

Modified Particle Swarm Optimization Applied to Integrated Demand Response and DG Resources Scheduling

Pedro Faria, João Soares, Zita Vale, Hugo Morais and Tiago Sousa

Abstract—The elastic behavior of the demand consumption jointly used with other available resources such as distributed generation (DG) can play a crucial role for the success of smart grids. The intensive use of Distributed Energy Resources (DER) and the technical and contractual constraints result in large-scale non linear optimization problems that require computational intelligence methods to be solved.

This paper proposes a Particle Swarm Optimization (PSO) based methodology to support the minimization of the operation costs of a virtual power player that manages the resources in a distribution network and the network itself. Resources include the DER available in the considered time period and the energy that can be bought from external energy suppliers. Network constraints are considered. The proposed approach uses Gaussian mutation of the strategic parameters and contextual self-parameterization of the maximum and minimum particle velocities.

The case study considers a real 937 bus distribution network, with 20310 consumers and 548 distributed generators. The obtained solutions are compared with a deterministic approach and with PSO without mutation and Evolutionary PSO, both using self-parameterization.

Index Terms—Demand response, energy resource management, particle swarm optimization, virtual power player.

NOMENCLATURE

$\theta_{i(t)}$	Voltage angle at bus i in period t
θ_i^{\max}	Maximum voltage angle at bus i
θ_i^{\min}	Minimum voltage angle at bus i
$c_A(DG, t)$	Fixed cost coefficient of DG unit in period t
$c_B(DG, t)$	Linear cost coefficient of DG unit in period t

$c_C(DG, t)$	Quadratic cost coefficient of DG unit in period t
$c_{Ch}(S, t)$	Charge cost of storage S in period t
$c_{Dch}(S, t)$	Discharge cost of storage S in period t
$c_{Red_A}(L, t)$	$RedA$ program cost, for load in period t
$c_{Red_B}(L, t)$	$RedB$ program cost, for load in period t
$c_{Red_C}(L, t)$	$RedC$ program cost, for load in period t
$c_{EAP}(DG, t)$	Excess available power cost coefficient of DG unit in period t
$c_{NSD}(L, t)$	Non-supplied demand cost of load L in period t
B_{ij}	Imaginary part of the element in admittance matrix corresponding to the row and j column
G_{ij}	Real part of the element in admittance matrix corresponding to the row and j column
N_B	Total number of buses
N_{DG}	Total number of distributed generators
N_{DG}^i	Total number of DG units for the bus i
N_k	Total number of lines
N_L	Total number of loads
N_L^i	Total number of L loads for the bus i
N_S	Total number of storage units
N_S^i	Total number of S storage units for the bus i
N_{SP}	Total number of external suppliers
N_{SP}^i	Total number of SP external suppliers for the bus i
$P_{Ch}(S, t)$	Active power charge of storage S in period t
$P_{Ch}(S, t, i)$	Active power charge of storage S at bus i in period t
$P_{DG}(DG, t)$	Active power generation of distributed generation unit DG in period t
$P_{DG}^i(DG, t)$	Active power generation of distributed generation unit DG at bus i in period t

$P_{DGMax(DG,t)}$	Maximum active power generation of distributed generator unit DG in period t
$P_{DGMin(DG,t)}$	Minimum active power generation of distributed generator unit DG in period t
$P_{Dch(S,t)}$	Active power discharge of storage S in period t
$P_{RED-A(L,t)}$	<i>RedA</i> active power reduction, for load L in period t
$P_{RED-A(L,t)}^i$	<i>RedA</i> active power reduction, for load L at bus i in period t
$P_{RED-B(L,t)}$	<i>RedB</i> active load curtailment, for load L in period t
$P_{RED-B(L,t)}^i$	<i>RedB</i> active power reduction, for load L at bus i in period t
$P_{RED-C(L,t)}$	<i>RedC</i> active load curtailment, for load L in period t
$P_{RED-C(L,t)}^i$	<i>RedC</i> active power reduction, for load L at bus i in period t
$P_{EAP(DG,t)}$	Excess available power by DG unit in period t , relative to take or pay contracts
$P_{Load(L,t)}$	Active power demand of load L in period t
$P_{MaxDR-A(L,t)}$	Maximum reduction active power, in <i>RedA</i> program, for load L in period t
$P_{MaxDR-B(L,t)}$	Maximum reduction active power, in <i>RedB</i> program, for load L in period t
$P_{MaxDR-C(L,t)}$	Maximum reduction active power, in <i>RedC</i> program, for load L in period t
$P_{NSD(L,t)}$	Non-supplied demand for load L in period t
$P_{NSD(L,t)}^i$	Non-supplied demand for load L at bus i in period t
$P_{SP(SP,t)}$	Active power acquired from supplier S in period t
$P_{SP(SP,t)}^i$	Active power generation of <i>SP</i> external supplier at bus i in period t
$P_{SPMax(SP,t)}$	Maximum active power of <i>SP</i> external supplier in period t
$Q_{DG(DG,t)}$	Reactive power generation of distributed generation unit DG in period t
$Q_{DG(DG,t)}^i$	Reactive power generation of distributed generation unit DG at bus i in period t
$Q_{DGMax(DG,t)}$	Maximum reactive power generation of distributed generator unit DG in period t
$Q_{DGMin(DG,t)}$	Minimum reactive power generation of distributed generator unit DG in period t
$Q_{Load(L,t)}^i$	Reactive power demand of load L at bus i in period t
$Q_{SP(SP,t)}$	Reactive power acquired from supplier S in period t

$Q_{SP(SP,t)}^i$	Reactive power generation of <i>SP</i> external supplier at bus i in period t
$Q_{SPMax(SP,t)}$	Maximum reactive power of <i>SP</i> external supplier in period t
S_{Lk}^{max}	Maximum apparent power flow established in line k that connect the bus i and j
T	Total number of periods
$\overline{U}_{i(t)}$	Voltage at bus i in polar form in period t
$V_{i(t)}$	Voltage magnitude at bus i in period t
V_i^{max}	Maximum voltage magnitude at bus i
V_i^{min}	Minimum voltage magnitude at bus i
$X_{DG(DG,t)}$	Binary variable of DG unit related to accept the active power generation in period t
\overline{y}_{ij}	Series admittance of line that connect the bus i and j
\overline{y}_{Sh-i}	Shunt admittance of line connected in the bus i

I. INTRODUCTION

ELECTRIC power systems are not the same anymore.

Beginning with the liberalization of electricity markets, several changes have been occurring [1]. The increasingly intensive use of Distributed Generation (DG), the creation of Demand Response (DR) programs [2], [3], and the increasing requirements in terms of energy quality and network reliability have increased the complexity of the infrastructure operation and planning, and aim at bringing to practice the concept of Smart Grid (SG) [4].

In this competitive and complex environment, computational intelligence methods will be required for obtaining solutions for large dimension problems, in an acceptable time [5]. Reference [4] attests the importance of using computational intelligence in many aspects of SG as the system optimization. Particle Swarm Optimization (PSO) is an effective method to determine the solution of large-scale non linear optimization problems [6]. PSO has been successfully applied to several power systems problems [7]–[10].

Aggregation of small-scale distributed resources, as well as their operation, in a competitive environment leads to the creation of Virtual Power Players (VPP) [11]. VPP can aggregate diversity of players and of energy resources, including DR, making them profitable [11].

DR [14], [15] is a very promising resource in the context of electricity markets [12], [13] and SG [14], [16]. A method to determine the DR capacity in a distribution network is presented in [14]. Reference [15] proposes a method to maximize consumers' benefits, regarding their demand reduction in face of the variation in electricity prices and their uncertainties.

In the context of smart grids operated by a virtual power player, the distributed energy resources scheduling gains high relevance due to the competitive environment of smart grid operation. References [17]–[20] report important recent works

on this field. Those works use different resources optimization points of view: [17], [19], and [20] optimize the grid operation, whereas [18] optimizes the consumer installation. Although network constraints are very relevant in this context, these are usually not included in the proposed optimization models. This inclusion can be done embedding the network simulation in the problem formulation or using a simpler approach, namely the validation of the obtained solutions. The later method is used in [17] which uses a real time digital simulator to validate the solutions. References [19], [20] do not consider network constraints. In this way, the present work is innovative in considering the network constraints in the problem formulation. Moreover, most works that propose a heuristic optimization approach do not assess the quality and the efficiency of the solution by comparing it with the solution obtained with a deterministic approach which is done in the present paper.

This paper deals with the integrated management of demand response and DG in the scope of smart grids. An efficient management of these resources requires the use of adequate methods able to cope with the large-scale non linear optimization problems that result from the large number of distributed energy resources and from the need to ensure that the technical and contractual constraints are not violated. The deterministic approaches are not suitable because their execution times are too high for the operation time constraints. Computational intelligence methods have proved to be able to provide good solutions for the envisaged type of problems in much shorter times.

The present paper proposes a particle swarm optimization based methodology to support the minimization of the operation costs of a virtual power player that manages the resources in a distribution network and the network itself. Those resources include the distributed energy resources available in the considered time period and the energy that can be bought from external energy suppliers. Demand response resources are divided into three capacity programs, namely RedA, RedB, RedC, with distinct price and power characteristics. Network constraints are considered using an AC power flow.

The proposed PSO approach uses Gaussian mutation of the strategic parameters and self-parameterization of the maximum and minimum particle velocities, according to the context. This work is an evolution of the work published in [21]. The previous

paper [21] did not consider the network constraints and thus the optimization model used only linear constraints. Additionally, the generation resources are now individually considered whereas in [21] they were aggregated in four distinct types. The proposed PSO approach has been adapted to this new realistic model considering the non linear network constraints. A power flow model [22] has been embedded in the algorithm to enable the analysis of network violations for the swarm solutions. This leads to more accurate solutions than the ones obtained in [21]. The self-parameterization algorithm presented in [21] has been redesigned to deal with the new model.

After this introduction section, Section 2 explains the formulation of the proposed scheduling problem and Section 3 explains the proposed PSO methodology. A case study that considers a real 937-bus distribution network, with 20310 consumers and 548 distributed generators is presented in Section 4. Finally, the most important conclusions of the work are presented in Section 5.

II. ENERGY RESOURCE SCHEDULING FORMULATION

The proposed problem features the minimization of the VPP costs and can be modeled as a mixed-integer non linear optimization problem. The energy resource management requires a multi-period optimization, and the formulation is modeled for a specified time period T . This formulation has been implemented in General Algebraic Modeling System (GAMS) [23]. The objective function can be expressed as (1), shown at the bottom of the page.

This objective function leads to the minimization of the costs considering the reduction of load in three different and successive steps (demand response capacity programs RedA, RedB, and RedC), the costs of the energy provided by the external suppliers, and costs of the energy provided by photovoltaic, wind, Combined Heat and Power (CHP), Municipal Solid Waste (MSW), biomass, fuel cell, hydro, and storage. The problem formulation considers the network constraints accounted by an AC power flow.

The constraints of the problem are the following equations (2)–(13):

- The network active (2) and reactive (3) power balance in each period and in each bus . in each period. During

$$\text{Minimize } C = \sum_{t=1}^T \left[\begin{aligned} & \sum_{DG=1}^{N_{DG}} \left(c_{A(DG,t)} \times X_{DG(DG,t)} + c_{B(DG,t)} \times P_{DG(DG,t)} \right) \\ & + c_{C(DG,t)} \times P_{DG(DG,t)}^2 + P_{EAP(DG,t)} \times c_{EAP(DG,t)} \Big) \\ & + \sum_{SP=1}^{N_{SP}} c_{SP(SP,t)} \times P_{SP(SP,t)} \\ & + \sum_{L=1}^{N_L} \left(c_{RED-A(L,t)} \times P_{RED-A(L,t)} + c_{RED-B(L,t)} \times P_{RED-B(L,t)} \right) \\ & + c_{RED-C(L,t)} \times P_{RED-C(L,t)} + P_{NSD(L,t)} \times c_{NSD(L,t)} \Big) \\ & + \sum_{S=1}^{N_S} \left(c_{Dch(S,t)} \times P_{Dch(S,t)} - c_{Ch(S,t)} \times P_{Ch(S,t)} \right) \end{aligned} \right] \quad (1)$$

the operation of a power system, both active and reactive power generation must meet the verified demand.

$$\begin{aligned}
& \sum_{DG=1}^{N_{DG}} \left(P_{DG(DG,t)}^i - P_{EAP(DG,t)}^i \right) \\
& + \sum_{SP=1}^{N_{SP}} P_{SP(SP,t)}^i + \sum_{S=1}^{N_{SP}} \left(P_{Dch(S,t)}^i - P_{Ch(S,t)}^i \right) \\
& - \sum_{L=1}^{N_L} \left(P_{Load(L,t)}^i - P_{DR-A(L,t)}^i - P_{DR-B(L,t)}^i - P_{NSD(L,t)}^i \right) \\
& = \sum_{j=1}^{N_B} V_{i(t)} \times V_{j(t)} \left(G_{ij} \cos(\theta_{i(t)} - \theta_{j(t)}) \right. \\
& \quad \left. + B_{ij} \sin(\theta_{i(t)} - \theta_{j(t)}) \right) \\
& \quad \forall t \in \{1, \dots, T\}; \forall i \in \{1, \dots, N_B\} \quad (2)
\end{aligned}$$

$$\begin{aligned}
& \sum_{DG=1}^{N_{DG}} Q_{DG(DG,t)}^i + \sum_{SP=1}^{N_{SP}} Q_{SP(SP,t)}^i - \sum_{L=1}^{N_L} Q_{Load(L,t)}^i \\
& = \sum_{j=1}^{N_B} V_{i(t)} \times V_{j(t)} \left(G_{ij} \sin(\theta_{i(t)} - \theta_{j(t)}) \right. \\
& \quad \left. - B_{ij} \cos(\theta_{i(t)} - \theta_{j(t)}) \right) \\
& \quad \forall t \in \{1, \dots, T\}; \forall i \in \{1, \dots, N_B\} \quad (3)
\end{aligned}$$

- Bus voltage magnitude (4) and angle (5) limits in each bus must be assured. In the reference bus, the voltage magnitude and angle are fixed and set by the user.

$$V_i^{\min} \leq V_{i(t)} \leq V_i^{\max} \quad (4)$$

$$\theta_i^{\min} \leq \theta_{i(t)} \leq \theta_i^{\max} \quad (5)$$

- Line thermal limits, which represent the maximum power that can flow in a line due to its characteristics;

$$\begin{aligned}
& \left| \overline{U_{i(t)}} \times \left[\overline{y_{ij}} \times (\overline{U_{i(t)}} - \overline{U_{j(t)}}) + \overline{y_{sh-i}} \times \overline{U_{j(t)}} \right] \right| \leq S_{Lk}^{\max} \\
& \quad \forall t \in \{1, \dots, T\}; \forall i, j \in \{1, \dots, N_B\}; \\
& \quad i \neq j; \forall k \in \{1, \dots, N_k\} \quad (6)
\end{aligned}$$

- Resources active (7), (9) and reactive (8), (10) power generation limits in each period t respectively for DG units (7), (8) and upstream suppliers (9), (10). The maximum active power that can be reduced in each consumer, in each step, is assured by (11), (12), (13).

$$\begin{aligned}
& P_{DGMin(DG,t)} \times X_{DG(DG,t)} \leq P_{DG(DG,t)} \\
& \leq P_{DGMax(DG,t)} \times X_{DG(DG,t)} \quad (7)
\end{aligned}$$

$$\begin{aligned}
& Q_{DGMin(DG,t)} \times X_{DG(DG,t)} \leq Q_{DG(DG,t)} \\
& \leq Q_{DGMax(DG,t)} \times X_{DG(DG,t)} \\
& \quad \forall t \in \{1, \dots, T\}; \forall DG \in \{1, \dots, N_{DG}\} \quad (8)
\end{aligned}$$

$$P_{SP(SP,t)} \leq P_{SPMax(SP,t)} \quad (9)$$

$$\begin{aligned}
& Q_{SP(SP,t)} \leq Q_{SPMax(SP,t)} \\
& \quad \forall t \in \{1, \dots, T\}; \forall SP \in \{1, \dots, N_{SP}\} \quad (10)
\end{aligned}$$

$$P_{RED-A(L,t)} \leq P_{MaxRED-A(L,t)} \quad (11)$$

$$P_{RED-B(L,t)} \leq P_{MaxRED-B(L,t)} \quad (12)$$

$$\begin{aligned}
& P_{RED-C(L,t)} \leq P_{MaxRED-C(L,t)} \\
& \quad \forall t \in \{1, \dots, T\}; \forall L \in \{1, \dots, N_L\} \quad (13)
\end{aligned}$$

- Storage technical constraints in each period - The storage units' operation constraints considered in the proposed methodology and implemented in the proposed methods are the ones presented in [24]. Those include multi-period balance of the power in each storage unit as well as the charge and discharge rates.

III. MUTATED PARTICLE SWARM APPROACH

Particle Swarm Optimization (PSO) was created with an initial experiment of a swarm simulator first published in [25]. The authors foresaw its potential for optimization problems, namely to mitigate the difficulties of solving complex problems in terms of computational time. PSO belongs to the category of swarm intelligence methods [26] and computational intelligence. It is used in the present paper to solve the energy resource scheduling problem due to being effective in difficult optimization tasks, namely for non linear large dimension problems [27]. A PSO modified version (PSO-MUT), using Gaussian mutation of the strategic parameters, and self-parameterization is proposed for this purpose. The results and the performance of the proposed method are compared with those obtained with conventional techniques using the professional optimization tool GAMSTTM, with the version of PSO without mutation as well as Evolutionary Particle Swarm Optimization (EPSO) found in [28]. The three versions implemented in this paper use a specific modification, namely self-parameterization of the maximum and minimum velocities according to the problem context already introduced in [21]. This will enable a fair comparison of the PSO methodologies in the case study rather than only using the self-parameterization on the proposed PSO-MUT. Self-parameterization was improved from the authors' conference paper [21] to be used in the present ERM problem. Self-parameterization relies on the automatic adjustment of PSO parameters, namely the maximum and the minimum velocities to be set independently from user configuration enabling easy and fast use of the method and also better results. The proposed self-parameterization has been specifically designed for the ERM problem formulation. For other ERM formulations the algorithm rules should be carefully adapted and tested. The maximum and the minimum velocity limits are calculated according to the following: *Vector of Prices* vector with generator marginal cost prices and loads demand response cut prices.

For each element (i) of Vector of Prices apply (14) where the variables with lower price will have higher velocities.

$$\maxVel_i = 1/(\text{Vector of Prices}_i)^{1.5} \quad (14)$$

Fig. 1 depicts the proposed PSO approach for the demand response scheduling problem presented in this paper. The power flow algorithm included in the meta-heuristics is based on the theory given in [22]. The minimum velocity limits for load reduction variables are higher if the highest energy supplier price tends to be expensive compared to the other prices. If the energy

TABLE I
GENERATOR AND SUPPLIER DATA—EXAMPLE

	Price Parameters			Limits	
	a (m.u.)	b (m.u./kW)	c (m.u./kW ²)	Lower (kW)	Upper (kW)
Generator 1	0	0.20	0.001	0	50
Generator 2	0.5	0.10	0.002	0	20
Energy supplier 1	0	0.30	0	0	-

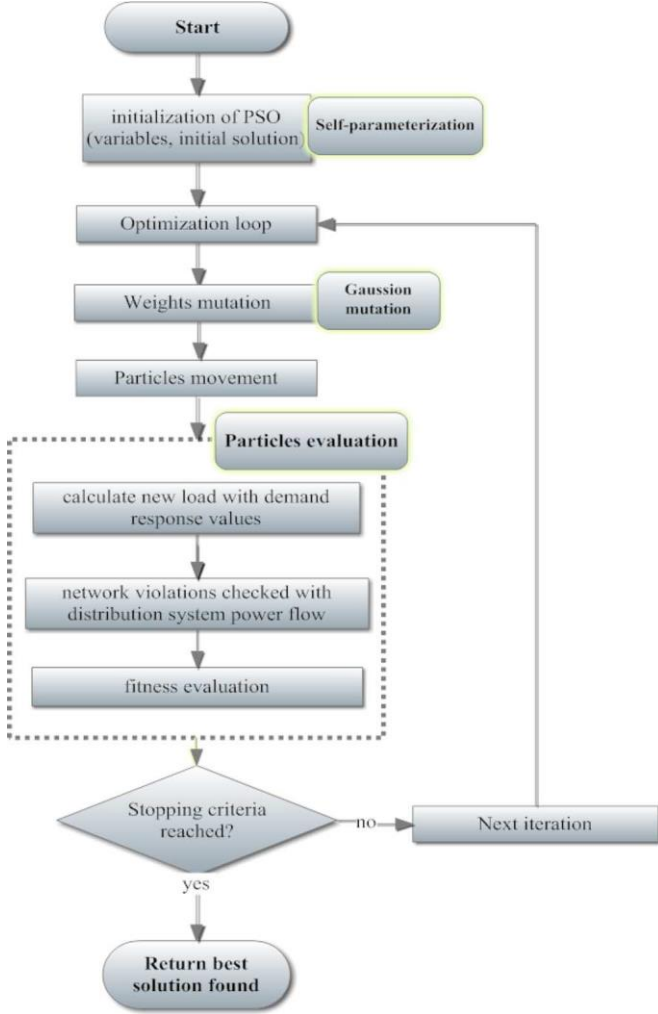


Fig. 1. PSO-MUT for the proposed energy resource scheduling problem.

supplier price tends to be cheaper, then the minimum velocity limits tend to be lower in order to have less load cuts.

The minimum velocity limits are calculated as in (15):

$$\min Vel = -\frac{\text{Number of variables}}{\text{Position in price rank}} \quad (15)$$

For better understanding of the above equations, let consider the following example of two generators (Table I) and two loads (Table II). Prices are in monetary units (m.u.).

There are three considered demand response capacity programs with a minimum load reduction for each step. First, the marginal costs of the generators, MC1 for generator 1 (16) and MC2 for generator 2 (17) (shown at the bottom of the page), are calculated using generators' upper limit.

Then, applying (14) for each element of *Vector of Prices*, we determine $\max Vel$ for each of the variables (Table III).

This means that the variable with higher velocity would be the one that corresponds to Generator 2 because it has the lower energy price. On the contrary, the price of RedC of Load1 is the less desired variable to increase given the considered scenario.

The minimum velocity limits of variables are calculated according to the rank position (lowest to highest) of the higher energy supplier contract price, according to (15). In this case there is only one energy supplier contract; it appears in the 7th place along with RedA of Load1. In this case, considering position 7 and a total of 9 variables, we have: $\min Vel = -9/7 \cong -1.29$. If this price was the lowest, i.e., the less expensive, therefore being in the 1st position of the price rank, this would become: $\min Vel = -9/1 \cong -9$.

In what concerns the mutation of strategic parameters, used only in PSO-MUT, the strategic parameters (w_i), are: inertia, memory, and cooperation. The particles movement is ruled by (18).

$$*v_i = w_{i(\text{inertia})}v_i + w_{i(\text{memory})}(b_i - x_i) + w_{i(\text{coop})}(bG - x_i) \quad (18)$$

The Gaussian mutation is used in each PSO iteration, introducing more diversification in the search process rather than the standard version using fixed and random only weights. At the beginning of the process the values of the corresponding weights are randomly generated between 0 and 1. After that, the particle's (i) weights (w_i) are changed in each iteration of PSO using a Gaussian mutation method according to (19):

$$*w_i = w_i + \delta N(0, 1) \quad (19)$$

$$MC1 = \frac{0.20 \frac{\text{m.u.}}{\text{kW}} \times 50 \text{ kW} + 0.001 \frac{\text{m.u.}}{\text{kW}^2} \times (50 \text{ kW})^2}{50 \text{ kW}} = 0.25 \text{ m.u./kW} \quad (16)$$

$$MC2 = \frac{0.5 \text{ m.u.} + 0.10 \frac{\text{m.u.}}{\text{kW}} \times 20 \text{ kW} + 0.002 \frac{\text{m.u.}}{\text{kW}^2} \times (20 \text{ kW})^2}{20 \text{ kW}} = 0.17 \text{ m.u./kW} \quad (17)$$

TABLE II
LOAD CURTAILMENT PRICES—EXAMPLE

Load		Load reduction price			Maximum load reduction in each program (kW)
ID	Power (kW)	RedA (m.u./kW)	RedB (m.u./kW)	RedC (m.u./kW)	
1	5	0.30	0.40	0.41	1
2	25	0.20	0.35	0.40	4

TABLE III
MAXIMUM VELOCITY LIMITS OF VARIABLES

Variables	Generators		Supplier	Load1 cut steps			Load2 cut steps		
	1	2		A	B	C	A	B	C
Vector of Prices	0.25	0.17	0.30	0.30	0.40	0.41	0.20	0.35	0.40
maxVel	8.0	14.27	6.09	6.09	3.95	3.81	11.18	4.83	3.95

where $*wi$ are the resulting particle's weights after mutation, and δ is the learning parameter, externally fixed between 0 and 1. A high value of δ gives 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.

It must be clarified that all the solutions obtained by the PSO based methods use an AC power flow in order to consider the network constraints and the power losses.

IV. CASE STUDY

The present case study illustrates the application of the proposed methodology to a set of consumers connected to a real Portuguese distribution network. The considered network is operated by a VPP that aims to minimize the operation costs. VPP operates the existing sources (DG and suppliers) and the demand response capacity programs. In each period, with the aim of facing the existing load demand, the VPP performs the scheduling of the existing resources. Due to the space limitation for presenting results, a single period was considered and the existence of storage units is not taken into account.

Firstly the characterization of the case study scenario is presented in sub-section A. The obtained results with the proposed methodology, with the other PSO approaches and the deterministic approach are then shown and compared in Sub-section B.

A. Scenario Characterization

The network used in this case study is a real 30 kV distribution network, supplied by one high voltage substation (60/30 kV) with 90 MVA of maximum power capacity distributed by 6 feeders, with a total number of 937 buses and 464 MV/LV transformers [24]. Fig. 2 shows the summarized scheme of the distribution network. The number of consumers and the demand in each feeder is also shown.

This distribution network has already been in use for many years and it has suffered many reformulations. It is partly composed of aluminum conductors and partly of copper conductors and the distribution is made by power lines and underground cables. The 20 310 consumers connected to this network are classified into five consumer types. The peak power demand is 62 630 kW.

Regarding the participation of the consumers in each one of the proposed demand response capacity programs (three successive reduction steps—RedA, RedB, and RedC), a determined power reduction and the respective remuneration price were established for each consumer type. Each reduction step only can be used after the previous one have been fully used (e.g., RedC only can be used when RedA and RedB have been already fully used). For this case study, the maximum power reduction was fixed equal to 10%, 5%, and 5% of each load nominal value, respectively for demand response capacity programs RedA, RedB, and RedC. Table IV presents the values of demand reduction costs in each demand response capacity program. These values correspond to the remuneration values that are paid to the consumers participating in each demand response capacity programs, which are considered fixed for each consumer type.

Table IV also presents the total capacity of demand reduction in each demand response capacity program, regarding the consumer types, for the considered network.

As the original network does not have distributed generation, the energy sources considered for this case study resulted from a study regarding the allocation of DG. Table V presents the values of prices (unitary operation costs), total available capacity, and the number of units for each type of DG technology. The respective values for the ten considered suppliers, connected to the network in the substation, are also presented. Only the linear component of the sources cost functions is considered in this case study.

As it was explained in Section III, the considered optimization has been solved using a deterministic approach and 3 PSO variants approaches (without mutation—PSO—and with mutation—PSO-MUT and EPSO [28]). Table VI presents the values/description of both PSO methods' parameters. The values for the learning parameter in EPSO were set to 0.8 and the replica was set to 1. Self-parameterization is also introduced in EPSO to enable a closer comparison.

This case study corresponds to a total of 62046 variables. In the PSO methods these variables are coded in memory vectors, i.e., each particle has a dimension space of 62046. The max position of each particle's dimension is defined by the capacity limits of demand response capacity programs and generators/aggregators upper limit power whereas the min position is

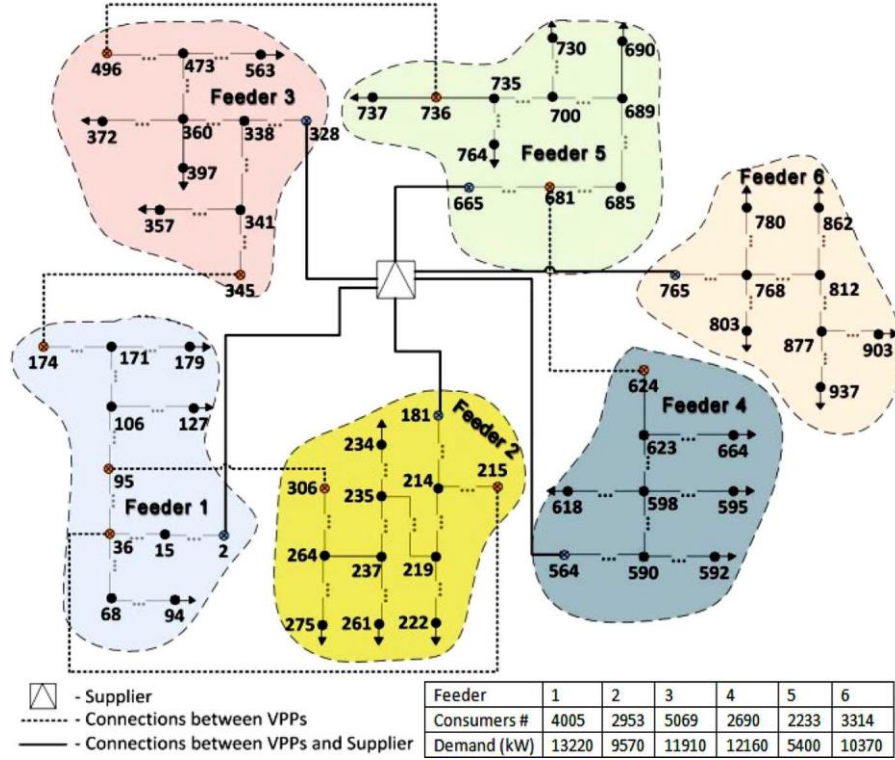


Fig. 2. Distribution network.

TABLE IV
DEMAND RESPONSE CAPACITY PROGRAMS CHARACTERIZATION

Type of consumer	Reduction capacity (kW)			Reduction costs (m.u./kWh)		
	RedA	RedB	RedC	RedA	RedB	RedC
Domestic	936.9	468.47	468.47	0.16	0.20	0.24
Small Commerce	798.3	399.17	399.17	0.15	0.19	0.22
Medium Commerce	1125.4	562.74	562.74	0.18	0.20	0.26
Large Commerce	1088.0	544.02	544.02	0.17	0.24	0.26
Industrial	2314.2	1157.1	1157.1	0.17	0.26	0.28
Total	6262.8	3131.5	3131.5	-	-	-

TABLE V SOURCES
CHARACTERIZATION

Resource	Price (m.u./kWh)	Capacity (kW)	Units #	Resource	Price (m.u./kWh)	Capacity (kW)
PV	0.2	7061.2	208	Supplier3	0.09	3000
Wind	0.05	5866.0	254	Supplier4	0.11	3000
CHP	0.08	6910.1	16	Supplier5	0.13	3000
Biomass	0.15	2826.5	25	Supplier6	0.15	3000
MSW	0.11	53.1	7	Supplier7	0.17	3000
Hydro	0.15	214.0	25	Supplier8	0.19	3000
Fuel cell	0.3	2457.6	13	Supplier9	0.21	10000
Supplier1	0.05	3000.0	-	Supplier10	0.23	10000
Supplier2	0.07	3000.0	-	Total	-	69388

TABLE VI
PARAMETERS OF PSO METHODS

Parameters	PSO Methodologies	
	PSO	PSO-MUT / EPSO
Inertia Weight	1	Gaussian mutation weights
Acceleration Coefficient	2	
Best Position	2	
Cooperation Coefficient	2	
Initial swarm population	Randomly generated between the upper and lower bounds of the variables	
Stopping Criteria	150 iterations	
Max. velocity	Refer to Section III	
Min. velocity	Refer to Section III	

B. Results

This sub-section presents the results obtained for this case study energy resources management. In order to evaluate the effectiveness of the PSO methods and of the proposed energy resources management methodology, the results are shown regarding the three approaches (deterministic mixed integer non linear programming optimization obtained in GAMS; heuristic optimization obtained the proposed PSO, labeled as “PSO”; and heuristic optimization obtained by the proposed mutated version of PSO, labeled as “PSO-MUT”). The number of particles assigned to PSO and PSO-MUT methods was 20. The number of iterations was 150 for both versions in order to allow comparing the results. The details of the results shown in Figs. 3 to 6 correspond to a random solution obtained by the PSO and by the PSO-MUT.

Fig. 3 shows the results of the resource scheduling. The solutions obtained by the deterministic approach (labeled as “GAMS”) are considered as the reference. It is possible to see

zero. This case study uses 20 particles and 150 iterations. These values were obtained by empirical experimentation. Increasing the number of iterations and particles would result in more execution time without significant solution quality gains.

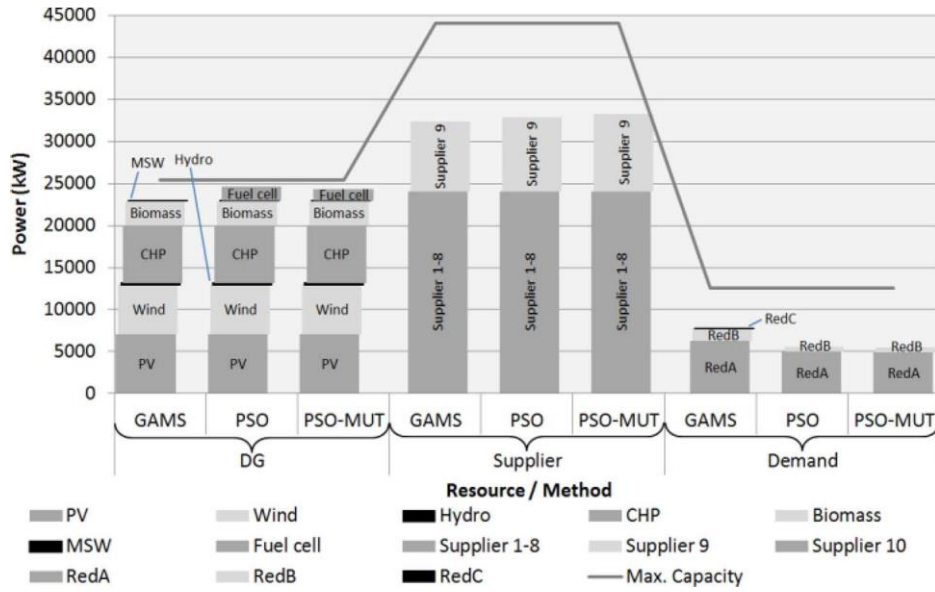


Fig. 3. Energy resource scheduling.

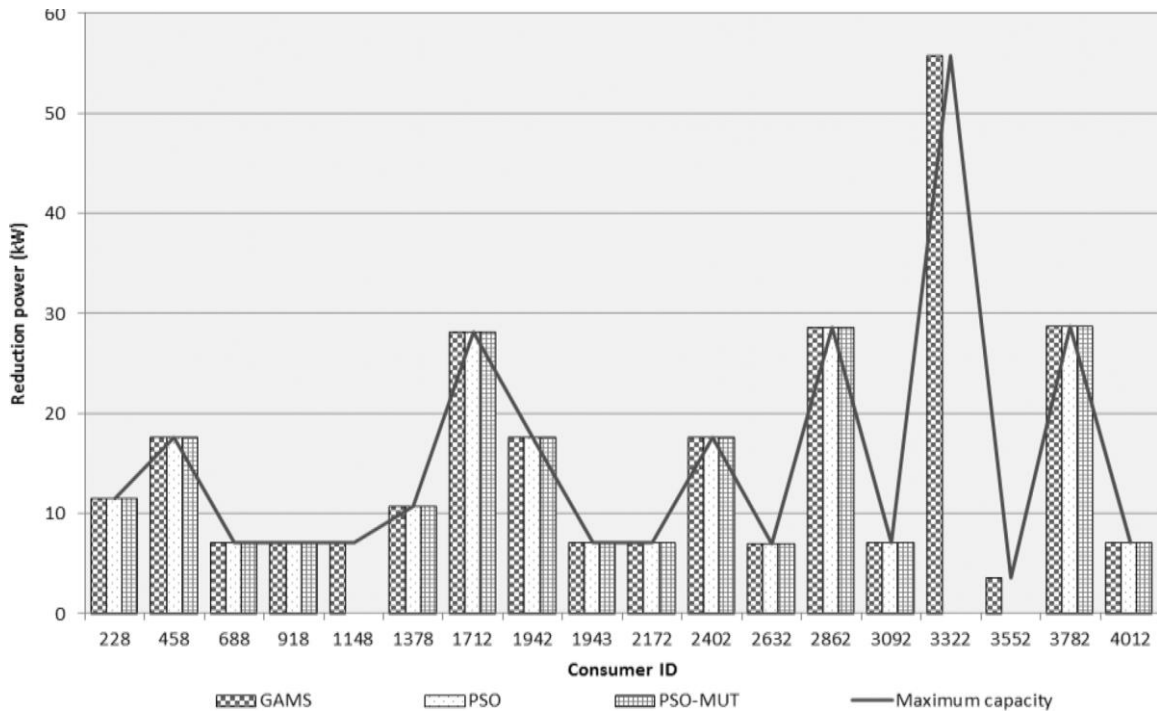


Fig. 4. Feeder 1 medium commerce consumers schedule in the RedA program.

that the PSO methods schedule all the resources (but not all their available capacity), while the deterministic approach does not make use of fuel cell units due to their operation costs. On contrary, demand response capacity programs are more used in the solution obtained by GAMS. The energy provided by the suppliers is more used by the solution obtained by PSO-MUT. The proposed methodology schedules each resource individually. However, here the results are presented in a condensed form, showing the total aggregated amount of power scheduled for each type of DG technology, each type of consumer, etc. Fig. 4 shows more detailed results for the medium com-

merce consumers in feeder 1 in what concerns the schedule in the RedA demand response capacity program.

For these consumers, the deterministic approach schedules all the consumers for participation in the demand reduction program whereas the solutions obtained by the PSO methods do not scheduled some of the consumers for participation.

Fig. 5 presents the solutions costs obtained for each type of resource. Three components of the objective function are represented, namely DG, supplier and demand response costs. The costs of demand response capacity programs are calculated according to the consumers scheduled by each method. As ex-

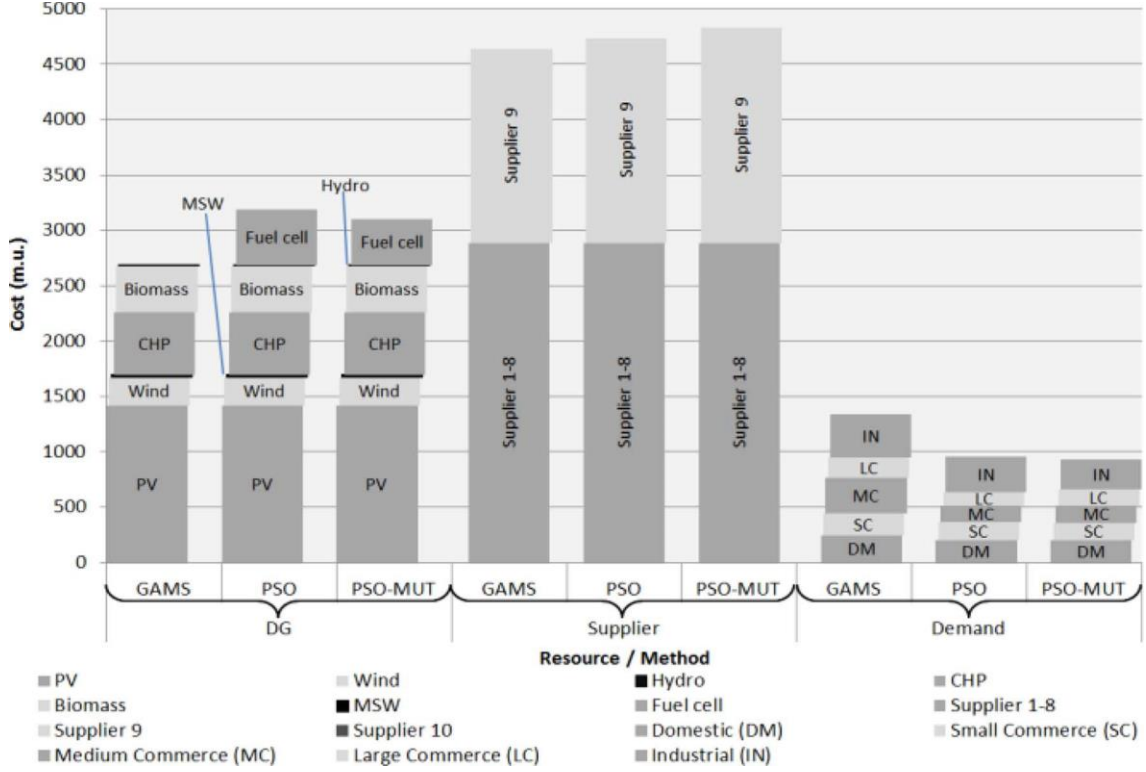


Fig. 5. Energy resource scheduling costs.

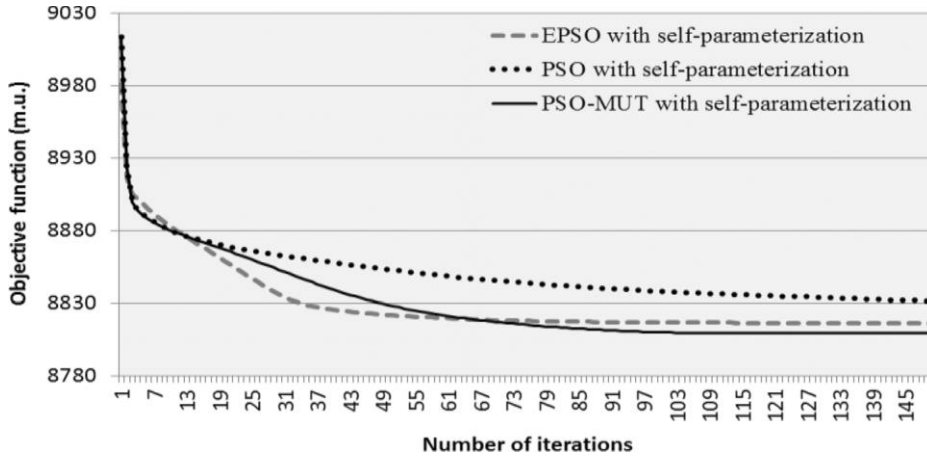


Fig. 6. Evolution of the average solutions of the PSO methods.

pected, the differences between the solutions obtained by the three approaches are related to the schedules presented in Fig. 3.

Fig. 6 shows the average solution found in each iteration for 1000 runs of the three considered PSO based approaches. It is clear that the proposed PSO-MUT has a faster evolution to the solution, which is also the best found solution among the PSO methods.

Table VII shows the values of both operation costs and execution time for the four considered approaches.

These results show that the three PSO-based methods are able to obtain solutions very close to the value obtained with the deterministic approach (8662.6 m.u.) in much faster execution time. The proposed PSO-MUT leads to the best average

value (8809.2 m.u.) with the minimum standard deviation. The proposed PSO-MUT execution time is slightly higher than the one of the PSO without mutation and significantly lower than the EPSO execution time. The EPSO execution time is higher mainly due to the replication of the swarm and to the required evaluations of the swarm and replica solutions.

V. CONCLUSION

The future context of operation of distribution networks, according to the smart grid paradigm, will accommodate large amounts of distributed generation. Enhancement of service quality, increase of energy efficiency and reduction of the operation costs are expected in the new context. Virtual power players will play an important role managing and operating

TABLE VII
EXECUTION TIME AND OPERATION COSTS VALUES COMPARISON

Method	Execution time		Objective function						
	(s)	(%)	Best		Worst		Average		Standard deviation
			(m.u.)	(%)	(m.u.)	(%)	(m.u.)	(%)	(m.u.)
GAMS	1510	100	8662.6	100	-	-	-	-	-
PSO	59	3.9	8768.2	101.1	8876.6	102.5	8831.3	101.9	24.8
EPSO	127	8.4	8745.1	101.0	8870.8	102.4	8816.1	101.8	29.3
PSO-MUT	68	4.5	8726.2	100.7	8876.9	102.5	8809.2	101.7	22.5

aggregated energy resources, which also include demand response. Due to the competitive environment, important decisions must be as efficient as possible and be taken in short time horizons; computational intelligence methods will be very important in this field.

In this paper, a Particle Swarm Optimization (PSO) based methodology is proposed and applied to the schedule of several energy resources, including demand response, distributed generation, and the energy that can be bought to a set of suppliers, minimizing the operation costs from the point of view of a VPP that operates the network. The proposed method uses Gaussian mutation of the strategic parameters and self-parameterization of the maximum and minimum particle velocities, according to the context.

The application of the proposed method has been illustrated with a case study based on a real 937 bus distribution network, with 20310 consumers and 548 distributed generators. The solutions obtained with the proposed method are compared with those obtained with a deterministic approach, the classic PSO, and the Evolutionary PSO (EPSO). The proposed PSO-MUT approach leads to the best average solution and presents execution times only slightly higher than traditional PSO.

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