Optimal energy management for a residential microgrid including a vehicle-to-grid system

Lucía Igualada, Cristina Corchero, Miguel Cruz-Zambrano, and F.-Javier Heredia

***Abstract*—An optimization model is proposed to manage a residential microgrid including a charging spot with a vehicle-to-grid system and renewable energy sources. In order to achieve a realistic and convenient management, we take into account: (1) the household load split into three different profiles depending on the characteristics of the elements considered; (2) a realistic approach to owner behavior by introducing the novel concept of range anxiety; (3) the vehicle battery management considering the mobility profile of the owner and (4) different domestic renewable energy sources. We consider the microgrid operated in grid-connected mode. The model is executed one-day-ahead and generates a schedule for all components of the microgrid. The results obtained show daily costs in the range of 2.82€to 3.33€; the proximity of these values to the actual energy costs for Spanish households validate the modeling. The experimental results of applying the designed managing strategies show daily costs savings of nearly 10%.**

***Index Terms*—Optimal management, smart grids, vehicle-to-grid (V2G), range anxiety, renewable generation, residential microgrids**

I. Notation

Sets

$\mathcal{R}$	Set of devices with shiftable load, $r \in \mathcal{R}$
$\mathcal{T}$	Set of time intervals, $t \in \mathcal{T}$
$\mathcal{U}_w$	Intervals where the EV is plugged ($\mathcal{U}_w \subseteq \mathcal{T}$)
$\mathcal{L}_r$	Intervals of shiftable load profile ($\mathcal{L}_r \subseteq \mathcal{T}$), $l \in \mathcal{L}_r$
$\mathcal{W}$	Set of electrical vehicles (EV fleet), $w \in \mathcal{W}$

Parameters

Δ_T	Duration of the time intervals
- Electric vehicle	
a	EV battery technical parameter [%]
$D^{EV}_{w,t}$	EV demand during trip periods [kW]
N_w	Battery capacity of the EV [kWh]
$\bar{P}^{EV}_w$	Maximum instantaneous power for the EV [kW]
$\underline{SOC_{I,w}}$	Initial SOC of the EV in $\mathcal{U}_w$ [%]
$\overline{SOC_w}$	Maximum SOC for the EV [%]
$\underline{SOC_{t,w}}$	Minimum SOC for each EV and time interval [%]
η	Discharge efficiency [%]
ξ	Charge efficiency [%]
-Charging point:	
n	Number of charging points
-Micro- wind turbine:	
$\bar{P}^{W}_t$	Maximum available wind power [kW]
-Photovoltaic module:	
$\bar{P}^{PV}_t$	Maximum available solar power [kW]
- Demand:	
D^{C}_t	Critical load [kW]
D^{A}_t	Adjustable load [kW]
$D^{S}_{l,r}$	Shiftable load profile [kW]
- Interconnection:	
$\bar{P}^{I}$	Grid tie capacity [kW]
- Costs:	
C^{EV}_w	Discharged cost of storage EV battery [€/kWh]
$C^{I_1}_t$	Day-ahead spot price [€/kWh]
C^{I_2}	Interconnection cost for capacity [€/kWh]
K^{A}	Penalty for undelivered load [€/kWh]
K^{RA}_w	Penalty associated with the EV range anxiety [€/kWh]

Variables

- Continuous positive variables:	
$d^{S}_{t,r}$	Shiftable load [kW]
d^{A}_t	Adjustable load [kW]
$SOC_{t,w}$	State of charge of the EV [%]
$p^{EVd}_{t,w}$	Discharging power rate of the EV [kW]
$p^{EVc}_{t,w}$	Charging power rate of the EV [kW]
p^{W}_t	Wind generation power level [kW]
p^{PV}_t	Photovoltaic generation power level [kW]
p^{Is}_t	Power rate sold to the grid [kW]
p^{Ip}_t	Power rate purchased from the grid [kW]
- Binary decision variables	
$x^{EV}_{t,w}$	Power flow direction in the EV battery
$x^{CP}_{t,w}$	Connection state in charging point of the EV
$x^{S}_{t,r}$	Interval where shiftable load begins to be supplied
x^{I}_t	Power flow direction in the interconnection

L. Igualada, C.Corchero and M. Cruz-Zambrano are with the Group of Energy Economics, Catalonia Institute for Energy Research, Barcelona, Spain, e-mail: ligualada,mcruz,ccorchero@irec.cat

F.-J. Heredia with the Group on Numerical Optimization and Modeling (GNOM) in Universitat Politcnica de Catalunya - BarcelonaTech, e-mail:f.javier.heredia@upc.edu

The research of L. Igualada, C. Corchero and M. Cruz-Zambrano was supported by the European Regional Development Funds (ERDF, FEDER Programa Competitividad de Catalunya 2007-2013) and the KIC Innoenergy within the framework of the KIC-EVCITY project.

II. Introduction

DUE to the current development of electric vehicle (EV) technology and its commercialization, the integration of the EV in the optimal management of residential energy systems will become a real need in the medium term. Moreover, the EV penetration levels could be increased if EV users' concern about running out of electricity before reaching their destination is mitigated. This increase would favour the environment aligning with the European energy objectives.

Thus, it is necessary to develop an optimal energy management system that integrates the realistic needs of owners to ensure a viable and regular use and an optimal schedule between demand and supply.

Smart-houses are going to be the next step in the distribution energy resources framework. This work will include what is called a residential microgrid, which could contain different generation resources, storage devices and a controllable load. The most common line of research in residential microgrids is the introduction of an optimal demand response system which exploits the demand elasticity and its management through a storage system [1]. In this paper, we maintain these objectives through three types of demand: critical, adjustable and shiftable. Assuming that most vehicles are at home during the night and middle afternoon, owners have at least 12 hours to use their vehicle as an additional storage device. This enables the so called *energy arbitrage*, which can be considered as one of the main applications of storage systems, and has been widely described in the literature [2]- [4]. To allow this use of electric vehicle batteries, a vehicle to grid (V2G) system is necessary. The energy storage unit or V2G system, as is considered in this work, can purchase energy at off-peak times when prices are low, and discharge it when prices are high. This process is used to generate savings (or profits) for the energy storage system owner, but may also have a wider benefit in protecting consumers from price spikes as well as reducing power system overloads during peak hours.

From the electric vehicle point of view, we can design optimal strategies in order to provide charge control to consumers, enabling them to overcome the anxiety of being stranded with no battery. We propose adding the term called *range anxiety* to the model, which prioritizes the charge of the vehicle depending on users' needs. This priority has been split into three levels: immediate, delayed and optimized. We will compare the optimal schedules obtained with these different levels.

The main objective of our work is to find the optimal management of a residential microgrid with the inclusion of a realistic use of local V2G capability. To achieve this goal, the arrival and departure times for the EV and its state-of-charge (SOC), the energy consumption of a household, and the operation of the microgrid components together with the day-ahead electricity prices have been considered and modelled.

A. State of the art

This work essentially deals with two different problems that are usually treated separately. Firstly, we consider the integration of electric vehicles and vehicle to grid systems. There are many works in the literature focused on the technical definition and control of V2G systems, [5]- [6] or the economical analysis of V2G systems [7]. Reference [8] proposes a model for the assessment of the contribution of V2G systems in the support to energy management in small electric energy systems; they include different energy resources and present a robust optimization model for a small energy systems aggregator with V2G capabilities for participation in the electricity market. Additionally, a thorough literature review in V2G systems including technical specifications and economic analysis can be found. Reference [9] also builds and solves an optimal bidding problem for an aggregator wanting to offer the energy from a set of EVs connected to a V2G system to the ancillary services market. These works present interesting optimization models for the integration of EVs but all of them focus on the point of view of the aggregator of EVs instead of the EV owner. Reference [10] considers the maximization of the owner profits in a parking scenario; an heuristic model is designed to exploit vehicle storage capacities in grid power transactions. Using a different approach, reference [11] studies the integration of EVs' second life batteries in micro grid buildings, and builds optimal equipment combinations to minimize microgrid costs in terms of economic cost, carbon footprint and other criteria.

The second problem addressed is the optimal management of different types of microgrids, on which there is an extensive literature; the most common objective is to minimize operating costs. Published studies differ mainly in their solution techniques and scope of the modeled microgrid. Reference [12] presents a survey on the existing energy management benefits of a microgrid. This survey includes regulatory issues, incentives, environmental issues, ancillary services and metering, economic benefits, algorithms used and their quantification. Some studies closely related to the work presented in this paper can be found in the literature on the optimal management of microgrids. Reference [13] designs a smart energy management system with similarities to the one presented in this work but solved using an heuristic algorithm. Reference [14] proposes a mixed integer programming model to minimize the operation costs of a residential microgrid. They consider both electrical and thermal load since the electric vehicle does not have a V2G system available in this case, it represents a load. Summarizing, both V2G systems and microgrid optimal management are active fields of research but, to our knowledge, no previous work in the literature deals with the optimization of a household smart grid with V2G systems, offering different optimization solutions to the user, depending on their battery performance preferences.

B. Contributions

The main contributions in this paper are listed below:

- An optimal management system for the tertiary control of a household smart microgrid is presented including:
  - a set of charging points
  - a set of manageable household appliances
  - the household load as three different profiles depending on its characteristics
  - a realistic approach to owner behaviour by introducing the novel concept *range anxiety*
- A V2G system is included in the household smart microgrid and optimized.
- The battery wear costs are included into the optimization management.

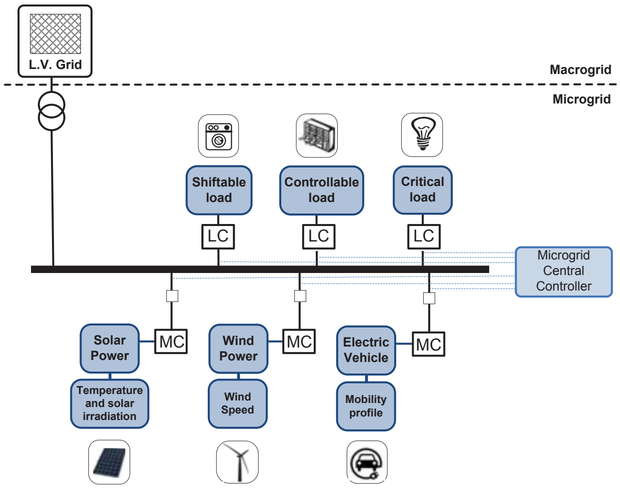

Figure 1. Residential microgrid representation. Light lines represent communication between microsource controllers (MC), load controller (LC) and the microgrid central controller (MCC).

III. Microgrid description

A. Microgrid control

The operation and management of the microgrid in different modes are controlled by local microsource controllers (MCs) and local load controllers (LCs). A microgrid central controller (MCC) is responsible for the overall coordination (see Fig. III-A). Within the MCC management in the short term, we identify three control levels: tertiary, secondary and primary. These control levels correspond to different time horizons and objectives. In this paper, we will focus on the tertiary control since it is the first natural step for the optimal control of a household microgrid.

Tertiary control is in charge of improving the profitability of the supply and demand balance by minimizing the economic cost. To this end, the system takes advantage of price differences between the peak and off-peak periods of the day and maximises the use of renewable energy sources. Daily forecasts regarding weather and demand are used as an input together with the energy price offered by the energy retailer. The final result is the optimal energy schedule for each quarter of an hour period within the 24 hours optimization horizon. The tertiary control time scope is divided in periods of 15 minutes, since in most of European countries generation group deviations are calculated on a 15 min basis.

B. Microgrid components

The residential microgrid considered for this work corresponds to one household and it is described in Fig. III-A. For the case in study, 3 LCs are needed, one for each different type of managed demand. The distributed energy resources considered are a micro-wind turbine, a photovoltaic module, and the battery of an EV.

The installed capacity of the considered components match the Spanish average on domestic field. This ensures that the obtained results are applicable.

C. Household load

The electric demand of the Microgrid is grouped into three different profiles depending on the extent to which the load can be controlled.

- Critical load (or non-controllable load): derives from devices or systems with a demand that must be compulsorily supplied to avoid user's dissatisfaction, such as lighting.
- Adjustable load: in case of contingency, a part of the household demand could became controllable in order to avoid a system fail. This quantity depends on the number of remote-controllable appliances. If a load management is necessary, some characteristic of the device will be remotely changed, decreasing the level of consumption during a pre-established period, for instance, the temperature level of an air conditioning.
- Shiftable load: the load profile for these devices can be shifted through the planning horizon. The EV demand is shiftable within the limits imposed by the available time to meet the load.

D. Market policy

The optimization procedure depends on the market policy adopted in the microgrid operation, with the MCC in charge of applying them. Different market policies can be found in the literature; this work focuses on maximizing the benefit of the microgrid system by buying and selling power to the grid [15]. A day-ahead approach has been considered, where the retail provider gives to the management system the 24 hourly prices for the next day.

IV. Mathematical model

The described microgrid is managed through an optimization algorithm implemented in the MCC. This algorithm is based on a mathematical programming problem which takes

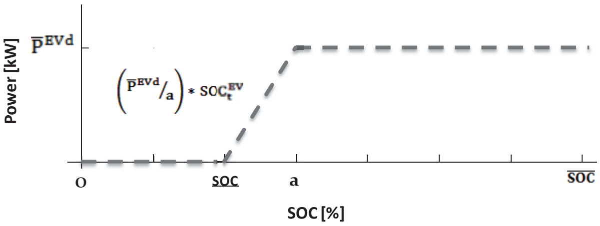

Figure 2. Power limit for the discharging process in the EV's battery.

into account the technical constraints of all the included elements and minimizes the total system costs. The mathematical models for each component of the household microgrid are described below.

A. Electric vehicle

The key aspects of the EV modelling are the battery performance together with user needs. The EV battery life depends on the charging-discharging cycles. Fig. 2 is a piecewise function which represents the manufacturer's recommendations for the discharging process of the EV's battery. It can be seen that the battery can be charged or discharged between two technical limits, the minimum and maximum state of charge levels. Moreover, between the minimum SOC and a certain limit a, the discharging power is limited by a linear function depending on the punctual SOC.

Let $\mathcal{U}_w$ be a set of periods where the EV $w \in \mathcal{W}$ is plugged to the charging point. Equations (1)-(3) define the power bounds for both of the charging and discharging processes:

$$0 \le p^{EVc}_{t,w} \le \overline{P}^{EV}_w x^{EV}_{t,w} \qquad \forall t \in \mathcal{U}_w, \forall w \in W \qquad (1)$$

$$0 \le p^{EVd}_{t,w} \le \overline{P}^{EV}_w (1 - x^{EV}_{t,w}) \qquad \forall t \in \mathcal{U}_w, \forall w \in W \qquad (2)$$

$$p^{EVd}_{t,w} \le \frac{\overline{P}^{EV}_w}{a} SOC_{t-1,w} \qquad \forall t \in \mathcal{U}_w, \forall w \in W \qquad (3)$$

where $x^{EV}_{t,w}$ are binary variables expressing the charging/discharging status of the battery of the associated EV:

- $x^{EV}_{t,w} = 1$ if the EV $w \in \mathcal{W}$ is charging in period $t \in \mathcal{U}_w$
- $x^{EV}_{t,w} = 0$ otherwise

and, $p^{EVc}_{t,w} \ge 0$ represents the charged power to the EV battery and $p^{EVd}_{t,w} \ge 0$ represents the discharged power from the EV battery. Let D^{EV}_w be the energy required by the vehicle while it is not connected i.e., the energy that will be used by the vehicle in the periods $t \in \mathcal{T} \setminus \mathcal{U}_w$. This demand affects to the state of charge $SOC_{t,w}$, let $P^{EV}_{t,w}$ be defined as:

$$P^{EV}_{t,w} = \begin{cases} (\xi p^{EVc}_{t,w} - \dfrac{p^{EVd}_{t,w}}{\eta})\Delta_T & \text{if} \quad t \in \mathcal{U}_w \\ -D^{EV}_{t,w} & \text{if} \quad t \in \mathcal{T} \setminus \mathcal{U}_w \end{cases}$$

then, the state of charge must be calculated in all periods considering the following relation:

$$N_w SOC_{t,w} = N_w SOC_{t-1,w} + P^{EV}_{t-1,w} \qquad \forall t \in \mathcal{T}, \forall w \in W \qquad (4)$$

$$\underline{SOC}_w \le SOC_{t,w} \le \overline{SOC}^{EV}_w \qquad \forall t \in \mathcal{T}, \forall w \in W \qquad (5)$$

where $SOC^{EV}_{t-1,w} = SOC^{EV}_{I,w}$ if $t = 1$.

Each charging point only allows a single EV to be plugged at each period $t \in \mathcal{T}$, the following constraint ensures that the number of EVs plugged is lower than the number of charging points, n:

$$\sum_{w \in \mathcal{W}} x^{CP}_{t,w} \le n \qquad (6)$$

where:

- $x^{CP}_{t,w} = 1$ if EV $w \in \mathcal{W}$ is plugged in the charging point at period $t \in \mathcal{T}$
- $x^{CP}_{t,w} = 0$ otherwise

The variables associated with the charging/discharging processes of EV $w \in \mathcal{W}$ can only take positive values at those potential charging periods $t \in U_w$ where the variable $x^{CP}_{t,w} = 1$:

$$0 \le p^{EVc}_{t,w} + p^{EVd}_{t,w} \le \bar{P}^{EV}_w x^{Chp}_{t,w} \qquad \forall t \in \mathcal{U}_w, \forall w \in W \qquad (7)$$

B. Interconnection point

At a given period $t \in \mathcal{T}$ the microgrid must be either selling ($p^{Is}_t \ge 0$) or purchasing ($p^{Ip}_t \ge 0$) energy from the grid (but not both simultaneously) through a grid tie with capacity $\bar{P}^I$:

$$0 \le p^{Is}_t \le \bar{P}^I x^I_t \qquad \forall t \in \mathcal{T} \qquad (8)$$

$$0 \le p^{Ip}_t \le \bar{P}^I (1 - x^I_t) \qquad \forall t \in \mathcal{T} \qquad (9)$$

where:

- $x^I_t = 1$ if the microgrid is selling the power surplus
- $x^I_t = 0$ if the grid is feeding power to the microgrid

This set of variables is needed because the cost associated with the access tariff must be paid regardless of whether the microgrid buys or sells power to the grid.

C. Demand

1) Critical Load: As aforementioned, the critical load corresponds to the non-controllable one, such as lighting. This critical load is represented through the parameter D^C_t. This load is delivered unless a general fault occurs.

2) Adjustable Load: The adjustable load corresponds to devices that can be lightly controlled in their demand request, such as air conditioning (if you increase or decrease the temperature set, the consumption will be increased or decreased). D^A_t represents the load profile of this set of devices.

$$0 \le d^A_t \le D^A_t \qquad \forall t \in \mathcal{T} \qquad (10)$$

If there is not enough generation to deliver all the demand, the optimal value for the adjustable load variable (d^A_t) will be lower than the forecasted one (D^A_t). This undelivered load $D^A_t - d^A_t$ has a penalty value K^A and an associated cost in the objective function: $K^A(D^A_t - d^A_t)$. The purpose of introducing this penalization is to guarantee that the adjustable load is the last element to be undelivered. In order to assure this last position, the penalty cost, K^A, should be a number greater than any other cost in the objective function. This will mathematically produce the expected effect in the optimization. This auxiliary cost is removed in the economical analysis of the results.

3) Shiftable Load: The shiftable load is the one corresponding to the devices that can be moved through the planning horizon. Each appliance $r \in \mathcal{R}$ has a load profile $D^{S}_{l,r}$ during $\mathcal{L}_r \subseteq \mathcal{T}$. This load profile $D^{S}_{l,r}$ gives the power that must be supplied for each time interval during the whole appliance cycle. For example, during the 1h30m cycle of a washing machine, there is a load vector for each 15 minutes.

Let $x^{S}_{t,r}$ be a set of binary variables which determines the instant in which the device is started:

- $x^{S}_{t,r} = 1$ if $t \in \mathcal{T}$ is the start-up period of appliance $r \in \mathcal{R}$
- $x^{S}_{t,r} = 0$ otherwise

Equation (11) assures that during the optimization period each appliance starts just once.

$$\sum_{t=1}^{\mathcal{T}-(\mathcal{L}_r-1)} x^{S}_{t,r} = 1 \quad \forall r \in \mathcal{R} \tag{11}$$

Equation (12) modelled the appliance load. From the start-up time interval t up to $t + \mathcal{L}_r$ the load profile $D^{S}_{l,r}$ must be supplied.

$$d^{S}_{t,r} = \sum_{l=1}^{\mathcal{L}_r} D^{S}_{l,r} x^{S}_{t-l+1,r} \quad \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{12}$$

D. Renewable resources

The renewable resources generation depends on the forecast for the meteorological data: irradiation, temperature and wind speed. The maximum power available for the photovoltaic module and the micro wind turbine is modelled by means of the forecast values following [16]- [17]. Equations (13)-(14) model the operational bounds for the renewable resources in each period $t \in \mathcal{T}$:

$$0 \le p^{W}_t \le \bar{P}^{W}_t \quad \forall t \in \mathcal{T} \tag{13}$$
$$0 \le p^{PV}_t \le \bar{P}^{PV}_t \quad \forall t \in \mathcal{T} \tag{14}$$

E. Power balance equation

The system load covering constraint imposes the balance between the total power production and consumption:

$$\begin{aligned} & p^{W}_t + p^{PV}_t + \sum_{w \in \mathcal{W}} p^{EVd}_{t,w} + p^{Ip}_t = \\ & D^{C} + d^{A}_t + \sum_{r \in \mathcal{R}} d^{S}_{t,r} + \sum_{w \in \mathcal{W}} p^{EVc}_{t,w} + p^{Is}_t \quad \forall t \in \mathcal{T} \end{aligned} \tag{15}$$

The left-hand side of (15) corresponds to the total available power in the microgrid at time period t: the expected wind and PV generation, the scheduled discharged power from the EV and the power purchased the grid. The right-hand side collects the total load: the critical and shiftable load, the power fed to the EV and the power sold to the grid.

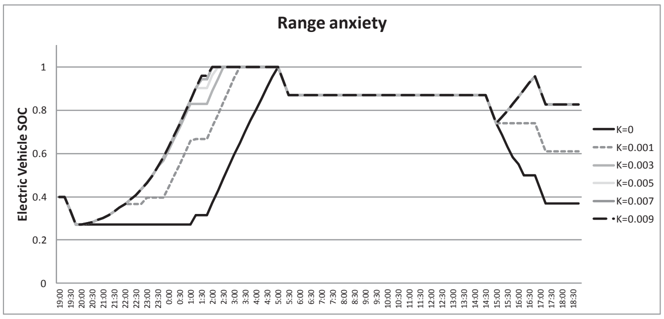

Figure 3. Range anxiety parameter definition

Table I
K^{RA}_w VALUES AND TESTS DEFINITION

ID	RA level	K^{RA}_w
T.1	optimized	0
T.2	delayed	0.001
T.3	immediate	0.005

F. Range anxiety

As discussed, one of the main issues on the electric cars framework is the *range anxiety* effect. Range anxiety is defined as the fear of running out of energy before the destination has been reached. To manage this potential problem, the model includes a term in the objective function (16) that represents, by means of a penalty parameter, the possible policies of this range anxiety effect.

$$\sum_{w \in \mathcal{W}} \sum_{t \in \mathcal{U}^{EV}_w} K^{RA}_w (1 - SOC^{EV}_{t,w}) N^{EV}_w \tag{16}$$

where K^{RA}_w is the economic penalty representing the cost for every kWh up to the full battery level. To evaluate the behaviour of this parameter and its influence in the results, a set of tests with different values of K^{RA}_w have been performed. From these tests (see Fig. 3), we can conclude that there are three values which can represent the different performances:

- The lower value, $K^{RA}_w = 0$ represents the model without range anxiety management, the objective function will not contain this term.
- The medium value, $K^{RA}_w = 0.001$, represents an intermediate behaviour, where the battery charge-discharge cycles are not as flexible as in the previous case.
- The upper value, $K^{RA}_w = 0.005$, represents the risk averse user, where the battery is fully charged as soon as possible.

Any highest value will produce the same effect as $K^{RA}_w = 0.005$; it can be seen as the technical limit for this parameter. As the range anxiety inclusion represents one of the main contributions of this work, these three options will define the three test cases analysed. Table I summarizes these values and defines the three optimization levels, denoted *optimized*, *delayed* and *immediate* respectively.

G. Objective function

The goal is to minimize the economic costs associated with the exchanged energy between the grid and the microgrid:

$$\text{Min} \quad \sum_{t\in\mathcal{T}} \Delta_T (C^{I_2}(p_t^{Ip} + p_t^{Is}) + C_t^{I_1}(p_t^{Ip} - p_t^{Is})) \quad (17)$$

$$+\sum_{t\in\mathcal{T}} \sum_{w\in\mathcal{W}} \Delta_T C^{EV} p_{t,w}^{EVd} \quad (18)$$

$$+\sum_{t\in\mathcal{T}} \Delta_T K^{A} (D_t^{A} - d_t^{A}) \quad (19)$$

where

(17) corresponds to the cost associated with grid tie. This term includes the cost of access to the grid C^{I_2} and the vector of final energy prices $C_t^{I_1}$.

(18) accounts for the discharged energy from the EV's battery. This cost is calculated considering the reduction in the number of complete charge/discharge cycles that a battery can perform before its nominal capacity falls below 80% of its initial capacity [18].

(19) penalizes the undelivered adjustable load.

H. Problem formulation

The set of constraints listed above together with the objective function define a mixed−integer linear program (MILP).

Min	Total energy cost	Eq. (16) + (17) + (18) + (19)
$s.t:$		
	Electric vehicle	Eq. (1)−(7)
	Grid tie	Eq. (8)−(9)
	Household load	Eq. (10)−(12)
	Renewable resources	Eq. (13)−(14)
	Balance equation	Eq. (15)

V. Results

The model has been implemented in C language and has been solved using CPLEX 12.5 with standard options [19].

As defined, three study cases are analysed in this paper, each one of them corresponding to different RA value, K_w^{RA} (see Table I). The underlying idea is that the algorithm will be adapted to the type of user that wants to manage its smart-house. In this way, depending on the user's level of range anxiety, one of the three scenarios will be implemented. The first two tests allow the management system to control the electric vehicle battery when plugged-in, while the third test is equivalent to the case without an energy management system, considering that the charge of the battery starts as soon as the EV is plugged in. This third test can be seen as the baseline case for the economic analysis of the management system.

The data used for the tests comes from different sources, all of them for a working summer's day. The tests are performed considering one EV with its charging point and the microgrid elements with the characteristics summarized in Table II. The selected profiles for both EV mobility and household load correspond to the Spanish Mediterranean area. The mobility profile, including the EV demand, has been obtained from [20]. In the case of the household load, we have used the database from [21]. The weather data used was

Table II
MICROGRID COMPONENTS CHARACTERISTICS

Time interval duration (h)	EV battery capacity (kWh)	Charging Point power limit (kW)
0.25	16	5
Interconnection capacity (kW)	**Wind turbine capacity (kW)**	**PV module capacity (kW)**
6.6	2.2	2

collected directly from our laboratory (Barcelona, Spain). For the selected scenario, we have only chosen one shiftable load profile: $\mathcal{R} = \{\text{washing machine}\}$ [21]. Finally, the final energy prices belong to the Spanish Electricity Market [22]. All data is available for interested readers.

The solution of each test case generates the energy scheduling for the next 24 hours with quarter hour intervals. This energy scheduling is detailed for every element in the microgrid, so we have the optimal operation of all the elements for the next 24h.

The results are presented in Fig. 4, Fig. 5 and Fig. 6, each one corresponding to T.1, T.2 and T.3 respectively. Abscissa axis correspond to the time horizon (hours) while ordinate axis correspond to active power (kW). Positive values on the active power axis correspond to generation while negative values represent consumption. In each period, the amount of energy provided or consumed by each source or device is represented by a vertical bar with a different gray scale. The time in which the EV is plugged into the charging point is represented by light grey background. The discontinuous line on the secondary ordinate axis represents the market energy price in €/kWh.

A. T.1: Optimized mode

In this Optimitzed mode test, the term 16 for the RA is not considered in the objective function. Fig. 4 shows the energy schedule for test T.1. It can be seen how the V2G system usage at night allows energy arbitrage between price peaks. Specifically, as the EV's battery is recharged during the early morning hours when the price is lowest; this energy stored in the battery can supply the household load between 10:00 and 12:00 without buying energy from the grid. Moreover, some surplus of renewable energy is expected. This surplus energy will be sold to the grid providing a benefit to the owner between 10:00 and 11:30, and will be used to recharge the EV's battery at 16:30. As can be expected, the washer load has been scheduled during the off-peak hours (between 4:00 and 6:15).

B. T.2: Delayed mode

In the second test case, the objective function is modified by adding the term associated with the *range anxiety* with an intermediate value. Fig. 5 shows the effect of the *range anxiety* on the delayed mode (T.2). In this case, the battery starts to be charged as soon as the owner arrives at home at 14:45 to minimize the RA during the evening. However, as in the previous test, the EV's battery supplies the household load

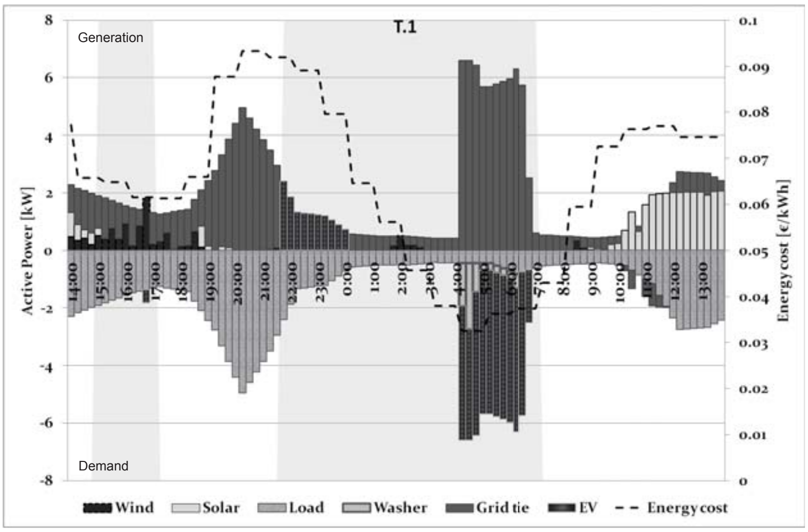

Figure 4. Energy schedule for test T.1 *Optimized*: the term for the range anxiety is not considered in the objective function.

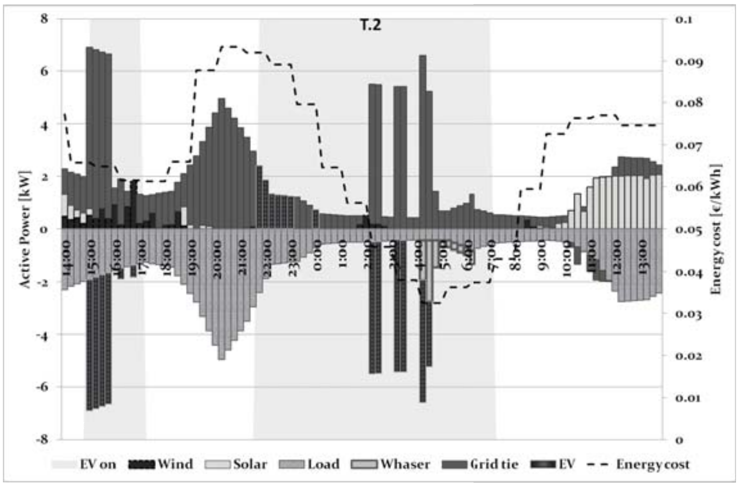

Figure 5. Energy schedule for test T.2 *Delayed*: the objective function is modified by adding the term associated with the range anxiety.

at night but the energy provided is lower than in the previous results. The washer load is also supplied during the off-peak hours. The main difference is that the charging process of EV is brought forward to 2:00.

C. T.3: Immediate mode

In the third test (Fig. 6), the user is defined as risk averse, the range anxiety is set at the highest value. Due to this fact, the EV's battery is charged as soon as the EV is plugged into the charging point and it is never discharged during the plug-in time. The other elements in the microgrid perform similarly to in the previous cases, with the only exception being the energy exchange with the grid tie which is higher during peak hours due to the absence of the EV battery energy resource.

D. Comparisons

For summarizing the results, Table III allows the comparison of the following parameters of the three tests:

1) Daily cost: calculated as the sum of the cost of the energy bought from the grid (17) and the battery degradation cost (18).
2) The economic saving compared with the *baseline* scenario: the benefit attributable to the percentage reduction in daily costs for each test compared to *T.3*.
3) The cost per consumed kWh defined as the daily cost divided by the total daily load.
4) The average SOC of the EV's battery during the hours where the EV is plugged into the charging point.

Table III shows that the best economic result is the one for T.1 (where ther is no range anxiety control), with the cheapest daily cost (2.816€) and the best average cost per consumed kWh (0.063€). These costs represent a daily saving of 15.5% compared with the baseline case (T.3). It must be noted that T.1 is the best from an economic perspective but from the

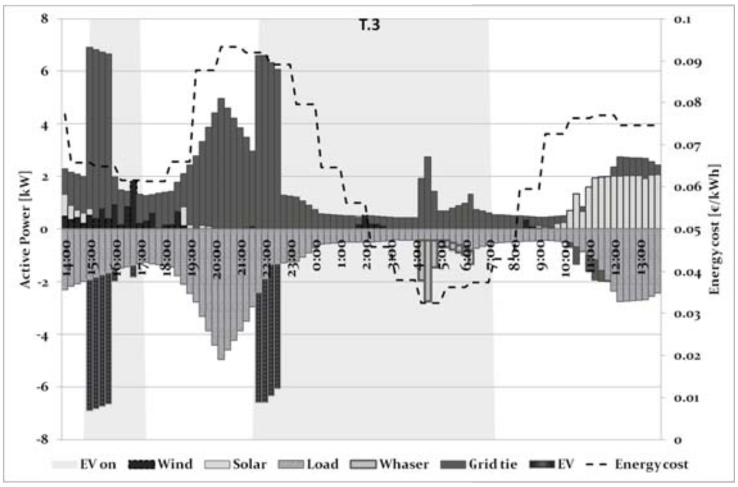

Figure 6. Energy schedule for test T.3 *Immediate*: baseline case defined assigning the highest value to the range anxiety term.

Table III
SUMMARY TABLE OF NUMERICAL RESULTS

ID	Daily cost [€]	Saving compared to T.3 [%]	Average cost per consumed kWh [€/kWh]	Average SOC of EV's battery [%]
T.1	2.816	15.5%	0.063	49.5
T.2	3.017	9.45%	0.068	82
T.3	3.332	0	0.075	98

point of view of the user, the EV is not ready for starting a trip at any moment, since the SOC may be lower than necessary. This may be problematic for the owner, although this issue is partially controlled since the minimum level of SOC required by the owner before the scheduled departure is always guaranteed by the management system. The second and third tests obtain an average SOC much closer to the maximum SOC. Specifically the mean SOC level for the optimized test is 49.2%, for the delayed test is 82% and for the immediate test it is 98%. In all cases, the SOC at 7:00 is 100% as the requested by the user.

Regarding the load supply, in these study cases the adjustable load is always delivered because there is enough energy available. The shiftable load is allocated during the off-peak hours in line with the lower energy prices.

The average annual cost of energy supply in Spanish households is around 990€ [21] (average daily cost of 2.71€). The results obtained show daily costs in the range of 2.82€to 3.33€. Therefore it can be concluded that the results obtained in this work are highly representative due to their proximity to actual energy costs for Spanish households.

VI. CONCLUSION

In this paper, we have presented an optimal management model for a smart-house with a V2G system, a set of manageable domestic devices and two renewable sources. This model aims to be generic and to consider various microgrid configurations. It is designed to allow the selection of the different elements thanks to their independent formulation. The optimal management system is formulated as a MILP problem for the tertiary control of a domestic smart microgrid. The main objective was to optimize the V2G system integration into a smart-house. In this management system, not only energy costs are considered but battery wear costs are also introduced in the minimization. Finally, in order to provide charge control to consumers, a novel concept defined as range anxiety has been introduced. Three test cases have been defined using three different range anxiety levels and have been compared, yielding the following results:

- The potential savings of V2G are highly dependent on the system flexibility. Since this flexibility is directly related to range anxiety, the system's potential savings are also very dependent on the level of range anxiety established.
- Savings obtained for the optimized case (zero range anxiety level) are up to 15.5%, while they are reduced to 9.45% for the delayed case (medium level range anxiety).
- The vehicle availability, measured as the average battery SOC while the vehicle is parked, is 49.5% for the optimized case, increasing to 82% for the delayed case.
- Results obtained shed some light on the question of when V2G will become commercially viable as a consumer application if set-up costs of V2G systems are compared to the saving potentials.

Moreover, the introduction of different types of load profiles allows the management system to control and operate with the load through the optimization horizon. Specifically, the shiftable load is allocated in the off-peak hours, producing savings in the global costs. Moving more devices from the critical load to the shiftable one would increase this effect. Further research is required for testing primary and secondary control layers in real field conditions. In this way the technical feasibility of the proposed control system could be assessed. Furthermore, in order to enlarge the scope of the analysis, the effects of grouping V2G systems should also be also included by means of considering a whole distribution network.

REFERENCES

[1] S. Choi, S. Park,D.-J. Kang, S. Han and H.-M. Kim, “Microgrid Energy Management System for Inducing Optimal Demand Response,” in *2011 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pp. 19-24.

[2] S. M. Schoenung and J. Eyer, “Benefit/Cost Framework for Evaluating Modular Energy Storage. A Study for the DOE Energy Storage Systems Program,” Sandia National Laboratories, Report SAND2008-0978, Feb. 2008.

[3] R. Walawalkar, J. Apt, and R. Mancini, “Economics of electric energy storage for energy arbitrage and regulation in New York,” *Energy Policy*, vol. 35(4), pp. 2558-2568, 2007.

[4] R. Sioshansi, P. Denholm, T. Jenkin and J. Weiss, “Estimating the value of electricity storage in PJM: Arbitrage and some welfare effects,” *Energy Economics*, vol. 31(1), pp. 269-277, 2009.

[5] J. Tomic and W. Kempton, “Using fleets of electric-drive vehicles for grid support”. *Journal of Power Sources*, vol. 168(2), pp. 459-468, 2007.

[6] W. Shi and V.W.S. Wong, “Real-time vehicle-to-grid control algorithm under price uncertainty” in *2011 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pp. 261-266.

[7] W.Kempton and J.Tomic, “Vehicle-to-grid power fundamentals: calculating capacity and net revenue”, *Journal of Power Sources*, vol. 144(1), pp. 268279, 2005.

[8] C. Battistelli, L. Baringob and A.J. Conejo, “Optimal energy management of small electric energy systems including V2G facilities and renewable energy sources,” *Electric Power Systems Research*, vol. 92, pp. 50-59, 2012.

[9] E. Sortomme, M.A. El-Sharkawi, “Optimal scheduling of vehicle-to-grid energy and ancillary services”, *IEEE Transactions on Smart Grids*, vol. 3(1), pp. 351-359, 2012.

[10] C.Hutson, G.K.Venayagamoorthy and K.A.Corzine, “Intelligent scheduling of hybrid and electric vehicle storage capacity in a parking lot for prot maximization in grid power transactions,” in *Proc. IEEE Energy 2030 Conference*, 2008.

[11] S. Beer, T. Gomez, D. Dallinger, I. Momber, C. Marnay, M. Stadler, and J. Lai, “An Economic Analysis of Used Electric Vehicle Batteries Integrated Into Commercial Building Microgrids,” *IEEE Transactions on Smart Grid*, vol. 3(1), pp.517-525, 2012.

[12] A.K. Basu, S.P. Chowdhury, S. Chowdhury, and S. Paul, “Microgrids: Energy management by strategic deployment of DERsA comprehensive survey,” *Renewable and Sustainable Energy Reviews*, vol. 15(9), pp. 4348-4356, 2011.

[13] C. Chen, S. Duan, T. Cai, B. Liu and G. Hu, “Smart energy management system for optimal Microgrid economic operation,” *IET Renewable Power Generation*, vol. 5(3), pp. 258267, 2011.

[14] P.O. Kriett and M. Salani, “Optimal control of a residential microgrid,” *Energy*, vol. 42(1), pp.321-330, 2012.

[15] A.G Tsikalakis and N.D. Hatziargyriou, “Centralized control for optimizing microgrids operation,” in *Proc. IEEE Power and Energy Society General Meeting*, 2011.

[16] M.K. Deshmukha, and S.S. Deshmukhb, “Modeling of hybrid renewable energy systems,” *Renewable and Sustainable Energy Reviews*, vol. 12(1), pp. 235-249, 2008.

[17] H. Yang, L. Lu and W. Zhou, “A novel optimization sizing model for hybrid solar-wind power generation system,” *Solar Energy*, vol. 81(1), pp. 76-84, 2007.

[18] R. Sioshansi and P. Denholm, “The Value of Plug-In Hybrid Electric Vehicles as Grid Resources” *The Energy Journal*, vol. 31(3), pp. 1-23, 2010.

[19] *CPLEX Optimization subrotine library guide and reference. Version 12.5*, ILOG Inc., Incline Village, NV, USA. License under IBM Academic Initiative.

[20] M. Cruz-Zambrano, A. Santandreu-Corretge, M.R. Mora-Marin, I. Cairo-Molins, A. Sumper and A. Sudria-Andreu,“Demand Side Management and Electric Vehicle Integration (VERDE),” in *Proc. of The 21st International Conference and Exhibition on Electricity Distribution (CIRED 2011)*.

[21] IDAE, ”Análisis del consumo energético del sector residencial en España, SECH-SPAHOUSEC project”. Institute for Energy Diversification and Saving (IDAE), Ministry of Industry, Energy and Tourism, Spain, 2011.

[22] CNE (National Energy Commission). Website: www.cne.es.

L. Igualada received the B.S degree in mathematics from Universidad de Murcia, Spain in 2010. Afterwards, she obtained an M.S degree in statistics and operations research from the Universitat Politecnica de Catalunya (UPC), Barcelona, in 2012. She is currently working as a researcher at the Catalonia Institute for Energy Research (IREC). Her interests include microgrid optimization algorithms and electric vehicle integration into the smart grid.

Dra. C. Corchero obtained the B.Sc.(2002) and M.Sc.(2004) degree in Statistics at the Universitat Politecnica de Catalunya. She received her Ph.D degree in Statistics and Operations Research in 2011 from the UPC. In 2004 she joined the Energy section of the Group of Numerical Optimization and Modelling (GNOM, UPC) as full-time researcher. She is currently researcher at the Catalonia Institute for Energy Research (IREC) in the Electrical Engineering Area. She has participated in European and National research projects. Her research focuses on energy economics and the application of stochastic optimization into the energy sector.

Miguel Cruz-Zambrano works as a researcher at the Catalonia Institute for Energy Research (IREC). He specialises in techno-economic, market and policy analysis of innovative energy systems, particularly with emphasis on electric vehicles, smart grids and renewable energy sources. He is currently involved in several national and international energy projects, especially in the FP7 Project Green eMotion. Before joining IREC worked as an R&D research fellow in the Electrical Engineering Department of the Polytechnic University of Catalonia, and also in the Spanish energy regulator (National Energy Commission).

Dr. F.-Javier Heredia received the B.Sc. degree in physics from the Universitat de Barcelona, Barcelona, Spain, in 1988 and the Ph.D. degree in operations research from the Universitat Politecnica de Catalunya (UPC), Barcelona, in 1995. He is currently a Professor of mathematical optimization and operations research at the Department of Statistics and Operations Research of the UPC. His research interests include modeling and optimization of power systems and electricity markets as well as optimization methods such as stochastic and nonlinear programming, dual methods, and networks flows.