{3}$$

where $C_{cap,tot}$, $C_{rep,tot}$ and $C_{main,tot}$ respectively stand for total capital, replacement and maintenance costs and are calculated by (4)-(6):

$$C_{cap,tot} = C_{cap,PV}.\, n_{PV} + C_{cap,ESS}.\, n_{ESS} \tag{4}$$

$$C_{rep,tot} = \sum_{n=1}^{N_P} \left(\frac{PV_{rep,flag}^{n}.\, C_{rep,PV}.\, n_{PV}}{(1+d)^n} + \frac{ESS_{rep,flag}^{n} C_{rep,ESS}.\, n_{ESS}}{(1+d)^n} \right) \tag{5}$$

$$C_{main,tot} = \sum_{n=1}^{N_P} \frac{C_{main,PV}.\, n_{PV} + C_{main,ESS}.\, n_{ESS}}{(1+d)^n} \tag{6}$$

where $C_{cap,PV}$ and $C_{cap,ESS}$ are PV and ESS capital costs, $C_{rep,PV}$ and $C_{rep,ESS}$ are PV and ESS replacement costs, $C_{main,PV}$ and $C_{main,ESS}$ are PV and ESS maintenance costs, n_{PV} and n_{ESS} are multiplication coefficients for PV and ESS sizing considering base size (1 kW and 1 kWh respectively), $PV_{rep,flag}$ and $ESS_{rep,flag}$ are PV and ESS replacement flags throughout project horizon, d is the real discount rate, and n is the year in N_P total project horizon (usually considered as 20 years for the economic lifetime of a renewable energy investment). It should be noted that capital cost is valid only for year zero while the period of maintenance cost starts with the first year (n=1) and replacement cost is only available for the periodical years when the usable lifetime of unit *i* ends that is considered by PV and ESS replacement flags.

On the other hand, in (1), TPV_{inc} represents the total present value of the incomes related to the annual total cost reduction (TCR) obtained in the total yearly cost of electricity consumption (TC) of the household by the additional benefits of several factors such as adding PV and ESS and also including DR for the total project lifetime and is calculated by:

$$TPV_{inc} = \sum_{n=0}^{N_P} \frac{TCR}{(1+d)^n} \tag{7}$$

where TCR is the difference between TC in base case (e.g. without additional PV and ESS) and TC in compared case, and accordingly calculated as:

$$TCR = TC_{base} - TC_{com} \tag{8}$$

Both the TC values for base (TC_{base}) and compared (TC_{com}) cases in (8) are calculated as the difference between the energy bought from the grid and the energy sold back to the grid by the household-owned assets that are able to provide energy (e.g. PV, ESS and EV which are considered to be available for base and compared cases) in year *n*. The price variables are time dependent, a fact that implies time varying prices for both bought and sold energy.

$$TC = \sum_{t} \left(\frac{P_t^{grid}}{K_T} \cdot \lambda_t^{buy} - \frac{P_t^{sold}}{K_T} \cdot \lambda_t^{sell} \right) \tag{9}$$

In (9), P_t^{grid} is the total power bought from the grid at time *t*, and $P_t^{sold}$is the total power sold back to the grid which comprises power values sold from PV, ESS and EV ($P_t^{PV,sold}$, $P_t^{ESS,sold}$and $P_t^{EV,sold}$). In this study we consider that the HEM system first sells energy from the PV, next from the ESS and finally from the EV battery.

The constraints presented below comprise the basic body of the HEM system operation. The model can be easily extended and adapted to other more specific implementations (e.g. by further modeling specific smart-appliances such as HVAC, water heaters, appliances with cycling operation and/or customer's contract details). Any time granularity can be used simply by selecting the appropriate K_T. For instance, for a 15-minute interval the K_T coefficient must be 4, as one hour comprises four 15-minute intervals.

Equation (10) states that the load consisting of the residential load (P_t^{other}), the charging needs of the EV ($P_t^{EV,ch}$) and the ESS ($P_t^{ESS,ch}$) is either satisfied by the grid (P_t^{grid}) or by the combined procurement of energy by the PV, the ESS and the EV ($P_t^{PV,used}$, $P_t^{EV,used}$and $P_t^{ESS,used}$).

$$P_t^{grid} + P_t^{PV,used} + P_t^{EV,used} + P_t^{ESS,used} = P_t^{other} + P_t^{EV,ch} + P_t^{ESS,ch} \quad \forall t \tag{10}$$

Equation (11) enforces the fact that the actual power provided by the ESS discharge ($P_t^{ESS,dis} \cdot DE_{ESS}$) can be used to cover a portion of the household needs ($P_t^{ESS,used}$) or injected back to the grid ($P_t^{ESS,sold}$). Constraints (12) and (13) are employed for preventing a possible simultaneous charging and discharging operation. Constraints (14) and (15) impose a limit on the charging ($P_t^{ESS,ch}$) and discharging ($P_t^{ESS,dis}$) power of the ESS. The idle ESS state can be described by any of these constraints by the time the respective power variable is allowed to have zero value. Equations (16)-(19) describe the state-of-energy of the ESS. Constraint (16) forces the state-of-energy at every interval (SOE_t^{ESS}) to have the value that it had at the previous interval (SOE_{t-1}^{ESS}) plus the actual amount of energy that is transferred to the battery if it is charging at that interval minus the energy that is subtracted if the battery is discharging during that interval. At the beginning of the time horizon the state-of-energy of the ESS coincides with the initial state-of-energy of the ESS ($SOE^{ESS,ini}$), as described by Eq. (17). Constraint (18) limits the state-of-energy of the battery to be less than the ESS capacity ($SOE^{ESS,max}$). Similarly, constraint (19) prevents the deep discharge of the battery by imposing a least state-of-energy limit ($SOE^{ESS,min}$). Lastly, constraint (20) limits the multiplication coefficient to be below an upper limit for ESS.

$$P_t^{ESS,used} + P_t^{ESS,sold} = P_t^{ESS,dis} \cdot DE_{ESS} \ \forall t \tag{11}$$

$$P_t^{ESS,ch} \leq N_1 \cdot u_t^{ESS} \ \forall t \tag{12}$$

$$P_t^{ESS,dis} \leq N_2 \cdot (1 - u_t^{ESS}) \ \forall t \tag{13}$$

$$P_t^{ESS,ch} \leq CR_{ESS} \cdot n_{ESS} \;\; \forall t \tag{14}$$

$$P_t^{ESS,dis} \leq DR_{ESS} \cdot n_{ESS} \;\; \forall t \tag{15}$$

$$SOE_t^{ESS} = SOE_{t-1}^{ESS} + CE_{ESS} \cdot \frac{P_t^{ESS,ch}}{K_T} - \frac{P_t^{ESS,dis}}{K_T} \;\; \forall t \geq 1 \tag{16}$$

$$SOE_t^{ESS} = SOE^{ESS,ini} \cdot n_{ESS} \;\; if\ t = 1 \tag{17}$$

$$SOE_t^{ESS} \leq SOE^{ESS,max} \cdot n_{ESS} \;\; \forall t \tag{18}$$

$$SOE_t^{ESS} \geq SOE^{ESS,min} \cdot n_{ESS}, \;\; \forall t \tag{19}$$

$$n_{ESS} \leq n_{ESS,max} \tag{20}$$

Equation (21) enforces the fact that the actual power provided by the EV discharge ($P_t^{EV,dis} \cdot DE_{EV}$) can be used to cover a portion of the household needs ($P_t^{EV,used}$) or injected back to the grid ($P_t^{EV,sold}$). Constraints (22) and (23) impose a limit on the charging ($P_t^{EV,ch}$) and discharging ($P_t^{EV,dis}$) power of the EV. The idle EV state can be described by any of these constraints by the time the respective power variable is allowed to have zero value. Equations (24)-(28) describe the state-of-energy of the EV. Constraint (24) forces the state-of-energy at every interval (SOE_t^{EV}) to have the value that it had at the previous interval (SOE_{t-1}^{EV}) plus the actual amount of energy that is transferred to the EV battery if it is charging at that interval minus the energy that is subtracted if the EV battery is discharging during that interval. At the arrival time of EV to household, the state-of-energy of the EV coincides with the initial state-of-energy of the EV ($SOE^{EV,ini}$), as described by Eq. (25). Constraint (26) limits the state-of-energy of the EV battery to be less than its capacity ($SOE^{EV,max}$). Similarly, constraint (27) prevents the deep discharge of the EV battery by imposing a least state-of-energy limit ($SOE^{EV,min}$). Eq. (28) represents the issue of having the EV battery fully charged in departure time of EV in the morning. Finally, Eq. (29) ensures that all the variables related to EV modeling are zero apart from the time interval between arrival time of EV to household (T^a) and departure time of EV from household (T^d).

$$P_t^{EV,used} + P_t^{EV,sold} = P_t^{EV,dis} \cdot DE_{EV} \;\forall t \in [T^a, T^d] \tag{21}$$

$$P_t^{EV,ch} \leq CR_{EV} \cdot u_t^{EV} \;\forall t \in [T^a, T^d] \tag{22}$$

$$P_t^{EV,dis} \leq DR_{EV} \cdot (1 - u_t^{EV}) \;\forall t \in [T^a, T^d] \tag{23}$$

$$SOE_t^{EV} = SOE_{t-1}^{EV} + CE_{EV} \cdot \frac{P_t^{EV,ch}}{K_T} - \frac{P_t^{EV,dis}}{K_T} \;\forall t \in [T^a, T^d] \tag{24}$$

$$SOE_t^{EV} = SOE^{EV,ini} \;\; if\ t = T^a \tag{25}$$

$$SOE_t^{EV} \leq SOE^{EV,max} \;\; \forall t \in [T^a, T^d] \tag{26}$$

$$SOE_t^{EV} \geq SOE^{EV,min} \;\; \forall t \in [T^a, T^d] \tag{27}$$

$$SOE_t^{EV} = SOE^{EV,max} \;\; if\ t = T^d \tag{28}$$

$$SOE_t^{EV} = P_t^{EV,used} = P_t^{EV,sold} = P_t^{EV,dis} = P_t^{EV,ch} = 0 \quad \forall t \notin [T^a, T^d] \tag{29}$$

Similarly to Eqs. (11) and (21), Eq. (30) enforces the fact that the actual power provided by the PV ($P_t^{PV,pro}$) can be used to cover a portion of the household needs ($P_t^{PV,used}$) or injected back to the grid ($P_t^{PV,sold}$). Lastly, similar to (20), constraint (31) limits the multiplication coefficient to be below an upper limit for PV.

$$P_t^{PV,used} + P_t^{PV,sold} = P_t^{PV,pro}.n_{PV}, \qquad \forall t \tag{30}$$

$$n_{PV} \leq n_{PV,max} \tag{31}$$

The total amount of power injected to the grid (P_t^{sold}) consists of the amount of power provided by the PV ($P_t^{PV,sold}$), the ESS ($P_t^{ESS,sold}$) and the EV ($P_t^{EV,sold}$) as mentioned before. This is enforced by Eq. (32).

$$P_t^{sold} = P_t^{PV,sold} + P_t^{ESS,sold} + P_t^{EV,sold}, \quad \forall t \tag{32}$$

Equations (33) and (34) implement the logic of power exchange. If power from the grid is needed to be drawn, then it is not possible to inject power back to the grid. The reverse case is also described by these constraints. N_3 is a positive integer value that imposes a limitation on the power that can be drawn from the grid. This limitation may represent a restriction posed by the aggregator or the responsible entity for the end-user electrification in order to face the situation where in its control area exist multiple households that own HEM system. The implementation of a time-varying peak power drawn from the grid limit as a different DR strategy can be easily adapted on this formulation, by replacing the N_3 by a time-dependent parameter. Similarly, N_4 imposes a limit on the power that can be injected back to the grid and also can be replaced by a time-dependent parameter.

$$P_t^{grid} \leq N_3 \cdot u_t^{grid}, \quad \forall t \tag{33}$$

$$P_t^{sold} \leq N_4 \cdot (1 - u_t^{grid}), \quad \forall t \tag{34}$$

Different consumer options and behavioral details can be expressed by fixing the charging and discharging variables of the ESS and EV to be zero in the appropriate time intervals. Different policies (e.g. energy selling back options) can be modeled by fixing the selling energy/power variables to zero or other desired values.

3. Test and Results

To evaluate the sizing of additional PV and ESS investment for the smart household case including a DR-based changing demand pattern, the MILP model is tested in GAMS v.24.1.3 using the solver CPLEX v.12 [34] and the obtained case studies based results are discussed in this section.

The household load demand is provided considering power values of real household appliances given in [35] for a smart home demonstration project. The utilized appliance data are presented in Table 1. Three case studies dealing with different household owner profiles are evaluated in this study:

Case-1: A 4-people family where there is a housewife that is all at home in weekdays.

Case-2: A 4-people family where both parents work and no one is at home in day time within weekdays.

Case-3: A single person that works within weekdays.

The obtained total household demand variation apart from additional EV and ESS operation based load are given in Figs. 1-3 for different household owner profiles. It is to be noted that impacts of seasonal conditions and weekday-weekend are all considered as seen from Figs. 1-3 to obtain a more realistic yearly load profile compared to the case of repeating 24 h of load demand for a single day to adjust to a yearly profile. It is also evident from the given power variations in Figs. 1-3 that the profile of household owner results in a considerable change in power pattern. Besides, Fig. 4 shows a real-time measured hourly average power production profile of a solar farm normalized to 1 kW base in 2013. This base power production profile is multiplied by n_{PV} value decided by sizing approach and accordingly adjusted to different kW power ratings for PV system.

A bi-directional EV operation including both V2G (meaning that EV sells energy back to the grid) and V2H (meaning that a portion of the energy stored in the EV battery is used to partly cover the household load) options can be considered. However, in order to better evaluate the sole impacts of additional PV and ESS installation, the V2G capability of EV is disabled as there will be case studies considering the impacts of increase in selling back flat rate that will directly increase also the sold back energy by EV via V2G.

The specifications of a Chevy Volt with a battery rating of 16 kWh are considered for the EV. The Chevy Volt is employed with a charging station limited to a charging power of 3.3 kW [36]. The same power limit is also assumed to be valid for the discharging operation in V2H mode. The charging and discharging efficiencies are considered 0.95. It is also considered that the initial EV battery energy is 8 kWh (50% state-of-energy) while arriving at home and the lower limit of EV state-of-energy is restricted to 4.8 kWh (30% state-of-energy) to avoid deep-discharging. The departure and arrival times are considered as given in Table 2 related to different case studies. It should be noted that for all case studies, EV is assumed to be at home all day on Sundays.

The following assumptions hold for the ESS; its initial state-of-energy is 1/2 of the maximum battery energy capacity and charging/discharging efficiencies are 0.95. The charging and discharging limits are 0.2 of the maximum battery capacity. Lastly, the deep-discharging limit of battery based ESS is 1/4 of its maximum energy capacity.

Integrating the two-way energy transactions between the end-user and the utility, the net-metering approach is utilized. When the available energy from the household-owned resources is sufficient to cover the total of the needs, the excess of energy can be sold back to the grid and vice versa. For pricing the bought energy from the grid, a dynamic pricing based DR scheme is considered. The time-varying price signal available for the consumer via the smart meter is shown in Fig. 5 [22], which is repeated to obtain data for 8760 h.

Besides, a constant flat rate is paid to the end-user for the energy sold-back to the grid. Payment of flat rates with net metering is an approach also used in practice in different countries. A dynamically changing rate for energy sold can also be easily applied within the provided formulation, as Eq. (6) is suitable both for considering flat and dynamic rates.

The capital cost data considered in this study related to sizing procedure are shown in Table 3 as decreasing step-wise functions denoting the cost advantage that arises with increased capacity. It is to be noted that PV and ESS sizes are bounded with upper limits of 10 kW and 10 kWh for this study. Any other upper limit can easily be applied considering roof area that PV can be applied, limit of volume dedicated to ESS installation, etc. The replacement cost of PV and battery are considered as the same as the capital costs and maintenance costs are assumed as 5% of capital cost in a yearly period. Besides, the replacement time of PV and ESS are considered as 20 and 10 years, respectively. Moreover, the real discount rate is assumed as 0.05 and project lifetime is taken into account as 20 years.

The results for the above given economic data considering DR activities based load pattern of the smart household are presented below.

The sizing results for different case studies together with the impacts of reduction in PV and ESS unit costs in comparison with changes in energy selling back flat rate are evaluated in order to conduct a case analysis and sensitivity analysis together. The corresponding results are presented in Tables 4-9 for different cases. It should be noted that all the costs (installation, replacement, maintenance) are considered to decrease with the same ratio.

It is clear from the results that PV and ESS size increase with the increase of flat rate of selling energy back to grid and decrease of individual costs as can be expected. Besides, it can be seen that if the algorithm decides that investment of PV and ESS is feasible, maximum limit of PV and ESS size is provided as the optimum configuration as more the capacity of such systems more the benefit is. The most profitable case is Case-2 as anyone is at home during the day and the load demand is minimum when the PV production is at the highest, which ensures more energy can be sold to grid without the need of covering a bigger household demand. This is especially more profitable when the flat rate to sell back energy is higher as HEM system always tries to sell back more energy to grid to increase benefits. As the case of flat rate of 0.05 $ and cost ratio of 50% provides feasibility of both PV and ESS investment in all cases, this case is examined in more detail. This case results in a TPV_{inc} value of 15789.671 $ and a TPV_{out} value of 11703.332 $ for Case-1, which in turn provides a BCR of nearly 1.35. As providing results for the 8760 h of the yearly period is significantly detailed, for the easiness of tracking, a random day is selected and the related results are presented from Case-1 under the conditions of flat rate of 0.05 $ and cost ratio of 50%.

For the date of 02.01.2013, the injected to grid and used power from PV system together with total production is presented in Fig. 6. It is observed that some of the produced energy by PV is injected back to the grid while a portion is utilized within the smart household in the evaluated sample case.

The battery based ESS power decomposition and the corresponding energy variation is shown in Figure 7. As seen, ESS provides a cycling based operation that stores energy and then sells back to grid or utilized this stored energy within household during higher price periods. Especially, if the time 7 pm which is the highest price period during the day time (see Figure 5) is examined, the ESS discharges till the maximum discharging power limit and accordingly helps to cover the household's load, as expected in order to reduce the power procurement from the grid in such a high price period.

A similar issue is also noticed within the EV power decomposition and energy variation shown in Figure 8. EV battery is charged and discharged considering price variations. As also seen, for the time of departure from home, EV battery is fully charged as requested. The periods between 8 am and 5 pm are idle periods when EV is not at home, thus all the power values are zero for this periods. The energy is shown as 8 kWh (initial energy level assumed when EV returns back home) for simplification in these periods but this is not totally known as the EV is not at home in these hours and the exact utilization periods for driving are not accordingly available for HEM system.

As the flat rate of selling back energy is always greater than price of buying energy from the grid, the case that total EV and ESS power values are greater than load demand means the rest of the energy is injected back to grid with this higher price when grid power is surely zero as load is covered by total of EV and ESS. However, such a condition is not always possible for lower flat rates of selling back energy as the algorithm decides the proper operation of each hour considering the individual values of buying and selling price of energy.

4. Conclusions

In this study, a MILP model for techno-economic optimum sizing of additional PV and ESS investment for a DR-based HEM system controlled smart household was provided. The novelty of this paper lies in the consideration of the notably changing load pattern due to DR activities, an important issue that has not been treated by the existing research studies. Besides, as an issue that is not considered in the broad part of literature on sizing, the impacts of increment in size of PV and ESS on unit costs are taken into account with a step-wise decreasing cost function. It is clear from the obtained results that considering DR based load pattern changes significantly the sizing results and thus such investments for new generation residential areas should cover this important impact during the planning phase. Additional case studies were also conducted to observe and present the sensitivity of PV and ESS techno-economic sizing on unit costs and cost of selling back energy to the grid. Hence, a new insight to the literature on sizing was given in this paper from a different perspective that can be promoted with new studies in the area.

The model is applicable to different geographical areas with proper extensions of the modeling by adding a mathematical formulation for the operation of more appliances, such as HVACs, electric heaters, water heaters, etc., which is the topic of a future study of the authors. Besides, the further analysis of PV and ESS sizing sensitivity to different pricing scenarios apart from a single dynamic daily profile, in order to provide a correlation map for aiding policy implications to promote smart grid applications in end-user areas, is also planned as a future study of the authors.

Acknowledgement

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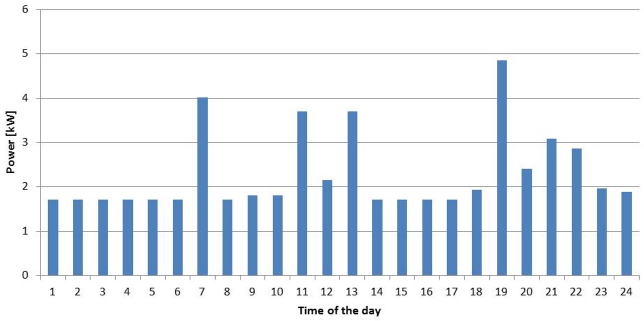
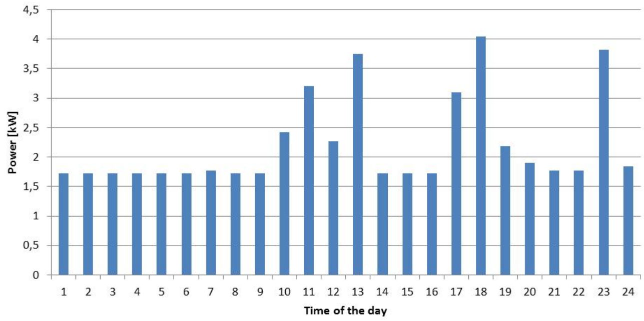
Figure Captions



(a) Spring weekday profile.



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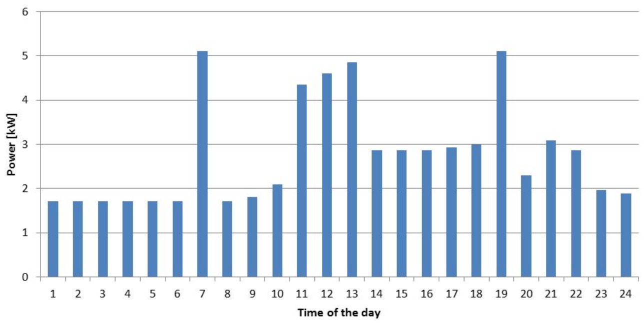

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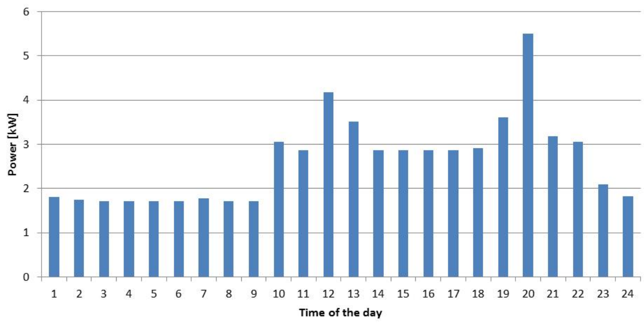

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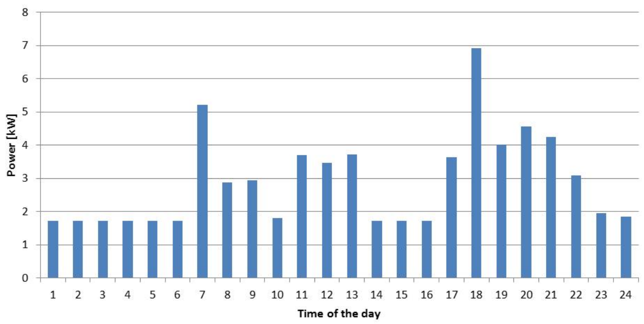

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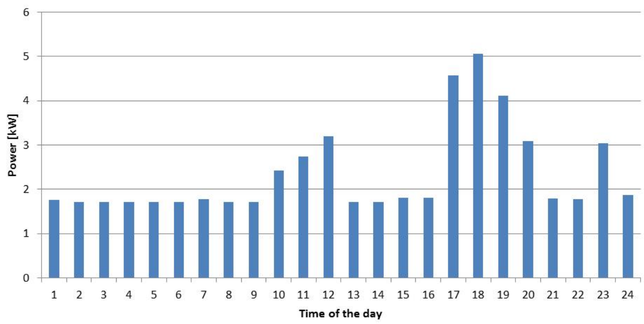

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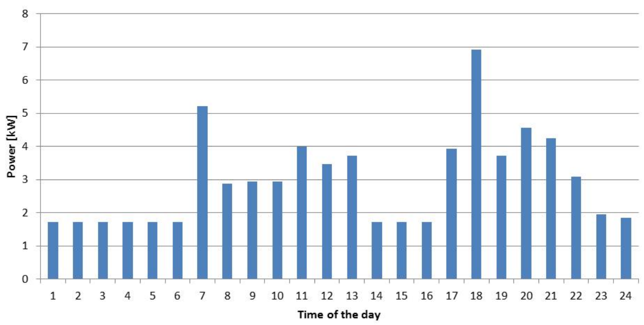

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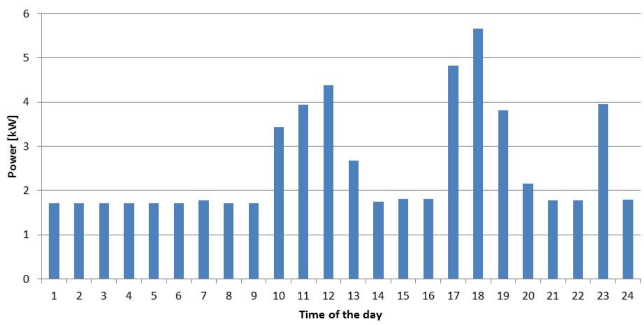
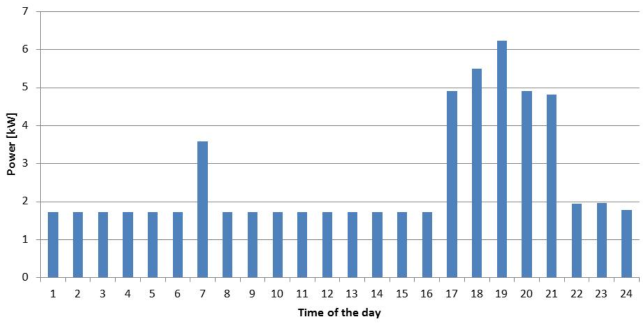


(h) Winter weekend profile.

Fig. 1. The household power profiles for Case-1.



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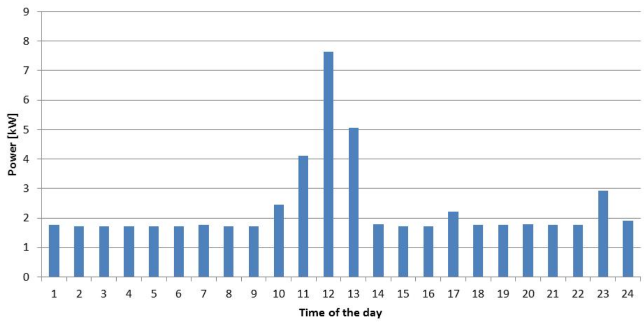

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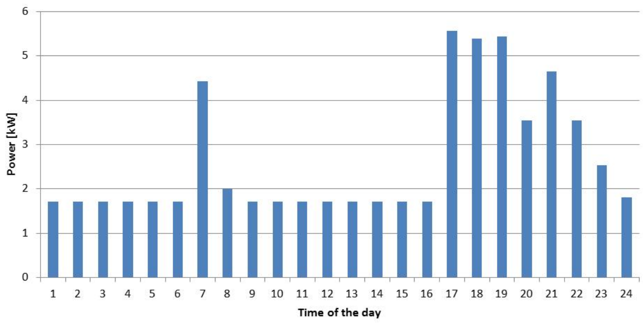

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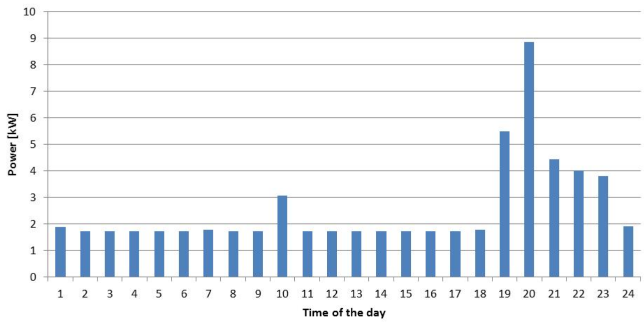

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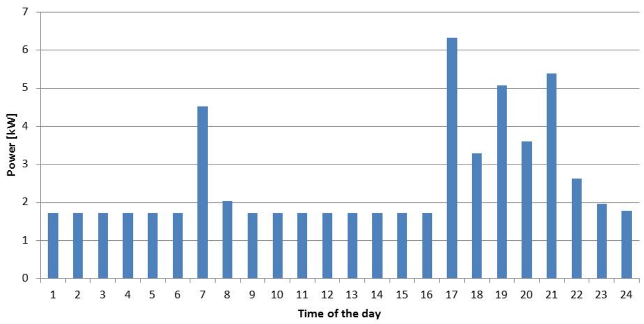

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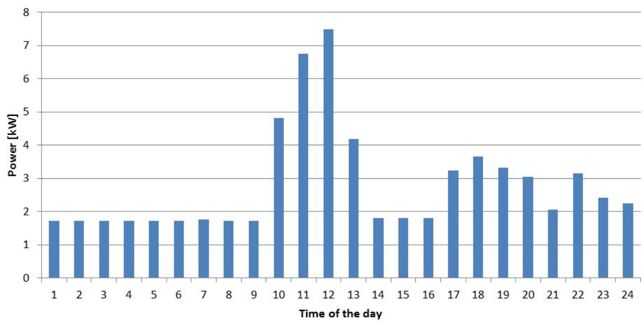

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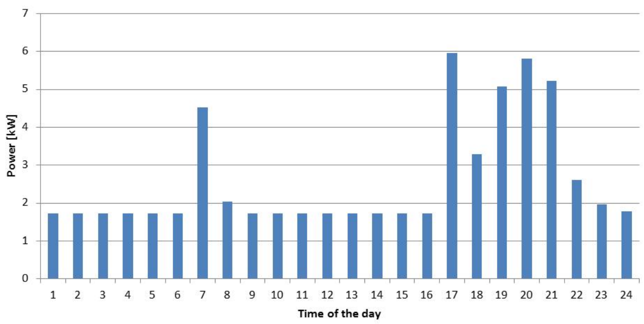

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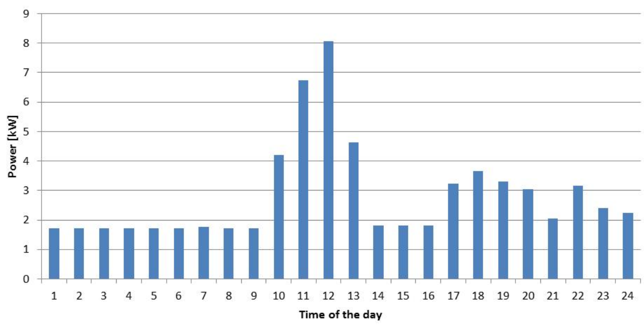
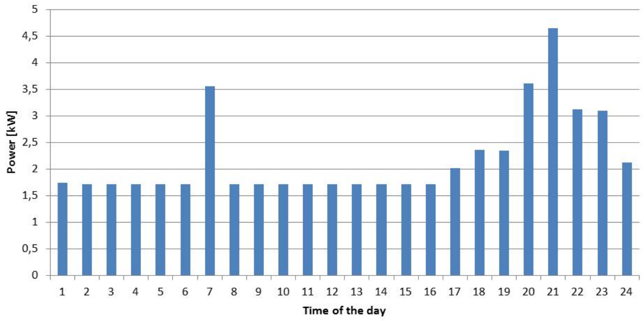


(h) Winter weekend profile.

Fig. 2. The household power profiles for Case-2.



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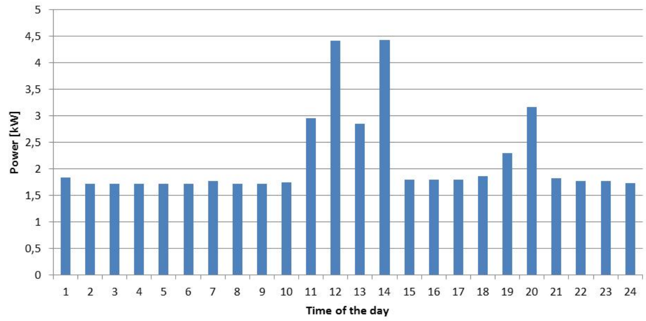

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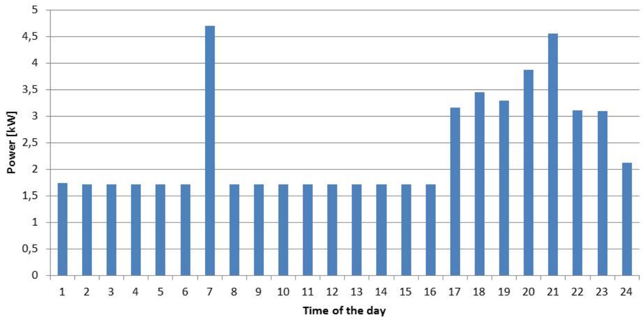

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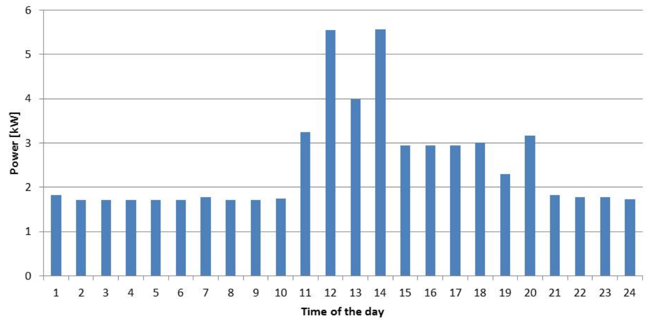

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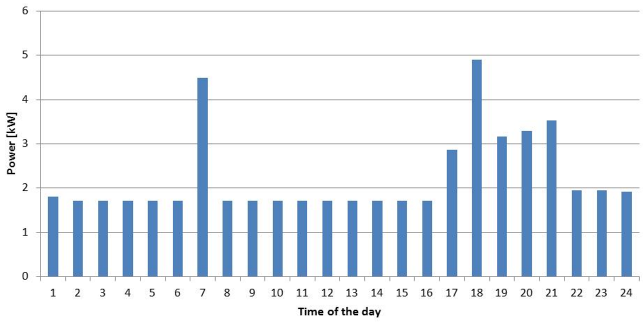

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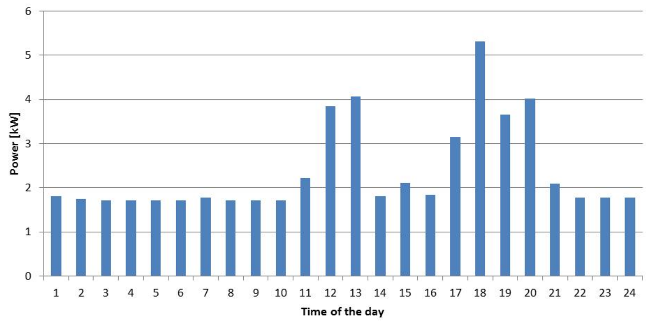

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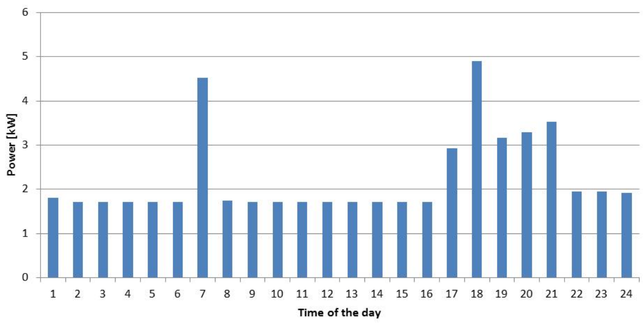

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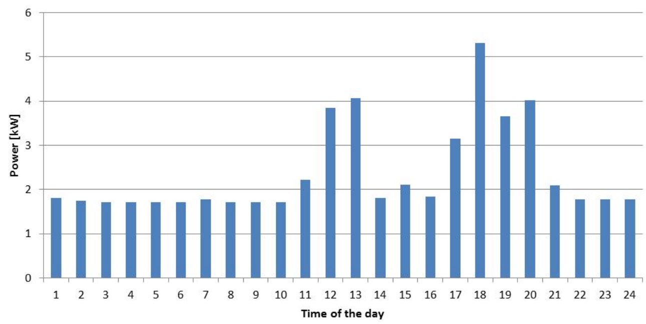

(h) Winter weekend profile.

Fig. 3. The household power profiles for Case-3.

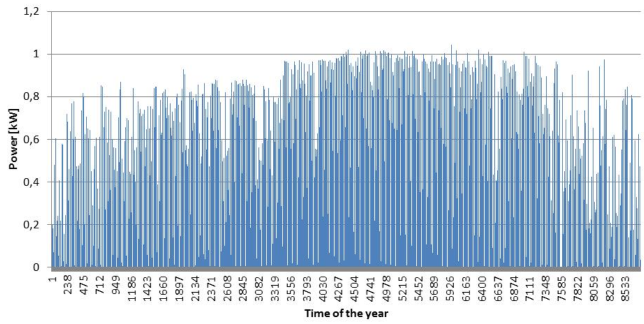

Fig. 4. The normalized power production for a 1 kW PV system.

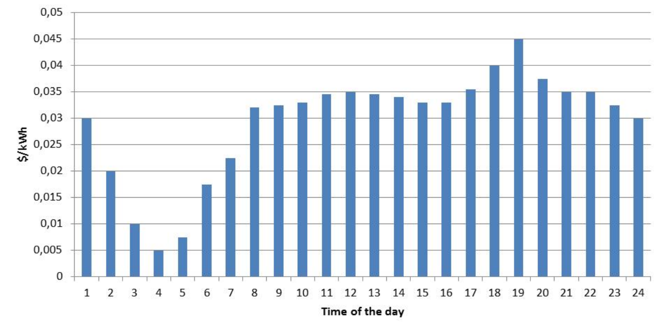

Fig. 5. The dynamic pricing data for DR activities within smart household.

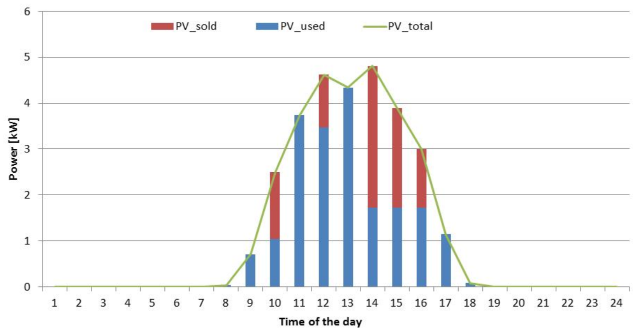

Fig. 6. The PV system power decomposition for the sample case.

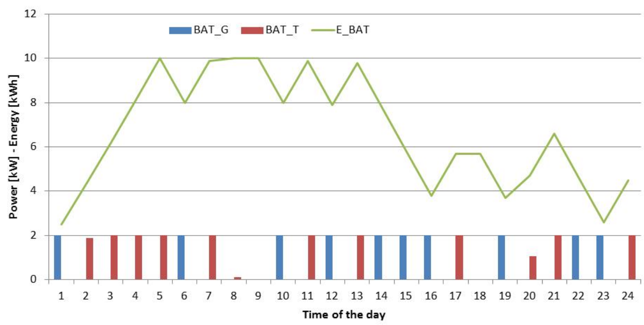

Fig. 7. The battery based ESS unit power decomposition and energy variation for the sample case.

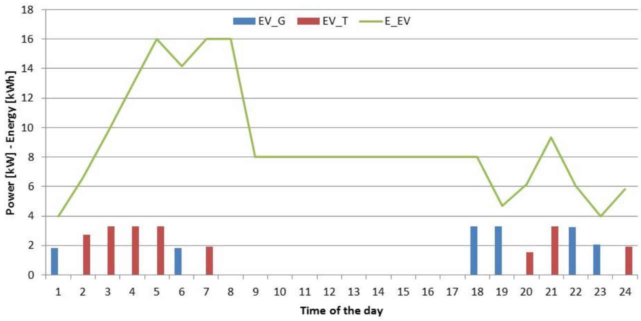

Fig. 8. The EV battery power decomposition and energy variation for the sample case.

Table Captions

Table 1. Household appliance data.

Appliance	Power [kW]
Oven	2.4
Cooker Hood	0.225
Microwave	1.2
Refrigerator	1.666
Washing Machine	1.4
Dishwasher	1.32
Iron	2.4
Toaster	0.8
Kettle	2
Hairdryer	1.8
Telephone	0.005
TV	0.083
Desktop Computer	0.15
Air Conditioner	1.14
Hair Straightener	0.055
Printer	0.011
Lighting	0.1
Other (Fixed)	0.05

Table 2. EV departure and arrival times for different case studies.

Season	Time of the week	Departure-Arrival	Case-1	Case-2	Case-3
Spring	Weekday	Departure	8am	8am	8am
		Arrival	7pm	5pm	5pm
	Weekend (Saturday)	Departure	9pm	6pm	9pm
		Arrival	11pm	11pm	12am
Summer	Weekday	Departure	8am	9am	8am
		Arrival	7pm	5pm	5pm
	Weekend (Saturday)	Departure	2pm	11am	9pm
		Arrival	6pm	7pm	12am
Autumn	Weekday	Departure	8am	9am	8am
		Arrival	6pm	5pm	5pm
	Weekend (Saturday)	Departure	9pm	2pm	10pm
		Arrival	11pm	5pm	12am
Winter	Weekday	Departure	8am	9am	8am
		Arrival	6pm	5pm	5pm
	Weekend (Saturday)	Departure	8pm	2pm	10pm
		Arrival	11pm	5pm	12am

Table 3. Step-wise decreasing unit costs for PV and battery based ESS.

Size interval (kW for PV, kWh for battery)	Unit cost for PV [$/kW]	Unit cost for battery [$/kWh]
0-1	1330	300
1-2	1300	290
2-3	1300	290
3-4	1270	270
4-5	1270	260
5-6	1210	260
6-7	1160	240
7-8	1150	230
8-9	1140	220
9-10	1120	200

Table 4. Case-1: Sensitivity of PV size to cost reduction and flat rate for selling energy back to grid.

		Flat rate for selling energy [$/kWh]				
		0.01	**0.02**	**0.03**	**0.04**	**0.05**
PV cost ratio	**50%**	0	0	0	10	10
	60%	0	0	0	0	10
	70%	0	0	0	0	0
	80%	0	0	0	0	0
	90%	0	0	0	0	0
	100%	0	0	0	0	0

Table 5. Case-1: Sensitivity of ESS size to cost reduction and flat rate for selling energy back to grid.

		Flat rate for selling energy [$/kWh]				
		0.01	**0.02**	**0.03**	**0.04**	**0.05**
ESS cost ratio	**50%**	0	0	0	0	10
	60%	0	0	0	0	0
	70%	0	0	0	0	0
	80%	0	0	0	0	0
	90%	0	0	0	0	0
	100%	0	0	0	0	0

Table 6. Case-2: Sensitivity of PV size to cost reduction and flat rate for selling energy back to grid.

		Flat rate for selling energy [$/kWh]				
		0.01	**0.02**	**0.03**	**0.04**	**0.05**
PV cost ratio	**50%**	0	0	0	10	10
	60%	0	0	0	0	10
	70%	0	0	0	0	10
	80%	0	0	0	0	0
	90%	0	0	0	0	0
	100%	0	0	0	0	0

Table 7. Case-2: Sensitivity of ESS size to cost reduction and flat rate for selling energy back to grid.

		Flat rate for selling energy [$/kWh]				
		0.01	**0.02**	**0.03**	**0.04**	**0.05**
ESS cost ratio	**50%**	0	0	0	0	10
	60%	0	0	0	0	10
	70%	0	0	0	0	0
	80%	0	0	0	0	0
	90%	0	0	0	0	0
	100%	0	0	0	0	0

Table 8. Case-3: Sensitivity of PV size to cost reduction and flat rate for selling energy back to grid.

		Flat rate for selling energy [$/kWh]				
		0.01	**0.02**	**0.03**	**0.04**	**0.05**
PV cost ratio	**50%**	0	0	0	10	10
	60%	0	0	0	0	10
	70%	0	0	0	0	10
	80%	0	0	0	0	0
	90%	0	0	0	0	0
	100%	0	0	0	0	0

Table 9. Case-3: Sensitivity of ESS size to cost reduction and flat rate for selling energy back to grid.

		Flat rate for selling energy [$/kWh]				
		0.01	**0.02**	**0.03**	**0.04**	**0.05**
ESS cost ratio	**50%**	0	0	0	0	10
	60%	0	0	0	0	0
	70%	0	0	0	0	0
	80%	0	0	0	0	0
	90%	0	0	0	0	0
	100%	0	0	0	0	0