Coordinated Operation of a Neighborhood of Smart Households Comprising Electric Vehicles, Energy Storage and Distributed Generation

Nikolaos G. Paterakis, *Member, IEEE*, Ozan Erdinç, *Member, IEEE*, Iliana N. Pappi, Anastasios G. Bakirtzis, *Fellow, IEEE*, and João P. S. Catalão, *Senior Member, IEEE*

***Abstract*—In this paper, the optimal operation of a neighborhood of smart households in terms of minimizing the total energy procurement cost is analyzed. Each household may comprise several assets such as electric vehicles, controllable appliances, energy storage and distributed generation. Bi-directional power flow is considered both at household and neighborhood level. Apart from the distributed generation unit, technological options such as vehicle-to-home and vehicle-to-grid are available to provide energy to cover self-consumption needs and to inject excessive energy back to the grid, respectively. The energy transactions are priced based on the net-metering principles considering a dynamic pricing tariff scheme. Furthermore, in order to prevent power peaks that could be harmful for the transformer, a limit is imposed to the total power that may be drawn by the households. Finally, in order to resolve potential competitive behavior, especially during relatively low price periods, a simple strategy in order to promote the fair usage of distribution transformer capacity is proposed.**

***Index Terms*—Coordination, energy management system, electric vehicle, energy storage system, net metering, photovoltaic, dynamic pricing, smart household, smart neighborhood.**

NOMENCLATURE

Sets and Indices

$h(H)$	index (set) of households.
$m(M)$	index (set) of controllable appliances.
$p(P)$	index (set) of operating phases of controllable appliances.
$t(T)$	index (set) of time periods.

Parameters

CE_h^{ESS}	charging efficiency of the ESS of household h.
CE_h^{EV}	charging efficiency of the EV of household h.
CP_t	critical period indicator.
DE_h^{ESS}	discharging efficiency of the ESS of household h.
DE_h^{EV}	discharging efficiency of the EV of household h.
$L_{h,t}$	inflexible load of household h in period t [kW].
$N_{h,m}$	number of times the controllable appliance m of household h must be operated during the optimization horizon.
$P_{h,m,p}^{ph}$	power consumed by controllable appliance m of household h while in phase p [kW].
$P_{h,t}^{PV,pro}$	available power of the PV system of household h in period t [kW].
$R_h^{ESS,ch}$	charging rate of ESS of household h [kW].
$R_h^{ESS,dis}$	discharging rate of ESS of household h [kW].
$R_h^{EV,ch}$	charging rate of EV of household h [kW].
$R_h^{EV,dis}$	discharging rate of EV of household h [kW].
$SOE_h^{ESS,ini}$	initial SOE of the ESS of household h [kWh].
$SOE_h^{ESS,max}$	maximum SOE of the ESS of household h [kWh].
$SOE_h^{ESS,min}$	minimum SOE of the ESS of household h [kWh].
$SOE_{h,t}^{EV,ini}$	initial SOE of the EV of household h [kWh].
$SOE_h^{EV,max}$	maximum SOE of the EV of household h [kWh].
$SOE_h^{EV,min}$	minimum SOE of the EV of household h [kWh].
T_h^a	arrival period of the EV of household h.
T_h^d	departure period of the EV of household h.
$T_{h,m,p}^{dur}$	duration of phase p of controllable appliance m of household h [number of ΔT-hour periods].

Manuscript received April 8, 2015; revised July 23, 2015 and October 4, 2015; accepted December 23, 2015. This work was supported in part by the FEDER funds through COMPETE, in part by the Portuguese funds through FCT under Grant FCOMP-01-0124-FEDER-020282 (Ref. PTDC/EEA-EEL/118519/2010), Grant UID/CEC/50021/2013, and Grant SFRH/BPD/103744/2014, in part by the Scientific and Technological Research Council of Turkey under Project 115E215, and in part by the EU Seventh Framework Programme FP7/2007-2013 under Grant 309048 (Project SiNGULAR). Paper no. TSG-00398-2015.

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

O. Erdinç is with the Department of Electrical Engineering, Yildiz Technical University, Istanbul 34220, Turkey, and also with the INESC-ID, Instituto Superior Técnico, University of Lisbon, Lisbon, Portugal (e-mail: oerdinc@yildiz.edu.tr; ozanerdinc@gmail.com).

I. N. Pappi and J. P. S. Catalão are with the Faculty of Engineering, University of Porto, Porto 4200-465, Portugal, also with the University of Beira Interior, Covilhã 6201-001, Portugal, and also with the INESC-ID, Instituto Superior Técnico, University of Lisbon, Lisbon 1049-001, Portugal (e-mail: iliananpappi@gmail.com; catalao@ubi.pt).

A. G. Bakirtzis is with the Aristotle University of Thessaloniki, Thessaloniki 54006, Greece (e-mail: bakiana@eng.auth.gr).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TSG.2015.2512501

TR_t^{lim}	power limit of the transformer in period t [kW].
UDC_t	uniformly distributed capacity of the transformer in period t [kW].
λ_t^{buy}	price at which energy is bought [€/MWh]
λ_t^{sell}	price at which energy is sold [€/MWh]
ΔT	time interval duration [h].

Variables

$P_{h,t}^{buy,G}$	portion of total power procured from the grid by household h in period t [kW].
$P_{h,t}^{buy,L}$	portion of power procured from the local neighborhood by household h in period t [kW].
$P_{h,t}^{buy,T}$	total power procured by household h in period t [kW].
$P_{h,t}^{ESS,ch}$	charging power of ESS of household h in period t [kW].
$P_{h,t}^{ESS,dis}$	discharging power of ESS of household h in period t [kW].
$P_{h,t}^{ESS,used}$	portion of the ESS discharging power of household h used to satisfy self-consumption in period t [kW].
$P_{h,t}^{EV,ch}$	charging power of EV of household h in period t [kW].
$P_{h,t}^{EV,dis}$	discharging power of EV of household h in period t [kW].
$P_{h,t}^{EV,used}$	portion of the EV discharging power of household h used to satisfy self-consumption in period t [kW].
$P_{h,t}^{excess}$	excess power of household h in period t [kW].
$P_{h,m,t}^{mach}$	power consumed by controllable appliance m of household h while in period t [kW].
$P_t^{N\to TR}$	total power flowing from neighborhood to transformer in period t [kW].
$P_{h,t}^{PV,used}$	portion of the PV power of household h used to satisfy self-consumption in period t [kW].
$P_{h,t}^{release}$	power capacity released of household h in period t [kW].
$P_{h,t}^{sell,ESS}$	portion of the ESS discharging power of household h injected to PCC in period t [kW].
$P_{h,t}^{sell,EV}$	portion of the EV discharging power of household h injected to PCC in period t [kW].
$P_{h,t}^{sell,G}$	portion of the power injected to PCC by household h that flows back to grid in period t [kW].
$P_{h,t}^{sell,L}$	portion of the power injected to PCC by household h that is locally used in neighborhood in period t [kW].
$P_{h,t}^{sell,PV}$	portion of the PV power of household h injected to PCC in period t [kW].
$P_{h,t}^{sell,T}$	total power injected to PCC household h in period t [kW].
$P_t^{TR\to N}$	total power flowing from transformer to neighborhood in period t [kW].
$SOE_{h,t}^{ESS}$	SOE of ESS of household h in period t [kWh].
$SOE_{h,t}^{EV}$	SOE of EV of household h in period t [kWh].
u_t^1	binary variable. 1 if neighborhood is drawing power from the transformer in period t; else 0.
$u_{h,t}^i$	binary variable. 1 if the power flows from transformer to PCC/if EV is charging/if ESS is charging ($i = \{2, 3, 4\}$) for household h in period t; else 0.
$x_{h,m,p,t}^{ph}$	binary variables. 1 if phase p of controllable appliance m in household h is beginning/ongoing/finishing ($x = \{y, u, z\}$) in period t; else 0.

I. Introduction

A. Motivation

Recent developments in automation, control and communication infrastructure enable the modernization of the existing power grid structure [1]. The so-called "smart-grid" is a structure that integrates monitoring and control of all the functional units of a power system from generation to end-users and features bi-directional flow of energy and information [2]. Demand response (DR) is a mechanism that allows customers to participate into the electricity markets. The utilization of DR can reduce the peak of the system load and as a result can render the operation of the power system more economical, reliable and environmentally friendly [3]. There are many DR programs that are addressed to large industrial and commercial customers. However, a few DR programs are developed to engage residential end-users [4] that are responsible for nearly 40% of the global electrical energy consumption [5].

Recent changes that are being fostered at residential end-user premises are likely to motivate system operators to develop residential DR programs. Firstly, the electrification of the transport sector through the commercialization of electric vehicles (EV) will cause severe deviations of the household load profiles from the current ones. Secondly, the reduction in the prices of small scale distributed generation units such as rooftop photovoltaics (PV) and energy storage systems (ESS) may lead residential end-users to cover a portion of their load from these sources or even inject energy back to the grid. Furthermore, a typical household already contains appliances that could be shifted within certain time intervals without causing comfort violation of the residents (e.g., washing machine). Nowadays, advanced metering infrastructure (AMI), e.g., smart meters, and communication protocols such as the home area network (HAN) allow for the coordination of the residential load and potentially available energy production and storage units in order to respect the targets of a DR program through an energy management system (EMS) [6]. There are mainly two types of DR programs that could be employed at residential end-user level: direct load control (DLC) and price-based DR through time-varying pricing tariffs. In the first case, several appliances, e.g., refrigerators [7] are supplied with a frequency sensitive relay that automatically disconnects the appliance when a frequency drop is noticed in the grid. In the second case, the residential end-users receive hourly varying signals through their smart meter in order to

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

be motivated to shift their loads in order to achieve electricity bill reductions [8], [9]. The presented study focuses on price incentivized DR.

The operation of a single EMS under a dynamic pricing DR program would attempt to shift as much load as possible to relatively low price periods. Considering that more customers would enroll to such programs in the future, more severe power peaks could occur during relatively low price periods causing violations to the voltage and current limits of the distribution system and increase market price volatility [10]. Additionally, the local distribution transformers that serve neighborhoods of such households could be stressed above their nameplate rating, causing failures and accelerated ageing of the infrastructure [11], [12]. Evidently, another option would be to upgrade the currently existing infrastructure capacity. Nevertheless, the main barriers in this case are the high investment cost required [12], [13] and potential over-sizing of the assets since these upgrades would just be provided to cover excessive loads for a limited amount of time. It appears that the most effective solution is to utilize the existing assets more efficiently. For this reason, it is of interest to develop coordination strategies at the level of a local distribution transformer in order to guarantee that the nominal operational conditions of the infrastructure are achieved while the residential end-users would still benefit from the dynamic pricing signals.

B. Relevant Background

There are many studies that propose EMS algorithms in order to optimally allocate the load of a single household. The interested reader may refer to a previous work of the Authors for more information regarding the state-of-the-art of EMS algorithms [14]. Recently, several studies have treated the problem of coordinating the activities of price-responsive residential consumers considering the distribution infrastructure operational limits. In [10] a DLC based residential end-user coordination scheme is proposed in order to satisfy the distribution system operational limits. A decentralized collaborative coordination strategy is proposed in [15] to achieve minimal cost for the load serving entity into the balancing market. Another decentralized hierarchical approach is proposed in [16] in order to achieve the maximal utility of a coalition of residential consumers. Shao *et al.* [11] proposed a DR-based load shaping strategy in order to mitigate the violation of the rating of a distribution transformer serving a neighborhood. Khamphanchai *et al.* [17] proposed a multi-agent based DR algorithm to maintain the load of a distribution transformer that serves a neighborhood under a specific limit while securing critical loads and mitigating the violation of the comfort of the residents. In [18] a two-stage decentralized residential load management strategy is proposed in which the network operational constraints are considered through nodal pricing. Also, in [19] a decentralized Lyapunov based cost minimization algorithm is proposed in order to coordinate the activities of a neighborhood of smart households in order to achieve cost minimization and satisfy the transformer capacity limits. In [20], authors presented an approach that is not directly linked to transformer capacity but related to sustaining a micro-grid system operation during fault conditions considering ESS, shiftable loads and distributed generation that can be considered similar to transformer capacity limitations during peak periods. In [21], a real-time retail price based dynamic DR controller approach is presented for peak load reduction in order to reduce the stress on power system assets during critical periods. Besides, a different incentive based peak load reduction strategy is also considered in [22] for load reduction and voltage improvement.

These studies have provided seminal insights into the problem of coordinating the smart household activities in a smart grid concept. Nevertheless, there are several important points that are not addressed. References [15] and [16] disregard the operational constraints of the DS infrastructure. References [10], [11], [17], and [20] do not consider the dynamically varying prices in their proposed DR strategy. References [18], [21], and [22] are based on pricing or incentive based strategies that do not guarantee the satisfaction of power system asset limitations due to relying on end-user preferences. Finally, all the aforementioned studies do not consider the possibility of bi-directional power flow and satisfaction of transformer capacity limitations combined with pricing based schemes.

C. Contribution and Organization of the Paper

This paper examines the simultaneous operation of several smart household in the context of a smart neighborhood. This study is based on a background of a detailed model of each smart household with ESS, EV, PV and shiftable appliances aiding minimization of cost under an hourly varying price tariff scheme. Here, the operational problem of a smart neighborhood is formulated as an optimization problem using Mixed-Integer Linear Programming (MILP) with the objective of minimizing the total energy procurement cost.

The main novel points of the proposed formulation are:

1. Bi-directional power flow is explicitly considered both at the level of a single household and at neighborhood level.
2. A two-step coordination strategy is proposed in order to mitigate unfair usage of the distribution transformer capacity during periods in which competitive behavior would appear among the EMS of different households (e.g., during low price periods, DR event).

The paper is organized as follows: the mathematical model is developed in Section II. Afterwards, the proposed methodology is evaluated through a test case in Section III. Finally, concluding remarks are presented in Section IV.

II. Formulation of the Optimization Problem

A. Overview of the Proposed Structure

The schematic diagram of a transformer serving a neighborhood composed of multiple smart households is depicted in Fig. 1. It should be noted that the point where all the smart households and the transformer unit have a common connection will be called "point of common coupling (PCC)" hereafter.

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

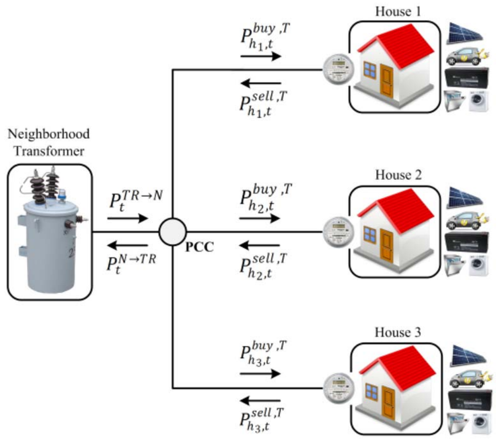

Fig. 1. The schematic diagram of a transformer serving a neighborhood composed of multiple smart households.

As it can be observed in Fig. 1, there is bi-directional power flow between the households and the PCC, and similarly, between the PCC and the grid across the transformer unit. It is considered that two types of power transactions are available, namely the power transactions between the neighborhood and the grid, and also the local power transactions within the neighborhood. As a result, the power that is consumed by a household may be procured by the grid and/or be produced locally and rendered available by other end-users by allowing them to sell their excessive energy.

Each end-user may possess any combination of several assets (EV, ESS, PV, controllable appliances) and technical capabilities such as vehicle-to-grid (V2G), vehicle-to-home (V2H), ESS-to-grid (ESS2G), ESS-to-home (ESS2H), PV-to-grid (PV2G) and PV-to-home (PV2H). All the consumers are assumed to be contracted under an hourly-varying pricing tariff scheme. Communication with the utility is performed by means of a smart meter.

Regarding the pricing of the energy that is injected to the PCC by each household, a net metering approach is adopted and therefore the prices of buying and selling energy are identical. Note that as current practice suggests, the wholesale market prices are directly passed (potentially, after–flat rate–taxation) to the end-users [23].

Finally, the distribution transformer that is serving the neighborhood is considered to be equipped with a transformer load monitoring unit which enables the control of excessive loading that may be harmful for the transformer unit due the acceleration of the ageing effect [24].

The proposed model is deterministic similarly to other models in the literature [17]. Despite the fact that there are several uncertainties related to the operation of the residential end-users (e.g., PV production, EV arrival/departure time etc.), a deterministic model instead of a stochastic one may be justifiable for two reasons.

First, the economic value of considering uncertainty at the scale of a few residential end-users is insignificant (scale of a few cents), while the complexity of a stochastic optimization problem is higher. In order to justify the solution of a stochastic optimization problem, significant differences in the cost savings should be noticed when considering the modeling of uncertainty. Undoubtedly, this would be the case for a larger consumer for whom the electricity bill constitutes a significant portion of the total expenses and the minimization of cost would yield significant welfare gain. However, since the differences in the daily hourly-time varying pricing schemes are typically very small (based on the historical data of utilities that offer such programs, e.g., [25], [26]), two typical measures that are used in order to assess the advantage of formulating stochastic programming problems instead of deterministic ones, namely the expected value of perfect information (EVPI) and the value of the stochastic solution (VSS) [27], would have a very little value in order to justify the additional complexity resulting from the formulation of a stochastic optimization problem. The rationale of the authors is further justified by the results of a recently published work [28] in which the risk of exposing the EMS scheduling to uncertainties is considered. As it may be noticed in Tables IV and V of [28], the cost differences for different levels of risk-aversion both under normal operation and under DR request for a residential end-user are of the scale of a few cents.

Second, in practice, there is the option of accurately learning the parameters of the end-user habits through adaptive systems and therefore make accurate decisions in the majority of the cases [29]. Besides, the fact that within an hour the electricity price is the same, renders the actual cost differences even less, significant providing in that way a natural degree of "robustness" to the estimations of such adaptive systems (e.g., whether the EV arrives at 6pm or at 6:20pm is practically indifferent from the economic point of view).

Taking into account end-user parameter related uncertainties is economically and technically meaningful for larger scale applications in which the behavior of a large number of end-users may be considered using appropriate probability distributions. A relevant discussion is performed in [30] regarding the disjunction between the uncertain behavior of a single EV and a fleet of EVs.

B. Mathematical Formulation

1) Objective Function:

Minimize

$$TNC = \sum_h HC_h$$

where

$$HC_h = \sum_t \left(\lambda_t^{buy} \cdot P_{h,t}^{buy,T} \cdot \Delta T - \lambda_t^{sell} \cdot P_{h,t}^{sell,T} \cdot \Delta T\right), \forall h \quad (1)$$

The objective of the optimization problem (1) is to minimize the total energy procurement cost of the smart neighborhood (total neighborhood cost- TNC). As stated before, this study focuses on a net-metering approach in which the price of buying and selling energy is the same for the households. Nevertheless, (1) may be adapted to any other pricing scheme regarding the energy that is sold back to the grid (e.g., feed-in-tariff).

The grid related tariffs that are calculated based on the total electricity consumption at the end of the billing period are not considered in the objective function. In addition, if the

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

grid related tariffs are calculated based on time-of-use principles, the proposed formulation is readily compatible with such policies as well, simply by adding a summation term in the objective function which aims at further minimizing the energy usage during periods that are pre-defined by the utility.

It is to be noted that investment and asset degradation costs, as well as appliance, control and communication infrastructure costs are not considered in the scope of this paper which focuses on the impact of the proposed strategy on operational costs.

2) Neighborhood Power Exchange Constraints: First of all, the power drawn from the PCC from each household comprises two components as in (2), where $P_{h,t}^{buy,L}$ represents the portion of the total power of household h that comes from the power injections to the PCC from other households, while $P_{h,t}^{buy,G}$ is the amount of power that is transferred from the transformer side to household h. Similarly, the power sold back to the PCC from each household comprises two components as in (3), where $P_{h,t}^{sell,L}$ represents the portion of the power injected to the PCC from household h that is used to cover the power requirements of other households in the neighborhood without passing through the transformer unit, while $P_{h,t}^{sell,G}$ is the portion of the injected power to the PCC from household h that flows through the transformer unit to the grid side. Furthermore, the injected power to be used in the neighborhood should be equal to the power that is being gathered from local sources at every given period as enforced by (4).

$$P_{h,t}^{buy,T} = P_{h,t}^{buy,G} + P_{h,t}^{buy,L}, \quad \forall h, t \tag{2}$$

$$P_{h,t}^{sell,T} = P_{h,t}^{sell,G} + P_{h,t}^{sell,L}, \quad \forall h, t \tag{3}$$

$$\sum_h P_{h,t}^{buy,L} = \sum_h P_{h,t}^{sell,L}, \quad \forall t \tag{4}$$

Equation (5) provides the total power that the neighborhood draws from the transformer, while (6) specifies the total power of the energy sold by the smart households and passes through the transformer.

Constraints (7) and (8) limit the total energy that the neighborhood may procure by the transformer and vice versa, respectively. Note that the binary variables u_t^1 are necessary in the mathematical model in order to force the transformer to provide power only to one direction (either from the grid to the neighborhood, or from the neighborhood to the grid) during a given time interval.

$$\sum_h P_{h,t}^{buy,G} = P_t^{TR\rightarrow N}, \quad \forall t \tag{5}$$

$$\sum_h P_{h,t}^{sell,G} = P_t^{N\rightarrow TR}, \quad \forall t \tag{6}$$

$$P_t^{TR\rightarrow N} \leq TR_t^{lim} \cdot u_t^1, \quad \forall t \tag{7}$$

$$P_t^{N\rightarrow TR} \leq TR_t^{lim} \cdot \left(1 - u_t^1\right), \quad \forall t \tag{8}$$

To better illustrate the concept that constraints (2)-(8) implement, let us consider the following numerical example. In Fig. 1 assume that Houses 1 and 2 have 0.5 and 1 kW of surplus power that is injected to the PCC, respectively. At the same time House 3 requires 2 kW of power to supply its requirements. Therefore, the total 1.5 kW of reverse power from House 1 and 2 will naturally flow to House 3 via the PCC together with an additional 0.5 kW that is procured from the grid and is transferred across the transformer in order to satisfy the 2 kW required by House 3. A similar numerical example can be also considered for reverse power flow, i.e., from the PCC to grid across the transformer unit, if the total excess power injected to the PCC by some households exceeds the power requirements of the rest of the households in the neighborhood.

To sum up, the direction in which the energy flows is defined by the power balance at the PCC. At each given time interval either of the following conditions holds: several households, having satisfied their internal energy balance, inject their excessive energy to the PCC, while other request energy from the PCC. In case the locally available energy is less than the energy that is required by the end-users with internal energy deficit, then the energy deficit of the neighborhood is covered by additional energy that is drawn by the PCC from the grid through the transformer unit. In the opposite case, i.e., if the locally available energy exceeds the demand of the end-users, then the energy surplus of the neighborhood is injected from the PCC to the grid through the transformer unit. Finally, if the locally available energy matches the energy that is requested by the end-users with internal energy deficit, then no energy flows through the transformer.

At this point, the following should be clarified: since the excess energy from any individual end-user is bought at the market price according to the net metering principles, the end-user de facto grants the right to the respective retailer to use it in its energy transactions. As a result, energy that is injected from the end-users to the PCC could not be physically dissociated from the energy that is provided by the grid through the transformer to the PCC and thus, no further separate consideration regarding its allocation, different than the concepts described in Section II-B4, to the end-users that request energy is required.

3) Household Power Exchange Constraints:

a) Power balance: The power balance of each household is described by (9).

$$P_{h,t}^{buy,T} + P_{h,t}^{PV,used} + P_{h,t}^{EV,used} + P_{h,t}^{ESS,used} = L_{h,t} + P_{h,t}^{EV,ch} + P_{h,t}^{ESS,ch} + \sum_m P_{h,m,t}^{mach}, \quad \forall h, t \tag{9}$$

b) Decomposition of power bought and sold: Constraints (10), (11) and (12) define the energy transactions between the house and the grid. The parameter N may be used to impose limits to the power that may be drawn or injected back to the grid as a part of an advanced DR strategy. If no power limits are defined, then this parameter is set to a sufficiently high positive value.

$$P_{h,t}^{sell,T} = P_{h,t}^{sell,PV} + P_{h,t}^{sell,EV} + P_{h,t}^{sell,ESS}, \quad \forall h, t \tag{10}$$

$$P_{h,t}^{buy,T} \leq N \cdot u_{h,t}^2, \quad \forall h, t \tag{11}$$

$$P_{h,t}^{sell,T} \leq N \cdot \left(1 - u_{h,t}^2\right), \quad \forall h, t \tag{12}$$

Note that the binary variables $u_{h,t}^2$ are necessary in the mathematical model in order to enforce the fact that a house may only draw or inject power back to the grid at a given time interval.

c) Electric vehicle: The EV model employed in this study is described by (13)-(19) for each household. Equation (13) defines the usage of power that comes from discharging the EV (V2H or V2G). Constraints (14) and (15) limit the charging and discharging power of the EV, respectively. The state-of-energy (SOE) of the EV battery is defined by (16) and (17), while (18) stands for the minimum and maximum SOE of the EV in order to avoid deep-discharge. Finally, (19) states that the EV should be fully charged at the end of the time horizon.

$$P_{h,t}^{EV,used} + P_{h,t}^{sell,EV} = DE_h^{EV} \cdot P_{h,t}^{EV,dis}, \quad \forall h, t \tag{13}$$

$$0 \le P_{h,t}^{EV,ch} \le R_h^{EV,ch} \cdot u_{h,t}^3, \quad \forall h, t \in \left[T_h^a, T_h^d\right] \tag{14}$$

$$0 \le P_{h,t}^{EV,dis} \le R_h^{EV,dis} \cdot \left(1 - u_{h,t}^3\right), \quad \forall h, t \in \left[T_h^a, T_h^d\right] \tag{15}$$

$$SOE_{h,t}^{EV} = SOE_{h,t}^{EV,ini} + CE_h^{EV} \cdot P_{h,t}^{EV,ch} \cdot \Delta T - P_{h,t}^{EV,dis} \cdot \Delta T, \quad \forall h, \ if \ t = T_h^a \tag{16}$$

$$SOE_{h,t}^{EV} = SOE_{h,t-1}^{EV,ini} + CE_h^{EV} \cdot P_{h,t}^{EV,ch} \cdot \Delta T - P_{h,t}^{EV,dis} \cdot \Delta T, \quad \forall h, t \in \left(T_h^a, T_h^d\right] \tag{17}$$

$$SOE_h^{EV,min} \le SOE_{h,t}^{EV} \le SOE_h^{EV,max}, \ \forall h, t \in \left[T_h^a, T_h^d\right] \tag{18}$$

$$SOE_{h,t}^{EV} = SOE_h^{EV,max}, \quad \forall h, \ if \ t = T_h^d \tag{19}$$

Note that the binary variables $u_{h,t}^3$ are necessary in the mathematical model in order to enforce the fact that the EV may only charge or discharge at a given time interval.

d) Energy storage system: The constraints that model the operation of the ESS of each household (20)-(25) are similar to the ones describing the operation of the EV. The basic difference is that unlike the EV, the ESS is available at the household premises all day.

$$P_{h,t}^{ESS,used} + P_{h,t}^{sell,ESS} = DE_h^{ESS} \cdot P_{h,t}^{ESS,dis}, \quad \forall h, t \tag{20}$$

$$0 \le P_{h,t}^{ESS,ch} \le R_h^{ESS,ch} \cdot u_{h,t}^4, \quad \forall h, t \tag{21}$$

$$0 \le P_{h,t}^{ESS,dis} \le R_h^{ESS,dis} \cdot \left(1 - u_{h,t}^4\right), \quad \forall h, t \tag{22}$$

$$SOE_{h,t}^{ESS} = SOE_{h,t-1}^{ESS} + CE_h^{ESS} \cdot P_{h,t}^{ESS,ch} \cdot \Delta T - P_{h,t}^{ESS,dis} \cdot \Delta T, \quad \forall h, t \ge 1 \tag{23}$$

$$SOE_{h,t}^{ESS} = SOE_h^{ESS,ini}, \quad \forall h, \ if \ t = 1 \tag{24}$$

$$SOE_h^{ESS,min} \le SOE_{h,t}^{ESS} \le SOE_h^{ESS,max}, \quad \forall h, t \tag{25}$$

Note that the binary variables $u_{h,t}^4$ are necessary in the mathematical model in order to enforce the fact that the ESS may only charge or discharge at a given time interval.

e) Controllable appliances: A typical household contains loads that operate on a predefined cycle, by means that both the duration of their operation as well as their consumption during operational phases is known (e.g., washing-machine and dishwasher). The EMS may shift their operation in order to exploit low-price periods. This type of loads is modeled using (26)-(31) for each household. Equation (26) implies that the power that the appliance m is consuming during period t depends on the operating phase that is currently active. Constraint (27) states that a machine cannot be in more than one operating phase simultaneously. Equations (28)-(30) enforce the phase sequence logic. Finally, (31) enforces the number of times a specific appliance must operate during the horizon. These constraints assume that there is not a user-preference related to when the appliances should perform their task. Nevertheless, if such options need to be considered, appropriate time limits may be enforced to (26)-(31).

$$P_{h,m,t}^{mach} = \sum_p \left(u_{h,m,p,t}^{ph} \cdot P_{h,m,p}^{ph}\right), \quad \forall h, m, t \tag{26}$$

$$\sum_p u_{h,m,p,t}^{ph} \le 1, \quad \forall h, m, t \tag{27}$$

$$y_{h,m,p,t}^{ph} = z_{h,m,p,\left(t+T_{h,m,p}^{dur}\right)}^{ph}, \quad \forall h, m, p, t \tag{28}$$

$$y_{h,m,p,t}^{ph} - z_{h,m,p,t}^{ph} = u_{h,m,p,t}^{ph} - u_{h,m,p,(t-1)}^{ph}, \quad \forall h, m, p, t > 1 \tag{29}$$

$$z_{h,m,p,t}^{ph} = y_{h,m,p+1,t}^{ph}, \quad \forall h, m, p < |P|, t \tag{30}$$

$$\sum_t y_{h,m,p,t}^{ph} = N_{h,m}, \quad \forall h, m, p \tag{31}$$

f) PV production: Equation (32) implies that the available PV production may be used to cover a portion of the household load and if it exceeds it, it is sold back to the grid.

$$P_{h,t}^{PV,used} + P_{h,t}^{sell,PV} = P_{h,t}^{PV,pro}, \quad \forall h, t \tag{32}$$

4) Coordination Strategy: According to the current practice (e.g., [26], [27]) utilities that offer time-varying pricing schemes are offering uniform prices to all their consumers. More specifically, the consumer is directly exposed to the market prices. Even in the scenario of passing nodal prices to the consumers, the EMSs of a neighborhood would receive the same prices. This leads to an adverse effect that is usually referred to as "DR concentration" which in essence means that by assuming that an EMS is a rational agent that acts on behalf of the residential end-user, it is logical to deduce that each EMS would allocate as much power as possible to the relatively lowest price periods. As a result, it is not necessary that dynamic pricing based DR will always lead to peak power reductions.

The behavior of the EMS may cause concerns as regards the utilization of the local transformer which of course has limited capacity. If the transformer capacity limit is neglected, then the optimization problem renders an optimal solution that corresponds to minimizing each individual household cost. This solution is fair from the point of view that each individual end-user may equally benefit from the dynamic pricing scheme. However, it is not practically a feasible case since transformer overloading, especially due to relatively long lasting EV charging loads, would potentially damage this important distribution asset (e.g., ageing acceleration).

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

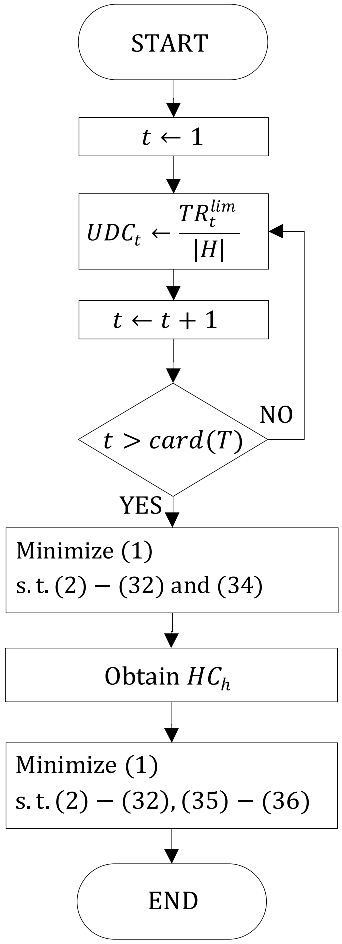

Fig. 2. Flow chart of the proposed coordination strategy.

Since the objective function as expressed by (1) involves the minimization of the total neighborhood energy procurement cost, different optimal solutions may exist in terms of combinations of optimal household costs. In that case, taking into account that (7) limits the total available transformer capacity, unfair allocation of power to different households may be noticed, especially during relatively low price periods. If the transformer limit is inconsiderately incorporated in the optimization problem as a constraint, then, a solution that favors one end-user over the other may occur. For example, one highly power intensive household may be allowed to procure power of the grid that stands for the 50% of the capacity of the transformer, while, the rest of the households would have to share the remaining 50%. Evidently, this is an unfair situation as regards the utilization of the transformer.

To mitigate this negative implication, a power allocation strategy is proposed that comprises the solution of two optimization problems, as it is displayed in Fig. 2.

The proposed strategy promotes the fair usage of the transformer capacity in the following way: firstly, the transformer capacity is assumed to be equally distributed among the end-users that are connected to the LV side of the same local distribution transformer. The household costs are then optimized from the perspective of each individual EMS. Practically, in the first step, the households are considered to be constrained by the uniformly distributed capacity (UDC_t) of the transformer as expressed by (33) and (34). The indicator parameter step is set to 1 and the optimization problem is solved. As a result, the optimal cost of the houses HC'_h is rendered known. This result could be considered fair but it may lead to underutilization of the transformer capacity since it is natural that several households are not fully exploiting their individually allocated capacity and as a result, there is spare capacity that could be used by other households that request more power.

Despite the fact that initially the transformer capacity is equally distributed to the consumers, they do not own this capacity which belongs to the utility. At this point, it is logical to assume that the rest of the households should have access to this unexploited transformer capacity by allowing them to draw more power ($P_{h,t}^{excess}$) than their initially allocated transformer capacity as expressed by (35). Naturally the request for more power renders a better optimal cost for the household that is given this right. However, also in this case, the optimal cost of any other household should not be reduced in comparison with the initial power allocation (this implies that the households utilize at least as much capacity as initially). For this reason, constraint (36) is enforced.

Practically, to solve the second optimization problem, the indicator parameter *step* is set to 2 and the optimization problem is solved considering also (35) and (36) that state that the houses may exceed the uniformly distributed capacity but the new individual household costs (HC_h) should be at least equal to what they achieved in the previous step. This constraint prevents the cost of several households to be increased in favor of others and especially those that do not need to consume more power than the uniformly distributed capacity in order to further minimize their individual cost.

The presented approach is also consistent with DR events that may be also issued by the DSO during specific hours.

$$UDC_t = \frac{TR_t^{lim}}{|H|}, \quad \forall t \tag{33}$$

$$P_{h,t}^{buy,G} \leq UDC_t, \quad \forall h, t, \ \mathit{if} \ step = 1 \tag{34}$$

$$P_{h,t}^{buy,G} \leq UDC_t + P_{h,t}^{excess}, \quad \forall h, t, \ \mathit{if} \ step = 2 \tag{35}$$

$$HC_h \leq HC'_h, \quad \forall h, t, \ \mathit{if} \ step = 2 \tag{36}$$

It is also interesting to notice that effective coordination could be achieved under the hypothesis that each individual end-user receives a suitably differentiated energy price signal (potentially complementary, i.e., one consumer receives relatively low prices when the other consumer connected to the LV side of the same local transformer receives relatively high prices). However, this is a highly complex task because of the number of the consumers that should be considered, compromises the basic rationale of hourly-varying pricing (to capture short-term cost of electricity in the market) and definitely it is not aligned with the current practice as regards the hourly-varying pricing of the energy.

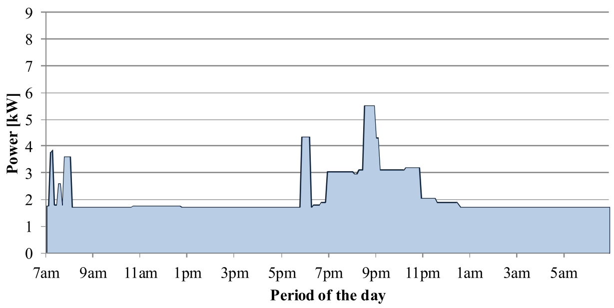

Fig. 3. Inelastic load of house 1 (single person household).

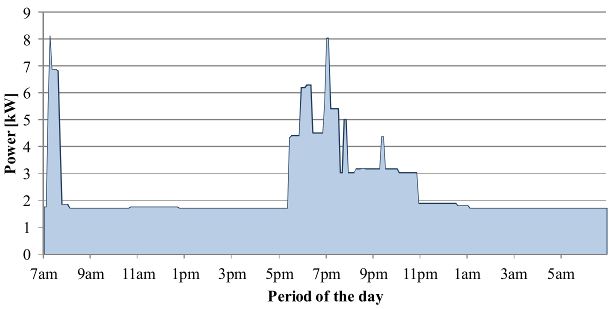

Fig. 4. Inelastic load of house 2 (couple working during the day).

III. Tests and Results

A. Input Data

The mathematical model described above has been implemented in GAMS v.24.1.3. and the optimization problem is solved using the commercial solver CPLEX v.12.

The utilized optimization interval is 5 minutes (0.083h) and as a result there are 288 periods. To demonstrate the proposed methodology, a sample neighborhood consisting of 3 houses that are supplied by a 25kVA single phase pole mounted transformer is considered, similarly to [11]. The houses are assumed to host different kinds of consumers.

The first house (house 1) is occupied by a single person that works during typical week-day hours. The corresponding inelastic load profile is presented in Fig. 3. The second house (house 2) has two residents that work during typical week-day hours. The inelastic load of this household is depicted in Fig. 4. Finally, the third house (house 3) is assumed to be occupied by a four-member family with a non-working parent and its inelastic consumption is portrayed in Fig. 5. These load profiles are created considering several typical domestic appliances the nominal power and the duration of usage of which are presented in Table I [31], [32].

All the three households are considered to be equipped with a washing machine and a dishwasher that have the ability to be appropriately shifted by the household EMS. The operational details of these appliances are presented in Table II [33].

Furthermore, each household has a battery based ESS and a rooftop PV installation. Since the households are considered to be close to each other, a normalized (per 1kW of installed capacity) photovoltaic power curve is used for all the houses (Fig. 6) measured in Yildiz Technical University, in March 2013.

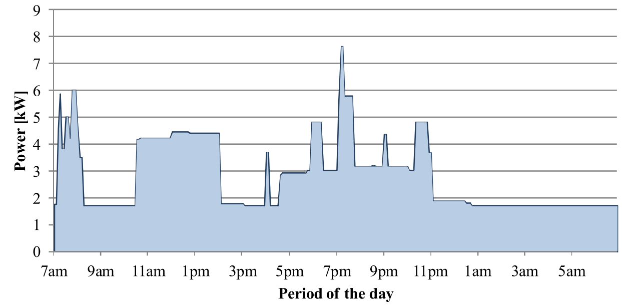

Fig. 5. Inelastic load of house 3 (four-member family).

TABLE I
Household Appliances Data

Appliance	Rated Power [kW]	Periods (5-min)		
		House 1	House 2	House 3
Refrigerator	1.67	288	288	288
Iron	2.4	6	13	18
Toaster	0.8	2	4	6
Kettle	2	2	4	6
Hairdryer	1.8	4	12	21
Telephone	0.005	288	288	288
TV	0.083	58	95	159
Desktop Computer	0.15	40	22	33
Air Conditioner	1.14	48	48	86
Hair Straightener	0.055	0	6	0
Oven	2.4	5	21	33
Microwave	1.2	2	2	8
Printer	0.011	0	2	2
Cooker hood	0.225	5	21	33
Lighting	0.1	71	88	93
Other (fixed)	0.1	288	288	288

TABLE II
Operational Phases of Controllable Appliances

	phase	1	2	3	4	5	6	7
Washing Machine	Power [kW]	0.15	2	0.15	2	0.15	0.3	0.15
	Duration (periods)	1	3	3	1	3	6	1
Dishwasher	Power [kW]	2.2	0.15	2.2	-	-	-	-
	Duration (periods)	7	8	6	-	-	-	-

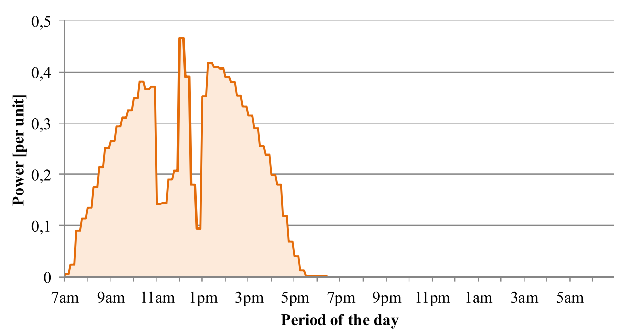

Fig. 6. PV production per 1kW installation.

There are already different types of EVs available on the market. For each household, a suitable EV to satisfy the needs of the residents is selected [34].

TABLE III
ASSET DATA OF EACH HOUSEHOLD

	House 1	**House 2**	**House 3**
		Electric Vehicle	
Model	Chevy Volt	Volkswagen E-Golf	BMW i3
Battery capacity [kWh]	16	24	22
Maximum Charging/Discharging rate [kW]	3.3	7.2	6.6
Charging/discharging efficiency [%]	95	95	95
Arrival time	5:25 pm	4:30pm	6:10pm
Initial SOE [%]	65	80	60
Minimum SOE [%]	50	20	14
		PV Installation	
Installed capacity [kW]	1.5	1.5	3
		Energy Storage System	
Battery capacity [kWh]	4	3	3
Maximum Charging/Discharging rate [kW]	0.6	0.6	0.6
Initial SOE [%]	75	80	75
Minimum SOE [%]	40	40	40
Charging/discharging efficiency [%]	90	90	90

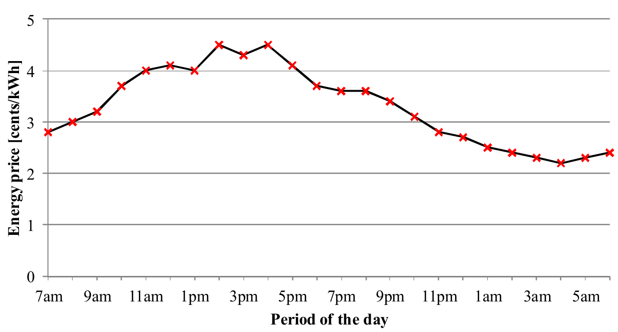

Fig. 7. Hourly energy price signal.

Data concerning the EV, the PV and the ESS of each household are presented in Table III. It is also assumed that the capability of selling energy back to the grid through V2G, ESS2G and PV2G is also available. These assets may be also used to partly or fully cover household energy needs through V2H, ESS2H and PV2H options.

The retailer announces a price signal for the 24h of the optimization horizon as displayed in Fig. 7. The prices are adapted from [25]. It has been stated before that the customer is reimbursed at the same price for the energy that is sold from the household back to the grid according to the net metering principles.

B. Results and Discussion

If the transformer capacity limit is not enforced, as expected, the optimization of each household EMS would render its minimum optimal cost. Nevertheless, all the households would allocate as much load related to the EV charging activities and the controllable appliances as possible to the relatively low price periods. As a result, during these periods, the distribution transformer would be overloaded. This condition is depicted in Fig. 8 that presents the total daily transformer load.

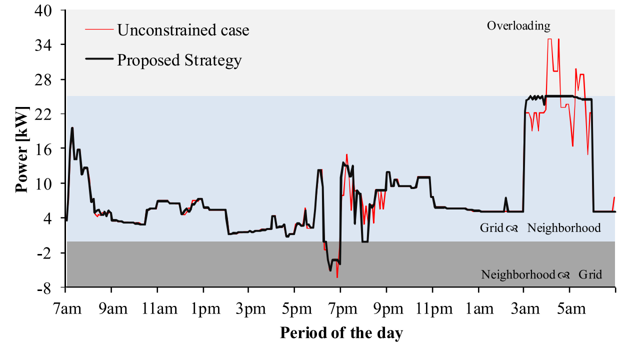

Fig. 8. Total transformer load.

In practice, short-term transformer overloading is acceptable [11], especially during hours with relatively low temperature. However, as it can be noticed in Fig. 8, the transformer is overloaded with an average of 123.2% for one hour and such a continuous overloading may be harmful for the transformer service life. This result is consistent with the one depicted also in Fig. 5 of [11].

TABLE IV
ECONOMIC RESULTS

	Optimal Daily Cost [cents]			
	$TR_t^{lim} \to \infty$	UDC_t	Only TR_t^{lim}	Proposed Strategy
House 1	165.769	165.780	165.918	165.780
House 2	174.090	174.746	174.239	174.334
House 3	216.075	216.624	216.145	216.188
Total	555.936	557.152	556.303	556.303

In Table IV the optimal energy procurement cost of each household is presented for different coordination strategies. As stated before in case that the transformer is not limiting the total power that may be drawn, the minimum optimal cost is achieved. If the available capacity is equally divided among the households, then the optimal cost for all the houses increases. Following this strategy, the transformer limit is not violated; however, the usage of the available capacity is not yet efficient.

Furthermore, if the only limit considered is the total capacity of the transformer, competitive behavior of the EMS of houses 1-3 may appear during low-price periods. This results into an increased cost for house 1 in favor of houses 2 and 3 even though it appeared to be the only house that would not violate the UDC. Finally, the proposed strategy guarantees that the cost of a household may not be increased more than the cost in the first step (UDC constrained).

One may notice that the prices presented in Table IV exhibit minor differences. However, the proposed strategy that promotes the fair allocation of the transformer capacity offers two benefits: 1) since hourly pricing schemes are directly linked with the market prices that may be volatile, residential end-users may be exposed to unstable price signals. In such a case the presented strategy guarantees that no house incurs excessive costs in favor of others due to limiting its allowable load.

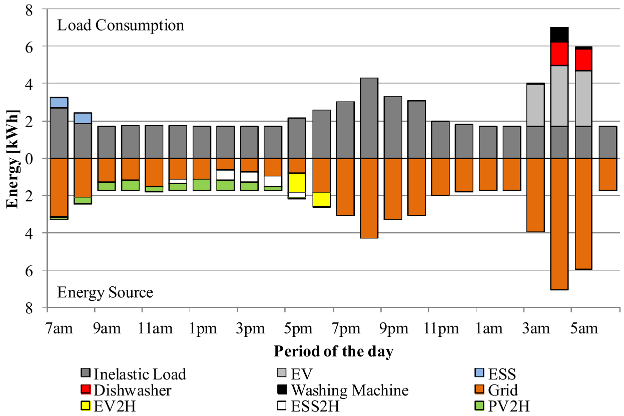

Fig. 9. Hourly energy analytics for house 1.

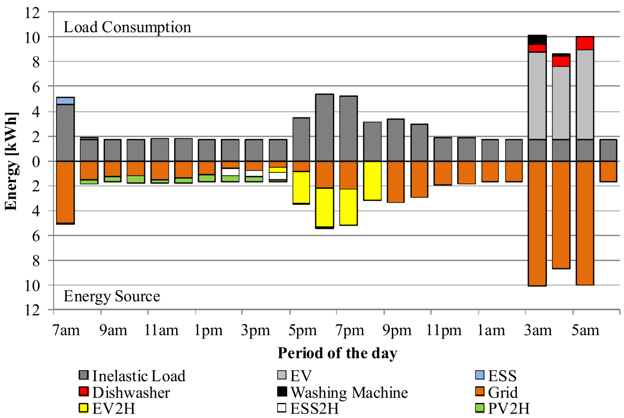

Fig. 10. Hourly energy analytics for house 2.

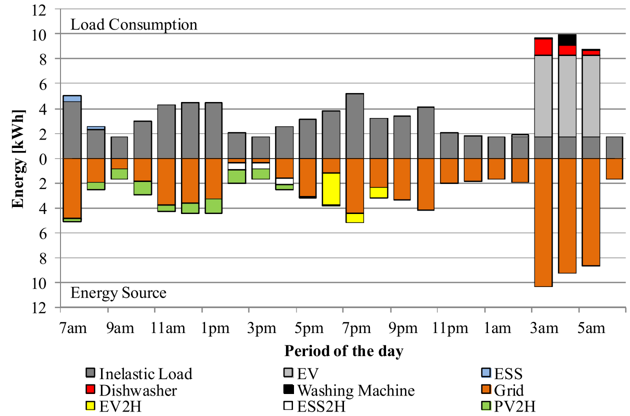

Fig. 11. Hourly energy analytics for house 3.

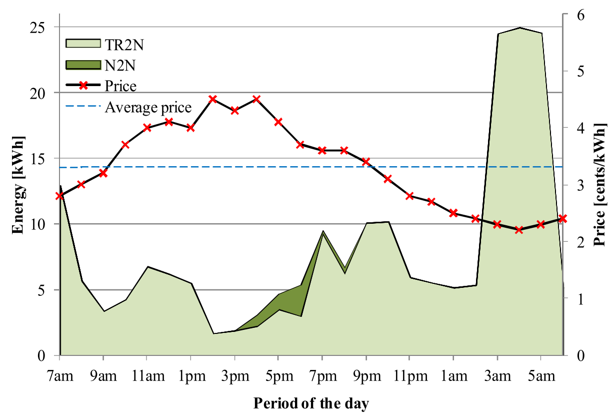

Fig. 12. Decomposition of the neighborhood load into grid and locally available power.

2) In several cases, the transformer load monitoring unit may receive a signal to further constrain its capacity during a specific period (DR event). In that case, the proposed strategy would allow all the households to request power from the transformer if it facilitates the minimization of their cost.

The total transformer load that emerges from the application of the proposed two-step strategy is also depicted in Fig. 8. It can be seen that the transformer is loaded at its nominal capacity during the lowest price periods (3am-5am). Also, during 6-7pm energy is injected from the neighborhood to the grid. Figures 9–11 the hourly energy analytics of each household under the proposed strategy are presented. The following are observed:

- In all three houses the power from the PV installation is used to cover self-needs as long as it is available.
- The ESS is charging during 7am and 8am. On the other hand, it is used as an energy source in order to cover a portion of the household load during 2-4pm for all the houses. The ESS operation is justified by the fact that 7 and 8 am offer the lowest electricity prices before the noon price peaks.
- As soon as the EVs arrive at the household they contribute to the household energy needs through V2H mode. These are periods of relatively high prices and as a result the EMS attempt to avoid buying energy from the grid. Especially, during 8pm the load of house 2 is exclusively supplied by the energy that is available in the EV. The EV charging is performed from 3am to 5am for all houses. These periods are the lowest price periods of the day.
- The controllable appliances (washing machine and dishwasher) of all the households are also shifted between 3am and 5am. In order to comply with the capacity limit of the transformer the starting periods are different. The dishwasher starts up at 4:15am, 3:45am and 3:25am and the washing machine at 3:55am, 3:05am and 3:55am for houses 1-3, respectively.

The energy that a household buys may be supplied by the grid through the transformer (transformer-to-neighborhood, TR2N) or it may be injected by other houses to the PCC (neighborhood-to-neighborhood, N2N). Figure 12 portrays the decomposition of the total energy that is procured by the neighborhood into TR2N and N2N, under the proposed strategy. The energy drawn by the houses during the time horizon comes mainly from the grid. Nevertheless, it is noticed that during 4-8pm a significant portion of the neighborhood load is served by locally available energy. This energy comes from the V2G operation. After the EVs satisfy the household load at a given period (in order to avoid buying energy from the grid), they inject excess energy back to the grid in order to profit from the electricity prices that are above the average price of

TABLE V
EV ARRIVAL TIME SCENARIOS

	EV1	**EV2**	**EV3**
Normal	5:25 pm	4:20 pm	6:10 pm
S1	6 pm	7:55 pm	9:10 pm
S2	9:30 pm	9:20 pm	8 pm

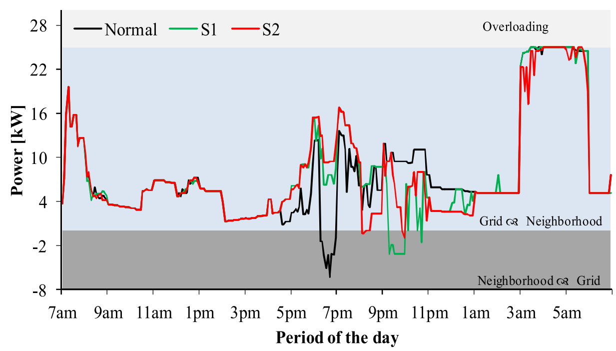

Fig. 13. Total transformer load for different EV arrival time scenarios.

TABLE VI
COMPUTATIONAL STATISTICS

	Step 1	**Step 2**
Equations	54,496	54,499
Variables	55,903	56,767
Discrete variables	38,789	38,789

the day. As a result, the transformer loading during these periods is relatively low despite the fact that the households have high inelastic load.

As a further study, the impact of different EV arrival times on the distribution transformer load is presented. Two scenarios (S1 and S2), as shown in Table V, are obtained using random sampling using the approach proposed in [30]. The relevant results are illustrated in Fig. 13. In S1, since two cars arrive in periods during which the prices are higher than those in the following periods, even if the energy that is injected from the neighborhood to the grid is reduced in comparison with the normal case, it is still profitable for the households to sell energy back to the PCC through V2G mode. In S2, as all the three EVs arrive in later periods in which the prices are relatively low, the energy that flows through the transformer to the grid side is drastically reduced as it is not profitable to sell energy back to the PCC and then charge the EV. Note that in all cases, the proposed strategy is successful in avoiding overcoming the power limitation of the transformer.

The computational statistics of the presented case study are provided in Table VI. The total solution time, considering an optimality gap of 0%, is 24 secs on a modern laptop computer (i7 at 2.4GHz, 4GB of RAM, 64bit Windows) and less than 1 sec in a workstation (two 6-core processors at 3.46 GHz, 96 GB of RAM, 64-bit Windows). As the computational capabilities of embedded systems that are needed to implement EMS increase, it appears that such complex algorithms will be practically applicable even for larger-scale systems.

IV. CONCLUSION

In this study, the operation of a neighborhood of smart households equipped with an EMS was studied. Under a dynamic pricing scheme, the EMS aim to minimize their individual energy procurement cost. Furthermore, a coordination strategy was proposed in order to satisfy the transformer capacity limits while promoting its economically fair usage by the households. All possible bi-directional power flows were considered in this study between each house and the grid and also between the houses which constitute the neighborhood. The application of the proposed approach would incentivize the users to shift their consumption in order to achieve lower electricity bills. Also, taking into account that the share of electric vehicles in the transportation market will increase in the following years, the proposed strategy promotes a smoother introduction of this new type of load at residential level. The presented case study is an example that could be expanded to neighborhoods of more houses, as it is suggested by the minimal computational time. The study of the impact of different consumer profiles and the effect of different price signals on the distribution transformer and the economic results, as well as the degradation of the equipment and especially the ESS because of frequent cycling of the batteries, will be the subject of future works to be pursued by the Authors.

REFERENCES

[1] V. C. Güngör *et al.*, "Smart grid technologies: Communication technologies and standards," *IEEE Trans. Ind. Informat.*, vol. 7, no. 4, pp. 529–539, Nov. 2011.
[2] W. Meng, R. Ma, and H.-H. Chen, "Smart grid neighborhood area networks: A survey," *IEEE Netw.*, vol. 28, no. 1, pp. 24–32, Jan./Feb. 2014.
[3] K. Samarakoon, J. Ekanayake, and N. Jekins, "Reporting available demand response," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 1842–1851, Dec. 2013.
[4] "Assessment of demand response and advanced metering," Dept. Energy, Federal Energy Regulatory Commission, Washington, DC, USA, Tech. Rep., Dec. 2012.
[5] K. J. Chua, S. K. Chou, W. M. Yang, and J. Yan, "Achieving better energy-efficient air conditioning—A review of technologies and strategies," *Appl. Energy*, vol. 104, pp. 87–104, Apr. 2013.
[6] M. Pipattanasomporn, M. Kuzlu, and S. Rahman, "An algorithm for intelligent home energy management and demand response analysis," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 2166–2173, Dec. 2012.
[7] D. Angeli and P.-A. Kountouriotis, "A stochastic approach to 'dynamic-demand' refrigerator control," *IEEE Trans. Control Syst. Technol.*, vol. 20, no. 3, pp. 581–592, May 2012.
[8] Z. Chen, L. Wu, and Y. Fu, "Real-time price-based demand response management for residential appliances via stochastic optimization and robust optimization," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1822–1831, Dec. 2012.
[9] K. M. Tsui and S. C. Chan, "Demand response optimization for smart home scheduling under real-time pricing," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1812–1821, Dec. 2012.
[10] W. Shi, N. Li, X. Xie, C.-C. Chu, and R. Gadh, "Optimal residential demand response in distribution networks," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 7, pp. 1441–1450, Jul. 2014.
[11] S. Shao, M. Pipattanasomporn, and S. Rahman, "Demand response as a load shaping tool in an intelligent grid with electric vehicles," *IEEE Trans. Smart Grid*, vol. 2, no. 4, pp. 624–631, Dec. 2011.
[12] R. Hermans, M. Almassalkhim, and I. Hiskens, "Incentive-based coordinated charging control of plug-in electric vehicles at the distribution-transformer level," in *Proc. Amer. Control Conf.*, Montreal, QC, Canada, 2012, pp. 264–269.
[13] A. D. Hilshey, P. Rezaei, P. D. H. Hines, and J. Frolik, "Electric vehicle charging: Transformer impacts and smart, decentralized solutions," in *Proc. IEEE PES Gen. Meeting*, San Diego, CA, USA, 2012, pp. 1–8.
[14] O. Erdinc, N. G. Paterakis, T. D. P. Mendes, A. G. Bakirtzis, and J. P. S. Catalão, "Smart household operation considering bi-directional EV and ESS utilization by real-time pricing-based DR," *IEEE Trans. Smart Grid*, vol. 6, no. 3, pp. 1281–1291, May 2015.

[15] T.-H. Chang, M. Alizadeh, and A. Scaglione, "Real-time power balancing via decentralized coordinated home energy scheduling," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1490–1504, Sep. 2013.
[16] G. Brusco, A. Burgio, D. Menniti, A. Pinnarelli, and N. Sorrentino, "Energy management system for an energy district with demand response availability," *IEEE Trans. Smart Grid*, vol. 5, no. 5, pp. 2385–2393, Sep. 2014.
[17] W. Khamphanchai, M. Pipattanasomporn, M. Kuzlu, J. Zhang, and S. Rahman, "An approach for distribution transformer management with a multiagent system," *IEEE Trans. Smart Grid*, vol. 6, no. 3, pp. 1208–1218, May 2015.
[18] B. Moradzadeh and K. Tomsovic, "Two-stage residential energy management considering network operational constraints," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 2339–2346, Dec. 2013.
[19] Y. Guo, M. Pan, Y. Fang, and P. P. Khargonekar, "Decentralized coordination of energy utilization for residential households in the smart grid," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1341–1350, Sep. 2013.
[20] C. Gouveia, J. Moreira, C. L. Moreira, and J. A. Pecas Lopes, "Coordinating storage and demand response for microgrid emergency operation," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 1898–1908, Dec. 2013.
[21] J. H. Yoon, R. Baldick, and A. Novoselac, "Dynamic demand response controller based on real-time retail price for residential buildings," *IEEE Trans. Smart Grid*, vol. 5, no. 1, pp. 121–129, Jan. 2014.
[22] C. Vivekananthan, Y. Mishra, G. Ledwich, and L. Fangxing, "Demand response for residential appliances via customer reward scheme," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 809–820, Mar. 2014.
[23] *ComEd Net Metering*. [Online]. Available: https://www.comed.com/customer-service/rates-pricing/interconnection/pages/net-metering.aspx, accessed Nov. 23, 2015.
[24] A. D. Hilshey, P. D. H. Hines, P. Rezaei, and J. R. Dowds, "Estimating the impact of electric vehicle smart charging on distribution transformer aging," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 905–913, Jun. 2013.
[25] *Comed Residential Real-Time Pricing Program*. [Online]. Available: http://rrtp.comed.com, accessed Nov. 23, 2015.
[26] *Power Smart Pricing.* [Online]. Available: http://www.powersmartpricing.org, accessed Nov. 23, 2015.
[27] J. R. Birge and F. Louveaux, *Introduction to Stochastic Programming*. New York, NY, USA: Springer-Verlag, 1997.
[28] Z. Wu, S. Zhou, J. Li, and X.-P. Zhang, "Real-time scheduling of residential appliances via conditional risk-at-value," *IEEE Trans. Smart Grid*, vol. 5, no. 3, pp. 1282–1291, May 2014.
[29] B. Asare-Bediako, W. L. Kling, and P. F. Ribeiro, "Home energy management systems: Evolution, trends and frameworks," in *Proc. 47th Int. Univ. Power Eng. Conf. (UPEC)*, London, U.K., 2012, pp. 1–5.
[30] S. I. Vagropoulos and A. G. Bakirtzis, "Optimal bidding strategy for electric vehicle aggregators in electricity markets," *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 4031–4041, Nov. 2013.
[31] O. Erdinc, N. G. Paterakis, I. N. Pappi, A. G. Bakirtzis, and J. P. S. Catalão, "A new perspective for sizing of distributed generation and energy storage for smart households under demand response," *Appl. Energy*, vol. 143, pp. 26–37, Apr. 2015.
[32] A. Tascikaraoglu, M. Uzunoglu, M. Tanrioven, A. R. Boynuegri, and O. Elma, "Smart grid-ready concept of a smart home prototype: A demonstration project in YTU," in *Proc. 4th Int. Conf. Power Eng. Energy Elect. Drives*, Istanbul, Turkey, May 2013, pp. 1568–1573.
[33] R. Missaoui, H. Joumaa, S. Ploix, and S. Bacha, "Managing energy smart homes according to energy prices: Analysis of a building energy management system," *Energy Build.*, vol. 71, pp. 155–167, Mar. 2014.
[34] *Plug-in Cars Reviews*. [Online]. Available: http://www.plugincars.com/, accessed Dec. 30, 2014.

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, working under the EU FP7 funded Project "Smart and Sustainable Insular Electricity Grids Under Large-Scale Renewable Integration." Since October 2015 he has been a Post-Doctoral Fellow with the Department of Electrical Engineering, Eindhoven University of Technology, Eindhoven, The Netherlands. His research interests include power systems operation and planning, renewable energy integration, ancillary services, demand response and smart grid applications.

Ozan Erdinç (M'14) received the B.Sc., M.Sc., and Ph.D. degrees from Yildiz Technical University, Istanbul, Turkey, in 2007, 2009, and 2012, respectively. Until May 2013, he worked in private sector in different positions including Electrical Installations, Renewable Energy Investments and Procurement Expert. He has been a Postdoctoral Fellow with the University of Beira Interior, Covilhã, Portugal, since May 2013, under the EU FP7 funded Project "Smart and Sustainable Insular Electricity Grids Under Large-Scale Renewable Integration." From February 2014 to January 2015, he worked as an Assistant Professor with the Department of Electrical-Electronics Engineering, Istanbul Arel University, Istanbul, Turkey. In January 2015, he joined the Department of Electrical Engineering, Yildiz Technical University, Istanbul, as an Assistant Professor. He is currently also a Researcher with the INESC-ID, Lisbon. His research interests are hybrid renewable energy systems, electric vehicles, power system operation, and smart grid technologies.

Iliana N. Pappi received the Dipl.Eng. degree from the Department of Electrical and Computer Engineering, Aristotle University of Thessaloniki, Thessaloniki, Greece, in 2012. She is currently working as a Research Associate 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." Her research interests include smart grid enabling technologies, smart-household operation and decision-making, energy efficiency in buildings, load profiling, and integration of smart grid solutions into the electrical grid.

Anastasios G. Bakirtzis (S'77–M'79–SM'95–F'15) received the Dipl.Eng. degree from the Department of Electrical Engineering, National Technical University, Athens, Greece, in 1979 and the M.S.E.E. and Ph.D. degrees from the Georgia Institute of Technology, Atlanta, in 1981 and 1984, respectively. Since 1986, he has been with the Electrical Engineering Department, Aristotle University of Thessaloniki, Greece, where he is currently a Professor. His research interests are in power system operation, planning, and economics.

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

He is currently a Professor with the Faculty of Engineering, University of Porto, Porto, Portugal, and a Researcher with INESC-ID, Lisbon, and C-MAST/UBI. He was the Primary Coordinator of the EU FP7 funded Project "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 co-authored over 400 publications, including, among others, 130 journal papers, 250 conference proceedings papers, and 20 book chapters, with an H-index of 25 (according to Google Scholar), and supervised over 35 post-doctoral, Ph.D., and M.Sc. students. He has edited the books entitled *Electric Power Systems: Advanced Forecasting Techniques and Optimal Generation Scheduling* (Boca Raton, FL, USA: CRC Press, 2012) and *Smart and Sustainable Power Systems: Operations, Planning and Economics of Insular Electricity Grids* (Boca Raton, FL, USA: CRC Press, 2015). 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 was a recipient of the 2011 Scientific Merit Award UBI-FE/Santander Universities, the 2012 Scientific Award UTL/Santander Totta, and four best paper awards at the IEEE Conferences. He is an Editor of the IEEE Transactions on Smart Grid and the IEEE Transactions on Sustainable Energy, and an Associate Editor of the *IET Renewable Power Generation*. 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 2012. He is 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, to be published in 2016.