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Performance assessment of PSO, DE and hybrid PSO–DE algorithms when applied to the dispatch of generation and demand

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ABSTRACT

This work presents a comparison of three evolutionary algorithms, the particle swarm optimization, the differential evolution algorithm and a hybrid algorithm derived from the previous, when applied to the generation and demand dispatch problem. An optimization problem is formulated in the context of a small grid with partially flexible demand that can be shifted along a time horizon. It is assumed that grid operator dispatches generation and flexible demand along the time horizon aiming at minimizing generation costs. Consumption restrictions associated with flexible demand are modeled by equality and inequality energy constraints. Power flow equality constraints and inequality constraints due to operational limits for each dispatch interval are represented. The paper discusses a methodology for evolutionary algorithms performance assessment and states the importance of using statistical tools. The comparison is initially conducted using the IEEE 30-bus test system. Problem dimension effect is addressed considering different number of dispatch intervals in the time horizon. Moreover, the algorithms are applied to the 192-bus system of a Brazilian distribution utility, in the particular context of a load management program for large consumers of the company. In this application, the quality of the near-optimal solution obtained with the stochastic algorithms is evaluated by comparing with an analytical optimization algorithm solution.

1. Introduction

How to implement demand participation is among the most important activities in power systems research nowadays. In electricity markets, demand participation provides efficiency by lowering energy costs, preventing peak prices and eliminating the necessity of price caps. The extensively studied topics of smartgrids and microgrids, conceived as a mean to integrate renewable resources on the local level, consider consumer participation as being an important resource for grid management [1–7]. Two related concepts are usually addressed: demand participation and demand dispatch. The first one refers to demand side activities that respond to system conditions and/or specific signals like energy price, dynamic tariffs or economic incentives offered by system operators or distribution companies [4–7]. On the other hand, Demand Dispatch (DD) involves the dispatch of loads by the system operator. Consumers engage on special programs offered by electricity companies and allow for the dispatch of their loads [5,7]. Sometimes, there exist demand aggregators that manage the loads of several consumers, enabling the participation of small consumers [5].

This research aims to contribute on the development and performance evaluation of optimization tools to address demand dispatch simultaneously with generation dispatch.

Among the different techniques that have been applied to the generation dispatch problem are the stochastic optimization algorithms like genetic algorithms, simulated annealing, evolutionary programming, differential evolution, particle swarm optimization and, also, other algorithms like honey bee mating optimization and shuffled frog leaping algorithm [4,8–17]. These are heuristic methods that, in despite of not assuring global optimality, provide good near-optimal solutions in an admissible computation time. In this work, the Particle Swarm Optimization (PSO) algorithm, the Differential Evolution (DE) algorithm and a hybrid algorithm are studied. The PSO and its many variants have been successfully applied to the economic dispatch, unit commitment and optimal power flow problems [10–13]. The DE has also been applied to the above problems [14–17]. Moreover, the application of several types of hybrid algorithms is also described in the power systems literature. Among them, there are the hybrids that combine two or more evolutionary optimization techniques that can improve optimization results [18–26]. For instance, in [19–23], hybrid algorithms are applied to the economic dispatch problem. In [19], a hybrid of the PSO with the bacterial foraging algorithm is studied. In [20] a hybrid algorithm from a fuzzy adaptive modified

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algorithm and the PSO are used for solving non-convex dispatch problems. In [21] a hybrid of the classical DE with evolution strategies is studied. In [22] strategies to accelerate convergence and to escape from local optimum are embedded into the original DE algorithm. In [23] a hybrid is formed with incorporating a mutation strategy into the PSO. In despite of the previous examples, one can observe that performance evaluation of these hybrid algorithms when applied to generation dispatch problems are not common. This work contributes with the evaluation of a hybrid algorithm obtained by combining the PSO and the DE algorithms.

The more specific problem of the simultaneous generation and demand dispatch problem, addressed in this work, has been studied in [27–30] employing analytical optimization methods. Stochastic optimization techniques are applied to this problem in [4,31,32]. In [31], the PSO algorithm is used to solve the simultaneous dispatch of generation and demand using a modified optimal power flow formulation. Demand dispatch is modeled through flexible loads that should be allocated along a time horizon, provided that certain energy consumption is attained. In [32], a genetic algorithm is used to define bidding strategies in the presence of responsive demand. In [4] a binary particle swarm optimization and the classical PSO algorithms are used in the development of a demand side management platform that simulates the operation of a smart home in which several distributed resources, like generation sources and storage, are available. One can notice that there are few studies that address the performance of evolutionary algorithms on demand dispatch applications.

In relation to the assessment of the quality of the solution obtained with stochastic evolutionary algorithms, various procedures are possible. Notice that, in general, these algorithms are used with multimodal objective functions; therefore, there are several local optimum and analytical methods do not perform well. One form of assessing the quality of the solution is to apply first the stochastic algorithm and then use the solution obtained as the initial point of an analytic algorithm in order to refine the optimum. This procedure is applied in [31] using an interior point algorithm to address the quality of the solution obtained with the PSO algorithm. Another possibility is to notice that results obtained from stochastic algorithms are random variables. In this sense, some applications in the power systems literature present an error analysis in order to evaluate the quality of the solution among different evolutionary techniques [8]. In [33–35], statistical tools are used to analyze the results from multi-objective optimization. This late approach is adopted in this research.

In the above context, this present work contributes in two aspects: the Generation and Demand Dispatch (GDD) problem solved by evolutionary optimization techniques is further studied and a performance assessment methodology for stochastic algorithms that allows improving the obtained solution is developed. More specifically, the demand dispatch modeling includes equality energy constraints and inequality energy constraints that model consumption along a time horizon and, also, economic incentives offered to consumers in order to reduce their loads. The paper reports on the performance of three evolutionary algorithms when applied to this type of optimization problem. The PSO and the DE algorithms are tested using their classical formulations and a hybrid algorithm that combines those two evolutionary techniques in a novel approach is compared. A methodology for performance comparison of the stochastic algorithms based on statistical tools, in which box plots are the aiding tools for the definition of the space search strategy, is proposed. Moreover, a reduction of the search space, inspired on [36], is considered.

The paper is organized in six sections. Section 2 presents the general formulation of the problem. A brief description of the three algorithms and main implementation details are included in Section 3. Illustrative results obtained with the IEEE 30-bus test system are presented in Section 4. In Section 5, a practical application is described. Finally, main conclusions are presented in Section 6.

2. General problem formulation

In this section, the optimization problem adopted for GDD is described. It is supposed that some consumers have a flexible consumption pattern and can shift part of their demand along a time horizon, provided that some energy restrictions are attained. Two types of consumers are distinguished, regarding the energy restrictions. While some consumers must ensure that a given amount of energy is consumed along the time horizon (type-I consumers), others can reduce their energy consumption over the time horizon (type-II consumers). Moreover, to reduce excessively high peaks in the load curve during some critical intervals of the time horizon, economic incentives are offered to type-II flexible consumers, by the system operator or by the local distribution company, in order to reduce their load. In the GDD problem, generation along the time horizon must be dispatched aiming at minimizing generation costs for the grid users. In addition, the most convenient demand pattern for both types of flexible consumers during the time horizon, including load reductions to be accomplished by type-II consumers, must be determined.

It must be noticed that, due to the energy consumption restrictions above mentioned, the optimization along the time horizon should be treated as a single problem. This time horizon would represent, for instance, peak hours during 1 day or the complete hourly dispatch over the day. Generation dispatch and flexible demand must be defined for each dispatch interval. Flexible consumption is treated by intertemporal constraints in the optimization problem [29–31].

2.1. Objective function

The optimization problem is formulated considering the point of view of the grid users. Costs due to energy generated by local generators and due to all the energy bought from the local distribution company and external generators, together with economic incentives received by certain grid users, are modeled. Therefore, the GDD problem seeks to minimize total generation costs minus total incentives during a time horizon of n_T dispatch intervals. The objective function (OF) is given by (1). Costs C_{Tot} associated to the n_G generators are represented by (2), which includes local generation costs and costs associated with energy bought from the local distribution company or from other generators.

$$OF = C_{Tot} - \sum_{j \in \Omega} \left(\sum_{i=1}^{n_R} I_i \cdot (p_{ref_i} - p_{r_{i,j}}) \right) \tag{1}$$

$$C_{Tot} = \sum_{t=1}^{n_T} \left(\sum_{i=1}^{n_G} C_{G_{i,t}} \right) \tag{2}$$

In (1) and (2), $C_{G_{i,t}}$ represents generator i generation costs during interval t; $p_{r_{i,j}}$ is the flexible load of type-II consumer i during interval j; p_{ref_i} is the load taken as reference in order to calculate the load reduction; n_R is the number of type-II flexible consumers that receive economic incentives in order to reduce load during critical intervals and Ω is the set formed by the critical intervals that are associated with incentives. In (1), it can be observed that economic incentives received by type-II consumers are proportional to their load reduction.

Local generation is supposed to be composed by thermal units with single-valve steam turbines, represented by quadratic generation cost functions, and by multi-valve steam turbines, in which valve-point effects are represented [37]. Moreover, linear generation costs are represented, in order to model energy bought from the distribution company or from other generators. General expressions of generation costs are given in (3). The last term of cost function $C_{G_{\text{ValvePt}}}$ corresponds to multi-valve point effect and is responsible for the multimodality of the objective function.

$$\begin{aligned} C_{G_{\text{Lin}}} &= a_l p_g \\ C_{\text{Quad}} &= a_q p_g^2 + b_q p_g + c_q \\ C_{G_{\text{ValvePt}}} &= a_v p_g^2 + b_v p_g + c_v + |e_v \cdot \sin(f_v(\underline{p} - p_g))| \end{aligned} \tag{3}$$

2.2. Network and operational constraints

For each dispatch interval of the time horizon, the active power balance equations and the operational limits, as given by (4) and (5), must be verified. For the electrical network, a linearized model is adopted and only active power flows are represented.

$$\mathbf{p}_{L_t} + \mathbf{A}_d \cdot \mathbf{p}_{d_t} + \mathbf{A}_r \cdot \mathbf{p}_{r_t} + \mathbf{B} \cdot \boldsymbol{\theta}_t - \mathbf{A}_g \cdot \mathbf{p}_{g_t} = 0 \tag{4}$$

$$\left.\begin{aligned} \underline{\mathbf{p}_g} \leqslant \mathbf{p}_{g_t} \leqslant \overline{\mathbf{p}_g}, \\ \underline{\mathbf{p}_d} \leqslant \mathbf{p}_{d_t} \leqslant \overline{\mathbf{p}_d}, \\ \underline{\mathbf{p}_r} \leqslant \mathbf{p}_{r_t} \leqslant \overline{\mathbf{p}_r}, \end{aligned}\right\} t \in \{1 \cdots n_T\} \tag{5}$$

In (4) and (5), for interval t, $\mathbf{p}_{g_t}$ is the $(n_G \times 1)$ generation vector; $\mathbf{p}_{L_t}$ is the $(n_B \times 1)$ fixed demand vector; $\mathbf{p}_{d_t}$ is the $(n_D \times 1)$ type-I consumer flexible demand vector and $\mathbf{p}_{r_t}$ is the $(n_R \times 1)$ type-II consumer flexible demand vector. The number of buses is given by n_B; n_D is the number of type-I consumers and n_R is the number of type-II consumers. $\mathbf{A}_g$ is the $(n_B \times n_G)$ bus-to-generator incidence matrix; $\mathbf{A}_d$ is the $(n_B \times n_D)$ bus-to-type-I flexible demand incidence matrix; $\mathbf{A}_r$ is the $(n_B \times n_R)$ bus-to-type-II flexible demand incidence matrix; $\mathbf{B}$ is the $(n_B \times n_B)$ linearized load flow matrix [27] and θ_t is the $(n_B \times 1)$ bus voltage angles vector.

2.3. Energy constraints

Consumer operating constraints that model production requirements are represented by equality and inequality energy constraints, as given by (6) and (7). Equality (6) refers to type-I consumers, it is an energy constraint that indicates the amount of energy to be consumed during the time horizon. Inequality (7) is an energy constraint which indicates the maximum amount of energy to be consumed by type-II consumers during the time horizon.

$$\mathbf{e}_T \cdot \mathbf{p}_{d_j} = E_j \quad j = 1 \cdots n_D \tag{6}$$

$$\mathbf{e}_T \cdot \mathbf{p}_{r_j} \leqslant E_{r_j} \quad j = 1 \cdots n_R \tag{7}$$

In (6) and (7), $\mathbf{e}_T$ is a $(1 \times n_T)$ vector of ones. Notice that type-II flexible consumers load is defined for the complete time horizon, as can be seen in (5), but the incentives are paid for the demand reduction attained during critical intervals, as the objective function (1) indicates. Therefore, due to the inequality energy constraint, type-II flexible consumer loads $\mathbf{p}_{r_t}$ during critical intervals ($t \in \Omega$) can be shifted to other intervals or reduced.

3. Algorithms description

This section presents a brief description of the three stochastic algorithms: the PSO, the DE and the hybrid PSO–DE, together with some relevant implementation details.

3.1. Particle Swarm Optimization, PSO

PSO is a population based stochastic optimization technique inspired on social behavior of bird flocking or fish schooling. The algorithm searches for the optimum using a group or swarm formed by possible solutions of the problem, which are called particles. The algorithm implemented in this work is inspired on [10,38]. Each particle is updated as indicated by (8a) and the group of particles moves through the search space as indicated by (8b).

$$\begin{aligned} V_{i,j}^k = [&w \cdot V_{i,j}^{k-1} + c_1 \cdot rand_1 \cdot (Pbest_{i,j} - P_{i,j}^{k-1}) + c_2 \cdot rand_2 \\ &\cdot (Gbest_i - P_{i,j}^{k-1})]FC \end{aligned} \tag{8a}$$

$$P_{i,j}^k = P_{i,j}^{k-1} + V_{i,j}^k \tag{8b}$$

In (8), for component i of particle j: $P_{i,j}^k$ represents its position and $V_{i,j}^k$ is called speed; c_1 and c_2 are the acceleration coefficients; FC is the contraction coefficient calculated as in (9) [10]; $rand_1$ and $rand_2$ are uniformly distributed random numbers in [0,1], sampled at each iteration k. The particles of the swarm are individually analyzed and the one that generates the best solution along the iterations, i.e. best local solution, is called *Pbest* (particle best). The best solution in the swarm is tracked in *Gbest* (group best). Parameter w, called inertia, indicates the contribution of the previous velocity to the new one. It is updated at each iteration k by (10) [38].

$$FC = \frac{2}{|2 - \phi - \sqrt{\phi^2 - 4\phi}|}, \quad with \quad \phi = c_1 + c_2 \geqslant 4 \tag{9}$$

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{N} \cdot k \tag{10}$$

In (10), N is the maximum number of iterations; $w_{\max}$ and $w_{\min}$ are, respectively, maximum and minimum inertia values. Higher values of w favor global exploration of the search space, while smaller values tend to facilitate local search.

3.2. Differential Evolution, DE

The differential evolution algorithm, proposed by Storn and Price in 1997 [39], is also a population based algorithm that uses the mutation, selection and crossing over processes. The DE implemented in this work is based on [14–17,39]. The mutation process initiates with the creation of a mutant vector: an individual is combined with its difference with the best individual and with a random term, as described in (11). The crossing over process is presented in (12).

$$\begin{aligned} V_{i,j}^k &= F * (Gbest_i^{k-1} - P_{i,j}^{k-1}) + F * (P_{i,ran1}^{k-1} - P_{i,ran2}^{k-1}) \\ Z_{i,j}^k &= P_{i,j}^{k-1} + V_{i,j}^k \end{aligned} \tag{11}$$

$$P_{i,j}^k = \begin{cases} Z_{i,j}^k & \text{if } (rand(i) \leqslant CR) \text{ or } (i = rnbr(i)) \\ P_{i,j}^{k-1} & \text{if } (rand(i) > CR) \text{ and } (i \neq rnbr(i)) \end{cases} \tag{12}$$

In (11) and (12), $Gbest^{k-1}$ is the best individual in iteration $(k-1)$ and P_j^{K-1} is the individual being updated; for component i of particle j, $ran1$ e $ran2$ are random numbers uniformly distributed in [1,nI] and represent two individuals randomly selected; nI is the number of individuals; F is the amplification factor, usually defined in interval [0,2]; V_j^K is the $(nI \times 1)$ obtained mutant vector; $rand(i)$ and $rnbr(i)$ are also random numbers uniformly distributed on [0,1] and on [1, nv], respectively; nv is the individual dimension; the crossing over parameter CR defines the crossing over probability.

3.3. Hybrid algorithm, PSO–DE

The hybrid algorithm implemented is inspired in the strategy suggested in [21–26] of exploring the search space first globally and then locally, using two different evolutionary algorithms.

Notice that the crossing over process of the DE algorithm promotes information exchange among individuals and favors search in new areas of the search space. The mutation process aims at increasing population diversity and the algorithm ability to escape from local minima [24].

In this work, due to the fact that in high dimension problems the PSO is easily trapped into local optima, resulting in a low optimizing precision or even failure [24], the proposal is to use the PSO algorithm during the first 30% of the iterations. In the sequel, during the remaining 70% of the iterations, the mutation and crossing over operators shown in (11) and (12) are used. The algorithm is structured in the steps shown bellow.

Step 1: *Initialization of the particles* – At the first iteration, component *i* of particle *j* is generated randomly, as indicated in (13), where *rd* is a uniformly distributed random number in [0,1].

$$P_{i,j}^{(k=1)} = P_{i,\min} + rd.(P_{i,\max} - P_{i,\min}) \tag{13}$$

Step 2: *Treatment of equality constraints and Pbest evaluation* – Power flow equality constraints and equality energy constraints are solved in two stages. Initially, an analytical constraint enforcement mechanism is used, in which power flow equations are solved and flexible demand in one randomly selected dispatch interval is used to attain the balance in the energy constraint. It is observed that, sometimes, this mechanism does not allow feasibility. In this case, a second stage with a penalty function approach is used [31]. In the first iteration, Pbest for each particle assumes the value of the corresponding particle.
Step 3: *Fitness evaluation* – The objective function value is determined for each particle.
Step 4: *Gbest evaluation* – The best particle, i.e. the one that gives lower generation costs among all the Pbest particle values, is identified as Gbest.
Step 5: *Velocity update* – The velocity is updated using (8a) or (11), depending on the current iteration number.
Step 6: Position update – The particle's position is updated using (8b) or (12), depending on the current iteration number.
Step 7: *Treatment of equality and inequality constraints* – Power flow equality constraints and equality energy constraints are solved in two stages as explained in Step 2. The inequality constraints are evaluated as indicated in (14):

$$P_{i,j}^{k} = \begin{cases} \underline{P_i} & \text{if } (P_{i,j}^{k} < \underline{P_i}) \\ \overline{P_i} & \textit{if } (P_{i,j}^{k} > \overline{P_i}) \end{cases} \tag{14}$$

Step 8: *Pbest evaluation* – For each particle, the objective function value is evaluated and compared with that of Pbest.
Step 9: *Check stopping criterion* – The stopping criterion involves a tolerance for the difference among the objective function associated to all particles values and for the feasibility condition of the optimization problem. If convergence is not attained, continue from Step 4.

4. Case studies results and comparison

This section presents a comparison of the three algorithms conducted using the IEEE 30-bus test system, shown in Fig. 1, with problem formulations presented in Section 2. The performance of the three algorithms is analyzed for two different problems, which differ in the type of flexible consumers. In problem P-I, all flexible consumers are type-I consumers and in problem P-II all flexible consumers are type-II consumers. Therefore, the performance of the algorithms in the presence of either equality energy constraints or inequality energy constraints that couple the dispatch intervals is addressed. Moreover, in order to address the effect of problem dimension, for each problem P-I and P-II, simulations with a time horizon of 12 intervals ($n_T = 12$) and with a time horizon of 24 intervals ($n_T = 24$) are conducted.

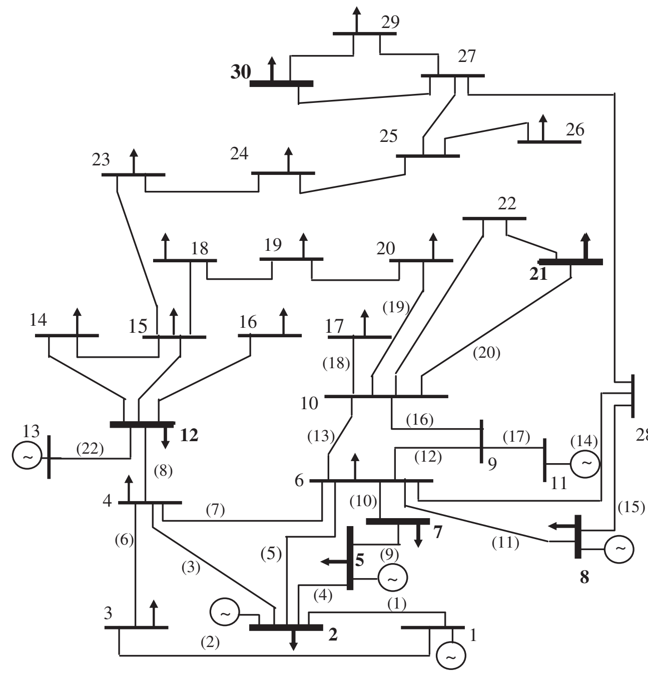

Fig. 1. IEEE-30 bus test system. Buses in bold are flexible consumers.

As shown in Fig. 1, the system has six generators, connected at buses #1, #2, #5, #8, #11 and #13, and seven flexible consumers, connected at buses #2, #5,#7, #8, #12, #21 and #30. Table 1 presents generators cost functions together with generation operational limits. Table 2 presents data related to flexible consumers: the operational limits of the flexible load and the amount of energy associated to the time horizon, which corresponds to parameters *E* and *Er* in (6) and (7).

In order to assess the effect of demand dispatch on the load curve and on generation costs, a reference case with no DD is simulated. Fig. 2 presents load curves (total load together with fixed load) for the reference case, for $n_T = 12$ and $n_T = 24$. The fixed loads shown are used for both problems P-I and P-II. It is assumed that with no demand dispatch, for $n_T = 12$ the flexible load is concentrated on peak intervals (intervals #6, #7 and #8) and for $n_T = 24$

Table 1
Generators cost functions and operational limits.

IEEE – 30bus	Cost function	Generation limits [p.u.]	
		$\overline{p_g}$	$\underline{p_g}$
G1	$K^a.\,p_g$	4.0	0.00
G2	$175p_g^2 + 175p_g$	0.4	0.01
G5	$625p_g^2 + 100p_g$	0.6	0.01
G8	$834p_g^2 + 325p_g + \lvert 30 \cdot \sin(30(\underline{p_g} - p_g))\rvert$	0.4	0.01
G11	$250p_g^2 + 300p_g + \lvert 20 \cdot \sin(40(\underline{p_g} - p_g))\rvert$	0.3	0.01
G13	$250p_g^2 + 300p_g + \lvert 15 \cdot \sin(30(\underline{p_g} - p_g))\rvert$	0.4	0.01

Table 2
Flexible load data for P-I and P-II: operational limits (valid for each dispatch interval) and amount of energy associated to the time horizon.

	Operational limits [p.u.]			Energy [p.u.-h]	
	$\overline{p_d}$		$\underline{p_d}$	$n_T = 12$	$n_T = 24$
	P-I	P-II			
L2	0.0015	0.0110	0.0000	0.1302	0.2604
L5	0.0628	0.0470	0.0000	0.5652	1.1304
L7	0.0152	0.0110	0.0000	0.1368	0.2736
L8	0.0200	0.0150	0.0000	0.1800	0.3600
L12	0.00757	0.0060	0.0000	0.0672	0.1344
L21	0.01167	0.0090	0.0000	0.1050	0.2100
L30	0.00707	0.0050	0.0000	0.0636	0.1272
Total	–	–	–	1.248	2.496

it is allocated on intervals #15 through #20. Moreover, in order to easy reproduce the results, Appendix A presents fixed load data in detail.

In order to characterize the stochastic results given by the algorithms, a thirty elements sample of the results, obtained from thirty optimizations that give feasible solutions, is used in each problem (reference case, P-I and P-II) for each algorithm. Comparisons considering the best results obtained are presented. Notice that the best result is the one that gives the lowest value for the objective function.

Moreover, box plot graphs are adopted as aiding tools in assessing the quality of the obtained result. These graphs are constructed using the thirty feasible simulations. In box plot graphs, for the thirty elements sample, the median and the 25th and 75th percentiles are presented and outliers are indicated by "+". Errors, measured as deviation of the best solution from the corresponding mean value, are reported.

Finally, notice that in some simulations the algorithm may fail to obtain a feasible solution. Therefore, a comparison of the convergence rate, defined as the number of simulations performed in order to obtain thirty simulations with feasible solutions, is presented.

Table 3 shows the parameters used in the PSO algorithm for all simulations in both problems P-I and P-II. The parameters adopted for the DE algorithm, for all simulations, are: 30 (thirty) individuals, 200 (two hundred) generations, the amplification factor is equal to 0.2 and the crossover factor is equal to 0.9. For the hybrid algorithm the parameters are the same adopted in PSO and DE algorithms for all simulations.

This section is organized in three subsections. First, results for P-I are presented. In the sequel, results for P-II are shown. Finally, a general discussion is given.

4.1. Problem P-I: Demand management with type-I consumers (equality energy constraints)

In this section, load curves with the obtained allocation for the flexible load along the time horizon are presented. The best result for the objective function, among the thirty elements sample, is also shown. Results are obtained for both $n_T = 12$ and $n_T = 24$ and for the three algorithms.

Table 3
Parameter values for the PSO algorithm.

	Parameters				
	nI	*nP*	C_1	C_2	c_p
$n_T = 12$	200	30	3	4	10^{10}
$n_T = 24$	500	50	3	4	10^{9}

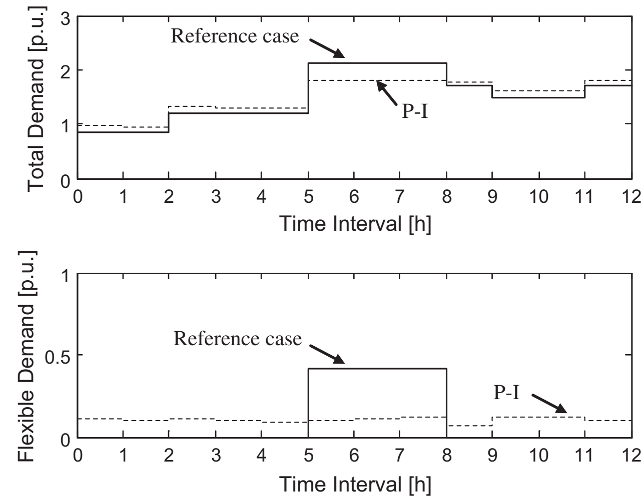

Fig. 3. Load curves, obtained with the PSO algorithm, $n_T = 12$. (a) Total load: reference case (solid) and P-I (dashed). (b) Flexible load: reference case (solid) and P-I (dashed).

4.1.1. Load curves for P-I by PSO algorithm

Fig. 3 presents the obtained load curves for the reference case and for problem P-I, for $n_T = 12$. Fig. 4 shows the load curves obtained for $n_T = 24$. In both figures, it can be noticed that flexible demand is shifted along the time horizon smoothing the total load curve.

4.1.2. Load curves for P-I by DE algorithm

In this case, only results for $n_T = 12$ are presented, due to the very low convergence rate obtained for $n_T = 24$. Fig. 5 presents load curves obtained for $n_T = 12$, for both the P-I problem and the reference case. It can be noticed that flexible demand is shifted along the time horizon smoothing the total load curve.

4.1.3. Load curves for P-I by hybrid algorithm

Fig. 6 presents the obtained load curves for P-I and for the reference case, for $n_T = 12$. Fig. 7 shows the same load curves for

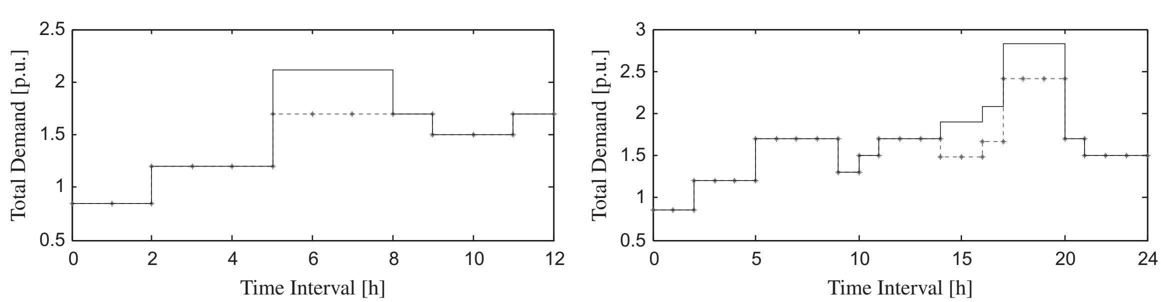

Fig. 2. Load curves for the reference case, for $n_T = 12$ and $n_T = 24$. Total load (solid); Fixed load (dashed).The same curves are adopted for both P-I and P-II.

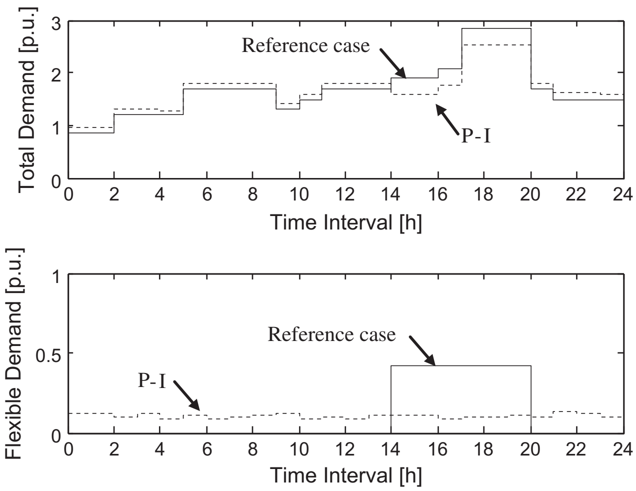

Fig. 4. Load curves, obtained with the PSO algorithm, $n_T = 24$. (a) Total load: reference case (solid) and P-I (dashed). (b) Flexible load: reference case (solid) and P-I (dashed).

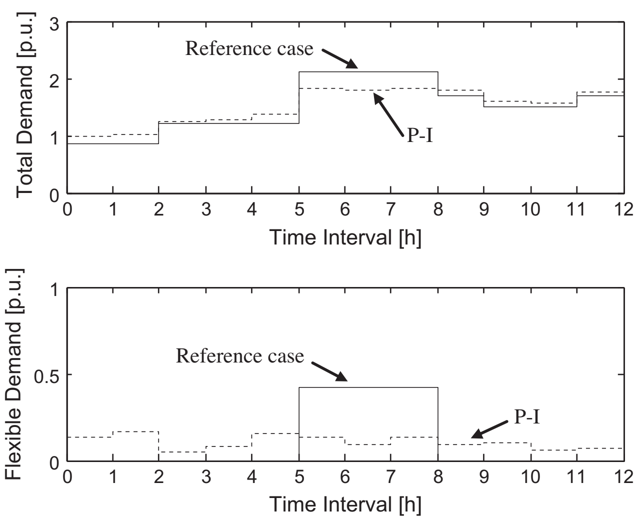

Fig. 5. Load curves, obtained with the DE algorithm, $n_T = 12$. (a) Total load: reference case (solid); P-I (dashed). (b) Flexible load: reference case (solid) and P-I (dashed).

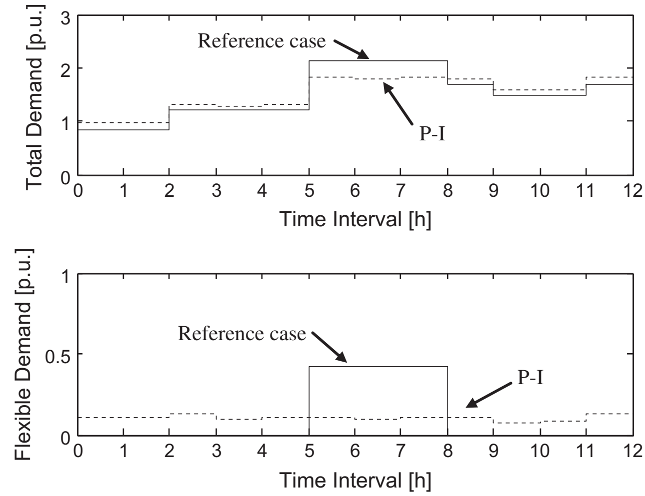

Fig. 6. Load curves, obtained with the hybrid algorithm, $n_T = 12$. (a) Total load: reference case (solid); P-I (dashed). (b) Flexible load: reference case (solid) and P-I (dashed).

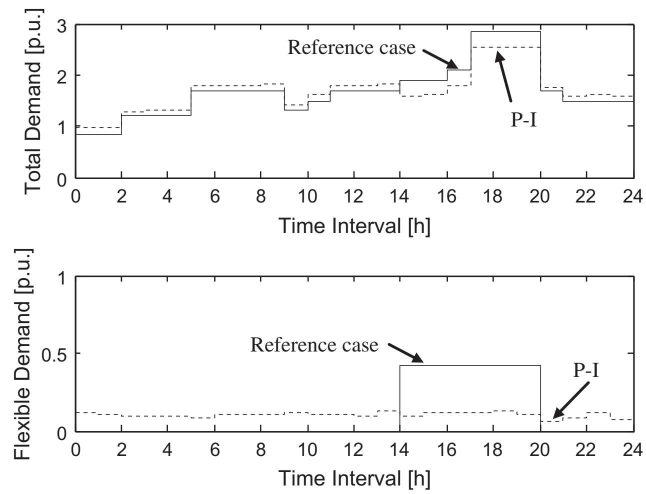

Fig. 7. Load curves, obtained with the hybrid algorithm, $n_T = 24$. (a) Total load: reference case (solid); P-I (dashed). (b) Flexible load: reference case (solid) and P-I (dashed).

$n_T = 24$. In both figures, it can be noticed that flexible demand is shifted along the time horizon smoothing the total load curve.

4.1.4. Comparison of obtained results for problem P-I

The comparison conducted in this section considers all three algorithms and aims at assessing the quality of the obtained results by comparing total generation costs. Initially, the numerical values of the objective function obtained with the three algorithms, together with mean execution times and errors (best value in relation to the mean value), are presented in Table 4, for $n_T = 12$ and $n_T = 24$. Moreover, notice that, in this special application, the inclusion of DD together with the generation dispatch should allow obtaining lower generation costs than those obtained by dispatching only generation. Therefore, results for problem P-I are compared against the results for the reference case, when simulating with the same algorithm.

For PSO algorithm, it can be observed that the objective function value for P-I is, in all cases, lower than for the reference case, as expected. For $n_T = 12$, the best (minimum) result for P-I is 1.24% lower than the best result for the reference case. The mean cost for P-I is 1.32% lower than for the reference case. For $n_T = 24$, the objective function for P-I is 1% lower than for the reference case in best simulations results. The mean cost for P-I is 2.33% lower than for the reference case.

For DE algorithm, when the mean of the objective function values among the thirty samples are compared, problem P-I attains a reduction of 2.80% of generation costs in relation to the reference case. However, considering best results in both problems, the algorithm does not attain lower costs with P-I.

For hybrid algorithm, the objective function value for P-I is lower than in the reference case in all cases, as expected. For $n_T = 12$, total cost in P-I is 2.67% lower than in the reference case for best results. The mean cost for P-I is 0.61% lower than for the reference case. For $n_T = 24$, total cost in P-I in 0.15% lower than for the reference case for best results. The mean cost for P-I is 1.55% lower than for the reference case.

Table 4 also presents dispersion parameters. Notice that for the PSO algorithm, the dispersion of the results is higher for P-I than for the reference case, for both $n_T = 12$ and $n_T = 24$. For the other two algorithms, dispersion of the results is higher for the reference

Table 4
Statistical performance for IEEE-30 bus system for problem P-I. Objective function values, mean execution times and errors.

Method	Best ($)		Worst ($)		Mean ($)		Standard deviation ($)		Mean execution time (s)		Error (%)	
	Ref.	P-I	Ref.	P-I	Ref.	P-I	Ref.	P-I	Ref.	P-I	Ref.	P-I
$n_T = 12$												
PSO	6304	6226	7094.5	7229	6732	6643	210	239	30.29	37.40	6.35	6.28
DE	6075	6196	7043.5	6928	6720	6532	256	173	51.94	160.34	9.60	5.14
Hybrid	5958	5799	6853.9	6768	6359	6315	250	229	36.08	66.19	6.30	8.17
$n_T = 24$												
PSO	14117	13975	1565.8	1541	14905	14557	301	351	103.35	141.39	5.28	4.00
Hybrid	13791	13770	1496.6	1460	14452	14228	314	223	141.87	361.23	4.57	3.22

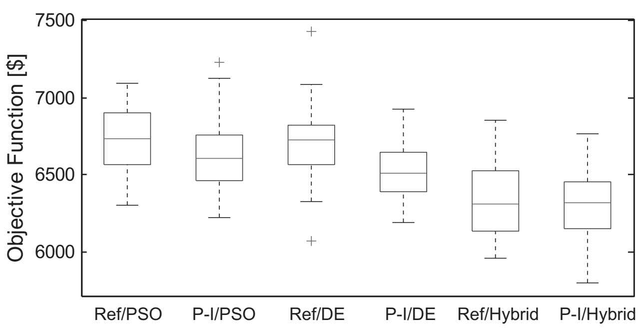

Fig. 8. Box plots of the objective function. Problem P-I and reference case, for $n_T = 12$ and all three algorithms.

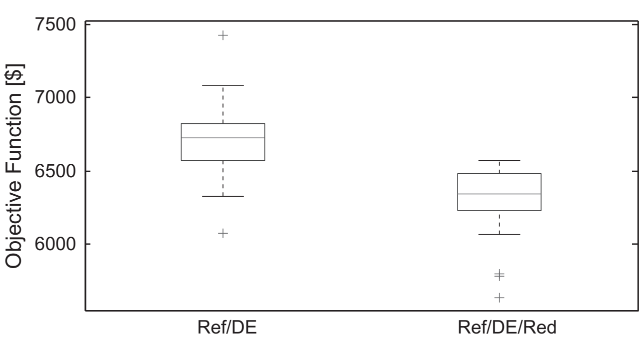

Fig. 9. Box plots of the objective function for the reference case, DE algorithm, $n_T = 12$.

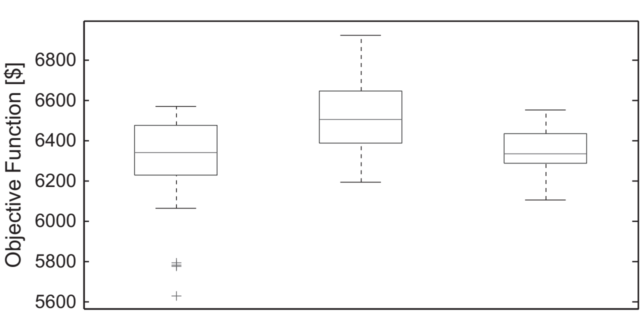

Fig. 10. Box plots of the objective function, for the reference case and for P-I, DE algorithm, $n_T = 12$.

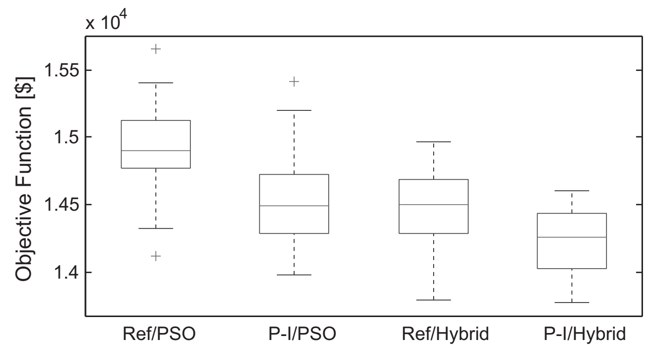

Fig. 11. Box plots of the objective function, $n_T = 24$, for P-I and the reference case.

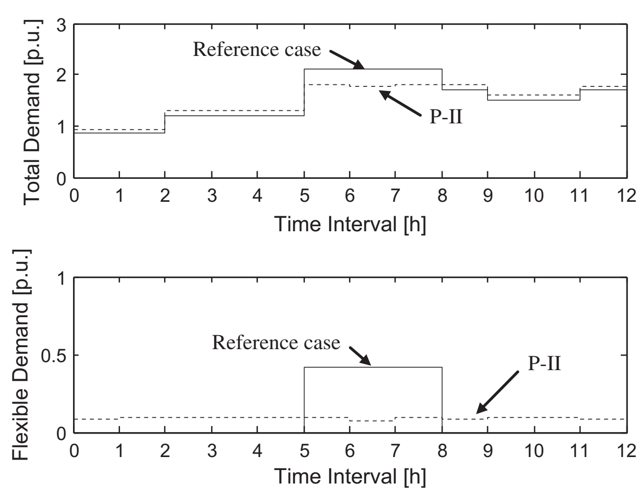

Fig. 12. Load curves for the PSO algorithm, problem P-II, $n_T = 12$. (a) Total load: reference case (solid) and P-II (dashed). (b) Flexible load: reference case (solid) and P-II (dashed).

case than for the P-I problem, for both $n_T = 12$ and $n_T = 24$. For the same problem P-I, the DE algorithm shows the least dispersion in the results, for both $n_T = 12$ and $n_T = 24$. For the reference case, the PSO algorithm presents the least dispersion in the results, for both $n_T = 12$ and $n_T = 24$. Notice that the mean execution time obtained in the P-I problem with $n_T = 12$ with the DE algorithm is significantly higher than the other cases. For $n_T = 24$, the hybrid algorithm presents a higher mean execution time for the P-I problem. Finally, one can observe that error values are of the same magnitude.

With stochastic algorithms, in general, it is desirable to obtain an indication about how the search space is explored. To this end, in order to easy visualize, it is proposed to use box plot graphs.

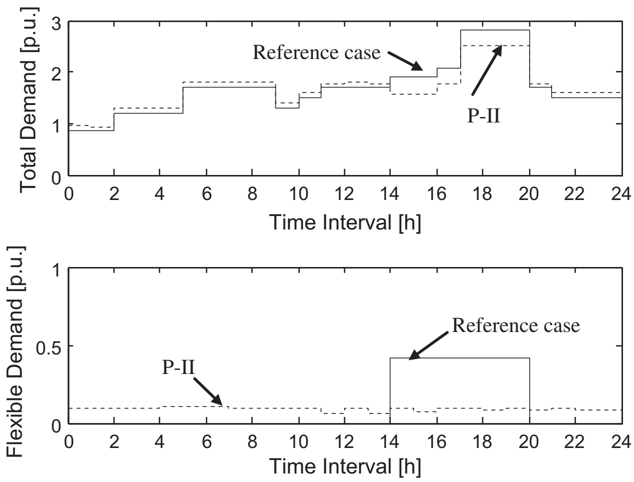

Fig. 13. Load curves for the PSO algorithm, problem P-II, $n_T = 24$. (a) Total load: reference case (solid) and P-II (dashed). (b) Flexible load: reference case (solid) and P-II (dashed).

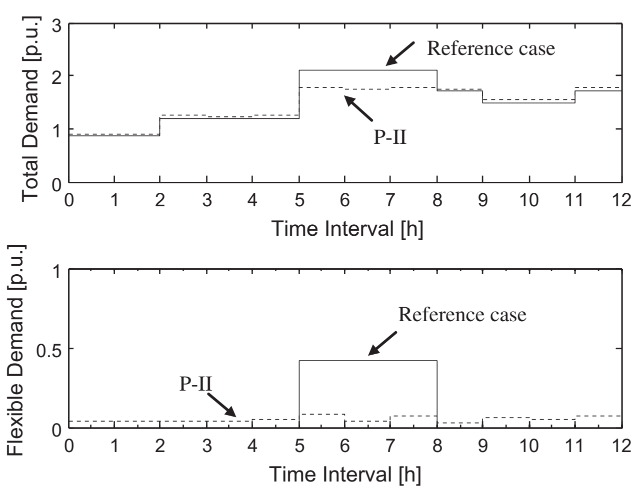

Fig. 14. Load curves problem P-II, by the DE algorithm, $n_T = 12$. (a) Total load: reference case (solid) and P-II (dashed). (b) Flexible load: reference case (solid) and P-II (dashed).

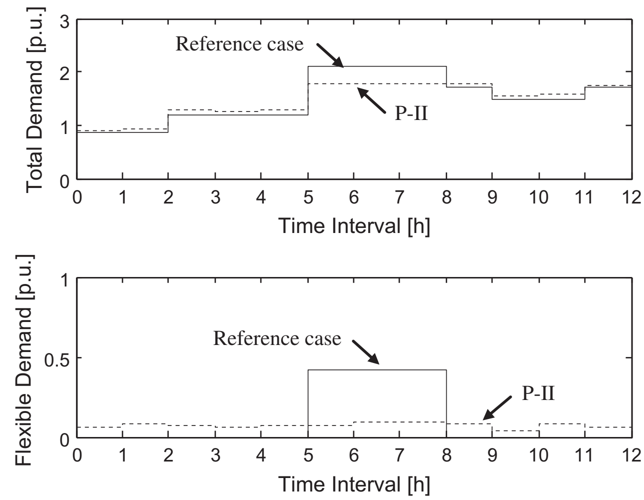

Fig. 15. Load curves problem P-II, by the hybrid algorithm, $n_T = 12$. (a) Total load: reference case (solid) and P-II (dashed). (b) Flexible load: reference case (solid) and P-II (dashed).

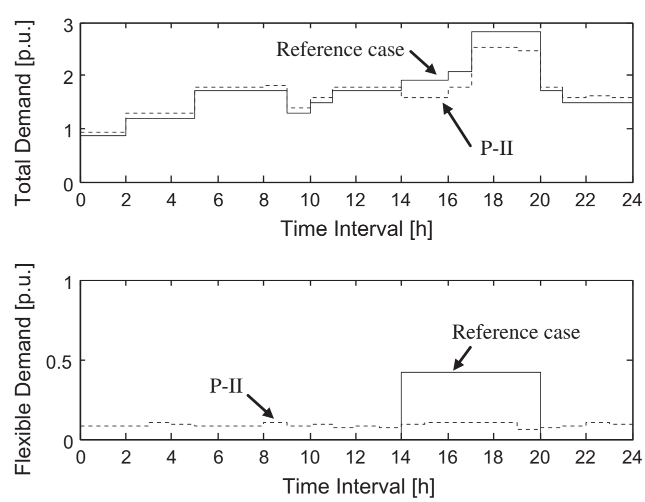

Fig. 16. Load curves problem P-II, by the hybrid algorithm, $n_T = 24$. (a) Total load: reference case (solid) and P-II (dashed). (b) Flexible load: reference case (solid) and P-II (dashed).

Fig. 8 presents the box plot for the objective function for all the simulations with $n_T = 12$. Results for problem P-I and for the reference case by the same algorithm are shown. Each box plot in Fig. 8 considers 30 (thirty) feasible solutions and the same search space is used for all box plots. It can be observed that for both the PSO and hybrid PSO–DE algorithms, the best result for the P-I problem has lower generation costs than the respective reference case. On the contrary, notice that for the DE algorithm the outlier on the reference case has lower generation costs than the best result for P-I problem. Outliers, in the context of this work, are feasible solutions of the optimization problem and must not be discarded. Observe that, when there is an outlier, the search space is not adequately explored around the outlier.

In order to improve the solution, a refined search around the outlier would be very helpful. Therefore, additional simulations for the reference case by DE algorithm are conducted considering a reduced search space centered on the outlier. Fig. 9 presents the result shown in Fig. 8 for the reference case, called Ref/DE, and the results obtained with the reduced search space, named Ref/DE/Red. Notice that these new simulations allow obtaining a lower value of the objective function for the reference case by the DE algorithm.

The next step is to compare the new value of the objective function, obtained for the reference case by restricting the search space, with the original best solution obtained in the P-I problem (Fig. 8), both with the DE algorithm. These comparison results are shown on Fig. 10. In this figure, Ref/DE/Red is the same box plot shown in Fig. 9; P-I/DE is the box plot shown in Fig. 8. An attempt is made in order to improve P-I/DE solution. Additional simulations, named P-I/DE/Red, are conducted for problem P-I using a restricted search space centered on the best solution of P-I/DE. On Fig. 10 it can be noticed that, although P-I/DE/Red gives a better solution than P-I/DE, it does not decrease generation costs in relation to the reference case Ref/DE/Red.

Fig. 11 presents obtained results for the P-I problem and $n_T = 24$, for the PSO and the hybrid algorithm. In this case, the best result for the P-I problem is lower than the corresponding best result for the reference case for both algorithms. Notice that an outlier is obtained in the reference case by PSO algorithm. In this case, the solution Ref/PSO should be refined around the outlier.

Table 5
Statistical performance for IEEE-30 bus system for problem P-II. Objective function values, execution times and errors.

Method	Best ($)		Worst ($)		Mean		Standard deviation		Mean execution time (s)		Error (%)	
	Ref.	P-II	Ref.	P-II	Ref.	P-II	Ref.	P-II	Ref.	P-II	Ref.	P-II
n_T = 12												
PSO	6304	5989	7094.5	6801.0	6732	6379	210	218	30.29	33.80	6.35	6.11
DE	6074	5881	7431.1	6582.3	6720	6248	256	202	51.94	71.49	9.61	5.87
Hybrid	5958	5469	6853.9	6738.9	6359	6099	250	262	36.08	41.96	6.30	10.32
n_T = 24												
PSO	14117	14447	15658	16263	14905	15305	301	516	103.35	71.49	5.28	5.61
Hybrid	13791	13339	14966	14773	14452	14076	314	379	141.87	247.34	4.57	5.24

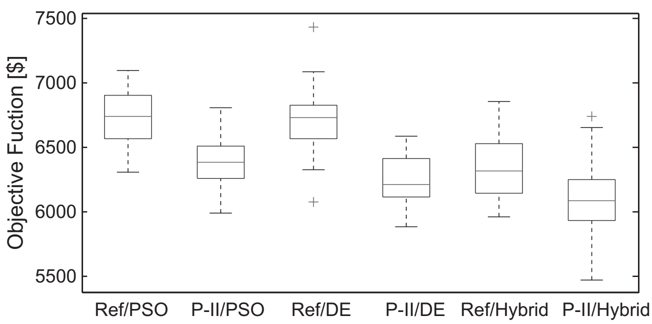

Fig. 17. Box plot of objective function for P-II, $n_T = 12$.

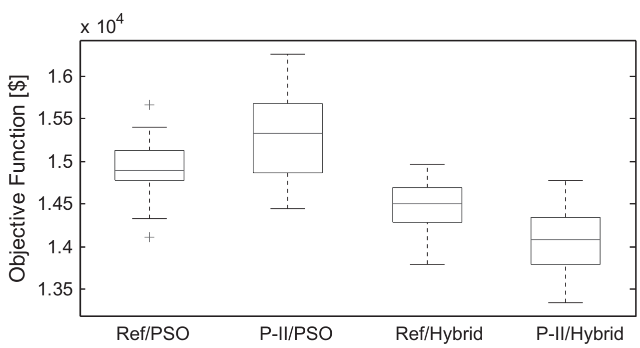

Fig. 18. Box plot of objective function for P-II, $n_T = 24$.

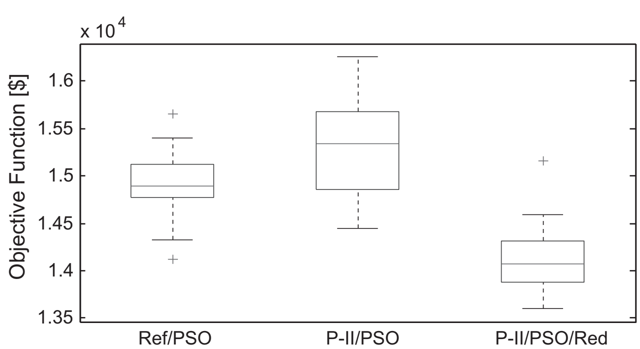

Fig. 19. Box plot of objective function for P-II, $n_T = 24$, PSO algorithm.

4.2. Results for P-II: Demand management with type-II consumers (inequality energy constraints)

In this section, the obtained results for problem P-II, in which the economic dispatch involves an inequality energy constraint,

Table 6
Energy associated with the flexible load. Problem P-II, for $n_T = 12$. Columns correspond to: enegy, total consumption in pu-h and in percentage, off-peak consumption values.

	E_{Rj} (pu-h)	Flexible energy (pu-h)	Flexible energy (% of E_{Rj})	Flexible energy in off-peak (pu-h)
PSO	1.248	1.0837	86.83	0.8194 (*75.61%*)
DE	1.248	0.5971	47.84	0.4162 (*69.70%*)
Hybrid	1.248	0.8698	69.70	0.6084 (*69.95%*)

Table 7
Energy associated with the flexible load. Problem P-II, for $n_T = 24$. Columns correspond to: enegy, total consumption in pu-h and in percentage, off-peak consumption values.

	E_{Rj} (pu-h)	Flexible energy (pu-h)	Flexible energy (% of E_{Rj})	Flexible energy in off-peak (pu-h)
PSO	2.496	2.1706	86.96	1.6471 (*75.88%*)
Hybrid	2.496	2.0963	83.98	1.5373 (*73.33%*)

are presented for both $n_T = 12$ and $n_T = 24$ and for the three algorithms. In all simulations, the corresponding same parameters defined in the previous section for all three algorithms are adopted.

4.2.1. Load curves for P-II by PSO algorithm

Fig. 12 presents the obtained load curves for P-II problem and for the reference case for $n_T = 12$. Fig. 13 shows the same load curves for $n_T = 24$. In both figures, it can be noticed that flexible demand is shifted along the time horizon smoothing the total load curve, as expected.

4.2.2. Load curves for P-II by DE algorithm

Fig. 14 presents the obtained load curves for problem P-II together with the respective load curves for the reference case for $n_T = 12$. It can be noticed that flexible demand is shifted along the time horizon smoothing the total load curve, as expected. Similarly as with P-I problem, convergence rate for $n_T = 24$ with this algorithm was extremely low and results are not presented.

4.2.3. Load curves for P-II by hybrid algorithm

Fig. 15 presents the obtained load curves for problem P-II together with the respective load curves for the reference case, for $n_T = 12$. Fig. 16 shows the same load curves for $n_T = 24$. In both figures, it can be noticed that flexible demand is shifted along the time horizon smoothing the total load curve.

4.2.4. Comparison of the obtained results for problem P-II

The comparison conducted in this section considers all three algorithms and aims at assessing the quality of the obtained results

Table 8
Incentive paid for type-II consumers, for the best result, for $n_T = 12$.

Dispatch interval	Incentive ($)		
	PSO	DE	Hybrid
6	32.44	33.75	34.03
7	34.11	38.03	32.32
8	31.83	34.92	32.32
Total	98.37	106.71	98.66

Table 9
Incentive paid for type-II consumers, for the best result, for $n_T = 24$.

Dispatch interval	Incentive ($)	
	PSO	Hybrid
15	16.17	16.04
16	17.38	15.72
17	16.36	15.69
18	15.93	15.63
19	16.62	15.84
20	16.18	17.93
Total	98.63	96.85

Table 10
Costs and incentives paid for type II consumers, for the best simulation.

	Objective function ($)	Generation costs ($)	Incentives ($)
$n_T = 12$			
PSO	5988.90	5890.53	98.37
DE	5881.40	5774.69	106.71
Hybrid	5469.30	5370.64	98.66
$n_T = 24$			
PSO	14447	14348.37	98.63
Hybrid	13339	13242.15	96.85

Table 11
Convergence rate for all three algorithms.

	PSO (%)	DE (%)	Hybrid (%)
P-I			
$n_T = 12$	16.48	8.77	31.91
$n_T = 24$	27.03	–	32.98
P-II			
$n_T = 12$	42.85	5.42	10.20
$n_T = 24$	25	–	14.35

when inequality energy restrictions are used. Results for problem P-II are compared against those results for the reference case, both using the same algorithm.

Table 5 presents the numerical values of the objective function obtained with the three algorithms, together with mean execution times and errors (best value in relation to the mean value), for $n_T = 12$ and $n_T = 24$.

For the PSO algorithm, for $n_T = 12$, in the best simulation result, the objective function value in P-II is 4.99% lower than in the reference case. When mean values are compared, the objective function value for P-II is 5.24% lower than for the reference case. However, for $n_T = 24$, the algorithm does not attain the reduction in the objective function for P-II.

The DE algorithm allows attaining a reduction of 7.02% in the objective function value when mean values are compared and a reduction of 3.17% when best values are compared, with the implementation of DD in P-II in relation to the reference case.

For the hybrid algorithm PSO–DE, it can be observed that the objective function values are lower than for the reference case, in all cases, as expected. For $n_T = 12$, in the best simulation result, the objective function value in P-II is 8.20% lower than in the reference case. The mean value of the objective function in P-II is 3.28% lower than in the reference case. For $n_T = 24$, the objective function value in P-II is 4.09% lower than in the reference case, for the best result. When mean values are compared, in P-II a reduction of 2.60% in relation to the reference case is obtained.

For PSO and the PSO–DE, $n_T = 12$, dispersion results indicate a slightly greater value for P-II. For the DE algorithm, the greater dispersion occurs in the reference case. For $n_T = 24$, dispersion parameters are greater for P-II than for the reference case for all algorithms.

Notice that the mean execution time obtained in the P-I problem with $n_T = 12$ with the DE algorithm is significantly higher than for the other cases. For $n_T = 24$, the hybrid algorithm presents a higher mean execution time for the P-I problem simulation. The error values obtained (best objective function value in relation to the mean value) are similar.

Fig. 17 presents box plots of the objective function for all algorithms, $n_T = 12$, for the reference case and for problem P-II. In all cases, in P-II the DD allows obtaining lower objective function values, as is expected.

Fig. 18 presents box plots of the total objective function for all algorithms, $n_T = 24$, for the reference case and for problem P-II. It can be observed that algorithm PSO does not attain cost reduction by DD implementation. Fig. 19 presents results for PSO, those shown in Fig. 18 together with new simulations obtained using a reduced search space centered on the best cost shown in Fig. 18.

Table 12
Generators cost functions and operational limits.

Generators			G20	G32	G101	G131	G140	G167	G169	G170	G171	G192
Cost (without fines) ($/pu-h)			4.07	3.86	3.89	4.13	4.71	4.16	4.16	4.16	4.16	4.06
3 × Cost (with fine) ($/pu-h)			12.21	11.58	11.67	12.39	14.13	12.48	12.48	12.48	12.48	12.18
$n_T = 12$												
Limits (p.u.)	Without fines	$\overline{p_g}$	1.38	2.6	4.28	10.08	3.17	0.5	0.66	1.33	3.63	0.98
		$\underline{p_g}$	0	0	0	0	0.0	0.25	0.33	0.8	1.8	0
	With fines	$\overline{p_g}$	6.9	13.0	21.4	50.4	15.85	1.25	1.65	2.65	9.15	4.9
		$\underline{p_g}$	0	0	0	0	0	0	0	0	0	0
$n_T = 24$												
Limits (p.u.)	Without fines	$\overline{p_g}$	1.08	1.60	2.28	2.08	1.17	0.50	0.66	0.83	1.63	0.98
		$\underline{p_g}$	0	0	0	0	0	0.15	0.23	0.20	1.0	0
	With fines	$\overline{p_g}$	5.4	8	11.4	10.4	5.85	1.75	2.15	3.15	3.15	4.9
		$\underline{p_g}$	0	0	0	0	0	0	0	0	0	0

Table 13
Flexible load data for P-I and P-II for the 192-bus test system: operational limits (valid for each dispatch interval) and amount of energy associated to the time horizon.

	Operational limits (p.u.) P-I and P-II		Energy (p.u.-h)
	$\overline{p_d}$	$\underline{p_d}$	
L1	0.1092	0	2.1840
L2	0.2220	0	4.4400
L3	0.0840	0	1.6800
L4	0.4224	0	8.4480
L5	0.1536	0	3.0720
L6	0.0480	0	0.9600
L7	0.0420	0	0.8400
L8	0.2520	0	5.0400
L9	0.6996	0	13.9920
L10	0.0432	0	0.8640
L11	0.0120	0	0.2400
L12	0.0228	0	0.4560
L13	0.0876	0	1.7520
L14	0.0144	0	0.2880
L15	0.1200	0	2.4000
L16	0.0024	0	0.0480
L17	0.1200	0	2.4000
L18	0.0720	0	1.4400
L19	0.1260	0	2.5200
L20	0.0900	0	1.8000
L21	0.0360	0	0.7200
L22	0.1440	0	2.8800
L23	0.0696	0	1.3920
L24	0.0792	0	1.5840
L25	0.1800	0	3.6000
L26	0.1632	0	3.2640
L27	0.0312	0	0.6240
L28	0.0480	0	0.9600
L29	0.0108	0	0.2160
L30	0.0468	0	0.9360
L31	0.0084	0	0.1680
Total	–	–	71.2080

These results show that initially (Fig. 18) the search space was not adequately examined by PSO algorithm, since a significant reduction in the objective function value is obtained.

Tables 6 and 7 show the amount of flexible energy (the energy associated with the flexible load) consumed during the time horizon, in pu-h and in percentage of the maximum for all algorithms, for $n_T = 12$ and $n_T = 24$ respectively. In Table 6, column two is the energy limit, column three is the energy consumed in pu-h, column four is the energy consumed in percentage of the limit and column five presents the percentage of the consumed energy during off-peak period. It can be noticed that algorithms PSO and hybrid algorithm PSO–DE give similar results, especially for $n_T = 24$. Results indicate that there exists a reduction in the energy consumed by type-II consumers and that flexible demand is mainly concentrated in the off-peak intervals.

Tables 8 and 9 present the incentive paid to type-II consumers for $n_T = 12$ and $n_T = 24$ respectively. It can be observed that the PSO and hybrid algorithms give very similar results.

Table 10 presents total values of the objective function, of generation costs and incentive paid by system operators or distribution companies. Incentives represent 2% of the total generation cost for $n_T = 12$ and 0.70% for $n_T = 24$.

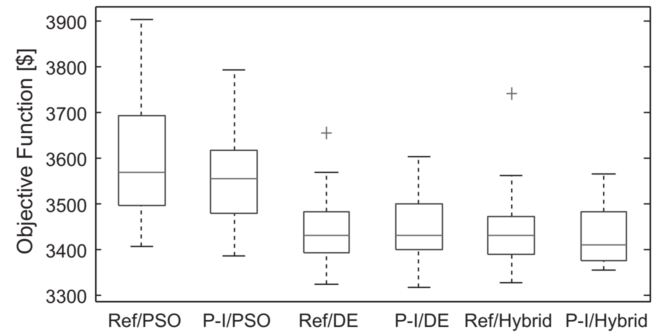

Fig. 20. Box plot of objective function for P-I, $n_T = 24$.

4.3. Results comparison

From comparisons conducted in the previous section it can be observed that, in some cases, the algorithms fail in obtaining lower generation costs for P-I or P-II in relation with the reference case. In some cases, it is possible to improve the solution by a better exploration of the search space. Mean execution times obtained and the error values are similar for all the algorithms in both problems P-I and P-II. Box plot graphs give a good indication about the quality of the search space exploration.

Table 11 presents convergence rates obtained for all three algorithms. It is interesting to notice that, in general, for the more complex problem ($n_T = 24$), convergence rates are higher. The exception was for the PSO algorithm in P-II problem for $n_T = 12$ intervals. It is observed that the dimension of the problem does not directly affect convergence rate of the algorithms. The hybrid algorithm presents better convergence rates for P-I. For P-II, the PSO algorithm shows better convergence rates. Notice that it is not possible to conclude about a relation between convergence rate and type of problem neither to the particular algorithm.

The DE algorithm showed the worst performance among the three algorithms. For problem P-I, it could not decrease the objective function value in relation to the reference case, even with a restricted search space. The other two algorithms succeeded in this aspect. For P-II, its performance is similar to PSO performance. The DE algorithm presented a very low convergence rate for higher number of dispatch intervals ($n_T = 24$).

Moreover, it can be concluded that the proposed hybrid algorithm has better performance. It attained lower generation costs in all cases: reference case, P-I and P-II.

5. Application to the DD program for large consumers of a distribution company

This section presents the application of the algorithms to the 192-bus system of a Brazilian distribution utility, in the context of a DD program for large consumers of the company [40]. The load

Table 14
Statistical performance for the 192-bus test system for problem P-I.

Method	Best ($)		Worst ($)		Mean		Standard deviation		Mean execution time (s)	
	Ref.	P-I	Ref.	P-I	Ref.	P-I	Ref.	P-I	Ref.	P-I
$n_T = 24$										
PSO	3407.3	3387.2	3904.8	3794.0	3597.3	3555.1	132.54	106.08	359.28	481.55
DE	3322.1	3316.7	3655.2	3604.9	3439.6	3446.8	72.02	72.92	339.72	471.91
Hybrid	3328.1	3356.0	3743.5	3566.5	3443.5	3432.2	77.58	64.77	482.76	495.32

Table 15
Statistical performance for the 192-bus test system for problem P-II.

Method	Best ($)		Worst ($)		Mean		Standard deviation		Mean execution time (s)	
	Ref.	P-II	Ref.	P-II	Ref.	P-II	Ref.	P-II	Ref.	P-II
n_T = 12										
PSO	1641.7	1020.4	2011.1	1409.9	1826.0	1236.9	111.79	86.38	214.02	231.48
DE	1353.3	1044.6	1920.1	1560.8	1637.9	1303.6	167.74	135.52	220.91	253.49
Hybrid	1368.9	1008.0	1952.4	1607.0	1706.6	1263.9	152.52	161.92	313.65	239.75

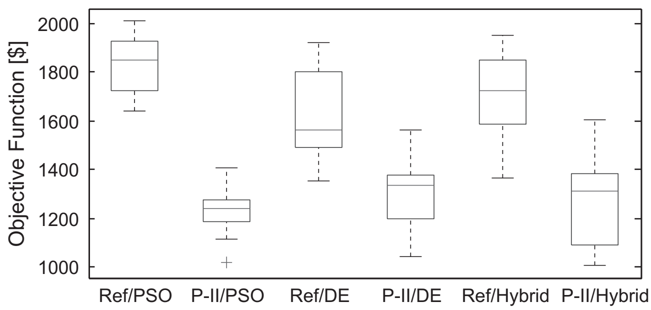

Fig. 21. Box plot of objective function for P-II, $n_T = 12$.

management program is meant to be launched in critical situations, in order to help the distribution company in achieving better operating conditions. It is based on the relief of part of consumer's demand during certain time intervals in exchange for economic benefits. An optimization problem allows selecting the loads to be reduced among those loads that are engaged in the program. The problem is formulated as in Section 2, with both equality and inequality energy constraints; however, the objective function is slightly different than the one presented in Section 2. Piecewise linear functions that represent the cost associated with the use of the transmission system are modeled. The energy bought from generators flows into the distribution system through 10 (ten) input points, which represent the connecting points with the bulk transmission system. A certain amount of capacity is contracted for each point. When the contracted capacity is exceeded, important fines are applied by the Brazilian Regulatory Agency [40]. Therefore, each input point is modeled as a generator with two different generation costs: a lower value that indicates no violation of the contracted capacity and a higher value that represents the fines applied when the contracted capacity is exceeded. The DD program implemented by the company considers reducing load in order to avoid the payment of fines in critical operating conditions; for instance, a contingency in which an important distribution line is lost.

The adopted generation cost functions associated with input points are presented in Table 12, together with operational limits. Simulations are carried for problem P-I, which represent consumers by equality constraints, for a time horizon of 24 dispatch intervals ($n_T = 24$) and for problem P-II, which represents consumers by inequality constraints, for a time horizon of 12 dispatch intervals ($n_T = 12$). It is assumed that 31 consumers are engaged in the DD program. Table 13 presents data related to flexible consumers: the operational limits of their flexible load and the amount of energy associated to the time horizon, which corresponds to parameters E and Er in (6) and (7).

All three evolutionary algorithms are applied to this problem. Table 14 presents the results obtained for problem P-I and Fig. 20 the corresponding box plot. Table 15 shows results for problem P-II and Fig. 21 the corresponding box plot. It can be noticed that the costs obtained with all the three algorithms are similar. In the box plot for problem P-I in Fig. 20, it is clearly observed that, for the hybrid algorithm, P-I problem simulation fails to reduce costs in relation to the reference case. In this case, the methodology illustrated in Section 4 must be applied, refining the solution around the best point. In the box plot for problem P-II shown in Fig. 21, the outlier obtained with the PSO algorithm in problem P-II simulation suggests that the search can be improved and a better solution could be obtained. From Table 14 and Table 15, one can observe that mean execution time for the hybrid algorithm is higher than with the other algorithms, except for problem P-II.

In this application, the quality of the best near-optimal solution obtained among all three evolutionary algorithms is evaluated using an analytical optimization algorithm. To this end, a neighborhood around the best solution obtained is defined and is used as the feasible region of the analytical problem. The interior point algorithm presented in [40] is used in order to refine the solution.

For problem P-I, the feasible region for applying the interior point algorithm is a neighborhood around the best result obtained from the DE algorithm. The cost obtained is 3232.60 $/pu-h. Therefore, there is an error equal to 2.6%. For the reference case, the comparison is, again, with the DE algorithm. The cost obtained with the interior point algorithm is equal to 3246.00 $/pu-h, which gives an error equal to 2.34%.

For problem P-II, the best solution obtained with the hybrid algorithm is used for defining the feasible region for the interior point algorithm. The cost obtained is 796.45 $/pu-h, which gives an error equal to 26.56%. For the reference case, the best solution obtained with the DE algorithm is used and the cost obtained is equal to 1245.60 $/pu-h, which gives an error equal to 8.56%.

Table A1
Fixed load data for IEEE-30 bus test system.

	Fixed load (p.u.)																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
n_T = 12																								
Ref.	0.85	0.85	1.2	1.2	1.2	2.1	2.1	2.1	1.7	1.5	1.5	1.7	–	–	–	–	–	–	–	–	–	–	–	–
P-I and P-II	0.85	0.85	1.2	1.2	1.2	1.7	1.7	1.7	1.7	1.5	1.5	1.7	–	–	–	–	–	–	–	–	–	–	–	–
n_T = 24																								
Ref.	0.85	0.85	1.2	1.2	1.2	1.7	1.7	1.7	1.7	1.3	1.5	1.7	1.7	1.7	1.9	1.9	2.1	2.8	2.8	2.8	1.7	1.5	1.5	1.5
P-I and P-II	0.85	0.85	1.2	1.2	1.2	1.7	1.7	1.7	1.7	1.3	1.5	1.7	1.7	1.7	1.5	1.5	1.7	2.4	2.4	2.4	1.7	1.5	1.5	1.5

6. Conclusion

This research aims at contributing with aiding tools to assess demand dispatch effects on the operations planning in power systems. It is proposed to apply evolutionary algorithms to the generation and demand dispatch problem. The paper presents a comparison of the performance of three stochastic optimization algorithms: the particle swarm optimization, the differential evolution and a hybrid algorithm obtained from the previous, when applied to solve the simultaneous dispatch of generation and demand. The performance of the algorithms when equality and inequality energy constraints are used is assessed. These constraints represent consumption restrictions of certain flexible consumers that can shift part of their load along a time horizon.

Simulation results obtained with the IEEE-30 bus test system and from a real distribution system were presented in the paper. Obtained results with the IEEE 30-bus test system allow concluding that the proposed hybrid algorithm PSO–DE presented the best performance and the DE algorithm presented the worst performance. In the practical application of demand dispatch, all three algorithms gave similar results when applied to the simulation of the distribution system.

The most relevant conclusion of this work refers to the importance of describing obtained results in the adequate manner. Stochastic algorithms like the ones used in this paper, give stochastic results that need to be adequately presented. The paper presented the results using a statistical tool: box plot graphs. This tool gave an important assistance in determining the quality of the obtained solution. The presence of outliers in box plot is very important, since they correspond to a feasible solution of the optimization problem. Therefore, they must not be discarded. It was observed that outliers indicate that there must be a region of lower objective function values that is not adequately explored. They suggest that a modified search strategy could improve results. In this paper, the strategy adopted was to conduct additional simulations considering a reduced search space centered on the best solution previously obtained.

Appendix A

See Table A1.

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