Day-Ahead Resource Scheduling Including Demand Response for Electric Vehicles

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Abstract—The energy resource scheduling is becoming increasingly important, as the use of distributed resources is intensified and massive gridable vehicle (V2G) use is envisaged. This paper presents a methodology for day-ahead energy resource scheduling for smart grids considering the intensive use of distributed generation and V2G. The main focus is the comparison of different EV management approaches in the day-ahead energy resources management, namely uncontrolled charging, smart charging, V2G and Demand Response (DR) programs in the V2G approach. Three different DR programs are designed and tested (trip reduce, shifting reduce and reduce+shifting). Other important contribution of the paper is the comparison between deterministic and computational intelligence techniques to reduce the execution time. The proposed scheduling is solved with a modified particle swarm optimization. Mixed integer non-linear programming is also used for comparison purposes. Full ac power flow calculation is included to allow taking into account the network constraints. A case study with a 33-bus distribution network and 2000 V2G resources is used to illustrate the performance of the proposed method.

Index Terms—Demand response, electric vehicle, energy re- source management, particle swarm optimization.

NOMENCLATURE:

Δt	Period t duration (e.g., 15 min., 30 min., 1 hour)
$\eta_{c(V)}$	Grid-to-Vehicle efficiency when the vehicle V is in charge mode
$\eta_{d(V)}$	Vehicle-to-Grid efficiency when the vehicle V is in discharge mode
θ_b	Voltage angle at bus b (rad)
$\theta_b^{\max}$	Maximum voltage angle at bus b (rad)
$\theta_b^{\min}$	Minimum voltage angle at bus b (rad)
θ_k	Voltage angle at bus k (rad)
B_{bk}	Imaginary part of the element in y_{bk} corresponding to the row b and column k
$c_{Charge(V,t)}$	Charge price of vehicle V in period t
$c_{DG(DG,t)}$	Generation price of DG unit in period t
$c_{Discharge(V,t)}$	Discharge price of vehicle V in period t
$c_{GCP(DG,t)}$	Generation curtailment power price of DG unit in period t
$c_{NSD(L,t)}$	Non-supplied demand price of load L in period t
$c_{Shift(V)}$	Trip shifting price for vehicle V
$c_{Supplier(S,t)}$	Energy price of external supplier S in period t
$c_{Trip\,Red(V,t)}$	Trip reduction price contracted with vehicle V in period t
$E_{BatCap(V)}$	Battery energy capacity of vehicle V
$E_{MinCharge(V,t)}$	Minimum stored energy to be guaranteed at the end of period t for vehicle V
$E_{Stored(V,t)}$	Active energy stored in vehicle V at the end of period t
$E_{Trip(V,t)}$	Vehicle V energy consumption in period t
$E_{Trip\,Red(V,t)}$	Demand response energy reduction of vehicle trip V in period t
$E_{TripRedMax(V,t)}$	Maximum energy reduction for vehicle V trip in period t
G_{bk}	Real part of the element in y_{bk} corresponding to the row b and column k
N_B	Total number of buses
N_{DG}	Total number of distributed generators
N_{DG}^{b}	Total number of distributed generators at bus b
N_L	Total number of loads
N_L^b	Total number of loads at bus b
N_S	Total number of external suppliers
N_S^b	Total number of external suppliers at bus b
N_V	Total number of vehicles V
N_V^b	Total number of vehicles at bus b

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$N_V^{b\_noShift}$	Total number of vehicles at bus b with original trips
$N_V^{b\_Shift}$	Total number of vehicles at bus b shifting their trips
$P_{Charge(V,t)}$	Power charge of vehicle V in period t
$P^b_{Charge(V,t)}$	Power charge of vehicle V at bus b in period t
$P_{ChargeLimit(V,t)}$	Maximum power charge of vehicle V in period t
$P_{DG(DG,t)}$	Active power generation of distributed generation unit DG in period t
$P^b_{DG(DG,t)}$	Active power generation of distributed generation unit DG at bus b in period t
$P_{DGMaxLimit(DG,t)}$	Maximum active power generation of distributed generator unit DG in period t
$P_{DGMinLimit(DG,t)}$	Minimum active power generation of distributed generator unit DG in period t
$P_{Discharge(V,t)}$	Power discharge of vehicle V in period t
$P^b_{Discharge(V,t)}$	Power discharge of vehicle V at bus b in period t
$P_{DischargeLimit(V,t)}$	Maximum power discharge of vehicle V in period t
$P_{GCP(DG,t)}$	Generation curtailment power in DG unit in period t
$P^b_{GCP(DG,t)}$	Generation curtailment power in DG unit at bus b in period t
$P^b_{Load(L,t)}$	Active power demand of load L at bus b in period t
$P_{NSD(L,t)}$	Non-supplied demand for load L in period t
$P^b_{NSD(L,t)}$	Non-supplied demand for load L at bus b in period t
$P_{Supplier(S,t)}$	Active power flow in the branch connecting to external supplier S in period t
$P_{SupplierLimit(S,t)}$	Active power flow in the branch connecting to upstream supplier S at bus b in period t
$P_{SupplierLimit(S,t)}$	Maximum active power of upstream supplier S in period t
$P_{TFR\_HV/MV(b,t)}$	Active power in HV/MV power transformer connected in bus b in period t
$P_{TFR\_MV/LV(b,t)}$	Active power in MV/LV power transformer connected in bus b in period t
$Q^b_{DG(DG,t)}$	Reactive power generation of distributed generation unit DG at bus b in period t
$Q_{DGMaxLimit(DG,t)}$	Maximum reactive power generation of distributed generator unit DG in period t
$Q_{DGMinLimit(DG,t)}$	Minimum reactive power generation of distributed generator unit DG in period t
$Q^b_{Load(L,t)}$	Reactive power demand of load L at bus b in period t
$Q^b_{Supplier(S,t)}$	Reactive power flow in the branch connecting to upstream supplier S at bus b in period t
$Q_{SupplierLimit(S,t)}$	Maximum reactive power of upstream supplier S in period t
$Q_{TFR\_HV/MV(b,t)}$	Reactive power in HV/MV power transformer connected in bus b in period t
$Q_{TFR\_MV/LV(b,t)}$	Reactive power in MV/LV power transformer connected in bus b in period t
T	Total number of periods
$S^{\max}_{bk}$	Maximum apparent power flow established in line that connected buses b and k
$S^{\max}_{TFR\_HV/MV(b)}$	Maximum apparent power in HV/MV power transformer connected in bus b
$S^{\max}_{TFR\_MV/LV(b)}$	Maximum apparent power in MV/LV power transformer connected in bus b
$S^{\max}_{bk}$	Maximum apparent power flow established in line that connected buses b and k
$V_{b(t)}$	Voltage magnitude at bus b in period t
$V^{\max}_b$	Maximum voltage magnitude at bus b
$V^{\min}_b$	Minimum voltage magnitude at bus b
$V_{k(t)}$	Voltage magnitude at bus k in period t
$X_{(V,t)}$	Binary variable of vehicle V related to power discharge in period t
$X_{DG(DG,t)}$	Binary decision variable of unit DG in period t
$Y_{(V,t)}$	Binary variable of vehicle V related to power charge in period t
y_{bk}	Admittance of line that connect buses b and k
y_{Shunt_b}	Shunt admittance of line connected to bus b
$Z_{(V)}$	Trip shifting decision binary variable

I. INTRODUCTION

The electrification of the transportation sector brings more challenges and offers new opportunities to the network planning and operation [1], [2]. The technology of using the energy stored in the gridable Electric Vehicles (EVs) batteries to supply power to the electric grid is commonly referred to as

Vehicle-to-Grid (V2G). Continuous improvements of EVs envisage their massive use, meaning that large quantities of EVs must be considered by future power systems, regarding the required supply to ensure their users' daily travels [3]. In future scenarios of intensive EVs penetration, the typical load diagram can be significantly changed from the present one without EVs [3], [4]. On the other hand, smart grids can use V2Gs intelligently as distributed energy resources when the vehicles are parked. All of these adds further complexity to planning and operation of smart grids operation requiring new methods and more computational resources [3]–[6].

In such a complex context, computational intelligence methods are important to obtain solutions for large dimension problems in an acceptable period of time [6]. Authors in [7] present a unit commitment model with V2G using the Particle Swarm Optimization (PSO) to reduce costs and emissions in smart grids. PSO is an effective method to determine the solution of large-scale nonlinear optimization problems [8].

Demand Response (DR) has already proven to be a valuable tool to ensure reliability of the bulk electric system and it is evolving and playing a great role in the electric industry [9]–[11]. For instance, during the summer heat wave of 2006, the Midwest ISO avoided firm load shed using interruptible load, demand-side management, and public appeals [11]. EVs have the possibility of providing a significant amount of DR through a variety of approaches while using their storage potential to enable a higher penetration of intermittent and variable generation such as wind and solar energy resources [11]. Several applications have been proposed in the literature [2], [12]–[15]. In [2] the authors describe how demand response using electric vehicle charging can be effectively used to provide significant gains without any further technological improvements, achieving financial savings in Ireland by optimizing the charging cycles of an EV. Authors in [12] proposes an optimal load management strategy for a residential consumer that uses the communication infrastructure of future smart grids. The results using two cases of a residential consumer in Zaragoza, Spain, show that the proposed model allowed users to reduce their electricity bill. The authors in [13] propose a distributed demand response algorithm for EVs charging needs using the concept of congesting principle in the internet traffic control. In [14] a heuristic method is implemented to minimize the EV charging cost in response to time-of-use price in a regulated market demonstrating that peak demand can be reduced. Authors in [15] focuses on the impacts of charging EVs on residential networks including the transformer. To alleviate the new load peaks a DR strategy is proposed consisting in load shaping taking into account consumers' preferences, load priorities and privacy. The present paper proposes a different kind of DR programs for EVs based on the reduction of the EVs trip distance and/or on trip time shifting, changing the initial travel requirements. The distribution network operator will remunerate the participation of EVs in the DR event, giving in this way an incentive to reach both economic and technical objectives related to the network operation.

The proposed application uses a modified Particle Swarm Optimization (PSO) approach which considers dynamic changing of velocity limits [16]. This enables its use to address real world large-scale problems in a shorter execution time than the deterministic methods, providing the system operators with adequate decision support and achieving efficient resource scheduling, even when a significant number of alternative scenarios should be considered [3], [16].

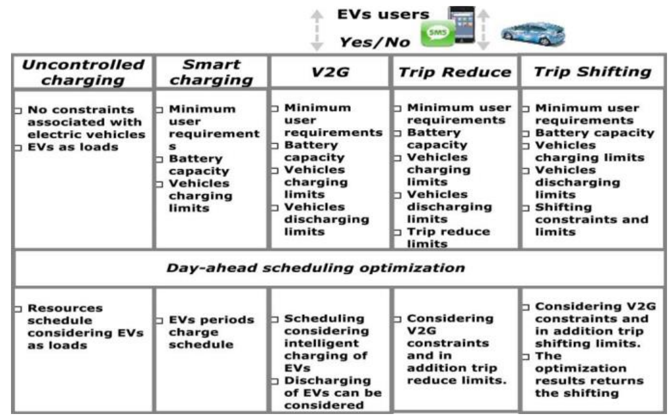

Fig. 1. EVs management and DR models considered.

In the present paper, it is assumed that efficient and adequate infrastructure and communications are able to guarantee the efficient tracking of each EV by the utilities/aggregators. Recent approaches to support the design of an efficient communication infrastructure can be supported by the existent cellular communication networks, by the emerging vehicular ad hoc networks (VANETs) with vehicle-to-infrastructure (V2I) communication capabilities and by the existent wireless networks for smart meters (used as auxiliary communication infrastructures) [17], [18].

The paper is organized as follows: after the initial introductory section, Section II explains the importance of V2G contracts and DR opportunities for EVs for energy resource management, in the scope of distribution systems, using the smart grid paradigm. Section III presents the problem formulation, including the resources and network constraints. Section IV presents the case studies using a 33-bus distribution network and considering 2000 vehicles. Section V presents the most important conclusions of the work.

II. Demand Response for EVs in Smart Grids

This section explains the concepts used in the paper regarding EVs management and DR models in the context of smart grids. Two DR programs are described in detail in this section: the trip reduce and trip shifting. The use of the proposed DR models can be activated every time the price of the energy reaches a predefined value. Other potential use of these programs can be fruitful regarding the network management or ancillary services [9], [19]. Fig. 1 presents the EVs management strategies considered in this paper and the DR proposed approaches. A brief description for each strategy is depicted in Fig. 1 presenting the main differences.

A. *Trip Reduce Demand Response Program*

The idea is to provide the network operator with another useful resource which consists in reducing vehicles charging necessities. This DR program enables EVs' users to get some profit by agreeing to reduce their travel necessities and minimum battery level requirements.

In phase 1 an initial optimization is made assuming that EVs which contracted DR option will participate. With the optimization results it is possible to identify which EVs' users are scheduled to participate in the event. After that, these EV's users can be invited to participate, e.g., through an internet application, SMS message, etc. The network operator should wait for a response within a time limit. With the responses of EVs's users, the optimization program reschedules the day-ahead problem with the updated information. Additionally, if EV's users are scheduled to participate in the DR program, according to the new optimization results, the operator should follow the same procedure. The users that do not respond within the time limit are excluded from the present DR event.

B. Trip Shifting Demand Response Program

In what concerns the trip shifting program it aims to provide another useful resource for the network operator. This DR program enables EVs' users to provide a list of optional travelling periods for their expected trips. The program enables the network operator to shift EVs load by remunerating their users, reducing operational costs and alleviating network contingencies. The shifting is limited to the alternatives that users impose, restraining the computational execution time of the optimization process at the same time. Phase 1 consists in considering users' alternative trips in the optimization model. After this step, the network operator can inform EVs' users about shifting results from the optimization phase 1 to know if they are able to participate in the next day. The acknowledgment of users' participation (phase 2) in the program is important for the network operator in order to obtain the appropriate resources scheduling and reduce the costs.

III. ENERGY RESOURCE SCHEDULING FORMULATION

This section presents the mathematical formulation of the proposed methodology including the EVs DR programs. The implemented PSO approach is also presented in this section.

A. Problem Formulation

This methodology is used to support the network operator to obtain an adequate energy resource management for the next day, including Electric Vehicles (EVs) resource, in the smart grid context. In terms of problem description, the network operator has contracts for managing the resources installed in the grid, including load demand. The load demand can be satisfied by the distributed generation resources, the discharge of EVs, and external suppliers (namely retailers, the electricity pool). The use of Vehicle-to-Grid (V2G) discharge, and the respective charge, considers V2G user profiles and requirements. The energy resource scheduling problem is a Mixed Integer Non-Linear Programming (MINLP) problem. The objective function considers all the costs with the energy resources. The energy resource model includes: distributed generation, energy acquisition to external suppliers, the V2G discharge or charge energy, the non-supplied demand, the excess available power [3], [5], trip reduce demand response and trip shifting demand response model for EVs. The present problem differs from previous works [3], [5] as it includes network constraints, important in real world operation, and the DR events.

In order to achieve a good scheduling of the available energy resources, it is necessary to apply a multi-period optimization; the presented formulation is generic for a specified time period (from period $t = 1$ to $t = T$) [3], [19].

$$Minimize\ f = \sum_{t=1}^{T} \left[\left(\begin{array}{l} \sum_{DG=1}^{N_{DG}} P_{DG(DG,t)} \times c_{DG(DG,t)} + \\ P_{GCP(DG,t)} \times c_{GCP(DG,t)} + \\ \sum_{S=1}^{N_S} P_{Supplier(S,t)} \times c_{Supplier(S,t)} + \\ \sum_{V=1}^{N_V} P_{Discharge(V,t)} \times c_{Discharge(V,t)} - \\ P_{Charge(V,t)} \times c_{Charge(V,t)} \\ + \sum_{L=1}^{N_L} P_{NSD(L,t)} \times c_{NSD(L,t)} + \end{array} \right) \times \Delta t \\ + \sum_{V=1}^{N_V} E_{Trip\,Red(V,t)} \times c_{TripRed(V,t)} + \\ \sum_{V=1}^{N_V} Z_{(V)} \times c_{Shift(V)} \right]. \quad (1)$$

The objective function considers Δt to allow different period t duration. For instance, for 30 minutes period t duration, the value of Δt should be 0.5 if the cost function is specified in an hour basis. In order to improve the solution feasibility, the mathematical model includes variables concerning the generation curtailment power $P_{GCP(DG,t)}$ and non-supplied demand $P_{NSD(L,t)}$. $P_{GCP(DG,t)}$ is important because the network operator can establish contracts with uninterruptible generation ("take or pay" contracts) with, for instance, producers based on renewable energy sources. In extreme cases, when the load is lower than the uninterruptible generation, the value of $P_{GCP(DG,t)}$ is different from zero. $P_{NSD(L,t)}$ is positive when the available resources are not enough to satisfy the load demand. The minimization of objective function (1) is subject to the following constraints:

- The network active (2) and reactive (3) power balance with power loss in each period t

$$\sum_{DG=1}^{N_{DG}^b} \left(P_{DG(DG,t)}^b - P_{GCP(DG,t)}^b \right) + \sum_{S=1}^{N_S^b} P_{Supplier(S,t)}^b + \\ \sum_{L=1}^{N_L^b} (P_{NSD(L,t)}^b - P_{Load(L,t)}^b) + \\ \sum_{V=1}^{N_V^b} (P_{Discharge(V,t)}^b - P_{Charge(V,t)}^b) = \\ \sum_{k=1}^{N_B} V_{b(t)} \times V_{k(t)} \left(G_{bk} \cos\left(\theta_{b(t)} - \theta_{k(t)}\right) \right. \\ \left. + B_{bk} \sin\left(\theta_{b(t)} - \theta_{k(t)}\right) \right) \\ \forall t \in \{1, \ldots, T\}\, ; k \neq b;$$

$$N_V^b = N_V^{b\_noShift} + N_V^{b\_Shift} \times Z_{(V,t)} \quad (2)$$

$$\sum_{DG=1}^{N_{DG}^b} Q_{DG(DG,t)}^b + \sum_{S=1}^{N_S^b} Q_{Supplier(S,t)}^b - \sum_{L=1}^{N_L^b} Q_{Load(L,t)}^b = \sum_{k=1}^{N_B} V_{b(t)} \times V_{k(t)} \left(G_{bk} \sin\left(\theta_{b(t)} - \theta_{k(t)}\right) - B_{bk} \cos\left(\theta_{b(t)} - \theta_{k(t)}\right)\right)$$
$$\forall t \in \{1, \ldots, T\}; k \neq b. \quad (3)$$

- Bus voltage magnitude and angle limits:

$$V_b^{\min} \leq V_{b(t)} \leq V_b^{\max} \quad \forall\, t \in \{1, \ldots, T\} \quad (4)$$
$$\theta_b^{\min} \leq \theta_{b(t)} \leq \theta_b^{\max} \quad \forall\, t \in \{1, \ldots, T\}. \quad (5)$$

- Line thermal limits:

$$\left| V_{b(t)} \times \left(\left[\left(V_{b(t)} - V_{k(t)}\right) y_{bk} \right]^* + \left[V_{b(t)} \times \frac{1}{2} y_{Shunt\_b} \right]^* \right) \right| \leq S_{bk}^{\max};\ \forall t \in \{1, .., T\}. \quad (6)$$

- HV/MV power transformers limits considering the power flow direction from HV to MV:

$$\sqrt{\left(\sum_{S=1}^{N_S^b} P_{Supplier(S,t)}^b\right)^2 + \left(\sum_{S=1}^{N_S^b} Q_{Supplier(S,t)}^b\right)^2} \leq S_{TFR\_HV/MV(b)}^{\max};\ \forall t \in \{1, .., T\};. \quad (7)$$

- MV/LV power transformers limits:

$$P_{TFR\_MV/LV(b,t)} = \sum_{DG=1}^{N_{DG}^b} \left(P_{DG(DG,t)}^b - P_{GCP(DG,t)}^b\right) + \sum_{L=1}^{N_L^b} (P_{NSD(L,t)}^b - P_{Load(L,t)}^b) + \sum_{V=1}^{N_V^b} (P_{Discharge(V,t)}^b - P_{Charge(V,t)}^b) \quad (8)$$

$$Q_{TFR\_MV/LV(b,t)} = \sum_{DG=1}^{N_{DG}^b} \left(Q_{DG(DG,t)}^b\right) - \sum_{L=1}^{N_L^b} \left(Q_{Load(L,t)}^b\right) \quad (9)$$

$$\sqrt{\left(P_{TFR\_MV/LV(b,t)}^2 + Q_{TFR\_MV/LV(b,t)}^2\right)} \leq S_{TFR\_HV/MV(b)}^{\max}$$
$$\forall t \in \{1, .., T\};. \quad (10)$$

- Maximum and minimum DG limit in each period t

$$P_{DG(DG,t)} \leq X_{DG(DG,t)} \times P_{DGMaxLimit(DG,t)}$$
$$P_{DG(DG,t)} \geq X_{DG(DG,t)} \times P_{DGMinLimit(DG,t)}$$
$$\forall\, t \in \{1, \ldots, T\}; \forall\, DG \in \{1, \ldots, N_{DG}\} \quad (11)$$

$$Q_{DG(DG,t)} \leq X_{DG(DG,t)} \times Q_{DGMaxLimit(DG,t)}$$
$$Q_{DG(DG,t)} \geq X_{DG(DG,t)} \times Q_{DGMinLimit(DG,t)}$$
$$\forall\, t \in \{1, \ldots, T\}; \forall\, DG \in \{1, \ldots, N_{DG}\}. \quad (12)$$

- Upstream supplier maximum limit in each period t

$$P_{Supplier(S,t)} \leq P_{SupplierLimit(S,t)}$$
$$\forall\, t \in \{1, \ldots, T\}; \forall\, S \in \{1, \ldots, N_S\} \quad (13)$$
$$Q_{Supplier(S,t)} \leq Q_{SupplierLimit(S,t)}$$
$$\forall\, t \in \{1, \ldots, T\}; \forall\, S \in \{1, \ldots, N_S\}. \quad (14)$$

- Vehicle technical limits in each period t
  - The vehicle charge and discharge are not simultaneous:

$$X_{(V,t)} + Y_{(V,t)} \leq 1$$
$$\forall t \in \{1, \ldots, T\};\ \forall V \in \{1, \ldots, N_V\};$$
$$X_{(V,t)}\, and\ Y_{(V,t)} \in \{0, 1\}. \quad (15)$$

- Battery balance for each EV. The energy consumption for period t travel has to be considered jointly with the energy from the previous period:

$$E_{Stored(V,t)} = E_{Stored(V,t-1)} + \eta_{c(V)} \times P_{Charge(V,t)} \times \Delta t$$
$$E_{Trip(V,t)} - \frac{1}{\eta_{d(v)}} \times P_{Discharge(V,t)} \times \Delta t$$
$$\forall t \in \{1, \ldots, T\};\quad \forall V \in \{1, \ldots, N_V\};$$
$$E_{Trip(V,t)} = P_{Trip(V,t)} \times \Delta t;. \quad (16)$$

- Discharge limit for each EV considering battery discharge rate:

$$P_{Discharge(V,t)} \leq P_{DischargeLimit(V,t)} \times X_{(V,t)}$$
$$\forall t \in \{1, \ldots, T\}; \forall V \in \{1, \ldots, N_V\}\ X_{(V,t)} \in \{0, 1\}. \quad (17)$$

- Charge limit for each EV considering battery charge rate:

$$P_{Charge(V,t)} \leq P_{ChargeLimit(V,t)} \times Y_{(V,t)}$$
$$\forall t \in \{1, \ldots, T\}; \forall V \in \{1, \ldots, N_V\};\ Y_{(V,t)} \in \{0, 1\}. \quad (18)$$

- EV battery discharge limit considering battery balance:

$$\frac{1}{\eta_{d(V)}} \times P_{Discharge(V,t)} \times \Delta t \leq E_{Stored(V,t-1)}$$
$$\forall t \in \{1, \ldots, T\}; \forall V \in \{1, \ldots, N_V\}; \Delta t = 1;. \quad (19)$$

- EV battery charge limit considering the battery capacity and previous charge status:

$$\eta_{c(V)} \times P_{Charge(V,t)} \times \Delta t \leq E_{BatCap(V)} - E_{Stored(V,t-1)}$$
$$\forall t \in \{1, \ldots, T\}; \forall V \in \{1, \ldots, N_V\}. \quad (20)$$

- Battery capacity limit for each EV:

$$E_{Stored(V,t)} \leq E_{BatCap(V)} \; \forall t \in \{1,\ldots,T\}; \forall V \in \{1,\ldots,N_V\}. \quad (21)$$

- Minimum stored energy to be guaranteed at the end of period t This can be seen as a reserve energy (fixed by the EVs users) that can be used for a regular travel or a unexpected travel in each period:

$$E_{Stored(V,t)} \geq E_{MinCharge(V,t)} - E_{TripRed(V,t)} \quad (22)$$

$$E_{MinCharge(V,tLast)} \geq E_{Trip(V,t)} \forall t \in \{1,\ldots,T\}; \forall V \in \{1,\ldots,N_V\} \quad (23)$$

$$E_{TripRed(V,t)} \leq E_{TripRedMax\,(V,t)} \forall t \in \{1,\ldots,T\}; \forall V \in \{1,\ldots,N_V\}. \quad (24)$$

B. *Particle Swarm Approach*

The PSO concept began as a simulation of simple social systems like the flocks of birds or the schools of fish [20]. The main advantage of PSO is its simplicity, while being capable of delivering accurate results consistently. It is fast and also very flexible, being applicable to a wide range of problems with limited computational requirements [8]. The original PSO relies on fixed velocity limits that are not changed during the swarm search process (PSO iterations) [20], [21]. Research work conducted by Fan and Shi [20], [22] has shown that an appropriate dynamic change of maximum velocities can improve the performance of the PSO algorithm.

In the present implementation to the problem of day-ahead scheduling, the maximum and minimum values of velocity limits can change dynamically throughout the search process. The initial velocities are set for each variable according to its type, e.g., the maximum velocities for generators reactive variables are set to 0.02, while the minimum velocities are set to -0.01. The maximum and minimum velocities for generators active power are calculated by a rank algorithm which takes into account the generators energy price.

In the evaluation phase, the implemented mechanism will check for constraint violations, namely bus lower and overvoltage violations (4)–(5), line thermal limits (6) and power transformers (7)–(10). If there is any violation of the above constraints, the algorithm will mark the variables that can possibly help alleviating these violations. In case of bus lower voltage violations, the mechanism will mark DG reactive power and V2G resources variables to increase reactive power and discharges, respectively. In case of bus overvoltage violations, the mechanism will mark DG reactive power variables to decrease and EVs to charge. The buses selected to get the appropriate V2G and DG resources are the buses in which violations occurred as well as the buses that were preceding it.

Line thermal limit and power transformers violations can be corrected in two ways: by reducing V2G charge or increasing generation in the downstream lines. The mechanism marks the V2G charge to be reduced and the DG generation to be increased. More information about voltage drop in radial distribution networks can be found in [23].

The velocity limits of the marked variables are changed according to the type of signaling. For instance, when DG reactive power variables are marked, the maximum velocities of these variables are increased by 20%. When the DG reactive power variables are marked to decrease, the minimum velocities of these variables are decreased by 20%.

The described mechanism contributes for a faster convergence to a solution without violations, as well as to improve the solution fitness. To improve the fitness function the mechanism works as follows:

- It tries to increase V2G charge variables values when V2G charge price is lower than mean generation cost increasing maximum velocity limits;
- It tries to increase V2G discharge variables values when V2G discharge price is lower than mean generation cost acting on minimum velocity limits;
- It tries to apply DR V2G trip reduce program (when available) by increasing the corresponding variables when DR program price is lower than the mean generation total cost and the respective vehicle charge price.

Regarding the problem formulation presented in Section A, namely the objective function, one can see why the above aspects improve the solution. The variables of DR trip shifting program are not controlled by the described mechanism.

The initial swarm population is randomly generated between the upper and lower bounds of variables, except from V2G variables that are initialized with zeros. During the swarm search, the algorithm checks whether to charge or discharge vehicles, and to apply DR trip reduce programs in case it is necessary or advantageous. DR shifting variables are randomly initialized by the swarm.

A robust radial power flow model from [24] is included in the modified PSO approach to check the solutions' feasibility during the swarm search process. The load flow is run before the fitness evaluation for each swarm solution. The load system balance (2)–(3) is validated by a power flow algorithm, and the power losses are compensated by the energy suppliers or DG generators. Vehicle battery balance constraints (19) are checked before fitness evaluation. The fitness function corresponds to the objective function (1) of the mathematical model. If the values of swarm solutions are not according to the constraint limits, the solution is corrected by the direct repair method. The direct repair method can be used instead of indirect repair, such as penalty factors which are efficient in correcting solutions before evaluating the fitness function [25].

IV. CASE STUDY

This section presents the case study used in this paper to illustrate the proposed models. For that, an exact method (MINLP) obtained using the software GAMS, is compared with the PSO in terms of execution time and solution quality.

This case study considers a 33-bus distribution network as can be found in [3]. An innovative tool [26], developed by the

TABLE I
SOURCES CHARACTERIZATION

Resource	Min. price (m.u./kWh)	Max. price (m.u./kWh)	Min. capacity (kW)	Max. capacity (kW)	Units #
PV	0.110	0.254	0	1,320	32
Wind	0.060	0.136	255	505	5
CHP	0.057	0.105	725	725	15
Biomass	0.136	0.186	350	350	3
MSW	0.076	0.102	210	210	2
Hydro	0.059	0.095	80	80	2
Fuel cell	0.115	0.180	240	240	7
Suppliers	0.075	0.188	3,350	3,350	10
EV discharge	0.025	0.025	8,625*	9,877	2,000
Total			13,735	16,657	2,076

*Estimated based on the cars connected to the grid.

TABLE II
PARAMETERS OF PSO METHODS

Parameters	Description
Number of particles	10
Inertia Weight	Gaussian mutation weights
Acceleration Coefficient Best Position	
Cooperation Coefficient	
Initial swarm population	Randomly generated between the upper and lower bounds, except from V2G variables.
Stopping Criteria	50 iterations
Max. Positions	Equal to the upper bound of variables
Min. Positions	Equal to the lower bound of variables

authors, was used to generate the EVs scenario and to model the behavioral pattern of the drivers.

Table I presents the prices for each resource, minimum and maximum available capacity, and the number of units for each type of technology. The values for the ten considered suppliers, connected to the network in the substation, are also presented. Only the linear component of the sources cost functions is considered in this case study. The cost of EV discharge is low, as it is considered a profit for EVs' users (objective function (1)–Section III). The EV charge and loads cost are considered 0 (m.u./kWh) because the main goal of the VPP is to minimize the operation cost, the load supply and the EV charge are mandatory services of VPP.

The paper presents the results of five scenarios using 2000 EVs. This number is adequate for the dimension of the given MV distribution network under study considering a high penetration of EVs in year 2040. Uncontrolled charging is not presented in the case study because the optimal solution with 2000 EVs is not found (unfeasible due to network constraints). The DR scenarios consider phase 1 of the described approach in Section II.

Regarding the parameterization of the PSO approach, the number of iterations is set to 50 for each scenario. The parameters definition of PSO can be seen in Table II. Gaussian mutation weights are used for mutation of the strategic parameters of PSO particles movement equation [27].

Figs. 2 and 3 show the load and the EVs charge for the scenario using both trip reduce and shifting DR programs. Fig. 2

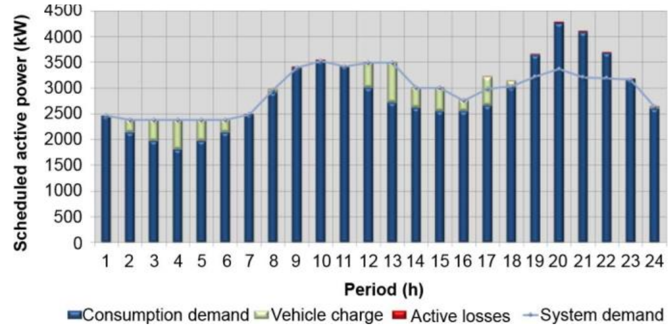

Fig. 2. Load and EVs charge profile of MINLP methodology.

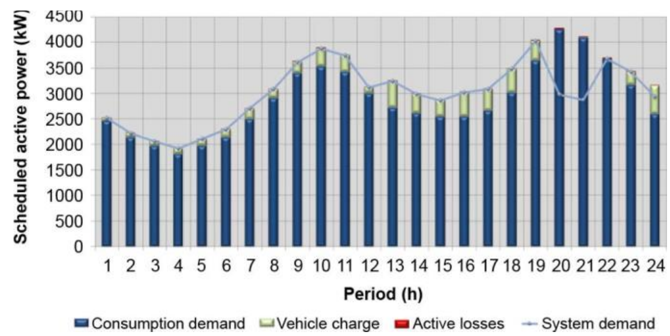

Fig. 3. Load and EVs charge profile of PSO methodology.

presents the results for the MINLP approach and Fig. 3 depicts the results for the PSO approach. The system demand considers the EVs discharges as can be seen in peak periods.

The results are similar; however, MINLP schedules more vehicles to charge in the night hours, minimizing the impact during the day. The vehicle charge that occurred in periods 23 and 24 in PSO's solution are due to the fact that batteries must have at least 30% at the end of the day. In MINLP these charges occurred in other periods and the minimum level was guaranteed. In both solutions, none of the approaches increased the peak load as verified in period 20 without EVs.

Table III presents the summary of the results for MINLP and the PSO approach for the five scenarios. In this case study PSO is approximately 2,700 times faster than the MINLP methodology, and the objective function is close to its cost in the five scenarios. The solutions for the scenarios presented in the paper for the PSO approach are selected from 1,000 trials, trying to present the average cases, thus not representing the best or the worst case of those trials yet aiming to show an average case. The solution cost of the PSO approach is higher than the exact method compared because meta-heuristics, such as PSO, give an approximate solution that converges in a local optimum [20]. The MINLP execution time is high and uses more than 24 hours to solve the optimization problem. This execution time is expected to rise exponentially with the increase of the number of resources and the complexity of the opportunities used in EVs, such as DR programs. Neither PSO nor MINLP can guarantee a global optimum. The modifications in PSO aim to improve the quality of the solution by satisfying problem's constraints

TABLE III
RESULTS OF THE MINLP AND PSO APPROACHES

	Operation cost (m.u.)		Problem variables	Execution time (s)	
	MINLP	PSO		MINLP	PSO*
Smart Charging	8,350.23	8,408.68	53,472	85,475	30.99
V2G	8,177.47	8,219.66	197,472	89,748	31.98
Trip Shifting	8,165.03	8,190.59	199,472	88,657	32.10
Trip Reduce	7,627.97	7,887.03	245,472	95,657	33.19
Trip Reduce + Shifting	7,584.63	7,750.77	293,472	97,416	34.20

*average values obtained with 1000 trials

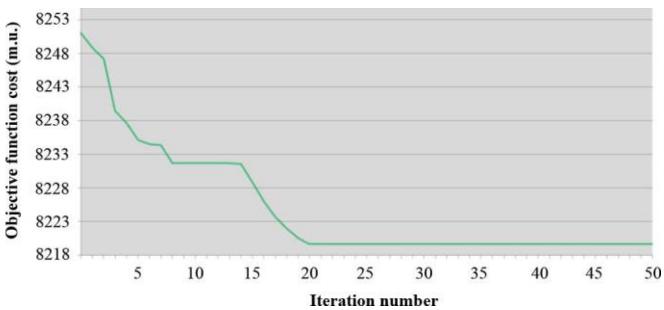

Fig. 4. Objective function cost evolution by iteration using the PSO approach.

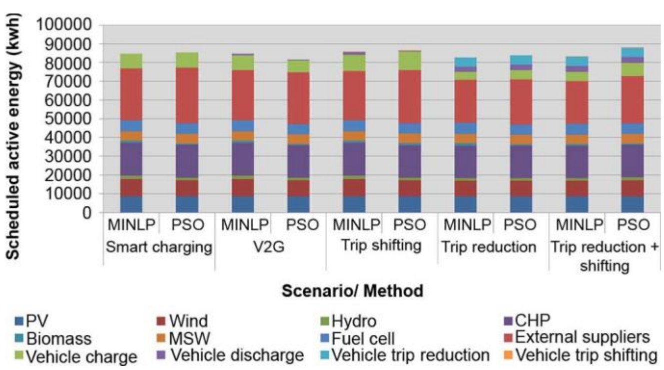

Fig. 5. Energy resource scheduling for the five scenarios.

and by obtaining lower costs. The lower cost, while satisfying problem's constraints, means a higher quality of the solution.

Fig. 4 shows the objective function evolution of the 1,000 trials average for the V2G scenario using the PSO approach, therefore presenting its convergence characteristics.

The robustness test using 1,000 trials presented a maximum objective function cost of 8,340 m.u., a minimum cost of 8,180 m.u. and an average cost of 8,252 m.u. The variability of the PSO approach is low with a standard deviation of 21 m.u.

Fig. 5 shows the energy resource scheduling for the five scenarios in the case study. In this figure are presented the results for the MINLP and PSO approaches. Also, the active power scheduling per type of resource, scenario and method can be compared with each other.

Fig. 6 shows the charge and discharge profile obtained for the five scenarios. The PSO approach uses more charging than the MINLP approach except for V2G scenario.

Even though there is a mechanism to optimize EVs charging (see Section III, subsection B), this happens due to PSO's

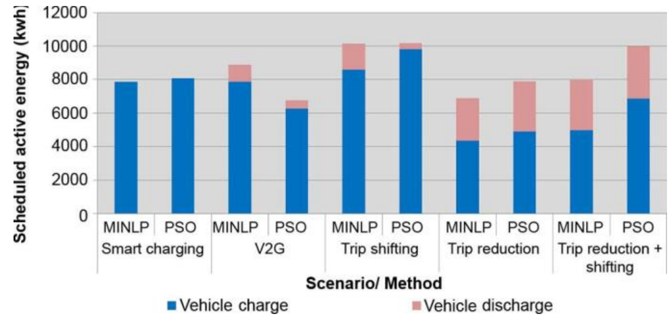

Fig. 6. Charge and discharge scheduling for the five scenarios.

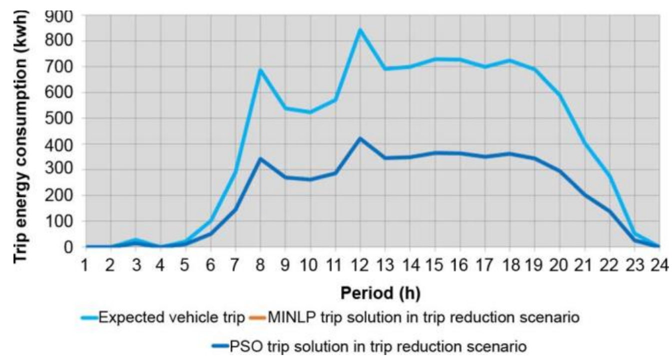

Fig. 7. Charge and discharge profile for the trip shift scenario.

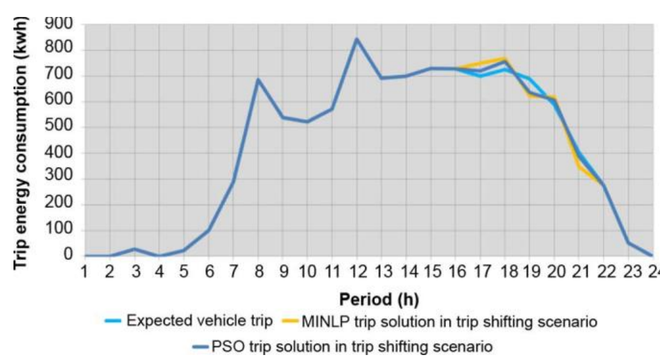

Fig. 8. Charge and discharge profile for the trip shift scenario.

stochasticity nature, whereas MINLP is more accurate, thus providing solutions with lower cost.

Fig. 7 depicts the trips energy consumption for DR trip reduce DR scenario. For the reduce program all the vehicles can participate reducing at most 50% of the needs of their travels. In this scenario almost all vehicles reduce their trips according to optimization results.

Fig. 8 concerns the trip shifting program results. This scenario considered at most 200 vehicles to participate between periods 17–20.

In the optimization solution, using this program, the resulting trip of 110 EVs are dislocated from the initial forecasted trip. The network operator's decision prevails in order to use the DR programs.

V. CONCLUSION

The large amount of energy resources, including EVs, leads to an increase in the complexity of operation and planning of distribution networks. In this field, computational intelligence methods have an important role in the smart grid. A meta-heuristic widely used in several power systems problems (PSO) is applied to solve the problem of energy resource scheduling with EVs and DR programs in the day-ahead context.

In this paper a new kind of DR program specifically for EVs users is proposed. Two different programs are implemented, namely, the trip distance reduce and trip shifting DR programs. These programs can be used in the smart grids context with significant penetration of EVs in which users might be able to join and participate in DR events. The optimization model includes the constraints associated with the proposed DR programs for EVs. These programs, as it is demonstrated with the case study, can provide effectiveness regarding the reduction of the operation costs from the network operator point of view.

To solve the large mixed-integer non-linear combinational problem a PSO approach is developed with integrated ac power flow. In each case study scenario a reference technique MINLP, developed in GAMS, is used to be compared with PSO in terms of execution time and solution quality. The PSO approach is 2,700 times faster when compared with MINLP, presenting low variability of the results and providing satisfactory solutions for the day-ahead problem. The PSO took an average of 30 to 34 seconds depending on the scenario, while MINLP took between 85,475 and 97,416 seconds (24–27 hours). The objective function of the PSO when compared with MINLP ranged between 0 and 3% difference.

REFERENCES

[1] K. Clement-Nyns, E. Haesen, and J. Driesen, "The impact of charging plug-in hybrid electric vehicles on a residential distribution grid," *IEEE Trans. Power Syst.*, vol. 25, pp. 371–380, Feb. 2010.

[2] P. Finn, C. Fitzpatrick, and D. Connolly, "Demand side management of electric car charging: Benefits for consumer and grid," *Energy*, vol. 42, no. 1, pp. 358–363, Jun. 2012.

[3] T. Sousa, H. Morais, Z. Vale, P. Faria, and J. Soares, "Intelligent energy resource management considering vehicle-to-Grid: A simulated annealing approach," *IEEE Trans. Smart Grid, Special Issue on Transportation Electrification and Vehicle-to-Grid Applications*, vol. 3, no. 1, pp. 535–542, Mar. 2012.

[4] A. Y. Saber and G. K. Venayagamoorthy, "Resource scheduling under uncertainty in a smart grid with renewables and plug-in vehicles," *IEEE Syst. J.*, vol. 6, no. 1, pp. 103–109, Mar. 2012.

[5] J. Soares, T. Sousa, H. Morais, Z. Vale, and P. Faria, "An optimal scheduling problem in distribution networks considering V2G," presented at the IEEE SSCI Symp. Computat. Intell. Applicat. in Smart Grid (CIASG), Paris, France, 2011.

[6] G. K. Venayagamoorthy, "Dynamic, stochastic, computational and scalable technologies for smart grids," *IEEE Computat. Intell. Mag.*, vol. 6, no. 3, pp. 22–35, Aug. 2011.

[7] A. Y. Saber and G. K. Venayagamoorthy, "Plug-in vehicles and renewable energy sources for cost and emission reductions," *IEEE Trans. Ind. Electron.*, vol. 58, no. 4, pp. 1229–1238, Apr. 2011.

[8] Y. del Valle, G. K. Venayagamoorthy, S. Mohagheghi, J. C. Hernandez, and R. G. Harley, "Particle swarm optimization: Basic concepts, variants and applications in power systems," *IEEE Trans. Evol. Comput.*, vol. 12, no. 2, pp. 171–195, Apr. 2008.

[9] J. Medina, N. Muller, and I. Roytelman, "Demand response and distribution grid operations: Opportunities and challenges," *IEEE Trans. Smart Grid*, vol. 1, no. 2, pp. 193–198, Sep. 2010.

[10] A. J. Conejo, J. M. Morales, and L. Baringo, "Real-time demand response model," *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 236–242, Dec. 2010.

[11] M. Mallette and G. Venkataramanan, "The role of plug-in hybrid electric vehicles in demand response and beyond," presented at the 2010 IEEE PES Transmission and Distribution Conf. and Exposition: Smart Solutions for a Changing World, New Orleans, LA, 2010.

[12] J. M. Lujano-Rojas, C. Monteiro, R. Dufo-Lopez, and J. L. Bernal-Agustin, "Optimum residential load management strategy for real time pricing (RTP) demand response programs," *Energy Policy*, vol. 45, pp. 671–679, Jun. 2012.

[13] Z. Fan, "A distributed demand response algorithm and its application to PHEV charging in smart grids," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1280–1290, Sep. 2012.

[14] C. Yijia, T. Shengwei, L. Canbing, Z. Peng, T. Yi, Z. Zhikun, and L. Junxiong, "An optimized EV charging model considering TOU price and SOC curve," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 388–393, Mar. 2012.

[15] S. Shengnan, 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.

[16] J. Soares, "Modified Particle Swarm Optimization for Day-Ahead Distributed Energy Resources Scheduling Including Vehicle-to-Grid," M.Sc. thesis, Sch. Eng., Polytechnic Inst. Porto, Porto, Portugal, 2011.

[17] X. S. Shen, "Empowering the smart grid with wireless technologies," *IEEE Network*, vol. 26, no. 3, pp. 2–3, 2012.

[18] H. Su, M. Qiu, and H. Wang, "Secure wireless communication system for smart grid with rechargeable electric vehicles," *IEEE Commun. Mag.*, vol. 50, no. 8, pp. 62–68, Aug. 2012.

[19] H. Morais, P. Kadar, P. Faria, Z. A. Vale, and H. M. Khodr, "Optimal scheduling of a renewable micro-grid in an isolated load area using mixed-integer linear programming," *Renewable Energy*, vol. 35, no. 1, pp. 151–156, Jan. 2010.

[20] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proc. 1995 IEEE Int. Conf. Neural Networks Proc.*, Perth, WA, 1995, vol. 1–6, pp. 1942–1948.

[21] K. Y. Lee and M. A. El-Sharkawi, *Modern Heuristic Optimization Techniques : Theory and Applications to Power Systems*. Piscataway, NJ: IEEE Press, 2008.

[22] H. Fan and Y. Shi, "Study on vmax of particle swarm optimization," in *Proc. Workshop on Particle Swarm Optimization*, Purdue Sch. Eng. Technol., Indianapolis, IN, Apr. 2001.

[23] C. J. Dent, L. F. Ochoa, and G. P. Harrison, "Network distributed generation capacity analysis using OPF with voltage step constraints," *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 296–304, Feb. 2010.

[24] D. Thukaram, H. M. W. Banda, and J. Jerome, "A robust three phase power flow algorithm for radial distribution systems," *Electric Power Syst. Res.*, vol. 50, no. 3, pp. 227–236, Jun. 1999.

[25] Z. Michalewicz, "A survey of constraint handling techniques in evolutionary computation methods," in *Evolutionary Programming IV*. Cambridge, MA: MIT Press, 1995, pp. 135–155.

[26] J. Soares, B. Canizes, C. Lobo, Z. Vale, and H. Morais, "Electric vehicle scenario simulator tool for smart grid operators," *Energies*, vol. 5, pp. 1881–1899, Jun. 2012.

[27] R. A. Krohling, "Gaussian particle swarm with jumps," in *IEEE Congr. Evolutionary Computation*, 2005, vol. 1–3, pp. 1226–1231.