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Short-term economic dispatch of smart distribution grids considering the active role of plug-in electric vehicles

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ABSTRACT

A new methodology to dispatch in an economic and controlled manner the energy requirements of multiple energy storage devices, dispersed generators and loads belonging to a smart distribution grid (SDG) is presented in this paper. Plug-in electric vehicles (PEV) are mainly managed over a 24-hour time window. To maximize the economic social welfare of both a utility and PEV working as prosumers, this short-term economic dispatch (ED) problem incorporates two optimization processes interacting as an integrated model. In the first, aggregators located in the SDG maximize the economic benefits obtained by a PEV group. Fuzzy inference systems are used to estimate the decisions made by each PEV during its participation in energy exchanges with the SDG, which influence the PEV benefits. Using these results and a Mean-Variance Mapping Optimization algorithm, the economic benefits of the utility are maximized in the second process and, the ED is then solved.

1. Introduction

The transportation industry is gradually replacing current vehicles with mobility alternatives more efficient, reliable, environmentally friendly, more reliable, safer and smarter [1]. This paradigm shift in vehicular mobility is caused by the price volatility of fossil fuels and environmental and public health concerns (climate change and harmful emissions). In the short term, the technology more used will continue been PEV that integrate batteries in their propulsion systems, which turns each PEV into a prosumer with the capacity to consume, store and supply energy [2].

The energy consumption and supply requirements coming from multiple PEV should be coordinated into the ED of a smart distribution grid. Nowadays, the operational analyses performed by the distribution network operators (DNOs) do not include the ED, but the development of SDGs and PEV will require its implementation [3]. Such ED should foresee PEV charging cycles, eventual injection of energy from PEV into the SDG and the possibility of storing energy in PEV batteries. In addition, this ED should satisfy the requirements imposed by numerous distributed energy resources (DER), loads and the Wholesale Electricity Market (WEM). DER concern both dispersed generators as well as energy storage. For this reason, the ED requires sophisticated smart devices and calculation tools to manage the new active-passive role of PEV in a controlled manner. These developments should avoid the saturation of communication links with huge volumes of data, facilitate data exchange and control actions (with low latency) between the Distribution Management System (DMS) and numerous small loads and energy sources, and incorporate adequate storage media and data processing systems [4]. These conditions could be fulfilled by the implementation of hierarchical control architectures (HCAs) into the SDG. For adequate functionality, the HCAs should include advanced calculation tools and algorithms designed by the DMS and devices for local resource management such as aggregators. Due to the monopolistic behavior of Latin American power markets, this paper considers aggregators as intelligent devices (software and hardware) located in the SDG, whose main function is to improve the interaction between the DMS and some PEV through economic signals. It is noted that in Latin American countries, the distribution network and retailing activities are combined within the traditional distribution system, which is operated and exploited by a single utility [5].

Diverse alternatives have been designed to dispatch a SDG and its energy resources, such as Refs. [6–36]. Nevertheless, some papers do not integrate a HCA to manage PEV [6–9]. Other do not consider the distribution network features and its operational constraints [10–18]. The power supplied from PEV is not included in some researches such as Refs. [12–14] and Refs. [21–24]. Costs related with the degradation of the lifespan of PEV batteries are not included in multiple works such as Refs. [18–20]. Finally, the approach presented in this work differs of the arguments exposed in Refs. [6–36], which jointly analyze decisions adopted by PEV owners regarding energy purchase-sale prices

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Nomenclature

Acronyms

AMI Advanced metering infrastructure
APS Analysis of all possible solutions
CDS Charge-discharge system
DER Distributed energy resources
DMS Distribution Management System
DNO Distribution network operator
EB Economic benefits
ED Economic dispatch
ENS Energy not supplied
ESLQ Energy supplied with low quality
ESW Economic social welfare
FIS Fuzzy inference systems
HCA Hierarchical control architecture
HV/MV High voltage/medium voltage
MV/LV Medium voltage/low voltage
MVMO Mean-variance mapping optimization
PEV Plug-in electric vehicles
PV Photovoltaic systems
SDG Smart distribution grid
TS Transformer station
VAD Distribution added value
WEM Wholesale Electricity Market

Variables

$C_{DEG,t}$ Degradation cost of batteries lifespan in t
$C_{DER,t}$ / $C_{WEM,t}$ Costs of energy purchased from the DER/WEM in t
$C_{ENS,t}$ / $C_{ESLQ,t}$ Costs of the ENS/ESLQ in t
$C_{PEV,t}^{LL}$ / $I_{PEV,t}^{LL}$ Costs/incomes of energy purchased/sold by PEV, obtained in LL and t
$C_{PEV,t}^{UL}$ / $I_{PEV,t}^{UL}$ Costs/incomes of energy purchased/sold by PEV, obtained in UL and t
$E_{i,t}^{b}$/ $E_{i,t}^{s}$ Energy purchased/sold by the PEV i in t
$E_{final,i,t}$/ $E_{final,i,t-1}$ Battery state of charge of the PEV i at the end of t/ t-1
E_t^{ENS}/ E_t^{ESLQ} ENS/ESLQ in t
E_t^{WEM} Energy supplied by the WEM in t
$I_{INL,t}$ Incomes by energy supplied to the inelastic demand in t
$P_{trf,k,t}^{MV/LV}$ / $Q_{trf,k,t}^{MV/LV}$ Active/reactive power through the MV/LV TS k in t
P_t^{WEM}/ Q_t^{WEM} Active/reactive power exchanged by the WEM in t
$\pi_{i,t}^{c}$/ $\pi_{i,t}^{v}$ Energy purchase/sale price used by the PEV i that supplies/purchases energy
$\chi_{i,t}^{b}$/ $\chi_{i,t}^{s}$ Availability of PEV i to purchase/sell energy in t (Binary variables)

Parameters

$d_{DoD,i}$ Depth of discharge (DoD) used to determine $L_{c,i}$, related with the PEV i
$E_{B,i}$ Battery capacity of PEV i
$E_{j,t}^{DER}$ Energy supplied by the DER j in t
$E_{i,t}^{d}$/ $P_{i,t}^{d}$ Energy/power used by the PEV i during its mobilization in t
E_i^{f} Minimum state of charge required by the PEV i when it leaves the CDS
$E_{B,i}^{\max}$ / $E_{B,i}^{\min}$ Maximum/minimum limit of energy storage in the battery of the PEV i
$E_{r,t}^{INL}$ Energy supplied to inelastic demand r in t
$L_{c,i}$ Battery cycle life of the PEV i at a certain DoD
$P_{g,t}^{agg,ch}$/ $P_{g,t}^{agg,dch}$ Active power purchased/supplied by PEV managed in the aggregator g in t
$P_{i,t}^{ch}$/ $P_{i,t}^{dch}$ Charge/discharge power of the PEV i in t
$P_{j,t}^{DER}$/ $Q_{j,t}^{DER}$ Active/reactive power of the DER j in t
$P_{r,t}^{INL}$/ $Q_{r,t}^{INL}$ Active/reactive power of inelastic demand r in t
$\eta_{ch,i}$/ $\eta_{dch,i}$ Battery charging/discharging efficiency of the PEV i
$S_{\max\_trf,k,t}^{MV/LV}$ Maximum power transfer in the MV/LV TS k in t
$\pi_{j,t}^{DER}$ Energy purchase price from the DER j in t
π_t^{ENS}/ π_t^{ESLQ} Energy price for the ENS/ESLQ in t
π_t^{WEM} Energy purchase price from the WEM in t
$\vartheta_{DEG,i}$/ $\vartheta_{inv,i}$ Battery degradation/investment cost by PEV i
ϑ_f/ ϑ_v Fixed/variable value imposed on the inelastic demand in VAD
$\mu_{i,t}^{b}$/ $\mu_{i,t}^{s}$ Charge/discharge energy possibility of the PEV i in t, in per unit [p.u.]
$\chi_{i,t}^{d}$ Availability of the PEV i for mobilization in t (Binary variable)
$\gamma_{j,t}$ Availability of DER j in t (Binary variable)

Indices

b Acquisition
c Purchase
I Total number of PEV
i PEV exchanging energy
J Total number of DER
j DER supplying energy
T Period considered to elaborate the ED (24 hours in this work)
Δt Time used by the PEV i to mobilization or discharge energy or charge energy
k MV/LV TS
LL/UL Lower/upper level control
R Number of inelastic demands
r Inelastic demand
s Sale
t Subperiod (1 hour in this work)

established in the electricity market, intertemporal constraints related to the arrival-departure time of PEV and the batteries state-of-charge, energy consumption and supply requirements imposed by PEV, the maximization of economic benefits (EB) for all agents involved in the ED and the features and constraints of the distribution network. Energy purchase-sale prices represent economic signals to improve the interaction between the DMS and PEV, which is aligned with the transactive control concept promoted in the smart grid context. Transactive control is defined as “a set of economic and control mechanism that allows the dynamic balance of supply and demand across the entire electrical infrastructure using value as a key operational parameter”. In this manner, economic signals could be used to solve complex power system problems [22].

With the aim of enriching the diversity of existing research and efficiently manage the operation and dispatch of SDGs, this paper proposes an HCA for scheduling and economic control of an SDG and its energy resources. It is represented by a methodology used to solve the short-term ED, which considers mainly the new active role of PEV in the SDG and includes two optimization processes coupled as an integrated model. The first process is performed in an aggregator device and determines the optimal values of energy that each PEV should supply and consume to/from the SDG. Each aggregator processes the data coming from the PEV charge-discharge systems (CDSs) and/or the DMS, develops energy supply and consumption profiles, and adopts control actions on PEV states of charge. Pre-set values in each PEV will establish the automatic control actions, which include the energy prices that each PEV wishes to receive in accordance with its preferences. These prices are compared with energy prices sent from the DMS through two fuzzy inference systems (FIS) to establish if a PEV should sell or buy energy. The battery degradation cost, intertemporal constraints related to the batteries state of charge and arrival-departure time of PEV, and the energy required in PEV batteries when they leave the CDS are also included in the optimization process made by an aggregator. On the other hand, the second process maximizes the EB of a utility based on the results of the first process, the capacity and functionality limits of DER and loads, and AC network constraints. In order to solve the ED in the DMS, it is necessary to understand the ED as the actions that DNOs can adopt regarding the active participation of the PEV storage, the operative topology of the SDG and controllable or uncontrollable dispersed generation. ED results add to energy sale-purchase prices, which are used to encourage the participation of PEV owners during certain time sub-periods considered over a 24-hour time window. PEV charging their batteries regardless of the prevailing price are included in analyses. Through this integrated and iterative ED, the maximization of the economic social welfare (ESW) of both the utility and PEV is reached. An analysis of all possible solutions (APS analysis) is used in the first process to calculate the optimal energy exchange sub-periods of a PEV set. On the other hand, an MVMO algorithm is used in the second process and its results are compared with an APS analysis of the ED.

2. Hierarchical control architecture proposed

The components, functionality, mathematical approach and features of the HCA proposed are described in this section.

2.1. Components

Aggregators, DMS, DER, advanced metering infrastructure (AMI) and PEV are part of the HCA proposed in this work. Nevertheless, the main components are aggregators and PEV. The time a PEV is connected to the network, the battery state of charge and the daily mobility patterns are the main aspects conditioning PEV energy requirements. The first two aspects are conditioned by the CDS's features, the distance travelled by the PEV and the design features of each PEV (such as the size of the battery) [37].

Aggregators operate as an intelligent inference middleware between the DMS and PEV. In this paper, the aggregator is considered a software system located in the SDG and used by the integral optimization process for the communication of bidirectional data and information between PEV and DMS. Communication, data storage and processing devices are its main interior elements. This work focuses on main software features of aggregator, whose function is to store and manage data collected by sensors located in the electrical network and to adopt a set of decisions for the communication with the DMS or in local form. In this manner, massive connection of multiple PEV could be more easily and nimbly managed by the DNOs and information of high value for planning and operation studies (as the ED) could be obtained.

2.2. Features and functionality of the HCA

The short-term ED satisfies the elastic and inelastic demand integrated into an SDG at the lowest possible cost. It optimizes the operation of the SDG and the supply resources available and ensures a reliable, safe and quality electric service. The supply resources include DER, WEM and PEV that inject energy into the SDG. The inelastic demand includes industrial, residential and commercial consumption, and PEV charging their batteries represent the elastic demand.

Fig. 1 shows the HCA proposed by the ED, the information required in three control levels and the interaction between DMS, aggregators and PEV. In this regard, each aggregator builds energy consumption-

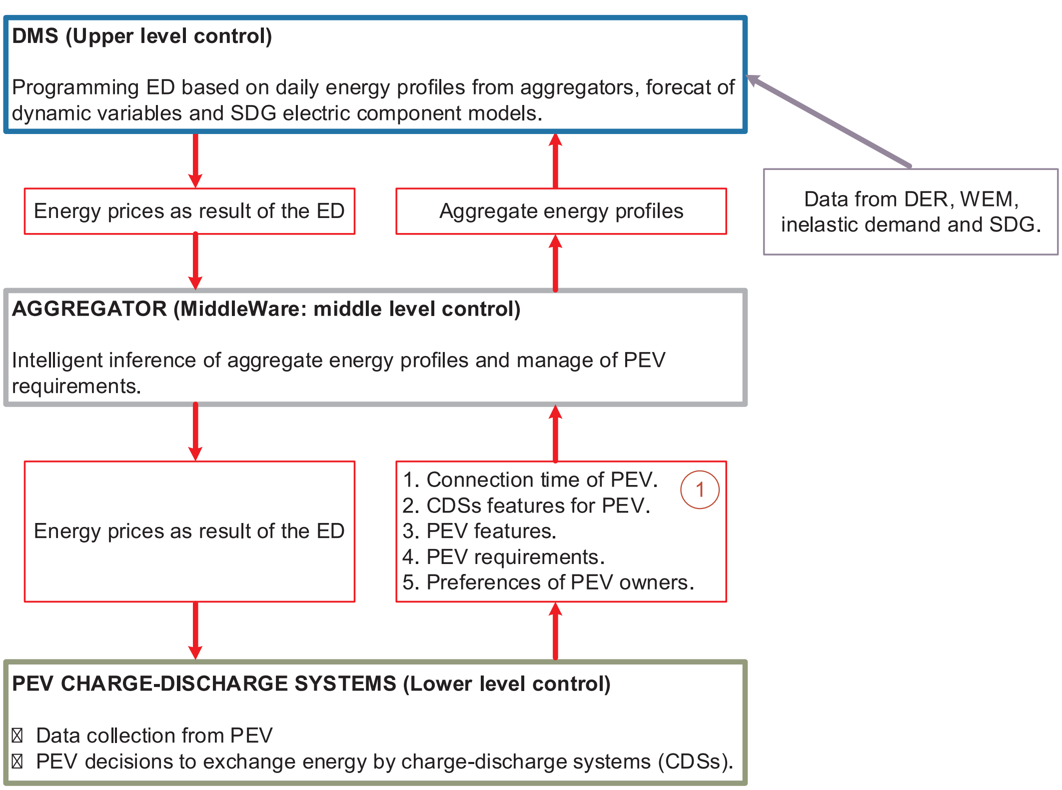


Fig. 1. Hierarchical control structure by the ED.

supply profiles as an equivalent model. A methodology incorporated into the aggregators is used to determine day-ahead energy profiles, which uses data gathered from DMS and PEV to optimize the quantities of energy that each PEV should supply and consume from/to an SDG. The data gathered from PEV includes features of PEV batteries, type of PEV, energy prices set by PEV owners, the connection time of PEV to the SDG, energy consumption and supply requirements and batteries state of charge. On the other hand, data received from the DMS includes energy purchase-sale prices estimated by DNOs to encourage the participation of PEV owners during certain time sub-periods of the ED.

The daily energy profiles are sent by each aggregator to the DMS located in a distribution control center in order to solve the day-ahead ED of the SDG. Forecasts for dynamic variables involved in the operation system, electric component models of the SDG and the rate scheme selected are also included in this ED. Dynamic variables include inelastic demand, energy spot prices, PEV information supplied from aggregators and energy supplied by DER. This information is introduced in a methodology that maximizes the EB of a utility. It considers as income the energy sold to elastic and inelastic demand, and as expense the energy purchased from the aggregators, WEM, DER, costs of energy supplied with low quality (ESLQ) and energy not supplied (ENS). The ENS refers to the economic compensation that the utility must pay to customers when they do not meet their demand due to the capacity of the SDG components is exceeded. This stochastic optimization problem subject to equality, inequality and intertemporal constraints is solved by the DMS. Intertemporal constraints refer to the final and initial PEV states of charge and PEV participation time during each interval considered in the ED. The ED results are sent to aggregators, which provide this information to the PEV located in their coverage area. Results mainly include energy sale-purchase prices, which are used in FIS to determine if a PEV will decide to participate in energy exchanges with the SDG. Moreover, these results are used again by aggregators to adjust the ED global model.

2.3. Mathematical formulation

Two sequential optimization processes interact in the SDG short-term ED proposed, which are coupled as an integrated model. The first is carried out by each aggregator located in the SDG and the second by the DMS. The objective functions and constraints of these processes are described below.

2.3.1. Formulation by aggregators

Each aggregator (Middleware: middle level control in Fig. 1) includes the objective function formulated in Eq. (1), which maximizes the EB calculated from the difference between incomes and costs incurred by a PEV set. Variables and parameters are described in the first section of this paper. The costs include $C_{PEV,t}^{LL}$ and $C_{DEG,t}$. The last cost occurs when a PEV supplies energy in deep cycling mode, which has been considered in this work and allows for the extraction of great quantities of energy stored in a battery [25]. On the other hand, $I_{PEV,t}^{LL}$ represents the incomes. The maximization of the EB is achieved by optimizing the quantities of energy that each PEV should consume and supply from/to the SDG during each sub-period included in the ED. $E_{i,t}^{s}$ and $E_{i,t}^{b}$ are the decision variables, meanwhile $\pi_{i,t}^{c}$ and $\pi_{i,t}^{v}$ are supplied by the DMS. The Eq. (2) is aligned with the arguments exposed in Ref. [25], where $d_{DoD,i}$ is the minimum limit of energy storage available in the battery. In this paper, this limit is 20% and is used to determine $L_{c,i}$. In Eq. (3), relationships between the energies $E_{i,t}^{b}$ and $E_{i,t}^{s}$ in the CDS terminals and the energies $E_{i,t}^{b_x}$ and $E_{i,t}^{s_x}$ in battery terminals are illustrated. The energies purchased ($E_{i,t}^{b_x}$) and sold ($E_{i,t}^{s_x}$) do not include the losses generated by electrical and electronic devices located between the CDS terminals and the battery. These relationships are used in Eqs. (4), (5) and (6).

$$\max\{\sum_{t=1}^{T}[I_{PEV,t}^{LL}-(C_{PEV,t}^{LL}+C_{DEG,t})]\}$$
$$=\begin{aligned}&\max\{\sum_{t=1}^{T}[\sum_{i=1}^{I}(\pi_{i,t}^{c}\times E_{i,t}^{s}\times\chi_{i,t}^{s}\times\mu_{i,t}^{s})\\&-(\sum_{i=1}^{I}(\pi_{i,t}^{v}\times E_{i,t}^{b}\times\chi_{i,t}^{b}\times\mu_{i,t}^{b})+\sum_{i=1}^{I}(\vartheta_{DEG,i}\times E_{i,t}^{s}\times\chi_{i,t}^{s}\\&\times\mu_{i,t}^{s}))]\}\end{aligned} \tag{1}$$

$$\vartheta_{DEG,i}=\vartheta_{inv,i}/(L_{c,i}*E_{B,i}*d_{DoD,i}) \tag{2}$$

$$E_{i,t}^{b_x}=\eta_{ch,i}\times E_{i,t}^{b}\quad;E_{i,t}^{s_x}=(1/\eta_{dch,i})\times E_{i,t}^{s} \tag{3}$$

The equation in (1) is subject to the intertemporal evolution of PEV batteries state of charge (4), batteries capacity (5) and (6), the minimum state of charge required by a PEV when it leaves a CDS (7) and the capacity of MV/LV nodes (8)–(10).

$$\begin{aligned}E_{final,i,t}=&E_{final,i,t-1}+(\eta_{ch,i}\times E_{i,t}^{b}\times\chi_{i,t}^{b})-(E_{i,t}^{d}\times\chi_{i,t}^{d})\\&-((1/\eta_{dch,i})\times E_{i,t}^{s}\times\chi_{i,t}^{s})\end{aligned} \tag{4}$$

$$(\eta_{ch,i}\times E_{i,t}^{b})\le[(E_{B,i}^{\max}-E_{final,i,t-1})\times\chi_{i,t}^{b}] \tag{5}$$

$$((1/\eta_{dch,i})\times E_{i,t}^{s})\le[(E_{final,i,t-1}-E_{B,i}^{\min})\times\chi_{i,t}^{s}] \tag{6}$$

$$E_{i}^{f}\ge(E_{i,t}^{d}+E_{B,i}^{\min}) \tag{7}$$

$$\sqrt{(P_{trf,k,t}^{MV/LV})^{2}+(P_{trf,k,t}^{MV/LV})^{2}}\le S_{\max\_trf,k,t}^{MV/LV} \tag{8}$$

$$\begin{aligned}P_{trf,k,t}^{MV/LV}=&\sum_{j=1}^{J}P_{j,t}^{DER}+\sum_{i=1}^{I}(P_{i,t}^{dch}\times\chi_{i,t}^{s})-\sum_{i=1}^{I}(P_{i,t}^{ch}\times\chi_{i,t}^{b})\quad\forall\ i,j,r\in k\\&-\sum_{r=1}^{R}P_{r,t}^{INL};\end{aligned} \tag{9}$$

$$Q_{trf,k,t}^{MV/LV}=\sum_{j=1}^{J}Q_{j,t}^{DER}-\sum_{r=1}^{R}Q_{r,t}^{INL};\quad\forall\ j,r\in k \tag{10}$$

$$E_{i,t}^{b}=P_{i,t}^{ch}\times\Delta t;\quad E_{i,t}^{s}=P_{i,t}^{dch}\times\Delta t;\quad E_{i,t}^{d}=P_{i,t}^{d}\times\Delta t \tag{11}$$

In Eq. (4), the battery state of charge by a PEV at the final of a period ($E_{final,i,t}$) is calculated as the battery state of charge at the beginning of that period ($E_{final,i,t-1}$), plus the energy charged by the PEV during that period ($\eta_{ch,i}\times E_{i,t}^{b}\times\chi_{i,t}^{b}$), minus the energy supplied by the PEV during that period ($(1/\eta_{dch,i})\times E_{i,t}^{s}\times\chi_{i,t}^{s}$) and minus the energy used by the PEV during its mobilization ($E_{i,t}^{d}\times\chi_{i,t}^{d}$). A PEV cannot charge energy, discharge energy and move from one place to another at the same time. On the other hand, Eqs. (5) and (6) avoid a quick reduction of the battery lifespan. In Eq. (5), a PEV can only charge its battery until the maximum limit of energy storage available in the battery. In Eq. (6), a PEV can only discharge its battery until the minimum limit of energy storage available in the battery. The Eq. (7) guarantees the daily mobility of each PEV and Eqs. (8)–(10) prevent the maximum capacity of transferable power through the MV/LV nodes have been exceeded.

2.3.2. Formulation by the DMS

The second optimization process implemented in the DMS (upper level control in Fig. 1) uses the results obtained by each aggregator independently. In this process, the objective function is formulated as (12) and consists of maximizing the EB obtained through the difference between the incomes and costs incurred by a utility. The costs include $C_{WEM,t}$, $C_{DER,t}$, $C_{PEV,t}^{UL}$, $C_{ESLQ,t}$ and $C_{ENS,t}$. The incomes include $I_{PEV,t}^{UL}$ and $I_{INL,t}$. Energy prices $\pi_{i,t}^{c}$ and $\pi_{i,t}^{v}$ are the main ED results and the decision variables of the problem proposed. The main constraints associated with (12) are the active and reactive power balance of the SDG (13) and (14) and the maximum and minimum limits of the power supplied from DER (15) and (16). The capacity of SDG components and nodal voltage limits are soft constraints and are included in the objective function. The maximum reactive and active power transfer in the HV/MV TS and the electrical links are part of the soft constraints. Besides, Y_{mn}, θ_{mn}, $V_{m,t}$, $V_{n,t}$, $\delta_{n,t}$ and $\delta_{m,t}$ are the electrical network parameters (admittance (Y_{mn}), voltages ($V_{m,t}$, $V_{n,t}$) and angles (θ_{mn}, $\delta_{n,t}$ and $\delta_{m,t}$)).

$$\max\left\{\sum_{t=1}^{T}\left[(I_{PEV,t}^{UL}+I_{INL,t})-(C_{WEM,t}+C_{DER,t}+C_{PEV,t}^{UL}+C_{ENS,t}+C_{ESLQ,t})\right]\right\}=$$
$$\max\left\{\sum_{t=1}^{T}\left[\begin{array}{l}\left[\sum_{g=1}^{G}C_{PEV,t}^{LL}\right]+\left[\left(1000\times\vartheta_f\times\sum_{r=1}^{R}E_{r,t}^{INL}\right)+\left(\vartheta_v\times\sum_{r=1}^{R}E_{r,t}^{INL}\right)\right]-[\pi_t^{WEM}\times E_t^{WEM}]\\-\left[\sum_{j=1}^{J}(\pi_{j,t}^{DER}\times E_{j,t}^{DER})\right]-\left[\sum_{g=1}^{G}I_{PEV,t}^{LL}\right]-[\pi_t^{ENS}\times E_t^{ENS}]-[\pi_t^{ESLQ}\times E_t^{ESLQ}]\end{array}\right]\right\} \tag{12}$$

$$P_t^{WEM}+\sum_{j=1}^{J}P_{j,t}^{DER}+\sum_{g=1}^{G}P_{g,t}^{agg,dch}=\sum_{g=1}^{G}P_{g,t}^{agg,ch}+\sum_{r=1}^{R}P_{r,t}^{INL}+\sum_{\substack{n=1\\m\neq n}}^{N}[V_{m,t}\times V_{n,t}\times Y_{mn}\times\cos(\theta_{mn}+\delta_{n,t}-\delta_{m,t})] \tag{13}$$

$$Q_t^{WEM}+\sum_{j=1}^{J}Q_{j,t}^{DER}=\sum_{r=1}^{R}Q_{r,t}^{INL}+\sum_{\substack{n=1\\m\neq n}}^{N}[V_{m,t}\times V_{n,t}\times Y_{mn}\times\sin(\theta_{mn}+\delta_{n,t}-\delta_{m,t})] \tag{14}$$

$$P_{j,t}^{DER}\leq(\gamma_{j,t}\times P_{j,t}^{DER,\max})\ ;P_{j,t}^{DER}\geq(\gamma_{j,t}\times P_{j,t}^{DER,\min}) \tag{15}$$

$$Q_{j,t}^{DER}\leq(\gamma_{j,t}\times Q_{j,t}^{DER,\max})\ ;Q_{j,t}^{DER}\geq(\gamma_{j,t}\times Q_{j,t}^{DER,\min}) \tag{16}$$

2.4. Calculation algorithm by intelligent device “aggregator”

Fig. 2 describes the calculation algorithm included in each aggregator, which optimizes PEV participation in energy exchanges with the SDG during their connection time to the CDS. Data gathered from PEV and the DMS in Section 2.2 and the mathematical approach in Section 2.3.1 are used. In this manner, the proposed algorithm maximizes the EB of a PEV group managed by an aggregator and includes constraints related with the PEV components and CDS for PEV, capacity of MV/LV TS and requirements imposed by PEV owners.

Data gathered are distributed to different calculation nodes through parallel and distributed computing techniques, which are part of the aggregator internal structure. Each node represents a PEV and includes sophisticated mathematical processes to determine in an iterative manner the greatest possible EB from a set of possible participation options. The last refers to a PEV being able to purchase energy, sell energy or not participate in energy exchanges during each sub-period of the ED. In this sense, the energy sale-purchase prices sent by the DMS could not provide incentive for the participation of PEV owners when they are lower (energy sale) or higher (energy purchase) with respect to the price established by each PEV. A PEV only establishes a daily energy price to purchase and sell energy. These particularities, features of the variables involved in the optimization process and the mathematical formulation described in Section 2.3.1, transform the problem into one

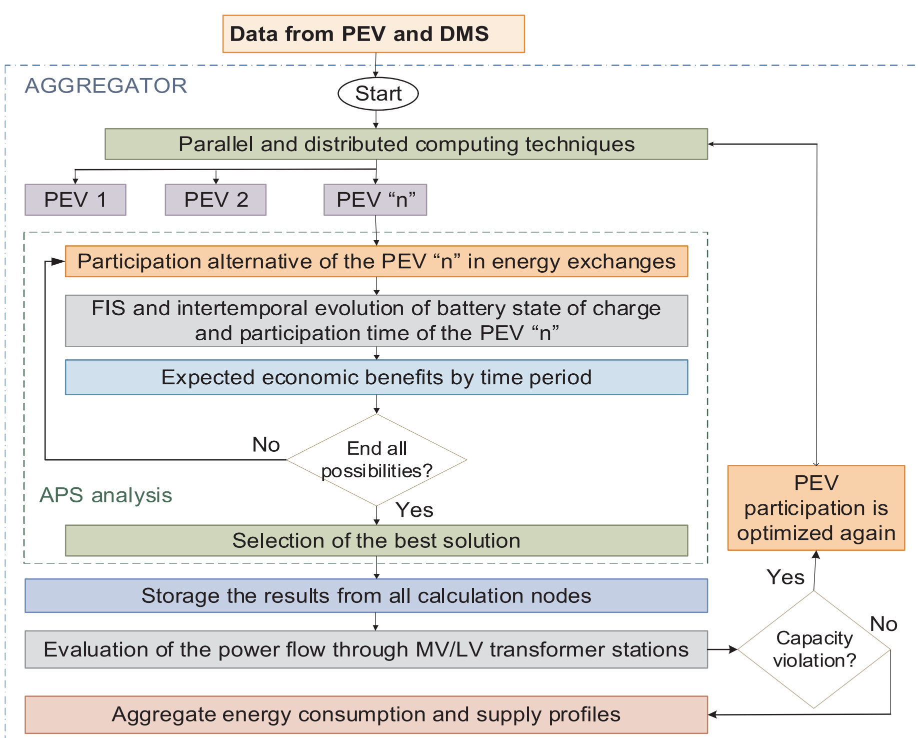


Fig. 2. Calculation algorithm included in aggregators.

to be solved by each aggregator in no-lineal, integer and mixed. An APS analysis is used in this work to calculate the optimal EB for each PEV.

Two FIS have been designed and implemented in the APS analysis to calculate charge and discharge possibilities of each PEV. The PEV battery state of charge, participation time and the difference between energy sale-purchase prices sent from the DMS and the energy price imposed by the PEV owner are the inputs provided by a PEV to FIS. It is noted that the first two inputs (state of charge and participation time) change during the connection time of each PEV to the CDS, as a function of their intertemporal relations. FIS outputs (charge and discharge possibilities) depend on the input variables, the fuzzy membership functions used and a set of conditional if-then rules. FIS inputs and the possible decisions adopted by a PEV are linked with these rules, which include preferences and operative conditions of the vehicle. The Mamdani-type fuzzy inference with trapezoidal membership functions (suitable for these cases [38]) is used to represent linguistic variables and assign a degree of membership (between 0 and 1) to each input value. It transforms numerical variables into fuzzy variables. Finally, FIS outputs represented by fuzzy sets are defuzzified through the centroid method described in Ref. [38]. Fig. 3 shows the FIS elaborated to calculate the PEV charge possibilities in % or p.u., which include linguistic variables and membership functions. In FIS, “L” is low, “M” is medium, “H” is high, “S” is short, “LO” is long, “ML” is medium-low and “MH” is medium-high. Discharge possibilities are calculated with these FIS and different if-then rules. Other general features of FIS could be reviewed in Ref. [39].

The FIS results are used in the calculation sequence of the APS analysis to evaluate the decisions adopted by each PEV and to calculate its EB. When the APS analysis has finished for all nodes, the aggregator gathers and stores these results and the maximum transferable power in the MV/LV TS is evaluated. If the capacity of a MV/LV TS is exceeded, the sub-periods with violation are identified and PEV participation connected in the TS is optimized again. In order to do so, energy exchanges from PEV with lower daily EB are restricted during the sub-periods with capacity violation. The power flow direction during the violation influences this restriction, which will condition the energy sale or purchase exchanges from one or multiple PEV. When the optimization process has finished, the aggregators elaborate aggregate energy consumption and supply profiles by day. Finally, these energy profiles are sent to the DMS.

2.5. Calculation algorithm by the DMS

The calculation algorithm implemented in aggregators is embedded in a second algorithm elaborated to solve the ED. Data from the WEM,

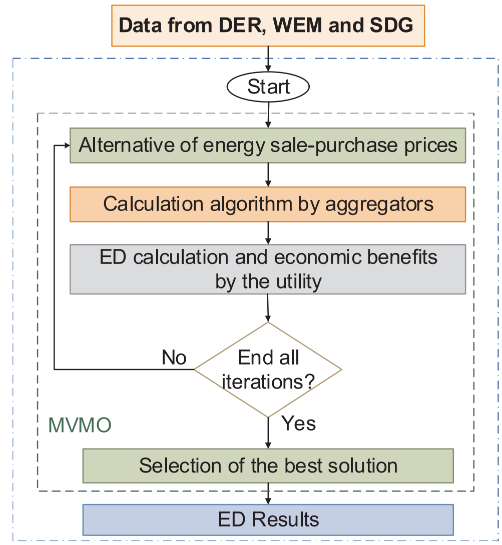


Fig. 4. Calculation algorithm included in the DMS.

DER and the features of the electrical network are received by the DMS. With these data, the DMS builds forecasts for the dynamic variables included in the ED and an MVMO algorithm is executed. These variables include the energy supplied by DER, energy spot prices and inelastic demand. MVMO features and functionality are presented in Ref. [40]. Using these forecasts, the electric component models of SDG and rate scheme selected, DMS elaborates the ED based on the mathematical equations showed in Section 2.3.2. The calculation algorithm included in the DMS is showed in Fig. 4.

In this regard, MVMO determines the optimal energy sale-purchase prices that encourage PEV participation in energy sale and/or purchase transactions with the SDG. For that, MVMO generates diverse alternatives of energy prices, which are sent from DMS to PEV by aggregators. Each aggregator executes the calculation algorithm described in Section 2.4 and builds aggregate energy consumption and supply profiles. This information is then gathered by the DMS, a power flow network analysis applying the Newton-Raphson method is completed and the EB by utility are determined. For solving the power flow and searching for capacity violations and/or voltages outside normal operating ranges in the SDG, the MATPOWER-MATLAB® package is used. MVMO finishes when all iterations are done, the best solution to the optimization process is picked and ED results are sent to PEV.

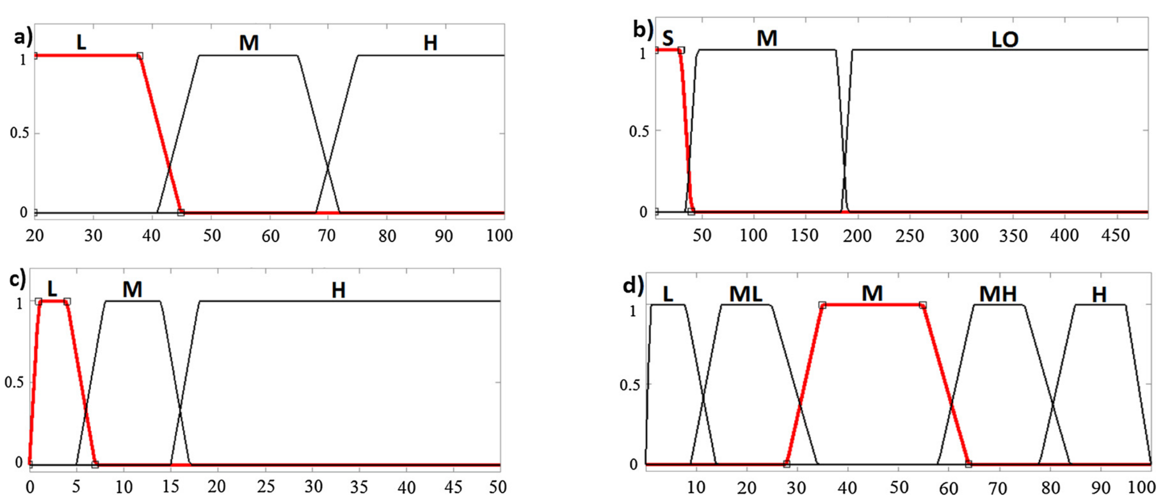


Fig. 3. FIS to calculate PEV charge possibilities. Inputs: (a) battery state of charge; (b) participation time; (c) difference between energy prices sent from the DMS and the price set in each PEV. Output: PEV charge possibility in (d).

3. Implementation and results

An example applying the ED proposed is described below.

3.1. Description

The test feeder IEEE 13 N shown in Fig. 5 and 600 PEV with same features are used in analyses. Two aggregators are included in the test network. The first is located in node 632 and manages the PEV in nodes 645, 646 and 633. The second is located in node 671 and manages the PEV integrated in nodes 675, 611 and 652. In Fig. 5, HV/MV TS refers to a high-voltage/medium-voltage transformer station and B means breaker.

The statistical time mobility behavior of vehicle users for an average week corresponding to the survey “Mobility in Germany” has been considered [41]. Technical MVMO and PEV features are described in Tables 1 and 2 based on Refs. [3] and [42]. It is noted that MVMO includes four selection strategies for offspring creation, which are explained in Ref. [40]. In this work, the sequential selection strategy for the first variable and the rest randomly is used. The range of energy prices used by the DMS to determine the ED solutions is 50–150 \$/MWh. PEV owners establish daily energy prices to sell and purchase in function of this price range. Energy prices used to calculate VAD, ENS, and ESLQ are showed in Tables 3 and 4. In addition, 10% of PEV charging their batteries regardless of the prevailing price has been assumed. Photovoltaic systems (PV) installed in homes and small-large buildings are included in the SDG. The capacity range for medium-scale PV is from 10 to 1000 kW, as long as small-scale PV could have rated power up to 10 kW [43]. In this work, 100 kW supplied from multiple PV located in nodes 645, 675 and 652 are included. The energy sale price by PV is 100 \$/MWh constant during one day. Energy prices used to purchase energy in the WEM are 90, 100, and 120 \$/MWh for valley, rest and peak demand, respectively. The node 650 is the energy exchange point between the utility and WEM.

With the hypotheses and information from previous sections, the ED proposed is assessed in nine scenarios shown in Table 5. The option “No” in the economic dispatch refers to analyzes without optimization. Such as, analyzes in scenario 3 include: (a) energy exchanges from PEV without optimization; (b) a daily curve of energy prices sent by the DMS; (c) PEV only charge energy and; (d) the economic dispatch results are calculated in function of the best benefit determined with the DMS objective function (EB1). Moreover, the results shown in scenario 6 (randomly selected) are compared with an APS analysis of the ED to determine the robustness and efficiency of the methodology proposed.

Table 1
PEV features.

Battery capacity ($E_{B,i}$)	kWh	24
Maximum limit of energy storage in a battery ($E_{B,i}^{max}$)	%	95
Minimum limit of energy storage in a battery ($E_{B,i}^{min}$)	%	20
Battery charging efficiency ($\eta_{ch,i}$)	%	88
Battery discharging efficiency ($\eta_{dch,i}$)	%	92
Energy used by PEV during mobilization ($E_{i,t}^{d}$)	Wh/km	142.9
Average daily distance traveled by a PEV	km	25 - 35
Charging voltage	V	240
Charging current	A	32
Investment cost in a new battery ($\vartheta_{inv,i}$)	\$/kWh	100
Battery cycle life at a certain depth of discharge ($L_{c,i}$)	cycles	4000
Battery depth of discharge (d_{DoDi})	p.u.	0.8

Table 2
MVMO features.

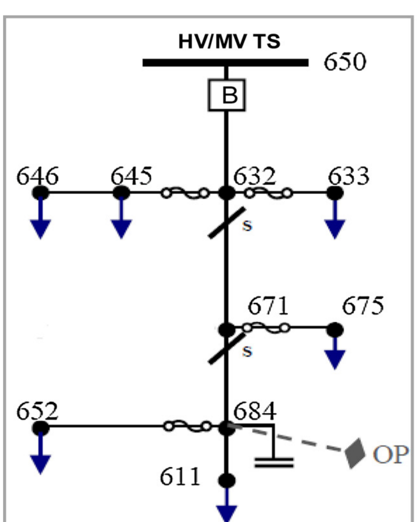
Maximum number of fitness evaluation	50
Variable selection strategy for offspring creation	4
Initial number of variables selected for mutation	4

Table 3
Energy prices used to calculate VAD and ENS.

		Demand Residential	Commercial	Industrial
Fixed value in VAD (ϑ_f)	\$/kW-month	6	5	4
Variable value in VAD (ϑ_v)	\$/MWh	20	30	50
Energy price for the ENS (π_t^{ENS})	\$/MWh	1500	2000	3000

Table 4
Energy prices used to calculate ESLQ.

Voltage	Energy price for the ESLQ (π_t^{ESLQ})
[p.u.]	[\$/MWh]
If 0.93 < V ≤ 0.95	150
If 0.90 < V ≤ 0.93	300
If V ≤ 0.90	500



Voltaje in HV/MV TS	p.u.	1.02
Base voltage	kV	13.2
Base power	MVA	100
Energy price in HV/MV TS	\$/MWh	100
Capacity of HV/MV TS	MVA	10

SDG Data	Length [km]	Max. Current [A]	Resistance [ohms]	Inductance [ohms]
650-632, 632-671	2.0	300	0.620	0.610
671-684	1.5	250	0.638	0.473
632-645, 645-646	0.5	190	0.300	0.200
684-611	0.5	130	0.600	0.203
632-633, 671-675	1.0	190	0.600	0.400
684-652	1.0	130	1.200	0.405

Fig. 5. Test feeder IEEE 13N and SDG data used in simulations.

Table 5
Scenarios to evaluate the methodology proposed.

Scenario	Economic dispatch		Functionality of a PEV		Energy prices from the DMS		Economic benefits[a]	
	No	Yes	Only charge	Charge/discharge	One price curve	Two price curves	EB1	EB2
1	X			X	X		X	
2	X			X		X	X	
3	X	X	X		X		X	
4		X	X		X		X	
5		X	X		X			X
6		X		X	X		X	
7		X		X	X			X
8		X		X		X	X	
9		X		X		X		X

[a] Economic benefit (EB) used to determine optimal energy prices: **EB1** = EB of the DMS. **EB2** = EB obtained in the DMS plus EB obtained in aggregators.

Table 6
Optimal energy prices calculated by the DMS.

	Energy prices [$/MWh]					
	Valley		Rest		Peak	
	Purchase	Sale	Purchase	Sale	Purchase	Sale
Sc. 4	120	120	140	140	150	150
Sc. 5	120	120	140	140	140	140
Sc. 6	130	130	140	140	140	140
Sc. 7	130	130	150	150	140	140
Sc. 8	150	100	150	120	150	140
Sc. 9	130	120	150	90	140	150

When $S^{MV/LV}_{\max\_trf,k,t}$ is exceeded, a reoptimization process developed in each aggregator is used to change the decisions adopted for one or some PEV in according to the daily EB. In Table 5, optimal ED results could be determined in function of the best benefit calculated with the DMS objective function (EB1) or by a joint analysis of the EB obtained by aggregators and the DMS (EB2). In EB2, the best ED solution occurs when the EB in aggregators and the DMS increase simultaneously. A computing cluster with 80 calculation nodes is used to conduct the simulations.

3.2. Results and discussion

Energy exchanges and economic transactions during a day obtained at the level of aggregators are described in Fig. 6, Fig. 7 and Table 7. These results are determined with and without the optimization process proposed, in according to the case analyzed. In this regard, abbreviations Agg. 1 and Agg. 2 are used to refer aggregators located in nodes 632 and 671, Sc. refers to scenario and Sum Agg. represents the sum of all EB obtained at the level of aggregators. For example, Sum Agg. is the sum of Agg.1 and Agg 2 in Table 7. The results in Fig. 6 shows that the energy exchanges in scenarios 1–3 are higher than the exchanges estimated by each aggregator in scenarios 4–9. Further, the energy sold in scenarios 6–9 is higher than the energy purchased in these scenarios. The corresponding EB are shown in Fig. 6, where negative economic benefits occur when the incomes are lower than the expenses or when PEV only purchase energy. In Table 6, energy prices (decision variables calculated in the ED) used to estimate the EB in scenarios 4–9 are described.

The lack of aggregators integrated in the SDG produces low EB for the PEV set in regard to scenarios with optimization. Table 7 compares in percentage the EB calculated in each scenario, considering the results obtained in scenario 3. In this sense, the highest EB is determined in scenario 8 (121% as regards scenario 3), where two energy price curves are used and PEV charge-discharge energy. The loss of EB for the PEV set in scenarios without optimization is caused for non-optimal energy exchanges, which occurs when PEV purchase and/or sale energy in different sub-periods and quantities in respect to an optimal exchange option. For these reasons, aggregators integrated in the HCA proposed are essential to process the requirements and data coming from PEV and the DMS, and to search for an optimal participation option for each PEV in energy exchanges.

Table 8 shows the main results obtained at the level of the DMS,

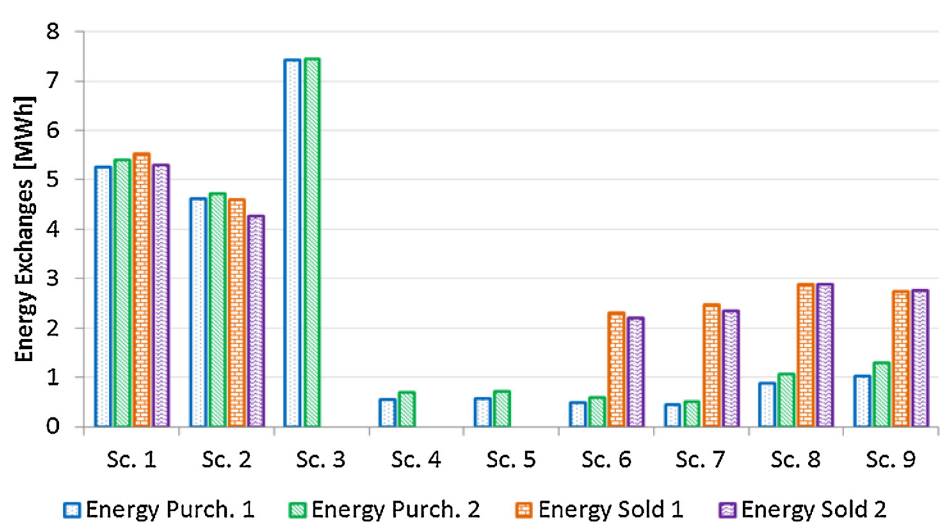


Fig. 6. Daily energy exchanges at the level of aggregators, with and without the optimization process proposed. The aggregator located in node 632 is 1 and the aggregator in node 671 is 2. Purch. means purchased.

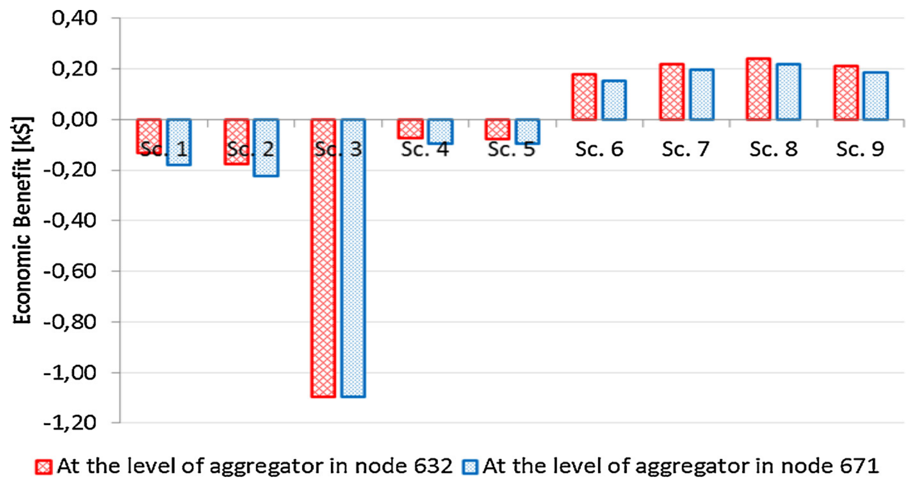


Fig. 7. Daily economic transactions obtained at the level of aggregators.

where the abbreviation Inel. Dem. refers to inelastic demand. In scenarios with optimization, the ESW of both the utility and PEV could be reached by EB1 or EB2. Scenarios 4, 6 and 8 use EB1 to calculate the EB in the DMS and EB2 is applied in the rest of scenarios (5, 7 and 9). It is noted that similar results are obtained through EB1 and EB2 in scenarios with similar features, such as scenarios 6 and 7 or 8 and 9. Hence, PEV participation during certain sub-periods of the ED could be incentivized by a daily curve of energy prices. In this manner, the quantity of data used by each PEV during its decision making to exchange energy is reduced. However, a utility could use two daily curves of energy prices to manage the PEV connection before specific requirements. For example, when a utility requires increasing the energy supplied from PEV during one or several sub-periods.

If incomes obtained by the sale of energy to the inelastic demand are not consider in Eq. (12), the EB described in the third column of the Table 8 are determined. These EB include the costs by ESLQ, ENS, energy purchased to the WEM and DER, power losses in the distribution network and the EB obtained by each aggregator. The last column in Table 8 shows the relation (in percentage) between these EB, where scenario 8 again provides the best solution (7.48% as regards scenario 3).

On the other hand, similar results are obtained through an MVMO (using 50 fitness evaluations) and an APS analysis. In this sense, the EB with MVMO and the APS analysis are $ 355.990k and $ 355.994k, respectively. The difference between both optimization methods is 0.0009%. However, MVMO just needs approximately 9 hours to solve the ED, whereas 10 days are required to complete this task in the APS analysis. This comparison demonstrates the robustness and efficiency of the methodology proposed. In turn, future developments will reduce this calculation time.

Table 8
Daily results obtained at the level of the DMS.

	Sum Agg. [k$]	EB of the DMS without Inel. Dem. [k$]	EB of the DMS with Inel. Dem. [k$]	Relation [%]
Sc. 1	−0.31	8.49	356.28	2.84
Sc. 2	−0.40	8.48	356.28	2.82
Sc. 3	−2.19	8.25	356.51	–
Sc. 4	−0.17	8.79	355.98	6.48
Sc. 5	−0.17	8.79	355.97	6.51
Sc. 6	0.33	8.77	355.99	6.32
Sc. 7	0.41	8.81	355.95	6.76
Sc. 8	0.46	8.87	355.90	7.48
Sc. 9	0.40	8.86	355.90	7.38

Advances in the operation and internal structure of batteries and the increase in the use of PEV will continue reducing the investment and degradation costs related with PEV batteries. A high degradation cost could significantly reduce the EB for each PEV. For example, $ 0.332k is the EB obtained for a PEV set in scenario 6, with a battery degradation cost of 31.25 $/MWh. The data in Table 1 and Eq. (2) are used to calculate this cost. If the batteries life cycles are reduced to 1000, the degradation cost is 125 $/MWh and the EB for the PEV set is $ −0.091k.

Finally, Fig. 8 describes the decisions adopted by a PEV during its participation in energy exchanges with the SDG. FIS shown in Section 2.4 are used to quantify these decisions by charge and discharge possibilities. In this case, the PEV only charges energy in the second sub-period and in the rest it does not participate. In the second sub-period, the charge possibility is higher than the discharge possibility mainly

Table 7
Daily results obtained at the level of aggregators.

	Energy exchanges [MWh]				Economic benefit [k$]			Relation [%]
	Purchase		Sale		Agg. 1	Agg. 2	Sum Agg.	
	Agg. 1	Agg. 2	Agg. 1	Agg. 2				
Sc. 1	5.26	5.40	5.54	5.31	−0.13	−0.18	−0.31	85.90
Sc. 2	4.62	4.73	4.59	4.27	−0.17	−0.22	−0.40	81.91
Sc. 3	7.44	7.45	0.00	0.00	−1.10	−1.10	−2.19	–
Sc. 4	0.56	0.71	0.00	0.00	−0.07	−0.09	−0.17	92.38
Sc. 5	0.58	0.71	0.00	0.00	−0.08	−0.09	−0.17	92.24
Sc. 6	0.49	0.61	2.31	2.21	0.18	0.15	0.33	115.15
Sc. 7	0.44	0.51	2.48	2.36	0.22	0.20	0.41	118.89
Sc. 8	0.88	1.08	2.88	2.89	0.24	0.22	0.46	121.10
Sc. 9	1.02	1.30	2.75	2.77	0.21	0.19	0.40	118.06

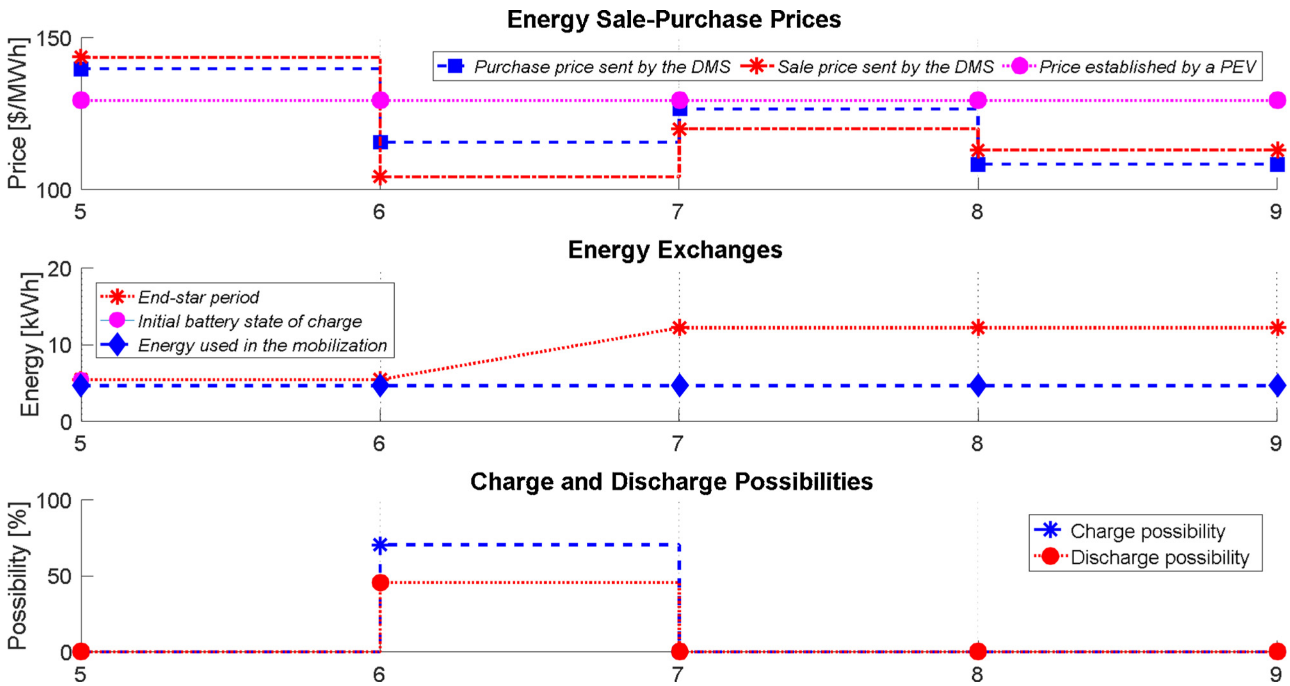


Fig. 8. Decisions adopted by a PEV during its participation in the ED.

due to a low battery state of charge and adequate energy purchase prices sent from the DMS in regard to the energy price established by the PEV. Moreover, FIS results depend on the time the PEV is connected to a CDS, which is considered "long" (4 hour) for this PEV. The PEV leaves the CDS with an adequate battery state of charge for its mobilization during the rest of the day.

4. Conclusions

An ED model has been proposed in this article to satisfy in an economic and coordinated manner the energy requirements coming from diverse prosumers (mainly PEV), DER and loads integrated in an SDG. The monopolistic behavior of the Latin American power markets is considered in the structuring of the ED, which is solved by two optimization processes interacting economically as an integrated model. Intelligent devices located in the SDG called "aggregators" are used to improve the intelligent link between a utility and PEV. Through this integrated ED, the EB for a PEV set and the utility are maximized jointly and the ESW is reached for both the utility and PEV.

An algorithm has been developed and implemented in each aggregator to determine the optimal energy exchanges for each PEV. Intertemporal constraints related to the batteries state of charge and arrival-departure time of PEV, batteries features, batteries degradation cost, energy prices estimated-calculated by DNOs, CDSs features, statistical time mobility behavior of PEV users and preferences imposed by PEV users are included in analyses. The last refers to the energy prices pre-set by PEV users in their vehicles, the energy required by each PEV when it leaves a CDS, the predisposition of each PEV to accept the energy prices sent from the DMS and the PEV connection time to a CDS. FIS elaborated in this work are used to evaluate all these preferences seen together.

A second algorithm has been developed to solve the ED in a distribution control center. The results obtained in the first optimization process, together with SDG design and operation features, DER and loads are included in analyses. A case study is used to demonstrate the functionality of the ED proposed and the advantages of using aggregators located in the SDG. With this ED, violations of the TS capacity, loss of EB of both the utility and PEV, and non-optimal energy exchanges from PEV could be avoided.

Future developments will introduce uncertainties related to energy spot prices, inelastic demand, battery state of charge reached when each PEV leaves a CDS and the energy supplied from PV.

Conflict of interests

Authors have no competing interests to declare.

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