Day-ahead resource scheduling in smart grids considering Vehicle-to-Grid and network constraints

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ABSTRACT

Energy resource scheduling becomes increasingly important, as the use of distributed resources is inten- sified and massive gridable vehicle use is envisaged. The present paper proposes a methodology for day- ahead energy resource scheduling for smart grids considering the intensive use of distributed generation and of gridable vehicles, usually referred as Vehicle-to-Grid (V2G). This method considers that the energy resources are managed by a Virtual Power Player (VPP) which established contracts with V2G owners. It takes into account these contracts, the users' requirements subjected to the VPP, and several discharge price steps. Full AC power flow calculation included in the model allows taking into account network con- straints.

The influence of the successive day requirements on the day-ahead optimal solution is discussed and considered in the proposed model.

A case study with a 33 bus distribution network and V2G is used to illustrate the good performance of the proposed method.

Keywords: Day-ahead scheduling, Distributed generation, Energy resource management, Smart grid, Vehicle-to-Grid, Virtual power player

1. Introduction

Governments in Europe as well as in United States and Asia are promoting and implementing incentives to increase the electric mobility use. The transportation sector will change from fossil fuel propelled motor vehicles to Electric Vehicles (EVs) as the fossil fuel is being depleted and regulations on CO_2 emissions are getting stricter according to Euro 6 emissions standard [1,2]. EVs include Plug-in Hybrid Electric Vehicles (PHEVs) and Battery Electric Vehicles (BEVs).

The electrification of the transportation sector brings more challenges and offers new opportunities to power system planning and operation. The possibility of using the energy stored in the gridable EVs batteries to supply power to the electric grid is commonly referred to as Vehicle-to-Grid (V2G). Continued improvements of EVs envisage their massive use, therefore meaning that large quantities of EVs must be considered by future power systems, in terms of the required supply to ensure their users' daily travels [3,4]. In future scenarios of intensive EVs penetration, the typical electric load diagram can be significantly different from the present one without EVs. On the other hand, power systems can use V2G as distributed energy sources when the vehicles are parked. This adds further complexity to planning and operation of power systems requiring new methods and more computational resources. Therefore, new scheduling methods are required to ensure low operation costs while guaranteeing the supply of load demand.

The smart grid concept appears as a suitable solution to guarantee the power system operation considering the intensive use of Distributed Energy Resources (DERs) and electricity markets. Essentially, the smart grid can be understood as a structure that has the main purpose to integrate different players, technologies and resources that act in this new power system context. In the smart grid context, it is possible to have several players with different responsibilities: Producers, Consumers, Independent System Operator (ISO), Market Operator (MO), Transmission System Operator (TSO), Distribution Network Operator (DNO) and aggregators such as Virtual Power Players (VPPs).

VPPs aggregate several energy resources, mainly in the distribution level. The aggregation of DERs can be seen as an important strategy to improve the management of these resources. This new paradigm implies a multi-level decentralized decision and control hierarchy. In the scope of this hierarchy, VPPs may assume the responsibility of one decision and control level, managing their aggregated resources as well as the electrical network in their geographic area. This decision and control model requires a close coordination among the several involved levels, namely between VPPs and the DNO or the TSO, depending on the level in which each VPP operates.

Apart from EVs, power systems will have to deal with other types of DERs at the distribution network level, such as Distributed Generation (DG), Storage Systems (SSs), and Demand Response

(DR). All the mentioned resources have to be considered in the energy scheduling problem, considering consequently their characteristics and requirements [5]. DER management can be performed by Virtual Power Players (VPPs) or by the distribution network operator [6–9]. However, DER should be strategically managed by their owners, according to their own goals, and not by distribution network operators which represent the network's interests. The intensive use of DERs in future smart grids, operating in a competitive and distributed decision environment, will require an agent capable of representing DER owners in the electricity markets [10,11]. VPPs can aggregate a set of DERs, in order to take the best possible advantage of the aggregated resources by strategically bidding in the market, either for buying or selling energy [12,13]. Therefore, the VPP needs adequate methodologies to efficiently support the DER scheduling so that the aggregated players can benefit from their aggregation [14].

This paper proposes a method to support VPP day-ahead resource scheduling in a smart grid context considering the intensive use of V2G and other distributed energy resources. The day-ahead optimal scheduling aims to obtain the best energy resource scheduling, meeting all the involved constraints, including the ones concerning EVs use. The main objective is to minimize the operation costs considering all the available resources for each operation period. Using the proposed method, VPPs are able to undertake a more effective management of their resources.

In order to take the best advantage of the hourly available resources, accurate EVs information is required. This information must be detailed, including the geographical area where vehicles are parked during each considered period, as well as the minimum battery energy required by their users for their daily trips. This information enables to determine EVs minimum battery charge required for each period in order to guarantee the aimed range [15].

The proposed methodology aims to help dealing with the intermittence of renewable based production and V2G driving patterns. It considers several discharge price steps, depending on the battery level of the V2G and aiming to establish a fair remuneration scheme, which prevents unnecessary battery deterioration. The technical viability is ensured by an AC power flow algorithm included in the mathematical formulation, which considers all the relevant network constraints (namely the limits concerning line thermal characteristics and bus voltage magnitudes and angles).

The problem is formulated as a Mixed-Integer Non-Linear Programming (MINLP), and it is implemented on Generic Algebraic Modeling System (GAMS) software [16].

The paper discusses the influence of successive day scenarios in the day-ahead scheduling. In fact, although the goal is to schedule the available energy resources for the next day, the scenarios that will become effective on the successive days will influence the optimal solution for the next day. Even though it is assumed that in principle the owners' are only committed to provide the manager with their requirements on a day-ahead basis, more information on the subsequent days may be available. For example, if a vehicle owner is able to provide the manager his requirements for the whole week, the manager will have this information at his disposal from the beginning of the week. The impact of considering data for the subsequent days is particularly important for the management of vehicle batteries and results in a significant objective function value reduction when the data for the subsequent day are considered. In fact, being the subsequent day requirements considered as an input of the scheduling problem allows better inter day battery management and prevents situations that can be impossible or very expensive to manage when only 1 day data is considered. This is modeled in the proposed methodology allowing obtaining more economic scheduling solutions.

The paper is organized as follows: after this introductory section, Section 2 presents the mathematical formulation of the envisaged problem. Section 3 presents the case study considering a scenario with 1000 V2G in the 33 bus distribution network with 66 DG plants and 32 loads. The main conclusions of this paper are provided in Section 4.

2. Energy resource scheduling

This section presents the proposed methodology to support Virtual Power Players (VPPs) efficient scheduling of the available resources, including Vehicle-to-Grid (V2G), in the smart grid context. As referred in Section 1, the VPP needs adequate tools to efficiently manage the available resources because, in the considered context, the resource scheduling is a large complex problem. Section 2.1 describes the concepts used to design the proposed method and presents its architecture. The mathematical formulation of the considered energy resource scheduling problem is presented in Section 2.2.

2.1. Proposed methodology conceptual design and implementation

The proposed method aims to obtain day-ahead scheduling for the available energy resources that are available in a smart grid managed by a VPP, considering an intensive use of V2G. The scheduling is undertaken on an hourly basis for the 24 periods of the next day. The goal of the resource scheduling is to satisfy load and V2G users' requirements, respecting all the involved constraints, at the minimum possible cost. V2G requirements are based on the contracts established between the VPP and their users. Some of these contracts consider that V2G users present day ahead detailed requests to the VPP. This requests concern the aimed trips for the next day, including details (e.g. trip range, V2G geographical location) according to contract clauses.

In order to satisfy the required load demand and requested V2G charges, the VPP can use the energy from several energy resources, namely Distributed Generation (DG) producers, external suppliers (including retailers, the electricity pool, and other VPPs) and can also discharge V2G batteries. It is considered that the VPP has contracts for managing the resources installed in the network, including generation and V2G charges and discharges. The costs of all the resources that are available in each period are determined according to the established contracts.

The energy resource scheduling model also includes the network simulation, through AC power flow calculation, which considers the relevant network constraints (line thermal limits and bus voltage magnitude and angle limits).

Although the goal is to schedule the available energy resources for the next day, the influence of successive day scenarios in the day-ahead scheduling should be considered. Experimental findings demonstrate that it is important to manage the available resources taking into account load and V2G requirements for the successive day. This effect is also described in [17] in which is stated that "unintended end effects in the optimization such as the tendency of the battery to deplete at the end of the time horizon can be partly avoided by a long time horizon".

This is especially important for scenarios involving intensive use of V2G, for which the successive day requirements can strongly influence the optimal solution for the next day. This is mainly justified by the fact that, according to the usual daily load, V2G, and price profiles, it is desirable that each day begins with a certain energy amount stored in EVs batteries. This amount and its geographical location, i.e. its distribution by the considered vehicles, depend on the V2G use that will occur in the successive day.

The diagram presented in Fig. 1 shows the scheduling target day, marked as light shadowed, and the days considered to take into account Successive Day Influence (SDI), dark shadowed. In

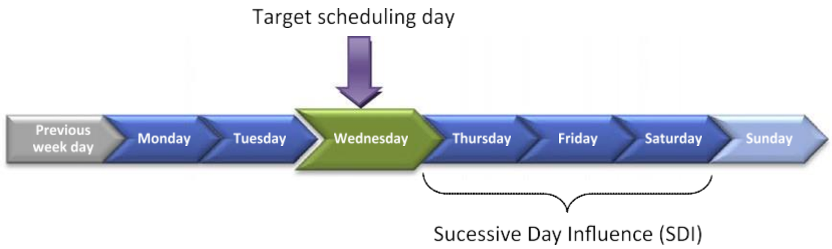

Fig. 1. Target scheduling day optimization schematic overview.

the example presented in this figure, three successive days are considered. In practice, one successive day is sufficient for most of the scenarios. Only scenarios exhibiting a successive significant increase in load and V2G trip requirements benefit from the consideration of more than two consecutive days.

This aspect has been incorporated in the proposed method. In fact, the day-ahead scheduling is actually performed for more than 24 h but only the scheduling for the first 24 h, corresponding to the next day, are effectively considered as the problem solution. The input data for the optimization problem for the next day considers the most detailed information and forecasts for the 24 h periods. In terms of EVs and V2G use, it considers the registered users' requirements concerning next day trips and the established V2G contracts. In what concerns the data for the successive day considered period, the input data concerning EVs use the most updated values.

Fig. 2 shows the schematic diagram of the proposed methodology. The core module is the Energy Resource Management in Smart grids (ERMaS) module which undertakes the problem optimization. The input data is represented in the left hand side and the considered costs and constraints are represented in the right hand side. The obtained results for the day-ahead scheduling are represented in the module located at the bottom of the figure.

The proposed methodology has been computationally implemented using MATLAB as the programming environment. GAMS is used to solve the MINLP scheduling problem. The next sub-section presents the used mathematical formulation.

2.2. Mathematical formulation

The energy resource scheduling problem is a Mixed-Integer Non-Linear Programming (MINLP) problem. The objective function adds all the involved costs, aiming to obtain the minimum operation cost for the VPP. The costs for the considered resources are modeled as linear functions. Considering that V2G are seen as distributed resources by the VPP, it is necessary to include a cost for the V2G charging and discharging. The VPP will have to pay for using the V2G discharge and when the V2G users need to charge their vehicles the VPP will receive a payment for supplying the required amount of energy. The discharging cost is considered positive in the operation cost for the VPP, and the charging cost is considered negative because it is seen as an income for the VPP.

In order to achieve a good scheduling of the available energy resources, it is necessary to undertake a multi-period optimization; the presented formulation is generic for a specified time period (from period $t=1$ to $t=T$). Please note that for day-ahead scheduling T is usually considered equal to 24. However, according to the proposed methodology and to the details presented in Section 2.1, the proposed method will, in fact, consider a value for T which is greater than 24, although only the scheduling for the first 24 periods is considered as the solution of the problem.

This mathematical formulation has been implemented in Generic Algebraic Modeling System (GAMS) software, with an AC power flow algorithm that allows considering network constraints [18]. GAMS DIscrete and Continuous OPTimizer (DICOPT) has been

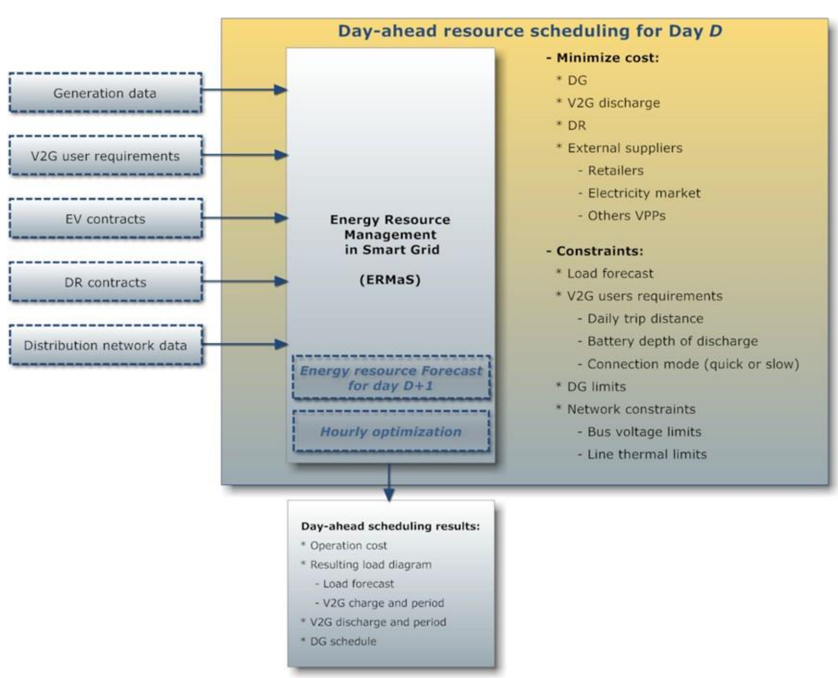

Fig. 2. Day-ahead resource scheduling for Day D.

used to solve the envisaged MINLP problem. DICOPT [19] allows obtaining the solution for the Non-Linear Programming (NLP) problems and the Mixed-Integer Programming (MIP) problems using the adequate solvers existing inside GAMS. Typically, the NLP problem is solved using the CONtinuous global OPTimizer (CONOPT) solver [20] and the MIP problem is solved using the simplex algorithm and IBM ILOG CPLEX Optimizer solver [21]. Although the proposed methodology cannot ensure that the optimal solution is obtained, it has been applied in realistic scenarios with good results [6,22]. The results obtained with the proposed method have consistently been better than the results obtained with alternative, metaheuristic based approaches [18,23].

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$$\min f=\sum_{t=1}^{T}\left[\begin{array}{l}\sum_{DG=1}^{N_{DG}} P_{DG(DG,t)}\times c_{DG(DG,t)}+\sum_{S=1}^{N_S} P_{Supplier(S,t)}\times c_{Supplier(S,t)}+\\ \sum_{V=1}^{N_V} P_{Discharge\_StepA(V,t)}\times c_{Discharge\_StepA(V,t)}+\sum_{V=1}^{N_V} P_{Discharge\_StepB(V,t)}\times c_{Discharge\_StepB(V,t)}+\\ \sum_{V=1}^{N_V} P_{Discharge\_StepC(V,t)}\times c_{Discharge\_StepC(V,t)}-\sum_{V=1}^{N_V} P_{Charge(V,t)}\times c_{Charge(V,t)}\\ \sum_{L=1}^{N_L} P_{NSE(L,t)}\times c_{NSE(L,t)}+\sum_{DG=1}^{N_{DG}} P_{EGE(L,t)}\times c_{EGE(L,t)}\end{array}\right] \quad (1)$$

where

$c_{DG(DG,t)}$	Generation cost of DG unit in period t
$c_{Charge(V,t)}$	Charge price of vehicle V in period t
$c_{Discharge\_StepA(V,t)}$	Discharge price of step A of vehicle V in period t
$c_{Discharge\_StepB(V,t)}$	Discharge price of step B of vehicle V in period t
$c_{Discharge:StepC(V,t)}$	Discharge price of step C of vehicle V in period t
$c_{EGE(DG,t)}$	Excess generated energy cost of DG unit in period t
$c_{NSE(L,t)}$	Non-supplied energy cost of load L in period t
$c_{Supplier(S,t)}$	Market energy price of upstream supplier S in period t
N_{DG}	Total number of distributed generators
N_L	Total number of loads
N_S	Total number of external suppliers
N_V	Total number of vehicles
$P_{Charge(V,t)}$	Power charge of vehicle V in period t
$P_{DG(DG,t)}$	Active power generation of distributed generation unit DG in period t
$P_{Discharge\_StepA(V,t)}$	Power discharge in step A of vehicle V in period t
$P_{Discharge\_StepB(V,t)}$	Power discharge in step B of vehicle V in period t
$P_{Discharge\_StepC(V,t)}$	Power discharge in step C of vehicle V in period t
$P_{EGE(DG,t)}$	Excess generated energy by DG unit in period t
$P_{NSE(L,t)}$	Non-supplied energy for load L in period t
$P_{Supplier(S,t)}$	Active power flow in the branch connecting to upstream supplier S in period t
T	Total number of periods

With the purpose of implementing a robustness MINLP formulation the authors included variables for the excess generated energy ($P_{EGE(DG,t)}$) and non-supplied energy ($P_{NSE(L,t)}$). $P_{EGE(DG,t)}$ is important because the VPP can establish contracts with uninterruptible generation, for instance with producers based on renewable energy. In extreme cases, when load is lower than uninterruptible generation the value of $P_{EGE(DG,t)}$ is different from zero. $P_{NSE(L,t)}$ is different from zero when the generation is not enough to satisfy load demand.

The minimization of this objective function is subjected to the following constraints:

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

P P^b ^{b} P^b P^b P^b P^b P^b

$$\begin{array}{l}\sum_{DG=1}^{N_{DG}^b}\left(P^b_{DG(DG,t)}-P^b_{EGE(DG,t)}\right)+\sum_{S=1}^{N_S^b}P^b_{Supplier(S,t)}+\sum_{V=1}^{N_V^b}P^b_{Discharge(V,t)}+\sum_{L=1}^{N_L^b}P^b_{NSE(L,t)}-\sum_{L=1}^{N_L^b}P^b_{Load(L,t)}-\sum_{V=1}^{N_V^b}P^b_{Charge(V,t)}=\\ \sum_{k=1}^{N_B}V_{b(t)}\times V_{k(t)}\left(G_{bk}\cos\left(\theta_{b(t)}-\theta_{k(t)}\right)+B_{bk}\sin\left(\theta_{b(t)}-\theta_{k(t)}\right)\right)\\ \forall t\in\{1,\ldots,T\};\quad k\neq b\end{array} \quad (2)$$

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

where

$\theta_{b(t)}$	Voltage angle at bus b in period t (rad)
$\theta_{k(t)}$	Voltage angle at bus k in period t (rad)
B_{bk}	Imaginary part of the element in Y_{BUS} corresponding to the b row and k column
G_{bk}	Real part of the element in Y_{BUS} corresponding to the b row and k column
N_b	Total number of buses b
N_{DG}^b	Total number of distributed generators at bus b
N_L^b	Total number of loads at bus b
N_S^b	Total number of external suppliers at bus b
N_V^b	Total number of vehicles at bus b
$P_{Charge(V,t)}^b$	Power charge of vehicle V at bus b in period t
$P_{DG(DG,t)}^b$	Active power generation of distributed generation unit DG at bus b in period t
$P_{Discharge(V,t)}^b$	Power discharge considering the steps A–C of vehicle V at bus b in period t
$P_{EGE(DG,t)}^b$	Excess generated energy by DG unit at bus b in period t
$P_{NSE(L,t)}^b$	Non-supplied energy for load L at bus b in period t
$P_{Supplier(S,t)}^b$	Active power flow in the branch connecting to upstream supplier S at bus b in period t
$P_{Load(L,t)}^b$	Active power demand of load L at bus b in period t
$Q_{DG(DG,t)}^b$	Reactive power generation of distributed generation unit DG at bus b in period t
$Q_{Load(L,t)}^b$	Reactive power demand of load L at bus b in period t
$Q_{Supplier(S,t)}^b$	Reactive power flow in the branch connecting to upstream supplier S at bus b in period t
$V_{b(t)}$	Voltage magnitude at bus b in period t (p.u.)
$V_{k(t)}$	Voltage magnitude at bus k in period t (p.u.)

- Bus voltage magnitude and angle limits;

$$V_b^{min} \leqslant V_{b(t)} \leqslant V_b^{max}; \quad \forall t \in \{1, \ldots, T\} \tag{4}$$

$$\theta_b^{min} \leqslant \theta_{b(t)} \leqslant \theta_b^{max}; \quad \forall t \in \{1, \ldots, T\} \tag{5}$$

where

θ_b^{max}	Maximum voltage angle at bus b (rad)
θ_b^{min}	Minimum voltage angle at bus b (rad)
V_b^{max}	Maximum voltage magnitude at bus b
V_b^{min}	Minimum voltage magnitude at bus b

- Line thermal limits;

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

where

S_{bk}^{max}	Maximum apparent power flow established in line that connected bus b and k
y_{bk}	Admittance of line that connect bus b and bus k
y_{Shunt_b}	Shunt admittance of line connected to bus b

- Maximum distributed generation limit in each period t;

$$P_{DGMinLimit(DG,t)} \leqslant P_{DG(DG,t)} \leqslant P_{DGMaxLimit(DG,t)}; \quad \forall t \in \{1, \ldots, T\}; \quad \forall DG \in \{1, \ldots, N_{DG}\} \tag{7}$$

$$Q_{DGMinLimit(DG,t)} \leqslant Q_{DG(DG,t)} \leqslant Q_{DGMaxLimit(DG,t)}; \quad \forall t \in \{1, \ldots, T\}; \quad \forall DG \in \{1, \ldots, N_{DG}\} \tag{8}$$

where

$P_{DGMaxLimit(DG,t)}$	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
$Q_{DGMaxLimit(DG,t)}$	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

- Upstream supplier maximum limit in each period t;

$$P_{Supplier(S,t)} \leqslant P_{SupplierLimit(S,t)}; \quad \forall t \in \{1, \ldots, T\}; \quad \forall S \in \{1, \ldots, N_S\} \tag{9}$$

$$Q_{Supplier(S,t)} \leqslant Q_{SupplierLimit(S,t)}; \quad \forall t \in \{1, \ldots, T\}; \quad \forall S \in \{1, \ldots, N_S\} \tag{10}$$

where

$P_{SupplierLimit(S,t)}$	Maximum active power of upstream supplier S in period t
$Q_{SupplierLimit(S,t)}$	Maximum reactive power of upstream supplier S in period t

- Technical limits of the vehicle in each period t;

– Battery balance for each vehicle. The energy consumption for period t travel has to be considered jointly with the energy remaining from the previous period and the charge/discharge in the period;

$$E_{Stored(V,t)} = E_{Stored(V,t-1)} + \eta_{c(V)} \times P_{Charge(V,t)} \times \Delta t - E_{Trip(V,t)} - \frac{1}{\eta_{d(V)}} \times P_{Discharge(V,t)} \times \Delta t; \forall t \in \{1, \ldots, T\}; \quad \forall V \in \{1, \ldots, N_V\}; \quad \Delta t = 1 \tag{11}$$

where

$E_{Stored(V,t)}$	Active energy stored in vehicle V at the end of period t
$E_{Trip(V,t)}$	Vehicle V energy consumption in period t
$\eta_{c(V)}$	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

– Discharge limit of step A, this step is activated until 70% of battery capacity;

$$0.7 \times E_{BatteryCapacity(V)} \leqslant P_{Discharge\_StepA(V,t)} \leqslant E_{Stored(V,t-1)}; \quad \forall t \in \{1, \ldots, T\}; \quad \forall V \in \{1, \ldots, N_V\} \tag{12}$$

– Discharge limit of step B, this step is activated until 40% of battery capacity;

$$0.4 \times E_{BatteryCapacity(V)} \leqslant P_{Discharge\_StepB(V,t)} \leqslant E_{Stored(V,t-1)}; \quad \forall t \in \{1,\ldots,T\}; \quad \forall V \in \{1,\ldots,N_V\} \tag{13}$$

– Discharge limit of step C, this step is activated until 20% of battery capacity;

$$0.2 \times E_{BatteryCapacity(V)} \leqslant P_{Discharge\_StepC(V,t)} \leqslant E_{Stored(V,t-1)}; \quad \forall t \in \{1,\ldots,T\}; \quad \forall V \in \{1,\ldots,N_V\} \tag{14}$$

where $E_{BatteryCapacity(V)}$ is the battery energy capacity of vehicle V

– Add the discharge powers of steps A–C for each vehicle;

$$P_{Discharge(V,t)} = P_{Discharge\_StepA(V,t)} + P_{Discharge\_StepB(V,t)} + P_{Discharge\_StepC(V,t)}; \quad \forall t \in \{1,\ldots,T\}; \quad \forall V \in \{1,\ldots,N_V\} \tag{15}$$

– Discharge limit for each vehicle considering the battery discharge rate;

$$P_{Discharge(V,t)} \leqslant P_{DischargeLimit(V,t)} \times X_{(V,t)}; \quad \forall t \in \{1,\ldots,T\}; \quad \forall V \in \{1,\ldots,N_V\}; \quad X_{(V,t)} \in \{0,1\} \tag{16}$$

where $P_{DischargeLimit(V,t)}$ is the maximum power discharge of vehicle V in period

– Charge limit for each vehicle considering the battery charge rate;

$$P_{Charge(V,t)} \leqslant P_{ChargeLimit(V,t)} \times Y_{(V,t)}; \quad \forall t \in \{1,\ldots,T\}; \quad \forall V \in \{1,\ldots,N_V\}; \quad Y_{(V,t)} \in \{0,1\} \tag{17}$$

where $P_{ChargeLimit(V,t)}$ is the maximum power charge of vehicle V in period t

– Vehicle charge and discharge are not simultaneous;

$$X_{(V,t)} + Y_{(V,t)} \leqslant 1; \quad \forall t \in \{1,\ldots,T\}; \quad \forall V \in \{1,\ldots,N_V\}; \quad X_{(V,t)} \text{ and } Y_{(V,t)} \in \{0,1\} \tag{18}$$

where $X_{(V,t)}$ is the binary variable of vehicle V related to power discharge in period t and $Y_{(V,t)}$ is the binary variable of vehicle V related to power charge in period t

– Vehicle battery discharge limit considering the battery balance;

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

– Vehicle battery charge limit considering the battery capacity and previous charge status;

$$\eta_{c(V)} \times P_{Charge(V,t)} \times \Delta t \leqslant E_{BatteryCapacity(V)} - E_{Stored(V,t-1)}; \quad \forall t \in \{1,\ldots,T\}; \quad \forall V \in \{1,\ldots,N_V\}; \quad \Delta t = 1 \tag{20}$$

– Battery capacity limit for each vehicle;

$$E_{Stored(V,t)} \leqslant E_{BatteryCapacity(V)}; \quad \forall t \in \{1,\ldots,T\}; \quad \forall V \in \{1,\ldots,N_V\} \tag{21}$$

– 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 an unexpected travel in each period;

$$E_{Stored(V,t)} \geqslant E_{MinCharge(V,t)}; \quad \forall t \in \{1,\ldots,T\}; \quad \forall V \in \{1,\ldots,N_V\} \tag{22}$$

where $E_{MinCharge(V,t)}$ is the minimum stored energy to be guaranteed at the end of period t, for vehicle V.

3. Case study

This section presents a case study that illustrates the use of the day-ahead resource scheduling method proposed in this paper. The case study considers a smart grid operated by a VPP, with a 33 bus distribution network, as seen in Fig. 3 [23,24]. The dashed lines represent reconfiguration branches that are not considered in the present case study. This network is connected to the upstream large distribution public network through bus number 0, allowing energy acquisition from external suppliers. The VPP serves 218 consumers with total peak consumption around 4.2 MW and the load diagram for the two considered consecutive days, as shown in Fig. 4.

The energy resource profile for this case study is established with projections of Distributed Generation (DG) and of Vehicle-to-Grid (V2G) penetration levels for the year 2040, corresponding to an intensive use of DG and V2G. Considering these DG projections, the distribution network includes 66 DG producers, 32 photovoltaic units, 15 cogeneration units, eight fuel cells units, five wind farms, three biomass units, two small hydro units, and one waste to energy unit. The case study considers 1000 V2G units divided into 100 groups, which corresponds to a V2G penetration level of around 40% [25].

The use of groups of 10 V2G units is justified by the reduction in the optimization execution time that can be obtained, without a significant loss in the solution quality. The comparison of the V2G grouped approach with the individual V2G approach has been extensively tested. In order to present some of these results, let us consider two approaches. The first one determines the resource scheduling considering individually 1000 V2G units, and the second one considers the same 1000 V2G divided into 100 groups with 10 V2G units each. The result of the first approach corresponds to a total operation cost of 6036.7 m.u. with an execution time of approximately 4.16 h, and the second one presents the same operation cost value and an execution time of 303.9 s. In this example, single-vehicle grouping makes the simulation run about 50 times longer without any actual benefits in the optimization function. Basically, the authors deliberately performed a tradeoff in aggregating the EVs in groups of 10, so that the problem can be solved in reasonable time. For all the tested case studies, the execution time increases exponentially with the number of considered V2G units, when they are individually considered in the optimization. Moreover, there is not a significant loss in the solution quality obtained by the V2G grouping approach. These scenarios have been tested without considering the discharge price steps which are considered in the present paper. As these steps lead to

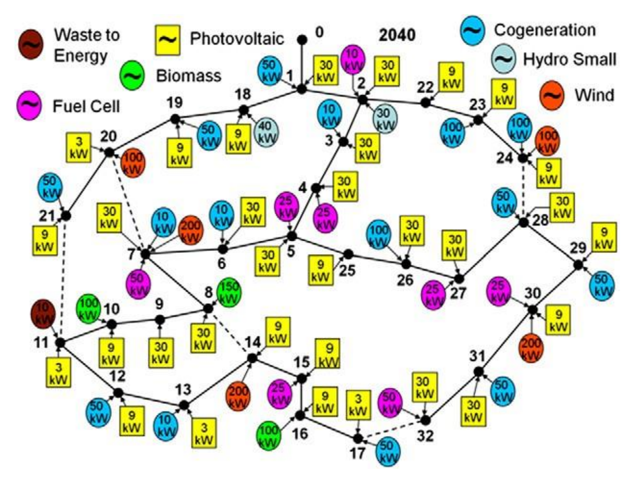

Fig. 3. Network configuration in 2040 scenario [23].

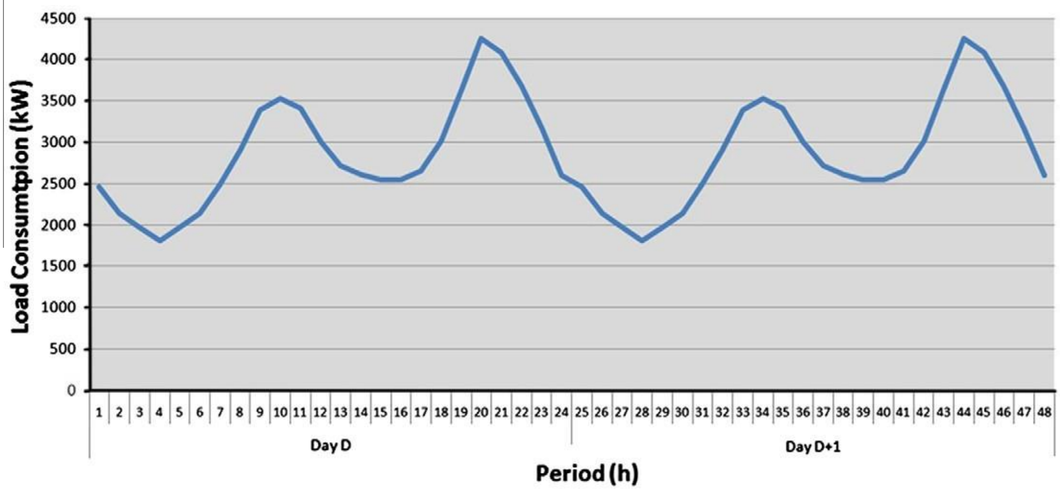

Fig. 4. Total load diagram for the 218 consumers.

a higher execution time, the time reduction obtained with the grouping approach is even more important. These are the main reasons for grouping the 1000 V2G units considered in this paper grouped in 100 groups of 10 V2G units.

This case study considers three discharge price steps. The first price is applied to V2G discharge power to the interval of 100% at 70% of the battery capacity. The second price is activated when the first price step has reached the 70% of battery capacity, and the interval of V2G discharge is between 70% and 40% of the battery capacity. The third price is only active when the V2G has stored 40% of the battery capacity, meaning that the first and second steps were used in previous periods. This step is used on the interval of 40–20% of the battery capacity. The first step is established with the lowest value, the second step has a mid-term price value and the third step corresponds to the highest price value of all three price steps.

The case study is divided into four scenarios (scenarios A–D). Each scenario considers the 24 h periods that correspond to the day ahead planning and a number of additional periods to consider the successive day influence on the resource scheduling for the first day. The number of additional periods differs from scenario to scenario. Load and V2G requirements for the second day are considered equal to the ones for the first day, because of data simplicity. The four scenarios consider the same behavior of the V2G driving patterns for regular working days. In all scenarios it is assumed that all V2Gs start with 30% charge of their battery capacity. These values are assumed as equal for all the considered vehicles of the presented case study. However, this is done only for easing the presentation of the input data and it is not a consequence of any limitation of the implemented method which supports individual vehicle values to be considered. A global value equal to 30% of the total battery capacity, considering the whole set of vehicles, is imposed at the end of the total simulation periods.

Scenario A considers a simulation horizon of 48 h. These 48 h correspond to the day-ahead 24-h periods and to the consecutive day, which is considered to take into account the Successive Day Influence (SDI), as explained in Section 2.1.

Scenario B considers a simulation horizon of 36 h, corresponding to the 24 day-ahead periods plus 12 additional hours for considering the successive day influence. After this simulation, the energy stored in each V2G at the end of the 24th hour is used as the initial state for another 24 h simulation. The total operation cost for the 2 days is the sum of the costs obtained for the first 24 h in the first simulation with the cost obtained for the second simulation.

Scenario C is simulated for 30 h, corresponding to the 24 h of the next day and to 6 additional hours for considering the successive day influence. The energy stored in the end of the 24th hour is used as the initial state of the second simulation of 24 h.

Scenario D is simulated for 24 h only, in order to allow taking conclusions concerning the advantages of using an additional simulation period to consider the influence of the successive day impact, when compared with a single optimization considering only the 24 hourly periods of the day ahead.

The results obtained for this case study correspond to the computational implementation of the proposed methodology. This implementation uses MATLAB as the programming environment with GAMS being used to solve the Mixed-Integer Non-Linear Programming (MINLP) problem. The case study has been tested on a computer with two processors Intel® Xeon® W3520 2.67 GHz, each one with two cores, 3 GB of random-access-memory (RAM) and Windows 7 Professional 64 bits operating system.

The following sub-sections present the details of the case study.

3.1. Case study characterization

This sub-section presents the characterization of the input data used for each resource. The 218 customers are divided into six groups – Domestic Consumers (DMs), Small Commerce (SC), Medium Commerce (MC), Large Commerce (LM), Medium Industrial (MI), and Large Industrial (LI) [23]. The number and types of the considered consumers are the ones used in [26] and in [27]. Table 1 presents the consumption in each bus in the 20th hour of the day for which the resource scheduling is going to be determined. Table 2 shows the number of consumers of each type and the total number of consumers in each bus.

Table 1
Network load in hour 20 (peak period).

Bus	Load (kW)	Bus	Load (kW)	Bus	Load (kW)
1	113.0	12	136.3	23	488.4
2	101.1	13	65.9	24	488.4
3	136.1	14	65.9	25	65.9
4	65.9	15	65.9	26	65.9
5	230.2	16	101.1	27	65.9
6	230.2	17	101.1	28	136.3
7	65.9	18	101.1	29	230.2
8	65.9	19	101.1	30	171.5
9	48.3	20	101.1	31	242.4
10	65.9	21	101.1	32	65.9
11	65.9	22	101.1	Total	4250.9

Table 2
consumer location and types.

Bus	Number of consumers						
	DM	SC	MC	LC	MI	LI	Total
1	–	2	2	1	–	–	5
2	2	5	–	–	–	–	7
3	4	4	–	–	–	–	8
4	7	2	–	–	–	–	9
5	8	–	–	–	–	–	8
6	4	1	–	2	–	–	7
7	–	1	1	2	–	–	4
8	9	1	–	–	–	–	10
9	10	–	–	–	–	–	10
10	4	2	–	–	–	–	6
11	6	1	–	–	–	–	7
12	7	–	–	–	–	–	7
13	5	2	2	–	–	–	9
14	6	–	–	–	–	–	6
15	7	1	–	–	–	–	8
16	5	2	–	–	–	–	7
17	2	4	1	–	–	–	7
18	–	–	2	2	–	–	4
19	3	–	3	1	–	–	7
20	–	4	4	–	–	–	8
21	–	2	2	1	–	–	5
22	2	5	–	–	–	–	7
23	2	1	–	–	–	4	7
24	–	1	–	–	1	4	6
25	7	–	–	–	–	–	7
26	5	1	–	–	–	–	6
27	8	–	–	–	–	–	8
28	2	2	3	–	–	–	7
29	–	1	1	–	3	–	5
30	–	1	–	–	3	1	5
31	–	–	2	4	–	–	6
32	5	–	–	–	–	–	5
Total	120	46	23	13	7	9	218

In terms of the DG producers used in this case study, the authors decided to divide the 66 DG units into 32 photovoltaic units, 15 cogeneration units, eight fuel cells units, five wind farms, three biomass units, two small hydro units, and one waste to energy unit. Table 3 depicts the information on several technologies of DG producers, in terms of nominal power, average selling price, and number of units.

3.2. Vehicle-to-Grid penetration description

The consumer's classification is used to define the number of vehicles that will be moving in the distribution network geographical area. Considering 40% penetration for the V2G in 2040, the number of V2G determined was established in 1000 units. Table 4 details the amount of V2G considered for each consumer type. The simulation with the 1000 V2G has been based on seven different electric vehicle models with V2G capacity, for which the technical information has been obtained from vehicle manufactures.

Table 5 presents the V2G locations in the considered case study. These locations are based on the vehicles profiles reported by the US Department of Transportation (DOT) in Ref. [28]. The first two columns in Table 5 refer to the V2G that are leaving a network bus and the other two columns refer to the V2G that are arriving to a network bus.

The case study considers two types of charge/discharge rates, which are the quick and slow rate. The quick and slow rates are due to different connections to the network. If the V2G is connected in residential or service buildings, the charging rate will be lower than when using a parking connection (with a three-phase system).

The case study considers three discharge price steps which remuneration is fixed at 0.02, 0.04 and 0.06 m.u./kW for steps A–C, respectively.

3.3. Optimal scheduling results

Table 6 shows the operation cost for days D and $D + 1$ for scenarios A–D. The operation costs for day D are the costs obtained for the first 24 h of the first simulation. The operation costs for days

Table 3
Distributed generation profile.

DG technology	Number of units	Total nominal power (MW)	Mean daily operation hours (h)	Price Scheme (m.u./kW)		
				Maximum	Mean	Minimum
Photovoltaic	32	1.32	6	0.254	0.1872	0.11
Wind	5	0.505	12	0.136	0.091	0.06
Small hydro	2	0.08	24	0.145	0.117	0.089
Biomass	3	0.35	24	0.226	0.2007	0.186
Waste to energy	1	0.01	24	–	0.056	–
Co-generation	15	0.725	24	0.105	0.0753	0.057
Fuel cell	8	0.44	24	0.2	0.055	0.01
External suppliers	10	5.8	24	0.15	0.105	0.06

Table 4
V2G scenario.

Type of consumer	Vehicle per consumer	Consumers in the network	V2G scenario				
			Penetration (%)		Number of V2G		
			PHEV	BEV	PHEV	BEV	Total
DM	2	120	25	5	60	12	72
SC	5	46	23	5	53	12	65
MC	20	23	28	12	129	55	184
LC	70	13	28	11	255	100	355
MI	50	7	30	6	105	21	126
LI	70	9	36	9	227	57	284
Total	–	218	–	–	829	257	1086

Table 5
V2G location for the day D.

Periods	Departure travel		Arrival travel	
	Bus number	Number of vehicles	Bus number	Number of vehicles
6 am	3;5;7; 10	40	–	–
7 am	2; 4; 5; 8; 9; 10; 17; 19; 21; 23; 24; 25; 26; 28; 31	170	–	–
8 am	6; 11; 14; 15; 18; 23; 29; 32	110	26; 15; 17; 19	40
9 am	9; 12; 13; 14; 18; 20; 23; 24; 26; 27; 30	120	2; 4; 6; 7; 8; 9; 10; 16; 18; 23; 24; 25; 31	160
10 am	4; 9; 21; 26; 27; 29; 30	80	5; 6; 10; 17; 18; 21; 23; 25; 27; 30	100
11 am	2; 6; 8; 9; 12; 17; 20; 24; 28; 30	130	4; 5; 11; 14; 20; 21; 23; 24; 28; 30; 32	120
12 am	4; 7; 11; 14; 16; 17; 18; 21; 22; 24; 26	190	7; 8; 15; 22; 23; 30	60
13 pm	7; 13; 15; 18; 19; 20; 30; 32	90	9; 10; 13; 15; 18; 23; 30; 31	100
14 pm	5; 8; 9; 11; 14; 18; 21; 23; 25; 26; 29	150	2; 4; 5; 7; 14; 15; 16; 17; 20; 21; 22; 24; 26; 29; 31	190
15 pm	5; 6; 8; 9; 11; 14; 25; 26; 30; 31; 32	160	2; 8; 13; 17; 19; 21; 31	80
16 pm	2; 10; 13; 15; 16; 17; 18; 19; 20; 24; 31	150	2; 5; 8; 9; 11; 14; 15; 16; 18;20; 26; 29	140
17 pm	8; 9; 15; 16; 17; 19; 20; 22; 24; 26	150	2; 9; 11; 17; 21; 22; 26; 28; 30	140
18 pm	4; 6; 8; 9; 14; 16; 18; 20; 23; 26; 29; 31	180	4; 6; 7; 12; 14; 16; 19; 20; 26; 31	130
19 pm	4; 22; 31	70	3; 8; 9; 16; 17; 18; 19; 20; 24; 31; 32	120
20 pm	2; 7; 14; 20; 22; 26	80	4; 6; 9; 12; 14; 16; 17; 20; 22; 25; 26; 28; 29; 30	170
21 pm	17; 20	40	3; 4; 11; 22; 26; 32	60
22 pm	–	–	2; 5; 8; 18; 21; 26; 32	70

Table 6
Results comparison.

Scenario	Day D							Day D +1							
	Execution time (s)	Generator cost (m.u.)	Discharge cost (m.u.)			Total cost (m.u.)	24th hour V2Gs battery state (%)	Execution time (s)	Generator cost (m.u.)	Discharge cost (m.u.)			Total cost (m.u.)	24th hour V2Gs battery state (%)	Total cost for days D and D + 1 (m.u.)
			Step A (100–70%)	Step B (70–40%)	Step C (40–20%)					Step A (100–70%)	Step B (70–40%)	Step C (40–20%)			
A	2365.75	6546.80	8.88	14.94	30.80	6570.90	30.80	2365.75	6519.63	10.96	19.28	9.12	6558.99	30	13,129.89
B	2163.10	6188.50	1.49	2.78	63.62	6256.39	9.38	1700.60	6913.70	0	2.66	0	6916.36	30	13,172.75
C	1077.60	6125.13	0	0	73.27	6198.40	5.22	1681.10	6986.50	0	2.48	1.32	6990.30	30	13,188.70
D	688.07	6067.96	44.07	0	0.91	6112.94	0.68	7144.22 (1.98 h)	No feasible solution						

Table 7
Number of variables for the scenarios.

Scenario	Execution time (s)	Number of variables			Number of constraints
		Binary variables	Real variables	Total	
A	4731.50	13,248	63,937	77,185	86,385
B	2163.10	9936	47,953	57,889	64,989
C	1077.60	8280	39,961	48,241	54,141
D	688.07	6624	31,969	38,593	42,993

D + 1 are the costs obtained for the 24 periods of the second simulation, which is run considering as initial state the V2G batteries state at the end of the 24th hour of the first simulation.

The Scenario A results correspond to the lowest operation cost, and to the maximum considered successive day influence period which has been a complete day. These results were obtained from the first simulation for 48 h, from which the results for day ahead scheduling are the results for the first 24 h. The Scenario A obtains a feasible solution for the considered days, with a cost of 13,129.89 m.u. in 4731.50 s (1.3 h). In this scenario the overall battery charge remains slightly above 30% of the total V2G battery capacity at the end of the 24th hour, helping the scheduling for the next day (day D + 1) and achieving an operation cost lower than the others scenarios.

In the scheduling for the first day (day D), scenarios B and C achieved lower costs than Scenario A, due to a lower value of energy stored in V2G batteries at the end of the 24th hour. For these two scenarios the energy stored in the V2G batteries at the end of the 24th hour is equal to 9.38% and 5.22%, respectively for Scenario B and for Scenario C. These lower stored energy values make the scheduling for the next day (D + 1) more costly for the VPP, being necessary to use more expensive energy to guarantee the required trip distances.

For Scenario D it was not possible to find a solution for the next day (D + 1), because the energy stored in the V2G batteries at the end of the first day (0.68%) is too low.

Table 7 shows the execution time, the number of variables and the number of constraints used in each scenario. The number of variables and the number of constraints increase with the number of periods that are considered. Scenario A, corresponding to a time horizon of 48 h, requires 77,185 variables (from which 13,248 binary) and 86,385 constraints whereas Scenario D, considering a 24 h time horizon, only requires 38,593 variables (from which 6624 binary) and 42,993 constraints.

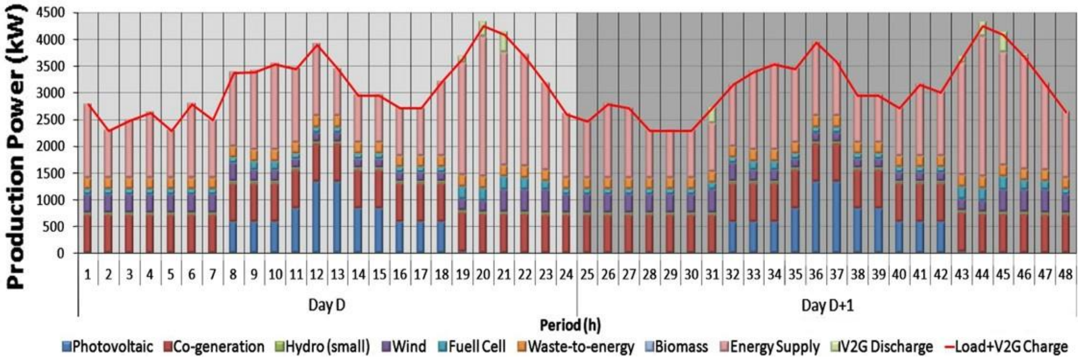

Fig. 5. Energy resource scheduling for Scenario A.

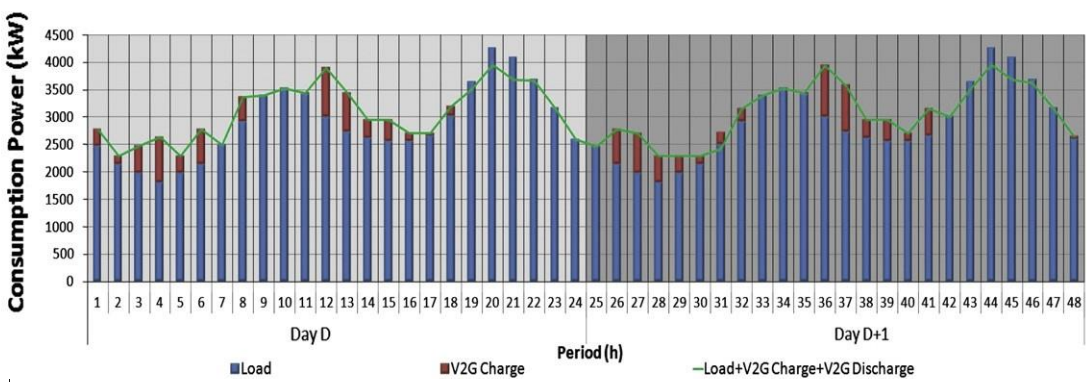

Fig. 6. Load diagram for Scenario A.

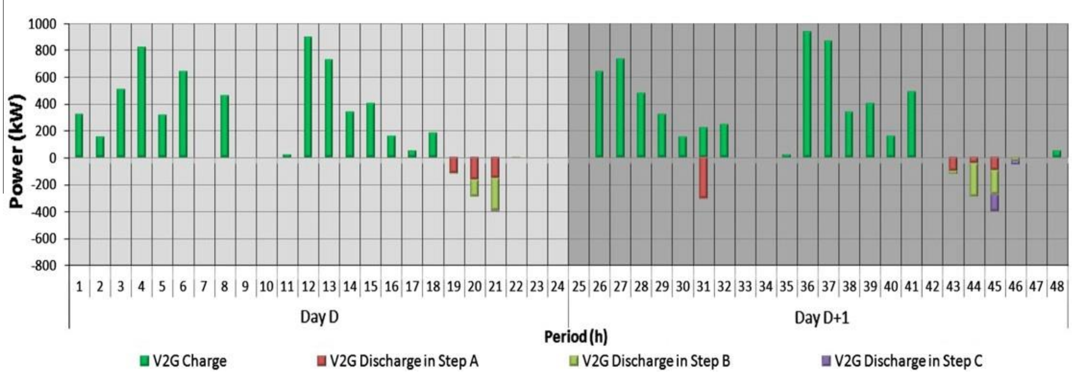

Fig. 7. Total charge and discharge profile for Scenario A.

The analysis of these results shows that the scenario that considers the influence of the successive day (Scenario A) in the day-ahead scheduling led to the best solution. Figs. 5–7 present the results obtained for Scenario A. Fig. 5 depicts the resulting energy resource scheduling over 48 h. It can be concluded from Fig. 5 that V2G discharge has been allocated in the peak periods (hours 19, 20, 21, 43, 44, 45 and 46). This is a good strategy for cost minimization due to the fact that in these periods the V2G discharge has lower cost than the other available resources. The solid line represents the sum of the load demand and the V2G charge. The difference between the displayed bar height and this line, for each period, corresponds to the power losses.

Fig. 6 illustrates the load diagram and the total V2G charge for the 48 h periods. The solid line represents the resulting load diagram considering the demand, the V2G charge and the load reduction effect achieved through the use of V2G discharge. The V2G charges are allocated in the off-peak periods (from hour 1 to hour 6 and from hour 25 to hour 32), because the charging costs are lower than in the other periods.

Fig. 7 shows the total V2G charge and discharge results obtained for scenario A, being possible to see the amount of energy that is used to discharge in each considered price step (steps A–C).

4. Conclusions

This paper proposed a methodology for day-ahead energy resource scheduling for smart grids, considering intensive use of distributed generation and Vehicle-to-Grid (V2G). It is considered that the smart grid resources are managed by a Virtual Power Player (VPP) that establishes contracts with resource owners, including V2G users. The day-ahead scheduling considers these contracts and also specific detailed information concerning V2G users' requirements which may be submitted to the VPP the day ahead, according to contract clauses.

The problem formulation considers several V2G discharge price steps, according to the actual battery level, in order to guarantee fair discharge remuneration preventing unnecessary battery deterioration. Full AC power flow calculation is included in the scheduling model allowing considering network constraints, namely line thermal limits and voltage magnitude and angle limits. The proposed method considers additional time periods in the scheduling simulation, allowing considering the influence of successive day in the day-ahead optimal scheduling.

A case study considering a 33 bus distribution network with intensive use of distributed generation and V2G is used to illustrate the application of the proposed method, allowing scheduling all the considered resources, including 1000 V2G. The experimental studies showed that the best results are achieved, in this case, when considering an additional complete day to take into account the successive day influence on the day ahead optimal scheduling. Lower additional periods led to worse results and even to unfeasible solution when considering only 6 additional hours. This is caused by the difficulties encountered to manage the required V2G battery charge in the considered context, when the energy stored at the end if the next day is not enough to cope with the successive day requirements.

The undertaken studies allow concluding that the consideration of an additional day for the simulation that envisages day-ahead resource scheduling represents the need to solve a significantly larger problem. In the presented case study, the total number of variables increases from 38,593 to 77,185 and the number of constraints increases from 42,993 to 86,385. This requires a higher execution time which increases from about 11.5 min to about 78.9 min. Although this increase is very significant, the higher execution timer is still affordable for the day-ahead scheduling. Moreover, it ensures a much more efficient battery charge management, avoiding high cost solutions or even the impossibility to ensure the vehicle requirements.

The proposed method highlighted its advantages and a good performance, both in terms of solution quality and execution time, to be used in real world problems.

Acknowledgements

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