Multi-objective Parallel Particle Swarm Optimization for Day-ahead Vehicle-To-Grid Scheduling

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***Abstract*—This paper presents a methodology for multi-objective day-ahead energy resource scheduling for smart grids considering intensive use of distributed generation and Vehicle-To-Grid (V2G). The main focus is the application of weighted Pareto to a multi-objective parallel particle swarm approach aiming to solve the dual-objective V2G scheduling: minimizing total operation costs and maximizing V2G income. A realistic mathematical formulation, considering the network constraints and V2G charging and discharging efficiencies is presented and parallel computing is applied to the Pareto weights. AC power flow calculation is included in the metaheuristics approach 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.**

Keywords—multi-objective, Pareto front, particle swarm optimization, scheduling, vehicle-to-grid.

NOMENCLATURE

Δt	Period t duration (e.g. 15 min., 30 min., 1 hour)
$\eta_{c(V)}$	Grid-to-Vehicle efficiency when the vehicle V is in charge mode
$\eta_{d(V)}$	Vehicle-to-Grid efficiency when the vehicle V is in discharge mode
θ_b	Voltage angle at bus b (rad)
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 b row and k column
$c_{Charge(V,t)}$	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
$P_{Discharge(V,t)}$	Power discharge of vehicle V in period t
$P_{Discharge(V,t)}^b$	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
$P_{GCP(DG,t)}^b$	Generation curtailment power in DG unit at bus b in period t
$P_{Load(L,t)}^b$	Active power demand of load L at bus b in period t

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$P_{NSD(L,t)}$	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

Engineers are daily faced with optimization problems that require conflicting objectives to be met. Evolutionary algorithms are often well-suited for optimization problems involving several, often conflicting objectives [1,2]. This paper deals with a weighted Pareto Parallel Particle Swarm Optimization (PSO) approach to solve multi-objective-based problems. Evolutionary characteristics are used in PSO, namely the mutation to improve its effectiveness [3,4]. Parallelization is also used as it helps reducing execution time and/or resources allocation of multi-objective problems in evolutionary algorithms [5].

In [6] a PSO methodology was applied to a V2G scheduling including distributed generation based on renewable energy resources. The methodology was compared with a conventional technique approach and the results of the case study show that PSO is about 148 times faster than Mixed-Integer Linear Programming in that case study. However, the work lacks the inclusion of a power flow model in the metaheuristics methodology approach. Instead, a validation of solution after optimization is made. An approach using power flow in [6] could result in a better solution quality and avoid network solution validation after the optimization. Besides that, vehicles are aggregated into groups of 10 to reduce variables quantity. An improved model using individual V2G contracts should be further investigated in a real-world like scenario. Further investigation is required in order to test metaheuristics multi-objective functions in this type of Distributed Energy Resources (DER) scheduling as well as real-world distribution systems.

Departing from the work presented in [6], the proposed methodology has steadily evolved presenting the following improvements:

- Realistic mathematical formulation, considering the network constraints and V2G charging and discharging efficiencies;
- Realistic and improved V2G scenario and profiles using a new tool called Electric Vehicle Scenario Simulator (EVeSSi) [7] developed by the authors;
- Faster, redesigned and reengineered metaheuristics called Signaled Particle Swarm Optimization proposed by the authors in [8] and used as the basis to solve the present problem;
- Multi-objective problem considering minimization of the total operation cost and maximization of the vehicle-to-grid profits;
- Parallel computing applied to Pareto weights.

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 and V2G but also from the point of the view of the Electric Vehicles (EVs) owners who want to maximize their income by selling energy from their vehicles' batteries. 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 PSO methodology to solve the multi-objective 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 V2G scheduling. The optimization problem presents a dual objective function that can be considered by the aggregator aiming at minimizing the total operation cost and maximizing the V2G income.

A. Problem formulation

This methodology is used to support the aggregator to obtain an adequate energy resource management for the next day, including electric vehicles resources, in the smart grid context. 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, consider V2G user profiles and requirements. The energy resource scheduling problem is a multi-objective Mixed Integer Non-Linear Programming (MINLP) problem. The first objective function (1) considers the minimization of all costs associated with the energy resources. The energy resource model includes: distributed generation, energy acquisition to external suppliers, the V2G discharge and charge energy, the non-supplied demand, and the generation curtailment power [6, 9]. The second objective function (2) considers the maximization of the V2G income that corresponds directly to the aggregator payments and for using the V2G resources.

In a day-ahead context, it is necessary to apply a multi-period optimization; the presented formulation is generic for a specified time horizon (from period t=1 to t=T).

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

$$\max \quad V2G\,Income = \sum_{t=1}^{T}\left[\left(\sum_{V=1}^{N_V}\left(\begin{array}{l}P_{Discharge(V,t)}\times c_{Discharge(V,t)}-\\ P_{Charge(V,t)}\times c_{Charge(V,t)}\end{array}\right)\right)\times\Delta t\right] \quad (2)$$

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 cost function is specified in an hour basis and 1.0 for 60 minutes (1 hour). In order to improve the solution feasibility the mathematical model includes variables concerning the generation curtailment power ($P_{GCP(DG,t)}$) and non-supplied demand ($P_{NSD(L,t)}$). $P_{GCP(DG,t)}$ is important because the aggregator can establish contracts with uninterruptible generation ("take or pay" contracts) with, for instance, producers based on renewable energy sources. In extreme cases, when the load is lower than the uninterruptible generation the value of $P_{GCP(DG,t)}$ is different from zero. $P_{NSD(L,t)}$ is positive when the available resources are not enough to satisfy load demand.

The minimization of objective function (1) and the maximization of the (2) is subject to the following constraints:

- The network active (3) and reactive (4) power balance with power loss in each period t:

$$\begin{array}{l}\sum_{DG=1}^{N_{DG}^b}\left(P_{DG(DG,t)}^b-P_{GCP(DG,t)}^b\right)+\sum_{S=1}^{N_S^b}P_{Supplier(S,t)}^b+\\ \sum_{L=1}^{N_L^b}(P_{NSD(L,t)}^b-P_{Load(L,t)}^b)+\sum_{V=1}^{N_V^b}(P_{Discharge(V,t)}^b-P_{Charge(V,t)}^b)=\\ \sum_{k=1}^{N_B}V_{b(t)}\times V_{k(t)}\left(G_{bk}\cos\left(\theta_{b(t)}-\theta_{k(t)}\right)+B_{bk}\sin\left(\theta_{b(t)}-\theta_{k(t)}\right)\right)\\ \forall t\in\{1,..,T\};\,k\neq b;\,N_V^b=N_V^{b\_noShift}+N_V^{b\_Shift}\times Z_{(V,t)}\end{array} \quad (3)$$

$$\begin{array}{l}\sum_{DG=1}^{N_{DG}^b}Q_{DG(DG,t)}^b+\sum_{S=1}^{N_S^b}Q_{Supplier(S,t)}^b-\sum_{L=1}^{N_L^b}Q_{Load(L,t)}^b=\\ \sum_{k=1}^{N_B}V_{b(t)}\times V_{k(t)}\left(G_{bk}\sin\left(\theta_{b(t)}-\theta_{k(t)}\right)-B_{bk}\cos\left(\theta_{b(t)}-\theta_{k(t)}\right)\right)\\ \forall t\in\{1,..,T\};\,k\neq b\end{array} \quad (4)$$

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

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

$$\theta_b^{min}\leq\theta_{b(t)}\leq\theta_b^{max} \quad \forall\, t\in\{1,...,T\} \quad (6)$$

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

$$\left|V_{b(t)}\times\left(\left[\left(V_{b(t)}-V_{k(t)}\right)y_{bk}\right]^*+\left[V_{b(t)}\times\frac{1}{2}y_{Shunt\_b}\right]^*\right)\right|\leq S_{bk}^{max};\ \forall t\in\{1,..,T\} \quad (7)$$

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

$$\sqrt{\left(\sum_{S=1}^{N_S^b}P_{Supplier(S,t)}^b\right)^2+\left(\sum_{S=1}^{N_S^b}Q_{Supplier(S,t)}^b\right)^2}\leq S_{TFR\_HV/MV(b)}^{\max};\ \forall t\in\{1,..,T\}; \quad (8)$$

- MV/LV power transformers limits:

$$\begin{array}{l}P_{TFR\_MV/LV(b,t)}=\sum_{DG=1}^{N_{DG}^b}\left(P_{DG(DG,t)}^b-P_{GCP(DG,t)}^b\right)\\ +\sum_{L=1}^{N_L^b}(P_{NSD(L,t)}^b-P_{Load(L,t)}^b)+\sum_{V=1}^{N_V^b}(P_{Discharge(V,t)}^b-P_{Charge(V,t)}^b)\end{array} \quad (9)$$

$$Q_{TFR\_MV/LV(b,t)}=\sum_{DG=1}^{N_{DG}^b}\left(Q_{DG(DG,t)}^b\right)-\sum_{L=1}^{N_L^b}\left(Q_{Load(L,t)}^b\right) \quad (10)$$

$$\sqrt{\left(P_{TFR\_MV/LV(b,t)}^{2}+Q_{TFR\_MV/LV(b,t)}^{2}\right)} \leq S_{TFR\_HV/MV(b)}^{\max} \quad \forall t \in \{1,..,T\}; \tag{11}$$

- 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:

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

$$Q_{DG(DG,t)} \leq X_{DG(DG,t)} \times Q_{DGMaxLimit(DG,t)}$$
$$Q_{DG(DG,t)} \geq X_{DG(DG,t)} \times Q_{DGMinLimit(DG,t)} \tag{13}$$
$$\forall t \in \{1,...,T\}; \forall DG \in \{1,...,N_{DG}\}$$

- Upstream supplier maximum limit in each period t:

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

$$Q_{Supplier(S,t)} \leq Q_{SupplierLimit(S,t)} \quad \forall t \in \{1,...,T\}; \forall S \in \{1,...,N_S\} \tag{15}$$

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

$$X_{(V,t)} + Y_{(V,t)} \leq 1 \quad \forall t \in \{1,...,T\}; \forall V \in \{1,...,N_V\}; X_{(V,t)} \text{ and } Y_{(V,t)} \in \{0,1\} \tag{16}$$

  - 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:

$$E_{Stored(V,t)} = E_{Stored(V,t-1)} - E_{Trip(V,t)} + \eta_{c(V)} \times P_{Charge(V,t)} \times \Delta t + \frac{1}{\eta_{d(v)}} \times P_{Discharge(V,t)} \times \Delta t \tag{17}$$
$$\forall t \in \{1,...,T\}; \forall V \in \{1,...,N_V\}; E_{Trip(V,t)} = P_{Trip(V,t)} \times \Delta t;$$

  - 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:

$$P_{Discharge(V,t)} \leq P_{DischargeLimit(V,t)} \times X_{(V,t)} \quad \forall t \in \{1,...,T\}; \forall V \in \{1,...,N_V\}; X_{(V,t)} \in \{0,1\} \tag{18}$$

  - 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:

$$P_{Charge(V,t)} \leq P_{ChargeLimit(V,t)} \times Y_{(V,t)} \quad \forall t \in \{1,...,T\}; \forall V \in \{1,...,N_V\}; Y_{(V,t)} \in \{0,1\} \tag{19}$$

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

$$\frac{1}{\eta_{d(V)}} \times P_{Discharge(V,t)} \times \Delta t \leq E_{Stored(V,t-1)} \quad \forall t \in \{1,...,T\}; \forall V \in \{1,...,N_V\}; \Delta t = 1; \tag{20}$$

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

$$\eta_{c(V)} \times P_{Charge(V,t)} \times \Delta t \leq E_{BatCap(V)} - E_{Stored(V,t-1)} \quad \forall t \in \{1,...,T\}; \forall V \in \{1,...,N_V\} \tag{21}$$

  - Battery capacity limit for each EV:

$$E_{Stored(V,t)} \leq E_{BatCap(V)} \quad \forall t \in \{1,...,T\}; \forall V \in \{1,...,N_V\} \tag{22}$$

- 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:

$$E_{Stored(V,t)} \geq E_{MinCharge(V,t)} \tag{23}$$

$$E_{MinCharge(V,tLast)} \geq E_{Trip(V,t)} \quad \forall t \in \{1,...,T\}; \forall V \in \{1,...,N_V\} \tag{24}$$

III. Methodology

This section presents the developed methodology to solve the multi-objective V2G scheduling problem. Firstly, the PSO equations of the proposed approach are shown. Secondly, the problem implementation with PSO and how the constraints of the V2G scheduling are handled is presented. Finally, the weighted Pareto Parallel PSO algorithm is explained.

A. Particle Swarm Optimization equations

The velocity limits are calculated according to equations (25) and (26) in which the velocity clamping factor (C_{factor}) is a parameter that linearly influences the velocity limits. This value should be between 0 and 1.

$$v_{\max} = C_{factor} \times (x_{\max} - x_{\min}) / 2 \tag{25}$$

$$v_{\min} = -v_{\max} \tag{26}$$

where:

$v_{\max}$	Maximum velocity limits of variables
$v_{\min}$	Minimum velocity limit of variables
$x_{\max}$	Upper bounds of variables
$x_{\min}$	Lower bounds of variables
C_{factor}	Velocity clamping factor

The present implementation uses mutation of the strategic parameters (w_k): inertia, memory, and cooperation, introduced in [10]. We have also considered the replication of the particles in order to increase the probability of finding more solutions enhancing the search space. However, due to the added computation time it was not used. Mutation of the strategic parameters is applied directly to the original swarm rather than the replicated swarm as in [10]. At the beginning of the process, the values of these weights are randomly generated between 0 and 1. After that, the particle's weights are changed in each iteration using a Gaussian mutation distribution according to (27):

$$^{*}w_k = w_k + \delta N(0,1) \tag{27}$$

where:

$^{*}w_k$	New mutated weights of particle *k*
w_k	Weights of particle *k*
δ	Learning parameter with a range between 0 and 1

A high value of δ adds more importance to mutation. In every iteration this value is randomly changed where *N(0,1)* is a random number following a normal distribution with mean equal to 0 and variance equal to 1. Once again, the strategic parameters are limited to values between 0 and 1.

Equation (28) allows the calculation of the new particle's velocity that depends on the particle's present velocity, on the best past experience (memory) and on the group's experience (cooperation).

$$^{*}v_{k,j} = {}^{*}w_{k(inertia)} v_{k,j} + {}^{*}w_{k(memory)} \left(b_k - x_{k,j}\right) + {}^{*}w_{k(coop)} \left(bG - x_{k,j}\right) \tag{28}$$

where:

b_k	Best past experience of particle *k*
bG	Best global experience of all the particles
$v_{k,j}$	Velocity of variable *j* of particle *k*
$^{*}v_{k,j}$	New calculated velocity of variable *j* of particle *k*
$x_{k,j}$	Position of variable *j* of particle *k*
$^{*}w_{k(inertia)}$	Inertia weight component of particle *k*
$^{*}w_{k(memory)}$	Memory weight component of particle *k*
$^{*}w_{k(coop)}$	Cooperation weight component of particle *k*

The new positions ($^{*}x_{k,j}$) for each particle are then calculated according to the movement equation (29).

$$^{*}x_{k,j} = x_{k,j} + {}^{*}v_{k,j} \tag{29}$$

where:

$^{*}x_{k,j}$	New calculated position of variable *j* of the particle *k*

After applying the movement equation to each particle, the fitness of new positions is evaluated and the best solution of the swarm group (*bG*) is stored.

The best solution of the swarm group (*bG*) in each iteration is also disturbed according to the following equation:

$$^{*}b_G = b_G + w_{k(perturbation)} \times N(0,1) \tag{29}$$

where:

$^{*}b_G$	Disturbed best solution of the swarm
$w_{k(perturbation)}$	Perturbation weight component of particle *k*

B. *Problem implementation and constraitns handling*

The considered fitness function for the present problem is depicted in equation (31). It considers the total operation cost and V2G income (see equation (1) and (2)). V2G income appears with a negative sign due to the fact that this fitness function is being minimized and the opposite is intended for the V2G income, i.e. to maximize it. Penalties correspond to the violations detected in the evaluation phase (See Fig. 1). The 46,848 variables correspond to the decision variables in the optimization problem regarding the generators active and reactive power and the vehicles charge and discharge. A radial distribution system power flow is used [11] to verify network conditions during swarm evolution. The power losses are compensated by the energy suppliers or DG generators.

$$fitness = \begin{bmatrix} TotalOperationCost \times pw_1 + (-V2GIncome) \times pw_2 \\ + penalties \end{bmatrix} \tag{31}$$

where:

pw_1	Pareto weight concerning the total operation cost objective
pw_2	Pareto weight concerning the V2G income objective

The penalties used in this problem to identify solutions with constraints violations are the following:

- A value of 1000 is added to the fitness function if the available generation (including DG, V2G 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 under-voltage 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.

Direct repair of solutions is also used in the present implementation. The constraints of vehicle battery balance are checked during the evaluation phase before fitness calculation. If the values from swarm solutions are not according to the constraint limits (battery limits and charging/discharging limits) the solution is corrected directly to match constraints. This is called a direct repair method. A direct repair method can be used instead of 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 [8] is adapted and used in the current paper to help the swarm to escape violations and improve fitness function. The mechanism works as follows:

- When a network bus under-voltage 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 over-voltage 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, if the weight w_1 is higher than w_2, 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;
- In order to improve the fitness function, if the weight w_2 is higher than w_1, 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 [8].

Table I presents the configuration used in the presented implementation of PSO for the scheduling problem. The number of iterations was set to 500 iterations.

TABLE I. PARAMETERS OF PSO METHOD

Parameters	Description
Number of particles	10
Inertia Weight	Gaussian mutation weights (initial weights randomly generated between 0 and 1)
Acceleration Coefficient Best Position	
Cooperation Coefficient	
Perturbation Coefficient	
Mutation learning parameter (δ)	0.20
Initial swarm population	Randomly generated between the upper and lower bounds of variables
Stopping Criteria	500 iterations
Velocity Clamping Factor (C_{factor})	1
Max. Positions (x_{max})	Equal to the upper bound of variables
Min. Positions (x_{min})	Equal to the lower bound of variables
Max. Velocities (v_{max})	According to velocity clamping factor equation
Min. Velocities (v_{min})	According to velocity clamping factor equation

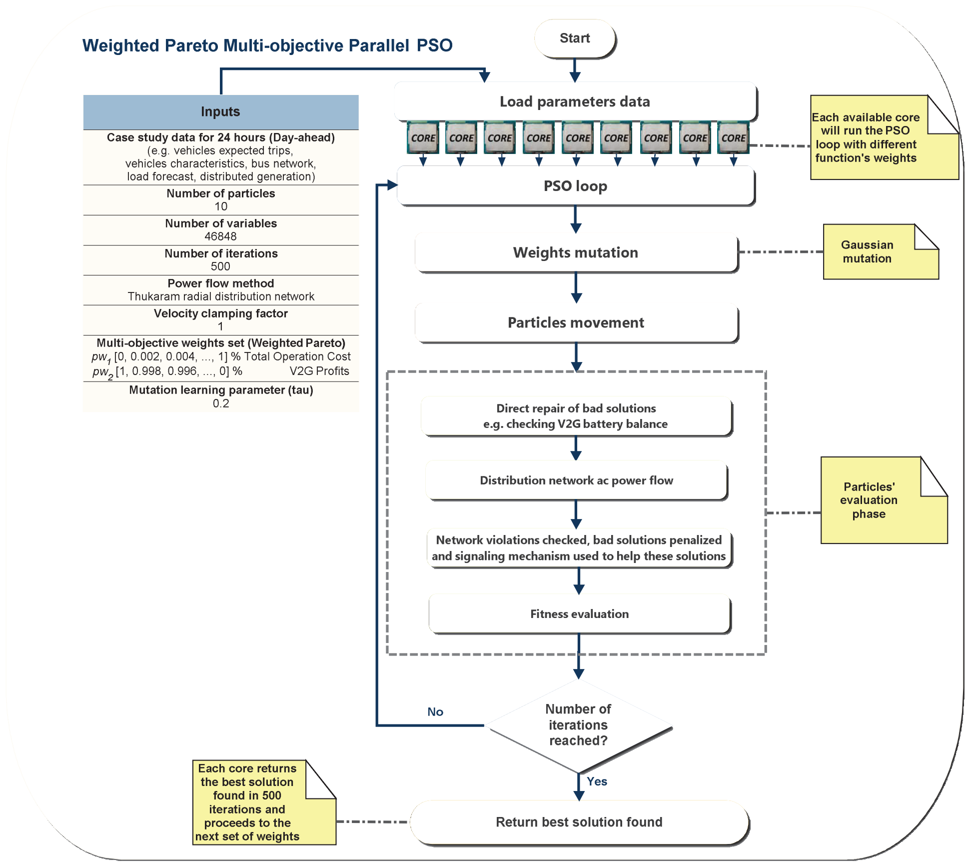

Figure 1. Flowchart of the weighted Pareto parallel PSO.

C. Weighted Pareto Paralell PSO

Weighted Pareto is used for the multi-objective problem presented in section II. Weights from 0 to 1 are assigned to w_1 and w_2, in which the sum of these are always equal to 1. Sequential set of weights are built before starting the optimization. The weight pw_1 corresponds to [0, 0.002, 0.004, …,1] and the weight pw_2 corresponds to [1, 0.998, 0.996, …,0], thus totaling 501 different set of weights in the case study of this paper. The total number of weights can be increased or decreased by changing the step (in this case it is 0.002).

Fig. 1 presents the flowchart of the proposed approach. MATLAB distributed computing and parallel computing toolbox are used to setup the parallel environment. The available cores in the parallel platform process individually each optimization problem with one single set of weights (pw_1 and pw_2) using the described proposed PSO in the previous subsections. When the total set of weights are processed by PSO the weighted Pareto algorithm ends. After running this algorithm, a Pareto front algorithm is used to find the non-dominated solutions and discard the dominated solutions. The basic idea of Pareto front is to pick up the set of points that are Pareto efficient in which these points are non-dominated by other feasible solutions, meaning that they are the best ones of the multi-objective problem. These set of points constitutes the Pareto optimal set [13, 14].

IV. Case Study

This section presents a case study to illustrate the application of the proposed method to a multi-objective scheduling problem in the context of smart grids. A 33-bus distribution network, as in [9], 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 given MV distribution network under study considering high penetration of EVs in 2040. The EVs scenario are created using EVeSSi, which is an innovative tool [7], 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 taking into account users travelling constraints.

The work was developed in MATLAB R2012a 64 bits software. The case study in this paper have been tested on two machines configured to use MATLAB distributed computing and parallel computing: one with two Intel® Xeon® X5650 (12M 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 and an Apple Mac Pro with two 2.4GHz 6-Core Intel Xeon with 6GB of RAM.

Fig. 2 presents the Pareto front for the 501 solutions. Each solution was obtained using a different set of weights as explained before. The Pareto front corresponds to 77 of those 501 solutions. To compute the 501 weighted solutions the algorithm took about 3 hours and 48 minutes in the parallel platform configured with 12 labs (MATLAB instances) each one running on a single core. Without the parallel system it would take about 42 hours. The more set of weights used in the Pareto method presented in this paper, the higher computation time will be required. To mitigate this problem the number of machines in the distributed and parallel computing platform can be increased.

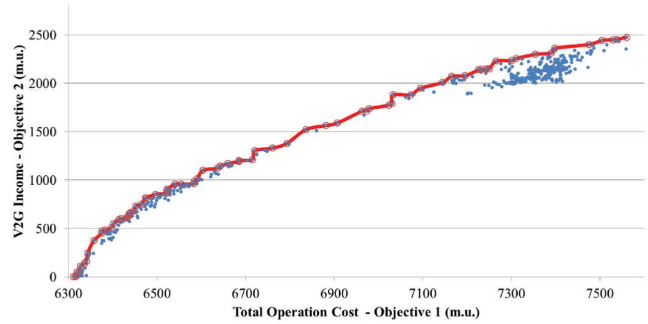

Figure 2. Pareto front for the last iteration (500th) of the PSO approach.

Table II presents three solutions of the Pareto front. These correspond to the solution with the highest V2G income (solution 27); to the solution with equal weights (pw_1 and pw_2) for both objectives (solution 251); and to the solution with the lowest total operation cost (solution 495).

TABLE II. SELECTED PARETO FRONT SOLUTIONS

Weight Set ID	pw_1	pw_2	Total Operation Cost (m.u.)	V2G Income (m.u.)
27	0.052	0.948	7537.49	2451.56
251	0.500	0.500	7230.79	2142.24
495	0.988	0.012	6316.34	0002.22

Fig. 3 presents the evolution of the objective function costs (objective 1 on the right axis and objective 2 on the left axis of the plot) for the solution 495. The presented values correspond to the mean value over 100 runs in each iteration.

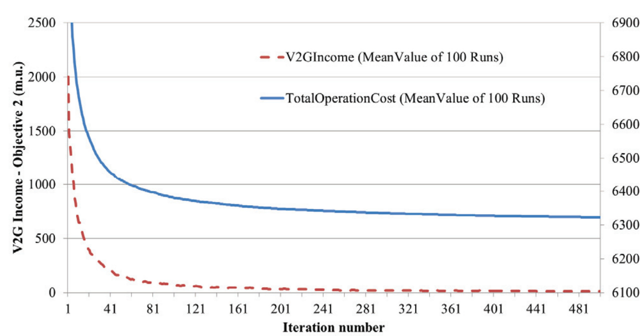

Figure 3. Evolution of the objective function costs (mean value over 100 runs) for weight set ID 495.

Fig. 4 presents the evolution of the fitness value presented in equation (31). The presented values correspond to the mean value over 100 runs in each iteration.

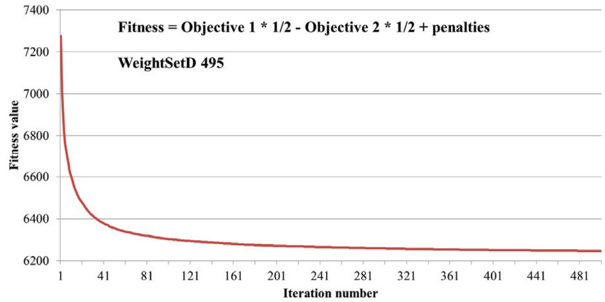

Figure 4. Evolution of the fitness value (mean value over 100 runs) for weight set ID 495.

V. Conclusions

The large amount of energy resources in smart grids, including EVs, leads to an increase in the complexity of operation and planning of distribution networks. In this field, computational intelligence methods have an important role in the smart grid.

This paper presented the evolving work related with the scheduling of V2G in smart grids that authors are working as well as the evolutionary weighted Pareto Parallel PSO approach to solve multi-objective-based problems. Evolutionary characteristics are used in PSO, namely mutation to improve its effectiveness.

The case study illustrates the application of the proposed PSO method to a multi-objective scheduling problem in the context of smart grids. A 33-bus distribution network is used for the test case and the paper presents the results for one scenario using 1800 EVs generated with scenario simulator called EVeSSi, previously developed by the authors.

Parallelization of multi-objective problems in evolutionary algorithms can help reducing execution time as it was demonstrated in the case study depending on the available computer power and on the number of processors.

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