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Decision support tool for Virtual Power Players: Hybrid Particle Swarm Optimization applied to Day-ahead Vehicle-To-Grid Scheduling

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***Abstract*— This paper presents a decision support tool methodology to help virtual power players (VPPs) in the Smart Grid (SGs) context to solve the day-ahead energy resource scheduling considering the intensive use of Distributed Generation (DG) and Vehicle-To-Grid (V2G). The main focus is the application of a new hybrid method combing a particle swarm approach and a deterministic technique based on mixed-integer linear programming (MILP) to solve the day-ahead scheduling minimizing total operation costs from the aggregator point of view. A realistic mathematical formulation, considering the electric network constraints and V2G charging and discharging efficiencies is presented. Full AC power flow calculation is included in the hybrid method to allow taking into account the network constraints. A case study with a 33-bus distribution network and 1800 V2G resources is used to illustrate the performance of the proposed method.**

***Index Terms*—hybrid technique, mixed-integer linear programing, optimal scheduling, particle swarm optimization, vehicle-to-grid.**

NOMENCLATURE

Δt	Period *t* duration (e.g. 15 min., 30 min., 1 hour)
$\eta_{c(V)}$	Grid-to-Vehicle efficiency when vehicle *V* is in charge mode
$\eta_{d(V)}$	Vehicle-to-Grid efficiency when vehicle *V* is in discharge mode
θ_b	Voltage angle at bus *b* (rad)
θ_b^{max}	Maximum voltage angle at bus *b* (rad)
θ_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*
$c_{Supplier(S,t)}$	Energy price of external supplier *S* 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*
$E_{Stored(V,t)}$	Energy stored in vehicle *V* at the end of period *t*
$E_{Trip(V,t)}$	Vehicle *V* energy consumption 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*
$P_{Charge(V,t)}$	Power charge of vehicle *V* in period *t*
$P_{Charge(V,t)}^b$	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*
$P_{DG(DG,t)}^b$	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*

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$P_{Discharge(V,t)}$	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*
$P^{b}_{Supplier(S,t)}$	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 bus *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 bus *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 bus *b* and *k*
y_{Shunt_b}	Shunt admittance of line connected to bus *b*

I. INTRODUCTION

Despite the promising scenario for the Distributed Energy Resources (DER) growth in Smart Grids (SGs), there are important aspects to consider, both of economic and technical nature. Issues such as the dispatch ability (namely for wind and photovoltaic technologies), the participation of small producers in the market and the high maintenance costs are problems that must be overcome to take advantage of an intensive use of DER [1].

Aggregating strategies can enable owners of renewable generation to gain technical and commercial advantages, achieving higher profits enabled by the specific advantages of a mix of several generation technologies and overcoming serious disadvantages of some technologies [2].

The aggregation of DER gives place to a new concept: the Virtual Power Player (VPP). VPPs are multi-technology and multi-site heterogeneous entities. In the scope of a VPP, producers can ensure their generators are optimally operated. At the same time, VPPs will be able to commit to a more robust generation profile, raising the value of non-dispatchable generation technologies [3].

In this context, VPPs require appropriate tools to ensure adequate scheduling of the aggregated resources. In this work the day-ahead scheduling problem is considered to minimize operation costs, namely energy costs, regarding the management of these resources in the smart grid context including Electric Vehicles (EVs). The basic idea of the problem is to schedule the energy generation considering all the available resources, such as Distributed Generation (DG) (photovoltaic panels, wind turbines, EVs) to match load demand in each hour for the successive day in future electricity grids, also known as smart grid.

In fact, large complex problems such as the ones in future power systems, characterized by an intensive use of DER, are hard to be addressed with deterministic approaches due to the time constraints related to operation tasks. Deterministic optimization techniques have difficulties in dealing with uncertain variables and require increasing computational resources to deal with real-world problems [4, 5].

Therefore, some alternative techniques, coming from Artificial Intelligence (AI), like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have been used to address this purpose. GA techniques are based on an algorithm that draws inspiration from the field of evolutionary biology, offering operators for crossover, mutation and selection of the best solutions. For certain optimization problems though, the overhead resulting from the application of these operators makes this technique less efficient than other simpler algorithms, such as the PSO [6, 7].

Conventional methods require the optimization function to be at least twice differentiable and convex. Most of the optimization problems in power systems do not have these characteristics. Methods coming from the AI become an alternative to conventional optimization technique to solve real-world problems having non-convexity, nondifferentiability and discontinuity. However, the evolutionary methods are suitable for many power system problems, the premature convergence and stagnation are some problems of these methods which sometimes compromise the quality of the solution. Hybrid methods based on conventional and evolutionary optimization can overcome the short comings of both [8, 9].

This paper results from the continuous research by the authors on the large-scale DER with V2G resources. Previous approaches have been presented by the authors in [4, 5] . This paper presents a new approach, namely a hybrid method based on PSO and a deterministic MILP technique approach. The proposed methodology has the objective of solving the optimal scheduling considering the point of view of an aggregator using different resources, with emphasis on distributed generation. A case study considering a 33-bus distribution network with 66 distributed generation plants, 10 energy suppliers, 32 loads and 1800 EVs is presented.

This paper is organized as follows: section II presents the energy resource scheduling problem and its mathematical formulation. Section III explains the developed Hybrid PSO (HPSO) methodology to solve the DER scheduling problem. A case study is presented in Section IV. Finally, section V presents the conclusions of the paper.

II. ENERGY RESOURCE SCHEDULING PROBLEM

This section presents the mathematical formulation of the day-ahead DER scheduling including V2G. The optimization presents a cost objective function that can be considered by the aggregator aiming to minimize the total operation cost.

A. *Problem formulation*

This methodology is used to support the aggregator to obtain an adequate energy resource management for the next day, including EVs resources and assuming that every vehicles has V2G capability. In terms of problem description, the aggregator has contracts for managing the resources installed in the grid, including load demand. The load demand can be satisfied by the distributed generation resources, by the discharge of EVs, and by external suppliers (namely retailers, the electricity pool). The use of V2G discharge, and the respective charge, considers V2G user profiles and their requirements. The objective function (1) is as follows:

$$\min \quad Total\,Operation\,Cost = \sum_{t=1}^{T}\left[\left(\begin{array}{l}\sum_{DG=1}^{N_{DG}}\left(P_{DG(DG,t)}\times c_{DG(DG,t)}+P_{GCP(DG,t)}\times c_{GCP(DG,t)}\right)+\\ \sum_{S=1}^{N_S}P_{Supplier(S,t)}\times c_{Supplier(S,t)}+\\ \sum_{V=1}^{N_V}\left(P_{Discharge(V,t)}\times c_{Discharge(V,t)}-P_{Charge(V,t)}\times c_{Charge(V,t)}\right)+\\ \sum_{L=1}^{N_L}P_{NSD(L,t)}\times c_{NSD(L,t)}\end{array}\right)\times\Delta t\right] \tag{1}$$

The function considers the minimization of all costs, namely DG, energy acquisition to external suppliers, the V2G discharge and charge energy, the non-supplied demand, and the generation curtailment power [4, 5]. The use of *Δt* allows different period *t* duration. For instance, for 30 minutes period *t* duration, the value of *Δt* should be 0.5 if the costs are specified in an hour basis.

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*:

$$\begin{array}{l}\sum_{DG=1}^{N_{DG}^b}\left(P_{DG(DG,t)}^b-P_{GCP(DG,t)}^b\right)+\sum_{S=1}^{N_S^b}P_{Supplier(S,t)}^b+\\ \sum_{L=1}^{N_L^b}(P_{NSD(L,t)}^b-P_{Load(L,t)}^b)+\sum_{V=1}^{N_V^b}(P_{Discharge(V,t)}^b-P_{Charge(V,t)}^b)=\\ \sum_{k=1}^{N_B}V_{b(t)}\times V_{k(t)}\left(G_{bk}\cos\left(\theta_{b(t)}-\theta_{k(t)}\right)+B_{bk}\sin\left(\theta_{b(t)}-\theta_{k(t)}\right)\right)\\ \forall t\in\{1,..,T\};k\neq b;N_V^b=N_V^{b\_noShift}+N_V^{b\_Shift}\times Z_{(V,t)}\end{array} \tag{2}$$

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

- Bus voltage magnitude and angle limits. Each network bus has voltage limits that have to be maintained:

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

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

- Line thermal limits. Each network line has a maximum admissible power flow:

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

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

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

- MV/LV power transformers limits:

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

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

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

- Maximum distributed generation limit in each period *t.* A binary variable is necessary to schedule the units. A value of 1 means that the unit is connected:

$$P_{DG(DG,t)} \le X_{DG(DG,t)} \times P_{DGMaxLimit(DG,t)}$$
$$P_{DG(DG,t)} \ge X_{DG(DG,t)} \times P_{DGMinLimit(DG,t)} \quad (11)$$
$$\forall\, t \in \{1,...,T\}; \forall\, DG \in \{1,..., N_{DG}\}$$

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

- Upstream supplier maximum limit in each period *t:*

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

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

- Vehicle technical limits in each period *t:*
  - The vehicle charge and discharge are not simultaneous. Two binary variables are necessary for each vehicle:

$$X_{(V,t)} + Y_{(V,t)} \le 1$$
$$\forall t \in \{1,...,T\};\ \forall V \in \{1,..., N_v\}; X_{(V,t)} \text{ and } Y_{(V,t)} \in \{0,1\} \quad (15)$$

  - Battery balance for each EV. The energy consumption for period *t* travel has to be considered jointly with the energy remaining from the previous period and the charge/discharge occurred in the period:

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

  - Discharge limit for each EV considering battery discharge rate. When connected to the grid the vehicle cannot discharge to the grid more than the admissible rate:

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

  - Charge limit for each EV considering battery charge rate. When connected to the grid the vehicle cannot charge the battery more than the admissible safety rate:

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

  - Vehicle battery discharge limit considering the battery balance. The vehicle cannot discharge more than the available energy in the battery:

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

  - Vehicle battery charge limit considering the battery capacity and the previous charge status. The vehicle cannot charge more than the battery limit capacity:

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

  - Battery capacity limit for each EV:

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

- 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 an unexpected travel in each period:

$$E_{Stored(V,t)} \ge E_{MinCharge(V,t)} \quad (22)$$
$$E_{MinCharge(V,tLast)} \ge E_{Trip(V,t)}\ \ \forall t \in \{1,...,T\}; \forall V \in \{1,..., N_V\} \quad (23)$$

III. HYBRID PARTICLE SWARM OPTIMIZATION

This section presents the HPSO methodology to solve the day-ahead V2G scheduling problem.

The hybrid technique consists in two methods. Firstly, a deterministic technique is used to solve the MILP problem, namely the formulation presented in section II A except from the network constraints (2-10), using a CPLEX solver in GAMS [10]. Secondly, a PSO approach is used to evaluate the solution provided by the first method. A radial distribution system power flow is used [11] to verify the network conditions during the swarm evolution in PSO. The power losses are compensated by the energy suppliers or DG generators. Equations (2-10) are handled by the PSO approach.

The MILP model consists of 88.224 binary variables (2 binary variables per vehicle and per period to control the charging and discharging (15) of 1800 EVs in addition to one binary variable for each of the 66 DG units and 10 energy suppliers (11-12). The number of continuous variables in the model is 137.376 corresponding to the active and reactive power of loads and generators and the charging and discharging power of EVs, as well as the stored energy in the batteries. In the second stage of the hybrid approach the PSO uses only 46.848 continuous variables (one variable for each EV in which a positive value corresponds to the charge and a negative value corresponds to the discharge and two variables for each generator). Fig. 1 presents the flowchart of the described HPSO method.

The penalties are set empirically in the PSO approach to identify solutions with constraint violations. A value of 1000 is added to the fitness function if the available generation (including DG, V2G discharges and energy suppliers) does not satisfy the required load demand according to the power flow results; a value of 100 is added to the fitness function for each network bus undervoltage or overvoltage according to the power flow results; a value of 100 is added to the fitness function for each violation verified in the network lines current capacity according to the power flow results.

The constraints of EVs (16-23) are checked during the evaluation phase before the fitness calculation. If the values from the swarm solutions are not according to the constraint limits, e.g., battery limits and charging/discharging limits, the solution is corrected to match the constraints limits. This is called a direct repair method. A direct repair method can be used instead of the indirect repair method (penalty factors) providing an efficient way of correcting solutions before evaluating the fitness function [12].

A signaling method presented by the authors in [13] is adapted and used in the current paper to help PSO escaping violations and improving the fitness function. When a network bus undervoltage is found the mechanism will try to discharge more vehicles and increase the DG reactive power generation in the geographic zone by marking the appropriate variables; when a network bus overvoltage is found the mechanism will try to increase the charging of vehicles and decrease the DG reactive power generation in the geographic zone by marking the appropriate variables; when network lines violations occur the mechanism marks V2G variables in order to attempt to reduce the charging and the DG generators to increase the production. In order to improve the fitness function, V2G charges are marked when V2G charge price is lower than mean generation cost and V2G discharges are marked when V2G discharge price is lower than mean generation cost. More comprehensive information on how the signaling method works can be found in [13].

IV. CASE STUDY

This section presents a case study to illustrate the application of the proposed method to the scheduling problem in the context of smart grids. A 33-bus distribution network present in [4] is used for the test case. The paper presents the results for a scenario using 1800 EVs. This number is adequate for the dimension of the MV distribution network under study considering a high penetration of EVs in 2040. The EVs scenario are created using EVeSSi, which is an innovative tool [14], developed by the authors, to generate the EVs scenarios and model the behavioral pattern of the drivers in the context of smart grids. This tool enables the generation of detailed realistic scenarios for EVs and hybrids specifically for distribution networks environment using a built-in movement simulator considering users' travelling constraints.

The work was developed in MATLAB R2010a 32 bits and GAMS 22.9 32 bits software [10]. The case study in this paper have been tested on one machine with two Intel® Xeon® X5650 (12MB Cache, 2.66 GHz, 6.40 GT/s Intel® QPI) processors, each one with 6 cores, 30GB of Random-Access-Memory (RAM) and Windows Server Enterprise 64 bits operating system.

Fig. 2 presents the resource scheduling achieved in the HPSO with the MILP initial solution. The results obtained with the HPSO approach disclose a better solution in terms of total operation cost (see Table I). The peak load and the average load are also lower in the HPSO approach. Fig. 3 presents the battery State Of Charge (SOC) for the PSO and HPSO approach. For the PSO approach, in the first period, the EVs start with a total of 17.7 MWh corresponding on average to 64% of the battery capacity (27.6 MWh).

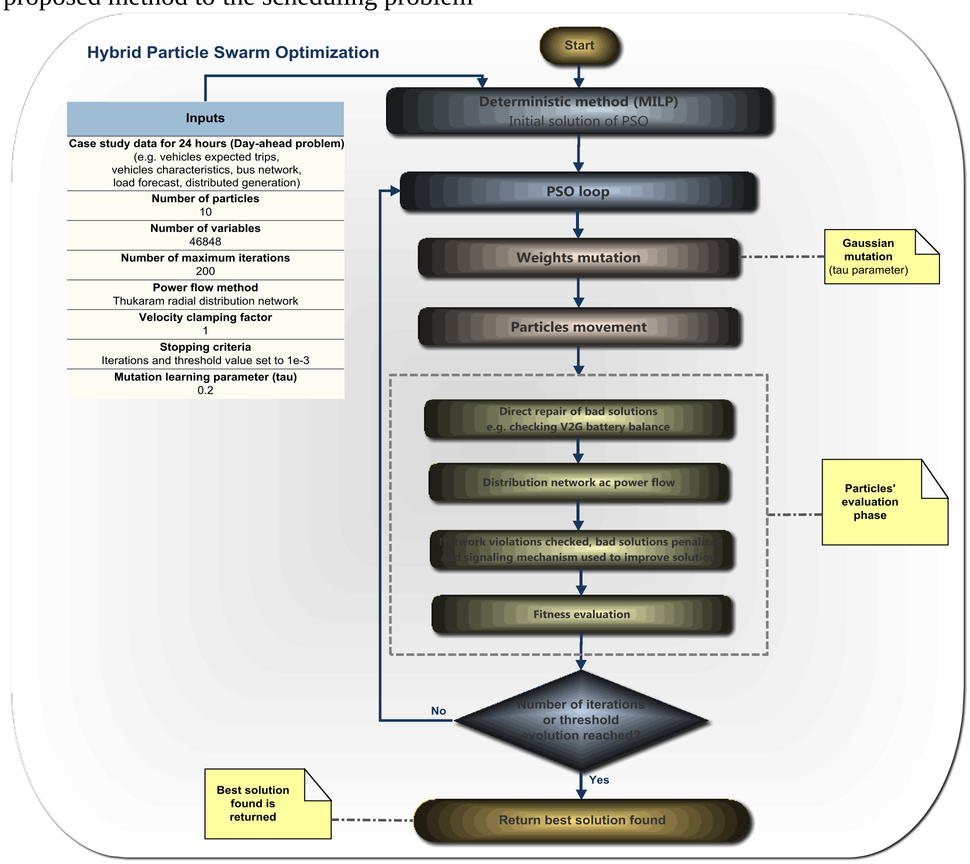

Figure 1. Flowchart of the HPSO.

In the last period (24) the EVs end up with 13.3 MWh after charges, discharges and travels along the day. In the HPSO approach the EVs end up with 7.6 MWh but still satisfying the minimum limit for the last period.

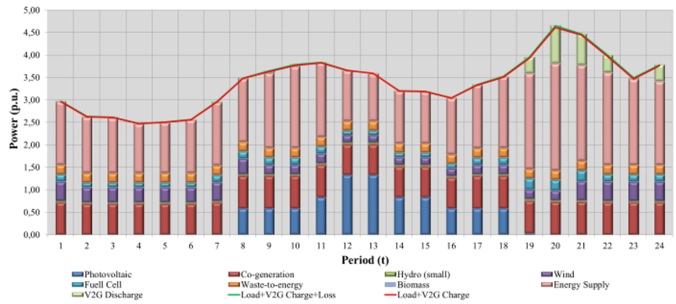

Figure 2. Resource scheduling in HPSO.

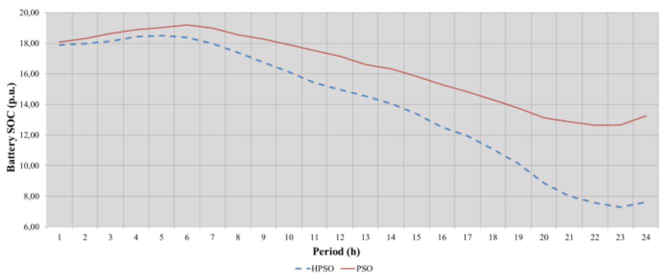

Figure 3. Battery (SOC) in PSO and HPSO.

Fig. 4 presents the voltage profile for period 20 (the peak period) in each network bus for the PSO and HPSO. The HPSO presents a better voltage profile in almost every bus.

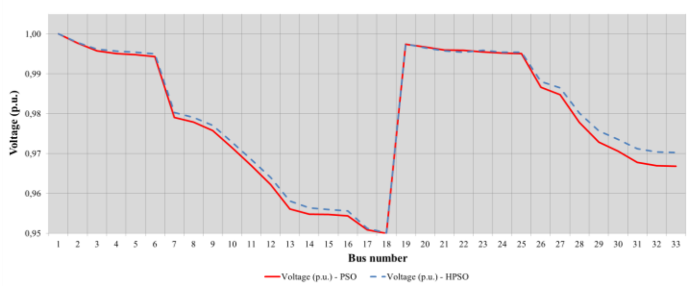

Figure 4. Voltage profiles in p.u. for period 20.

Table I presents the results for a robustness test of the PSO and HPSO approaches over a total of 100 trials. The execution time is lower using the PSO but total operation cost is higher. The 12% increase in the HPSO execution time is compensated by the lower operation cost that it allows to achieve.

TABLE I. PSO AND HPSO ROBUSTNESS TEST RESULTS - 100 RUNS

Technique	Average execution time (seconds)	Min. operation cost (m.u.)	Average operation cost (m.u.)	Max. operation cost (m.u.)
PSO	98 (100%)	6510	6531 (100%)	6563
HPSO	110 (112%)	6287	6324 (97%)	6353

V. CONCLUSIONS

The paper presents a Hybrid PSO approach to deal with the day-ahead energy resources scheduling including vehicle-to-grid in the context of smart grids and VPP operators. The hybrid approach uses a deterministic MILP method and a PSO technique. The deterministic method runs without network constraints and provides an initial solution to the PSO method which considers the network constraints.

A comparison between PSO and HPSO is made in a 33-bus distribution network system with high penetration of DG and a scenario with 1800 gridable vehicles. The results and the robustness test show that the execution time is slightly higher (12%) when compared with the PSO based approach but the solution is 3% better in terms of the total average operation cost.

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