An Optimal Scheduling Problem in Distribution Networks Considering V2G

João Soares, Tiago Sousa, Hugo Morais, Zita Vale, Pedro Faria
GECAD - Knowledge Engineering and Decision Support Research Center
ISEP / IPP - Institute of Engineering – Polytechnic of Porto
Porto, Portugal
{japs, tas, hgvm, zav, pnf}@isep.ipp.pt

***Abstract* — This paper addresses the problem of energy resource scheduling. An aggregator will manage all distributed resources connected to its distribution network, including distributed generation based on renewable energy resources, demand response, storage systems, and electrical gridable vehicles. The use of gridable vehicles will have a significant impact on power systems management, especially in distribution networks. Therefore, the inclusion of vehicles in the optimal scheduling problem will be very important in future network management. The proposed particle swarm optimization approach is compared with a reference methodology based on mixed integer non-linear programming, implemented in GAMS, to evaluate the effectiveness of the proposed methodology. The paper includes a case study that consider a 32 bus distribution network with 66 distributed generators, 32 loads and 50 electric vehicles.**

***Keywords* - Distributed Generation, Energy Resources Management, Optimal Scheduling, Particle Swarm Optimization, Plug-in Hybrid Vehicle, Vehicle to Grid**

NOMENCLATURE

b_i	Best past experience of Particle i
bG	Best past experience of the swarm
$c_{DG(DG,t)}$	Generation cost of DG unit in period t
$c_{Supplier(S,t)}$	Market energy price of upstream supplier S in period t
$c_{Discharge(V,t)}$	Discharge price of vehicle V in period t
$Load_{(L,t)}$	Active power demand of load L in period t
N_{DG}	Total number of distributed generators
N_L	Total number of loads
N_P	Total number of periods
N_S	Total number of upstream suppliers
N_V	Total number of vehicles
$P_{DG(DG,t)}$	Active power generation of distributed generation unit DG in period t
$P_{DGLimit(DG,t)}$	Maximum active power generation of distributed generator unit DG in period t
$P_{Supplier(S,t)}$	Active power flow in the branch connecting to upstream supplier S in period t
$P_{SupplierLimit(S,t)}$	Maximum active power of upstream supplier S in period t
$P_{Stored(V,t)}$	Stored energy in vehicle V in period t
$P_{BatteryCapacity(V)}$	Battery capacity of vehicle V
$P_{Charge(V,t)}$	Power charge of vehicle V in period t
$P_{ChargeLimit(V,t)}$	Maximum power charge of vehicle V in period t
$P_{Discharge(V,t)}$	Power discharge of vehicle V in period t
$P_{DischargeLimit(V,t)}$	Maximum power discharge of vehicle V in period t
$P_{MinTrip(V,t)}$	Minimum stored energy to be guaranteed in period t, for vehicle V
$P_{Trip(V,t)}$	Vehicle V consumption in period t
${}^{*}v_i$	New calculated velocity of particle i
${}^{*}x_i$	New calculated position of particle i
x_i	Actual position of particle i
${}^{*}w_i$	New mutated weights of particle i, in an iteration
w_i	Initial weights of particle i, in a iteration
${}^{*}w_{i(inertia)}$	Inertia weight component
${}^{*}w_{i(memory)}$	Memory weight component
${}^{*}w_{i(coop)}$	Cooperation weight component
$X_{(V,t)}$	Binary variable of vehicle V related to power discharge
$Y_{(V,t)}$	Binary variable of vehicle V related to power charge

I. INTRODUCTION

Currently, Power Systems (PS) have many kinds of resources available that should be adequately managed, requiring players in a liberalized market to change their strategies and the way they act. Some resources as Distributed Generation (DG), Renewable Energy (RE), Demand Response (DR), and storage systems have been gaining increasing

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importance. Some of these resources, such as wind generation, raise new problems to Independent System Operators (ISO) due to the intermittent nature of the natural resource.

Presently Electric Vehicles (EV) are positioning as a reliable solution to replace the typical Internal Combustion Vehicles (ICV), with the advantage of being a good way to reduce CO_2 emissions. Plug-in Hybrid Electric Vehicle (PHEV) batteries charging and discharging can be used in the scope of intelligent resource management, using the Vehicle-to-Grid (V2G) concept. Optimization techniques should be used to determine the optimal charging and discharging scheduling, with the objective to minimize the total operation cost. Depending on the network size, the optimization can turn naturally into a large combinatorial problem due to the huge number of network elements and to the diversity of energy resources with different specifications and requirements.

This fact makes the optimization problem suitable for the use of Artificial Intelligence (AI) based techniques, namely metaheuristics such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Simulated Annealing (SA). These techniques are advantageous due to their competitive computational resources requirements and good performances for solving large combinatorial problems when compared with deterministic approaches. PSO was chosen to be used in this paper due to its robustness and long-term success in PS applications. The obtained results are compared with a Mixed-Integer Non Linear Programming (MINLP) so that the advantages of each approach can be discussed later.

The presented methodology has the objective to solve the optimal scheduling considering the point of view of an aggregator using different resources, with emphasis on distributed generation and V2G. A case study considering a 32 bus distribution network with 66 distributed generation plants, 32 loads and 50 electric vehicles is presented.

This paper is organized as follows: section II presents the V2G concept and V2G impact on smart grid. Section III explains the proposed methodology, its mathematical formulation and presents the used PSO technique. A case Study is presented in Section IV. Finally, section V presents the conclusions of the paper.

II. V2G IN SMART GRID ENVIRONMENT

The electrification of vehicles will help to reduce CO_2 emissions and to increase the security of supply in the transportation sector [1]. Power system operators and other power system players should consider the use of EV as a new distributed energy resource to be considered in the scope of the diverse resources connected to the system. However, electric vehicles have very specific characteristics, namely in what concerns location change and their possible dual role as energy sources (discharging batteries when connected to the power grid) or loads (when charging their batteries, consuming energy from the grid). Denholm, P., *et al* [2] investigated the benefits of discharging EV to the grid and forecasted the influence of large-scale EV integration. They concluded that when vehicles are optimally dispatched from a power system perspective they can decrease the daily "cycling" of the power plants and increase the system's load factor.

Adersson, S., L. *et al* [3] simulated the conditions of Sweden and Germany real prices and activations of regulation power to perceive in what conditions electric vehicles can act as energy providers. An increased share of intermittent power production will lead to a higher demand of regulation power. It is also concluded that with a moderated fleet of electric vehicles it is possible to satisfy this regulation whereas with a high penetration of electric vehicles, fleets can be used as an operational back-up and to moderate wind power variations.

In [4] Saber and Venayagamoorthy presented a hybrid PSO approach handling variables in binary and integer form to balance between cost and emission reduction for Unit Commitment (UC) with up to 100.000 gridable vehicles. The results have shown that UC with V2G reduces operational cost and emission.

The same authors presented a PSO approach applied on dynamic data of physical resources to generate intelligent scheduling and control of green resources, gridable vehicles and conventional thermal units for a sustainable cyber-physical energy system [5]. The results shown that excess load from gridable vehicles is intelligently distributed to off-peak hours. However, the aimed cost and emissions reduction can only be achieved using renewable energy sources.

Figure 1 shows several ways in which electric vehicles can be connected with the power system. Dashed lines indicate electric flow from vehicles to the grid. This power flow should be controlled by the system operator, without violating the constraints on the whole system, including the aimed electric vehicles' charge profiles.

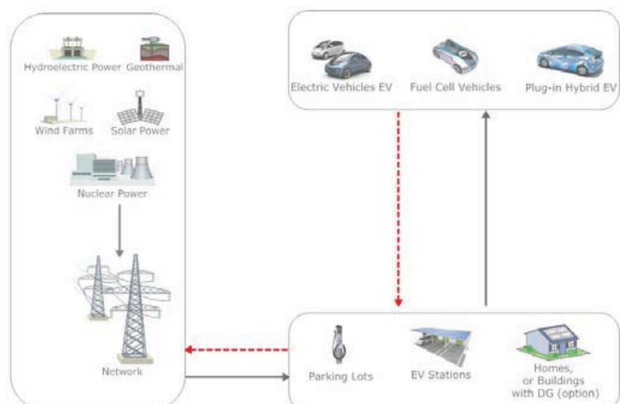

Figure 1. – V2G integration with the power system

A. *V2G Concept*

For the future electrification of the transportation sector, namely road transport, several technologies are already available:

- Plug-in Hybrid Electric Vehicle (PHEV): The main propulsion system is the electric motor powered by the battery; however a range-extender, typically an internal combustion engine, is used to improve vehicle range [6].
- Battery Electric Vehicle (BEV): the only source of energy is the battery. The range is far more limited than for a PHEV. However, BEV do not use any fuel and can also be charged from grid [7-9].

- Fuel-Cell Vehicle (FCV): a fuel-cell unit is used to generate power to the electric motor and/or to store energy in the battery.

Although there are several prototypes of FCVs, they are less likely to be introduced as fast as the PHEV and BEV because fuel-cell units are currently very expensive. FCVs are behind EV in terms of development and the hydrogen economy is still not competitive. We only considered PHEV and BEV future market based vehicles.

B. *Driving pattern*

The driving patterns are important because the impact on the power system depends on the vehicles are charging time schedule which affects the energy costs. Let us consider a typical daily drive for a person: starting from his/her house, then goes to work, maybe the person has lunch in other place, comes back home and/or makes a detour to the store. This means that during the day the vehicle can be in different places: for instance in the garage, in an employer's parking lot, a store parking lot or on the road. The main issue is to know where and when will the EV charge the battery and how many of them will do it simultaneously. This behavior must be studied in order to allow an adequate resource management.

In the United States of America (USA) [2] near 50% of the Americans drive less than 42 km per day and 90% less than 150 km per day while in Western Europe Cities (WEU) these values are lower: an average of 41 km per capita per vehicle contrasting with 85 km in the US cities [10]. Thus, the PHEV and BEV have the potential to meet almost America's daily automotive transportation and certainly WEU cities needs on battery alone, considering that most future commercial PHEV and BEV will have more than 150 km of range. In 2001, the U.S. Department of Transportation (DOT) studied the percentage of trips in a day, and the results have shown that almost all cars are parked at night [11].

C. *V2G impact on Smart Grid*

Market penetration is expected to vary regionally, depending on local government actions. In 2008 [1] a study on switching to EV and PHEV in the United Kingdom (UK) was carried out. The report estimates that in the worst case and with little incentives from the government the market penetration for electric vehicles should be 1% and 9% in 2020 and 2030 respectively. If proactive measures are undertaken, the penetration should be 5% and 37%.

The charge level is also important to be considered, e.g. in US 120V 15A in theory would be as much as 1.8 kW, while a 20 A circuit would be about 2.4 kW. In Europe the standard home outlet is 230V 16A corresponding to a maximum load of 3.7 kW. Proposed three-phase connections for faster charging in Europe could be as much as 50kW [12]. Power system and network investments must be planned for the future when market share of EV is significant [1, 2, 13-15]. Controlled charging of EV can help to reduce consumption impacts on the grids [14, 16]; however, good control strategies must be implemented to avoid secondary system peaks.

III. PROPOSED METHODOLOGY

In this section the mathematical formulation used in the considered scheduling problem is presented in sub-section A. Sub-section B explains how the Particle Swarm Optimization (PSO) algorithm has been adapted to solve this problem.

A. *Mathematical Formulation*

An optimal scheduling model for a 24 hour period has been used to minimize the total generation cost, which includes generation production cost and V2G discharge payment. In this paper a linear curve cost and steady-state constraints were used. Such constraints consider maximum line thermal limit, voltage limits, generator technical limits and V2G technical limits.

The objective function is formulated for each period (t), usually 1 hour, of the overall considered time (24 hours, in our study).

$$min\ f = \sum_{t=1}^{N_P} \left[\begin{array}{l} \sum_{DG=1}^{N_{DG}} P_{DG(DG,t)} \times c_{DG(DG,t)} + \\ \sum_{S=1}^{N_S} P_{Supplier(S,t)} \times c_{Supplier(S,t)} + \\ \sum_{V=1}^{N_V} P_{Discharge(V,t)} \times c_{Discharge(V,t)} \end{array} \right] \quad (1)$$

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

- Power balance in each period *t*

$$\begin{array}{l} \sum_{DG=1}^{N_{DG}} P_{DG(DG,t)} + \sum_{S=1}^{N_S} P_{Supplier(S,t)} + \sum_{V=1}^{N_V} P_{Discharge(V,t)} \\ = \sum_{L=1}^{N_L} Load_{(L,t)} + \sum_{V=1}^{N_V} P_{Charge(V,t)} \\ \forall t \in \{1,.., N_P\} \end{array} \quad (2)$$

- Maximum distributed generation limit in each period *t*

$$\begin{array}{l} P_{DG(DG,t)} \le P_{DGLimit(DG,t)} \\ t \in \{1,...,24\}; DG \in \{1,...,N_{DG}\} \end{array} \quad (3)$$

- Maximum upstream supplier limit in each period *t*

$$\begin{array}{l} P_{Supplier(S,t)} \le P_{SupplierLimit(S,t)} \\ t \in \{1,...,24\}; S \in \{1,...,N_S\} \end{array} \quad (4)$$

- Vehicle technical limits in each period *t*
  - Battery balance in each vehicle V

$$\begin{array}{l} P_{Stored(V,t)} = P_{Stored(V,t-1)} - P_{Trip(V,t)} \\ \qquad - P_{Discharge(V,t)} + P_{Charge(V,t)} \\ t \in \{1,...,24\};\ \ V \in \{1,...,N_V\}; \end{array} \quad (5)$$

The initial state balance of V2G batteries ($P_{Stored(V,1)}$) are set before optimization as an input data.

  - Battery energy limit for each vehicle V

$$P_{Stored(V,t)} \le P_{BatteryCapacity(V)}$$
$$t \in \{1,...,24\}; V \in \{1,...,N_V\} \quad (6)$$

- Maximum discharge limit in each vehicle V

$$P_{Discharge(V,t)} \le P_{DischargeLimit(V,t)} \times X_{(V,t)}$$
$$t \in \{1,...,24\};\ V \in \{1,...,N_V\};\ X \in \{0,1\} \quad (7)$$

- Maximum charge Limit in each vehicle V

$$P_{Charge(V,t)} \le P_{ChargeLimit(V,t)} \times Y_{(V,t)}$$
$$t \in \{1,...,24\};\ V \in \{1,...,N_V\}; Y \in \{0,1\} \quad (8)$$

- A vehicle V cannot charge and discharge at the same time period

$$X_{(V,t)} + Y_{(V,t)} \le 1$$
$$t \in \{1,...,24\};\ V \in \{1,...,N_V\} \quad (9)$$
$$X \ and \ Y \in \{0,1\}$$

- Vehicle V battery maximal discharge limit considering the battery balance

$$P_{Discharge(V,t)} - P_{Stored(V,t-1)} \le 0$$
$$t \in \{1,...,24\};\ \ V \in \{1,...,N_V\} \quad (10)$$

- Vehicle V battery maximal charge limit considering the battery capacity and previous charge status

$$P_{Charge(V,t)} + P_{Stored(V,t-1)} \le P_{BatteryCapacity(V)}$$
$$t \in \{1,...,24\}; V \in \{1,...,N_V\} \quad (11)$$

- Minimum stored energy to be guaranteed for vehicle *V* in each period *t*

$$P_{Stored(V,t)} \le P_{MinTrip(V,t)}$$
$$t \in \{1,...,24\}; V \in \{1,...,N_V\} \quad (12)$$

Technical network constraints (line thermal limits and bus voltage limits) are considered in different ways in the deterministic and in the PSO based approaches. In the deterministic approach these constraints are addressed through the use of AC load flow calculations. In the PSO based approach, these constraints are treated using heuristics, as described in sub-section B.

B. *Particle Swarm Optimization*

PSO has proved to be effective in several areas of power systems [17, 18]. The problem presented in this paper is classified as non-linear which is suitable for Artificial Intelligence (AI) techniques as PSO, due to reducing computational resources requirements in large scale problem as the case study of this paper.

In this work a variant of PSO has been implemented in MATLAB to solve the optimization problem. The results were then compared against a deterministic technique, mixed integer non-linear programming, implemented in GAMS software.

The explanation about PSO basis is out of the scope of this paper but several references on this subject can be consulted as [19]. Equation (13) allows the calculation of the new particle's velocity that depends on particle's present velocity, past experience (memory) and group's experience (cooperation).

$$^{*}v_i = {}^{*}w_{i(inertia)} v_i + {}^{*}w_{i(memory)} \left(b_i - x_i\right) + {}^{*}w_{i(coop)} \left(bG - x_i\right) \quad (13)$$

The new positions ($^{*}x_i$) for each particle are then calculated according to equation (14).

$$^{*}x_i = x_i + {}^{*}v_i \quad (14)$$

After applying the movement equation to each particle, PSO evaluates the fitness of the new positions and the best solution (*bG*) is stored across iterations. The variant of classic PSO that is used in this paper differs from the classic one because mutation of the strategic parameters (*w*) is added. The strategic parameters are inertia, memory and cooperation. During PSO iterations these weights are mutated according to expression (15). This process leads to a better diversity of the swarm and enables better quality solutions for the same execution time when compared with the classic PSO. The added computational resources to compute expression (15) are minimal compared to the benefits.

$$^{*}w_i = w_i + \delta N\left(0,1\right) \quad (15)$$

At the beginning of the process the values of these weights are randomly generated between 0 and 1. After that, the particle's weights change in each iteration using a Gaussian mutation method according to equation (15). δ is the learning parameter, externally fixed between 0 and 1, a high value of δ adding more importance to mutation. *N(0,1)* is a random number following a normal distribution with mean of 0 and a variance of 1 (squared scale). Once again the strategic parameters are limited to values between 0 and 1 in this stage. General parameters and PSO problem implementation are described in the following topics:

- The particle maximum and minimum positions defines the limit of variables;
- The V2G battery balance is controlled and corrected in each iteration, after swarm movement and before costs calculation;
- The V2Gs battery technical specifications are also checked and corrected before costs calculation and power balance check. User energy requirements for the vehicle battery are also checked and corrected;
- The active power balance of the system is also matched. When there is a surplus in generation the producers with higher costs are reduced or disconnected until power balance is matched;
- When there is a lack of generation the producers with lower costs are connected or already connected generators' power is increased;
- The binary variables of the problem are rounded to the nearest integer;
- The network constraints violations are added as penalties to the fitness function of each particle.

As previously referred, technical constraints are addressed using a heuristic approach, due to the relative computational complexity of using a power flow method. This complexity made us to assume some approximations in the way we verify the network electrical constraints.

There are two constraints to be verified - maximum acceptable voltage drop, and maximum electric current in a branch – after some preliminary calculations, as follows:

- Preliminary calculations

In a distribution network with a radial topology, the bus voltage limit is determined by the worst load flow scenario in the network (or radial area). We consider the worst load flow scenario as the one that has all loads of the radial area allocated in the last (more distant of the substation or other line begin) bus. The consideration of the Distributed Generators (DG) is assured by allocating all dispatched units for the present solution connected in the line beginning bus. The vehicles' charge and discharge power values are included, respectively, in load an DG total values. After this, the electric current in the line is calculated. Cable section changes give place to the consideration of a new radial area.

- Maximum acceptable voltage drop

In a real network, it is known the value of the maximum percentage voltage drop for a line, i.e. the minimum voltage in the last (more distant) bus. Considering the minimum voltage in the last bus and the electric impedance of the radial area, between the last bus at the beginning of the line, the maximum power that can flow in that line is easily determined. Obviously, the approximations above make us to have an error in the capacity usage of the line, i.e., a pessimistic heuristic is being used.

- Maximum current in a branch

With the calculations above, the electric current that, in the worst scenario, will flow in each one of the branches (the same value for all branches) is determined. This value is compared with the maximum capacity value provided by the cable technical data.

IV. Case Study

In this section, the 32 bus distribution network from [20] has been used to test the proposed PSO methodology and the effectiveness of the implemented algorithm. The scenario considers a penetration of 50 units of PHEV or EV. The PSO test results are compared with the MILP approach. The PSO considers a heuristic approach, described in section III.B, to handle AC load flow. This approach evaluates the network constraints to the worst load flow scenario.

The application has been developed in MATLAB R2009b 64 bits software. The case study has been tested on PC compatible with 2 processors Intel® Xeon® W3520 2.67GHz, each on with 2 Cores, 3GB of random-access-memory (RAM) and Windows 7 Professional 64bits Operating System.

A. *Distribution Network*

The 32 bus distribution network from [20] does not have any DG generator and it was necessary to include some DG in this 32 bus system because the study has the purpose to evaluate the V2G behavior in a network with intensive use of DG. Figure 2 depicts the network in 2040. Generation equipment is represented in each bus, distinguishing generation technology and indicating the value of the corresponding installed power. Dashed lines represent reconfiguration branches that are not considered in this case study. This network is connected to the large distribution public network through bus number 0. The loads are modeled with fixed power consumption for each period (24 hours).

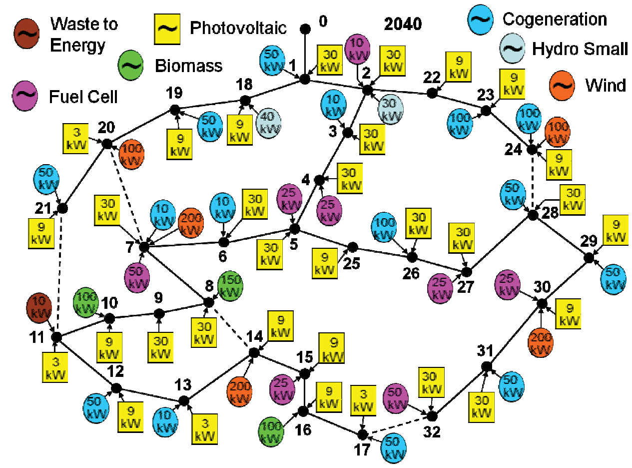

Figure 2. Configuration of the network in 2040

B. *50 EV Scenario*

This scenario considers 50 EV in the network, distributed in 10 groups, with 5 vehicles each. Table I shows the technical information for these vehicles.

TABLE I. V2G Technical Information

Vehicle Type	Battery Capacity (kWh)	Battery Range (km)	Charge Rate (%)		Discharge Rate (%)		Electric Vehicle ID	Price Discharge (€/kWh)
			Slow	Quick	Slow	Quick		
T1	16	160	0.14	1.6	0.21	0.7	V_1 V_8	0.07
T2	16	150	0.17	1.6	0.21	0.7	V_2 V_9	0.07
T3	22	160	0.13	1.6	0.21	0.7	V_3 V_{10}	0.07
T4	24	160	0.14	1.6	0.14	0.7	V_4	0.07
T5	15	160	0.13	1.6	0.22	0.7	V_5	0.07
T6	15	160	0.25	1.6	0.22	0.7	V_6	0.07
T7	16	150	0.14	1.6	0.21	0.7	V_7	0.07

Table II shows the vehicle location in the network. It details the period when vehicles leave and arrive in the network. The considered profiles are based on the "Highlights of the 2001 National Household Travel Survey" from DOT in 2001 [11]. Columns refer to each bus where vehicles can leave or enter; the rows refer to the time periods. VXO (D) means that vehicle number "x" left the bus corresponding to the number in the column header to undertake a "D" kilometers trip. VXI symbol indicates that vehicle number "x" arrived in the bus corresponding to the number in the column header.

Table III presents the optimal scheduling results, PSO results are compared with GAMS results for the same problem. The PSO results correspond to a total cost (production cost plus V2G discharge cost) equal to 5609.90 €. GAMS achieves a lower total cost (5313.31 €) than the PSO approach but with a much higher execution time. Presenting a solution only 5.6% higher than GAMS, the PSO approach reached a good solution in a competitive time execution, so we can conclude that it is effective to solve the considered problem. A scenario with no vehicles has also been considered. In this case, execution time has been 5.26 s and 641.67 s, for PSO and GAMS respectively. The objective function dropped to 5545.53 € and 5309.60 €, respectively for PSO and GAMS.

TABLE II. ELECTRIC VEHICLE LOCATION

Period	Bus Number															
	1	2	3	4	11	18	19	21	22	23	24	25	26	27	29	31
6 am					$V_7^O(15)$								$V_{10}^O(15)$			$V_5^O(25)$
7 am	V_{10}^I	V_5^I						V_7^I	$V_2^O(15)$	V_1^O (20)					$V_6^O(70)$	
8 am							V_1^I	V_2^I;V_6^I $V_3^O(15)$				$V_9^O(20)$		$V_4^O(20)$		
9 am							V_3^I		V_4^I		$V_8^O(25)$ V_9^I					
10 am									V_8^I							
11 am									$V_4^O(20)$							
12 am		$V_5^O(5)$		V_4^I			$V_1^O(5)$									
13 pm	$V_{10}^O(5)$		V_5^I	$V_4^O(20)$		V_1^I	$V_3^O(5)$									
14 pm			V_{10}^I $V_5^O(5)$			V_3^I $V_1^O(5)$	V_4^I									
15 pm		V_5^I	$V_{10}^O(5)$			$V_3^O(5)$	V_1^I $V_4^O(20)$									
16 pm	V_{10}^I			V_4^I			V_3^I	$V_2^O(15)$								
17 pm							$V_1^O(20)$	$V_6^O(70)$ $V_7^O(15)$	V_2^I							
18 pm				$V_4^O(20)$	V_7^I					V_1^I	$V_9^O(20)$				V_6^I	
19 pm	$V_{10}^O(15)$	$V_5^O(25)$					$V_3^O(15)$		V_4^I $V_8^O(25)$			V_9^I				
20 pm								V_3^I			V_8^I		V_{10}^I			V_5^I
21 pm									$V_4^O(20)$							
22 pm														V_4^I		

TABLE III. RESULT COMPARISON

Methodologies	Time (s)	Total Production Cost (€)	V2G Discharge Cost (€)	Total Cost (€)
GAMS	858.34	5291.45	21.86	5313.31
PSO	5.80	5557.34	52.57	5609.90

TABLE IV. PSO METHODOLOGY PERFORMANCE AND PARAMETERS

Performance	Total Cost (€)
Maximum	5618.71
Mean	5609.72
Minimum	5599.35
Standard Deviation	5.11
Time (s)	5.80
Case Study Parameters	
Iterations	120
Number Particles	20
Mutation Factor δ	0.90
Maximum Velocity	0.01
Minimum Velocity	-0.01

In this case study 30 PSO run trials were performed; maximum and minimum values are depicted in Table IV as well as the average time execution and PSO parameters. Minimum and maximum velocities for each particle are also shown.

Figures 3, 4 and 5 compare GAMS and PSO methodologies results. Figure 3 depicts the load demand and total V2G charge values for each time period. Both methodologies allocate the V2G charge in the off-peak periods, when the price of energy bought to the supplier is lower than the price of the peak periods. PSO methodology identifies these hours, however, don't use the optimal quantity, when comparing with the reference methodology (GAMS). Some V2G charge present in peak period is due to the minimum trip constraint (see equation 11).

Figure 4 shows the total charge and discharge values. Analyzing the energy sources costs V2G charge is scheduled in the period 4 as expected, whereas the PSO solution spreads the V2G charge along more periods. PSO uses a heuristic that charges V2G in periods when the energy sources costs are lower but does not seem to fully taking advantage of these periods for charging purposes. In GAMS solution, V2G discharging periods happen mainly in periods 20 and 21 because the energy source costs are higher than discharge price. In PSO solution, V2G discharging occurs in more periods because there is no heuristic information to control V2G discharge. This means solutions are selected according to the PSO fitness.

Figure 5 presents the total battery storage in each period. GAMS uses off-peak periods to charge V2G batteries. After that, the batteries are used during vehicle trips. At the end of the day, when V2G are connected to the grid, V2G batteries storage levels decrease. They are used as a supplier when the discharge price is lower than the other sources costs. In this case study, PSO uses V2G batteries in a more intensive way than GAMS. PSO considers the worst scenario of the network as described in section II and thus tries to alleviate network problems by increasing DG production and/or V2G discharges. In certain periods (7, 8, 9 and 10) the batteries storage levels decrease because PSO uses V2G discharge to guarantee that network constraints are not violated. This happens because V2G discharge price is lower than DG production costs.

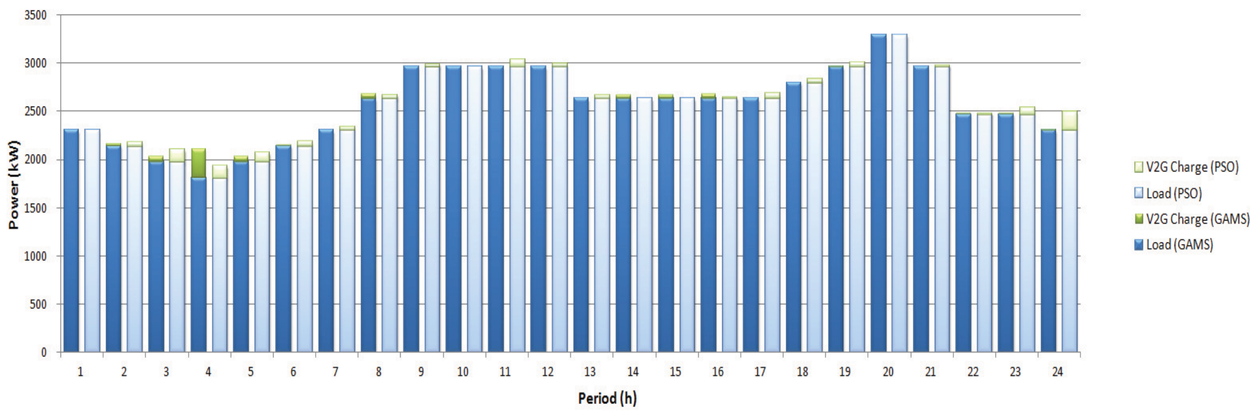

Figure 3. Load and V2G Charge Profile

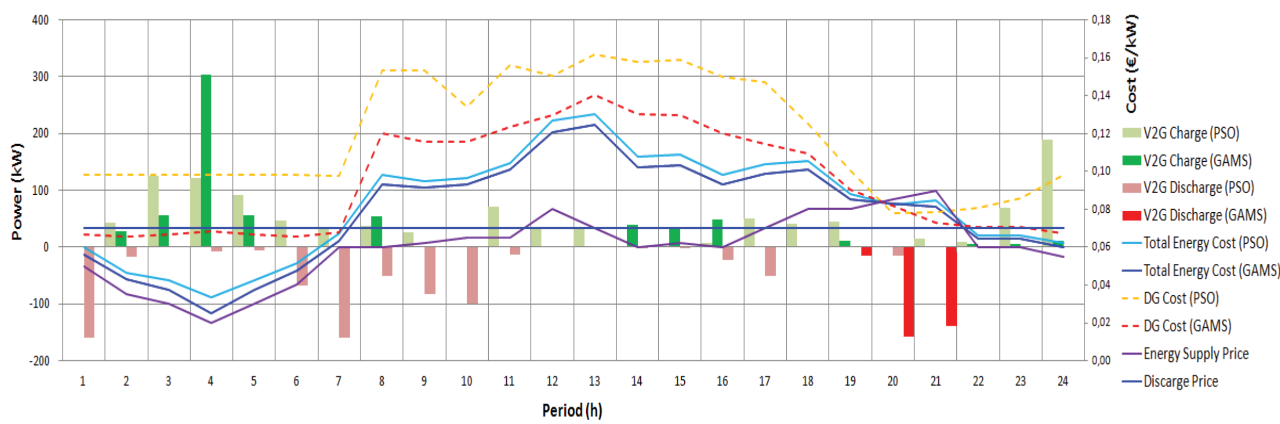

Figure 4. Total Charge and Discharge Profile

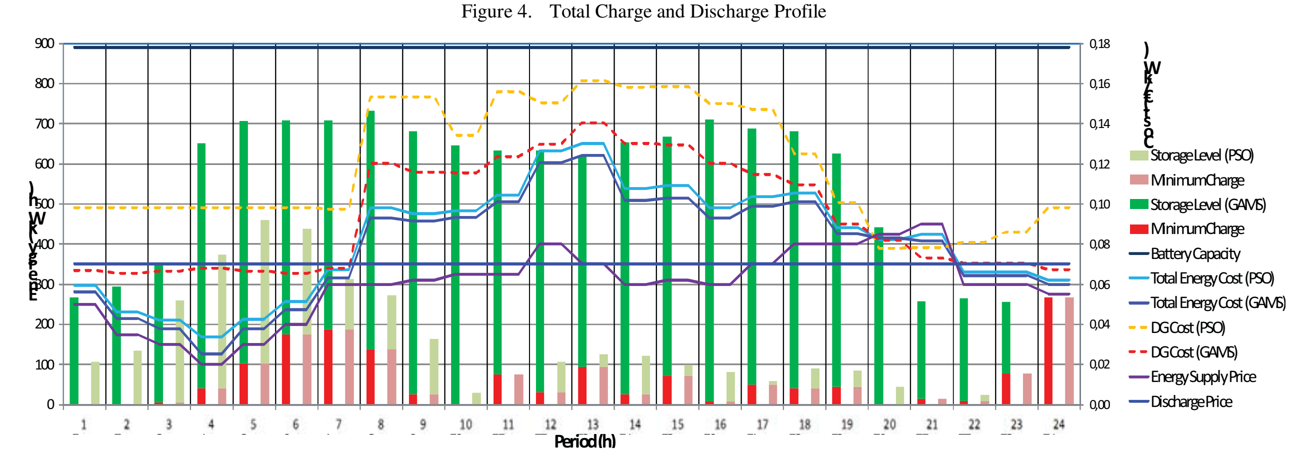

Figure 5. Total Battery Storage Profile

The proposed methodology has been test with higher dimension networks, namely with a 208 bus network and 5.000 EVs, for which the execution time average is around 10 seconds.

V. Conclusions

This paper proposes a Particle Swarm Optimization (PSO) approach to solve the optimal energy resources scheduling including V2G resources. A case study with a 32 bus network and 50 electric vehicles is presented and the results are compared against a deterministic approach (MINLP). The results prove the effectiveness of the proposed methodology for this type of problem in terms of solution quality (only 5.6% of difference in objective function value). PSO execution time is 148 times faster than the deterministic approach for this case study.

Future work will consist in integrating the proposed PSO approach with models of demand-response and ac power flow. More realistic electric vehicles profiles and battery models are also under consideration.

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