

Economic dispatch solution using efficient heuristic search approach

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Abstract

A new efficient hybrid differential evolution algorithm with harmony search (DE-HS) is proposed in this paper to solve the economic load dispatch (ELD) problem. The fresh individual generation mechanism of harmony search (HS) is utilized to enhance the local search capability of the original differential evolution (DE) method. The proposed hybrid algorithm is validated using the IEEE 30 bus test system and the practical Algerian 59 bus system. The results confirm the suitability of the proposed strategy to find accurate and feasible optimal solutions for ELD problems.

Keywords

Economic power dispatch (EPD); Differential Evolution (DE); Harmony Search (HS)

Introduction

Economic load dispatch is a fundamental function in modern power system operation and control. The conventional economic load dispatch (ELD) problem of power generation involves allocation of power output to different thermal units to minimize the operating cost subject to diverse equality and inequality constraints of the power system. This makes the ELD problem a large-scale highly nonlinear constrained optimization problem.

It is therefore of great importance to solve this problem as quickly and accurately as possible. Unfortunately, the input-output characteristics of modern units are inherently non-linear and non-convex because of valve-point loadings, prohibited operating zones and multiple fuels, and furthermore they may generate multiple local minimum points in the cost function. Conventional techniques offer good results, but when the search space is nonlinear and has discontinuities, these techniques become difficult to solve with a slow convergence ratio and not always seeking to the global optimal solution. New numerical methods are then needed to cope with these difficulties, specially, those with high speed search to the optimal and not being trapped in local minima.

The ELD problem has been solved via several traditional optimization methods including gradient-based techniques, newton methods, linear programming, and quadratic programming [1]. Most of these techniques are not capable to solve efficiently the optimization problems with a non-convex, non-continuous, and highly non-linear solution space.

Several heuristic global search tools have evolved in the last decades that have facilitated solving the ELD problems with non-smooth cost functions. Among these methods could be named the genetic algorithms [1, 2], evolutionary programming [3], neural networks [4], differential evolution [5], simulated annealing [6], tabu search [7], particle swarm optimization [8], and ant colony optimization [9]. Also the hybridization and combination of these methods have been used to solve more effectively ELD problems [10-12].

Differential evolution and harmony search algorithms are two of these global optimization techniques. Differential evolution (DE) algorithm which is inspired by biological and sociological motivations has been developed and introduced by Storn and Price [13] in 1995. DE algorithm improves a population of candidate solutions over several generations using the mutation, crossover and selection operators in order to reach an optimal solution [14]. In DE, the fitness of an offspring is one-to-one competed with that of the corresponding parent. This one-to-one competition makes convergence speed of DE faster than other evolutionary algorithms. Nevertheless, this faster convergence property yields in a higher probability of searching toward a local optimum or getting premature convergence [15-16].

Proposed by Geem et al. [17] in 2001, the harmony search (HS) method is inspired by the underlying principles of the musicians' improvisation of the harmony. In the HS algorithm, musician improvises the pitches of his/her instrument to obtain a better state of

harmony. The pitch of each musical instrument determines the aesthetic quality, just as the objective function value is determined by the set of values assigned to each decision variable [18]. On the other hand, HS is good at identifying the high performance regions of the solution space at a reasonable time. However, several studies [19-21] have shown that the original HS method has a limitation in dealing with the multimodal and constrained optimization problems.

To overcome the drawbacks of DE and HS, an efficient combination strategy of DE and HS (termed DE-HS) is introduced in this study. The proposed DE-HS consists essentially in a strong co-operation of DE and HS, since the DE-based update policy of existing individuals and HS-based generation strategy of new individuals are merged together [22].

In this study, a new efficient combined differential evolution and harmony search (DE-HS) algorithm is proposed for solving practical ELD problems. The performance of the proposed method is tested on two case studies using the IEEE 30 bus test system and the practical Algerian 59 bus system. Numerical results obtained by the proposed approach were compared with other optimization results reported in the literature recently.

Economic load dispatch problem formulation

The main objective of ELD is to minimize the total generation cost of the power system within a defined interval (typically 1h).

Objective function

The objective function for the ELD reflects the cost associated with generating power in the system. The objective function F for the entire power system can then be written as the sum of the fuel cost model for each generator:

$$F = \sum_{i=1}^{ng} F_i \quad (1)$$

where F_i is the fuel cost function of the i^{th} generator in (\$/h) and ng is the number of online generating units to be dispatched.

Traditionally, the fuel cost curve is approximated using a simple smooth quadratic function [5] given by:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i, \quad (2)$$

where P_i is the power of generator i . a_i , b_i and c_i are the cost coefficients of generator i .

Power balance constraint

This constraint is based on the principle of equilibrium between total system generation and total system loads P_D and transmission losses P_L [5]. That is

$$\sum_{i=1}^{ng} P_i = P_D + P_L \quad (3)$$

where P_L can be obtained using the B matrix loss formula [5], given by:

$$P_L = \sum_{i=1}^{ng} \sum_{j=1}^{ng} P_i B_{ij} P_j + \sum_{i=1}^{ng} P_i B_{i0} + B_{00} \quad (4)$$

where B_{ij} , B_{i0} and B_{00} are the loss coefficients.

Generator capacity constraints

For stable operation, the real power generation of each generator should be restricted between its lower and upper limits of generation. The generator capacity constraints are expressed as a pair of inequality constraints, as follows:

$$P_i^{\min} \leq P_i \leq P_i^{\max} \quad (5)$$

Overview of differential evolution algorithm

The differential evolution algorithm (DE) is a population based algorithm like genetic algorithm using the similar operators; crossover, mutation and selection. In DE, each decision variable is represented in the chromosome by a real number. As in any other evolutionary algorithm, the initial population of DE is randomly generated, and then evaluated. After that, the selection process takes place. During the selection stage, three parents are chosen and they generate a single offspring which competes with a parent to determine which one passes to the following generation. DE generates a single offspring (instead of two like in the genetic algorithm) by adding the weighted difference vector between two parents to a third parent. If

the resulting vector yields a lower objective function value than a predetermined population member, the newly generated vector replaces the vector to which it was compared.

An optimization task consisting of D parameters can be presented by a D -dimensional vector. In DE, a population of N_P solution vectors is randomly created at the start. This population is successfully improved over G generations by applying mutation, crossover and selection operators, to reach an optimal solution [14, 15]. The main steps of the DE algorithm are given below:

Initialization

Evaluation

Repeat

Mutation

Crossover

Evaluation

Selection

Until (*Termination criteria are met*)

Initialization

Typically, each decision parameter in every vector of the initial population is assigned a randomly chosen value from within its corresponding feasible bounds:

$$x_{j,i}^{(0)} = x_j^{\min} + \mu_j (x_j^{\max} - x_j^{\min}), \quad i = 1, \dots, NP, \quad j = 1, \dots, D, \quad (6)$$

where μ_j denotes a uniformly distributed random number within the range [0, 1], generated anew for each value of j . x_j^{\max} and x_j^{\min} are the upper and lower bounds of the j th decision parameter, respectively.

Mutation

The mutation operator creates mutant vectors x'_i by perturbing a randomly selected vector x_a with the difference of two other randomly vectors x_b and x_c , according to the following equation [17]:

$$x_i'^{(G)} = x_a^{(G)} + \alpha(x_b^{(G)} - x_c^{(G)}), \quad i = 1, \dots, NP, \quad (7)$$

where x_a , x_b and x_c are randomly chosen vectors among the N_P population, and $a \neq b \neq c$. x_a , x_b and x_c are selected anew for each parent vector. The scaling constant α is an algorithm control parameter used to adjust the perturbation size in the mutation operator and improve algorithm convergence.

Crossover

The crossover operation generates trial vectors x_i'' by mixing the parameters of the mutant vectors x_i' with its target or parent vectors x_i according to a selected probability distribution of the following form [17]:

$$x_{j,i}''^{(G)} = \begin{cases} x_{j,i}'^{(G)} & \text{if } \rho_j \leq C_R \text{ or } j = q \\ x_{j,i}^{(G)} & \text{otherwise} \end{cases}, \quad i = 1, \dots, NP, \quad j = 1, \dots, D \quad (8)$$

where ρ_j denotes a uniformly distributed random number within $[0, 1]$, generated anew for each value of j . q is a randomly chosen index $\in \{1, \dots, N_P\}$ that guarantees that the trial vector gets at least one parameter from the mutant vector. The crossover constant C_R is an algorithm parameter that controls the diversity of the population and aids the algorithm to escape from local minima.

Selection

The selection operator forms the population by choosing between the trial vectors and their predecessors (target vectors) those individuals that present a better fitness or are more optimal according to (9) [17].

$$x_i^{(G+1)} = \begin{cases} x_i''^{(G)}, & \text{if } f(x_i''^{(G)}) \leq f(x_i^{(G)}) \\ x_i^{(G)}, & \text{otherwise} \end{cases}, \quad i = 1, \dots, NP \quad (9)$$

This optimization process is repeated for several generations, allowing individuals to improve their fitness as they explore the solution space in search of optimal values.

DE has three essential control parameters which are: the scaling factor α , the crossover constant C_R and the population size N_P . The scaling factor is a value in the range $[0, 2]$ that controls the amount of perturbation in the mutation process. The crossover constant is

a value in the range [0, 1] that controls the diversity of the population. The population size determines the number of individuals in the population and provides the algorithm enough diversity to search the solution space.

Overview of harmony search algorithm

The harmony search (HS) is a music-inspired evolutionary algorithm, mimicking the improvisation process of music players searching for a perfect state of harmony [17-18]. The harmony in music is analogous to the solution vector and the behavior of musician's improvisation is analogous to local and global search schemes in optimization techniques.

In the HS algorithm, musical performances seek a perfect state of harmony determined by aesthetic estimation, as the optimization algorithms seek a best state (i.e. global optimum) determined by objective function value. The optimization procedure of the HS algorithm consists of the following steps:

1. Initialize algorithm parameters and harmony memory (HM).
2. Improvise a new harmony from HM.
3. Update harmony memory.
4. Repeat Steps 3 and 4 until the stopping criterion is met.

The detailed description of these steps is summarized in the following [18]:

- **Step 1.** Initialize the HS Memory (HM). The initial HM consists of a certain number of randomly generated solutions for the optimization problem under consideration. For a D-dimension problem, an HM with the size of HMS can be represented as follows:

$$HM = \begin{bmatrix} x_1^1 & x_2^1 & \dots & x_D^1 \\ x_1^2 & x_2^2 & \dots & x_D^2 \\ \dots & \dots & \dots & \dots \\ x_1^{HMS} & x_2^{HMS} & \dots & x_D^{HMS} \end{bmatrix} \quad (10)$$

where $[x_1^i \ x_2^i \ \dots \ x_D^i]$ ($i = 1, 2, \dots, HMS$) is a solution candidate.

- **Step 2.** Improvise a new solution $[x'_1 \ x'_2 \ \dots \ x'_D]$ from the HM. Each component of this solution, x'_j , is obtained based on the harmony memory considering rate (HMCR). The HMCR is defined as the probability of selecting a component from the present HM

members, and $1-\text{HMCR}$ is, therefore, the probability of generating it randomly:

$$x'_j \leftarrow \begin{cases} x'_j \in \{x_j^1 & x_j^2 & \dots & x_j^{\text{HMS}}\} & \text{with probability HMCR} \\ x'_j \in X_j & & & & \text{with probability } (1 - \text{HMCR}) \end{cases} \quad (11)$$

$$j=1, 2, \dots, D$$

where X_j is the set of the possible range of values for the j th decision parameter.

After, every component x'_j obtained from the HM is examined to determine whether it should be pitch-adjusted. This operation uses the PAR parameter, which is the pitch adjustment rate as follows:

$$\text{Pitch adjusting decision for } x'_j \leftarrow \begin{cases} \text{Yes with probability PAR} \\ \text{No with probability } (1 - \text{PAR}) \end{cases} \quad (12)$$

The PAR determines the probability of a candidate from the HM to be mutated. The value of $(1-\text{PAR})$ sets the rate of doing nothing. If the pitch adjustment decision for x'_j is Yes, then x'_j is replaced as follows:

$$x'_j \leftarrow x'_j \pm \sigma \text{ bw} \quad (13)$$

where bw is an arbitrary distance bandwidth and σ is a random number generated using uniform distribution between 0 and 1.

- **Step 3.** Update the HM. First, the new solution from Step 2 is evaluated. If it yields a better fitness than that of the worst member in the HM, it will replace that one. Otherwise, it is eliminated.
- **Step 4.** Repeat Step 2 to Step 3 until a termination criterion (e.g., maximal number of iterations) is met.

HS method is a random search technique which it does not require any prior domain information, such as the gradient of the objective functions. However, different from those population-based evolutionary approaches, it only utilizes a single search memory to evolve. Therefore, the HS method has the interesting characteristics of algorithm simplicity.

Hybridization of differential evolution and harmony search

During the past decade, hybridization of evolutionary algorithms has gained growing popularity, which can overcome their individual drawbacks while benefit from each other's

strengths [15, 22]. In this context, Gao et al. [22] have proposed a new hybrid optimization technique, namely DE-HS, by embedding the HS into the DE method.

Both the DE and HS have their advantages and weakness. Especially, the DE updates the current individuals based on only the differences among certain randomly selected ones. Unfortunately, it does not have an explicit mechanism for generating new chromosomes. On the other hand, the HS method has the distinguishing feature of using the combination of all the existing ones to obtain fresh individuals. Therefore, a natural idea is to embed this individual generation approach into the original DE so that it can converge in a faster way [22].

The iteration procedure of the DE-HS can be explained as follows [22]. The chromosomes in the DE population are first updated according to the DE principle in (6), (7) and (8). Next, these chromosomes are considered as the harmony memory members of the HS method. Note that the size of the HM is the same as that of the DE population, i.e., $HMS = N_p$. Thus, a new individual is produced either based on the HM members (DE population) or in a random manner as in Step 2 of HS algorithm. The key HS parameters, HMCR and PAR, are also used here. This fresh candidate is then compared with the worst DE individual for possible replacement as in Step 3 of the HS method. Finally, the whole population is updated, and the DE evolution continues to the next iteration. It can be seen from the above description that the DE and HS are complementary rather than competitive with each other. Incorporating the HS-based new individual generation strategy into the DE can indeed enhance its local exploration in the search space and result in a superior optimization performance.

The stopping criteria are the conditions under which the search process will stop. In this work, the search procedure will terminate whenever the predetermined maximum number of iterations G^{\max} is reached, or whenever the global best solution does not improve over a predetermined number of iterations.

Constraints handling

It is worth mentioning that the control variables are self-constrained. In order to keep the trial vectors within their bounds, the control parameter that exceeds a feasible bound is adjusted to the corresponding violated bound.

A penalty function approach is used to handle the power balance constraint and inequality constraints. The extended objective function \tilde{F} (or fitness function) is defined by:

$$\tilde{F} = F + K \left(\sum_{i=1}^{ng} P_i - P_D - P_L \right)^2 + \sum_{j=1}^{nc} PF_j \quad (14)$$

where K denotes the penalty factor of the equality constraint; nc represents the number of inequality constraints and PF_j is the penalty function for the j^{th} inequality constraint; given as:

$$PF_j = \begin{cases} K_j (U_j - U_j^{lim})^2 & \text{if violated} \\ 0 & \text{otherwise} \end{cases} \quad (15)$$

K_j is the penalty factor for the j^{th} inequality constraint; U_j^{lim} is the limit value of the variable U_j .

Results and Discussion

The proposed DE-HS approach was tested using the IEEE 30 bus benchmark system [16] and the practical Algerian 59-bus system [24]. In order to compare the results obtained from DE-HS, optimization problems are also solved using the conventional DE and HS methods. For all optimization methods (DE-HS, DE and HS), 50 independent runs were made in each case study using the same control parameter settings, as follows: population size (or HM size) $N_P = HMS = 20$, mutation factor $\rho = 0.50$, crossover constant $C_R = 0.99$, HM considering rate $HMCR = 0.99$, pitch adjustment rate $PAR = 0.10$, distance bandwidth $bw = 0.05$ and maximum number of iterations $G^{max} = 1000$. All the programs were implemented under the MATLAB computational environment, on an Intel Core 2 Duo 2.10 GHz Laptop computer with 3 GB RAM under Windows 7.

Case 1: Results for the IEEE 30 bus system

The IEEE 30 bus – 6 generators test system is described in [23], where the total load was set to 283.40 MW. Table 1 shows the data for the six generators. Over 50 repeated trials, the average solution cost achieved by DE-HS was 803.11 \$/h with a minimum cost of 803.10 \$/h, and a maximum cost of 803.18 \$/h (0.0099% difference). The average execution time

was 0.15 second. Table 2 gives the solution details for a minimum cost, which converged after 40 iterations and 0.14 second. It is important to point out that all variables were able to stay within their permissible limits shown in Table 1. The convergence of DE-HS for the trial run with the minimum fuel cost is shown in Fig. 1.

Table 1. Generators data of the IEEE 30 bus system

Parameter	Gen. 1	Gen. 2	Gen. 3	Gen. 4	Gen. 5	Gen. 6
a (\$/Mw ² h)	0.00375	0.0175	0.0625	0.00834	0.025	0.025
b (\$/MWh)	2.00	1.75	1.00	3.25	3.00	3.00
c (\$/h)	0	0	0	0	0	0
P_i^{\min} (MW)	50	20	15	10	10	12
P_i^{\max} (MW)	200	80	50	35	30	40

a, b and c = cost coefficients

Table 2. The best economic dispatch solution found by DE-HS for case 1

Parameter	Value
P_1 (MW)	177.70
P_2 (MW)	48.43
P_3 (MW)	20.99
P_4 (MW)	21.46
P_5 (MW)	12.60
P_6 (MW)	12.00
Total power generation (MW)	293.19
Total power demand (MW)	283.40
Fuel cost (\$/h)	803.10
Loss (MW)	9.79
Execution time (s)	0.14

Table 3 presents the comparison of the minimum, maximum, mean cost, mean iteration and average computation time for the simulation over 50 trial runs obtained by the proposed hybrid DE-HS with the DE and HS algorithms. As seen from Table 3, the best, worst and average solutions obtained with the proposed DE-HS algorithm are better than the best, worst and average results of all other methods. It is observed that the best solution found by DE-HS is identical to that found by DE. Besides, the mean cost given by DE-HS is better

compared to other methods. From Table 3, it is also clear that the suggested method converges in less iterations (43 iterations) compared to the conventional DE (63 iterations) and HS (578 iterations). The minimum cost and maximum cost are very close (0.0099% difference) indicating a good convergence characteristic and a great robustness of the proposed hybrid DE-HS.

Table 3. Comparison results of the three methods (DE-HS, DE and HS) for case 1

Method	Minimum cost (\$/h)	Maximum cost (\$/h)	Mean cost (\$/h)	Mean iteration	Average CPU Time (s)
HS	804.58	833.38	816.59	578	0.07
DE	803.10	803.55	803.15	63	0.20
DE-HS	803.10	803.18	803.11	43	0.15

HS = Harmony Search; DE = Differential Evolution

Fig. 1 represents the convergence curves of the best solutions found by DE-HS, DE and HS. This figure shows that DE-HS converges well and has the better convergence behavior than the DE and HS. This faster convergence behavior of the proposed DE-HS is due to the incorporation of the HS individual generation strategy into the original DE which enhances the local search capability of the original DE method.

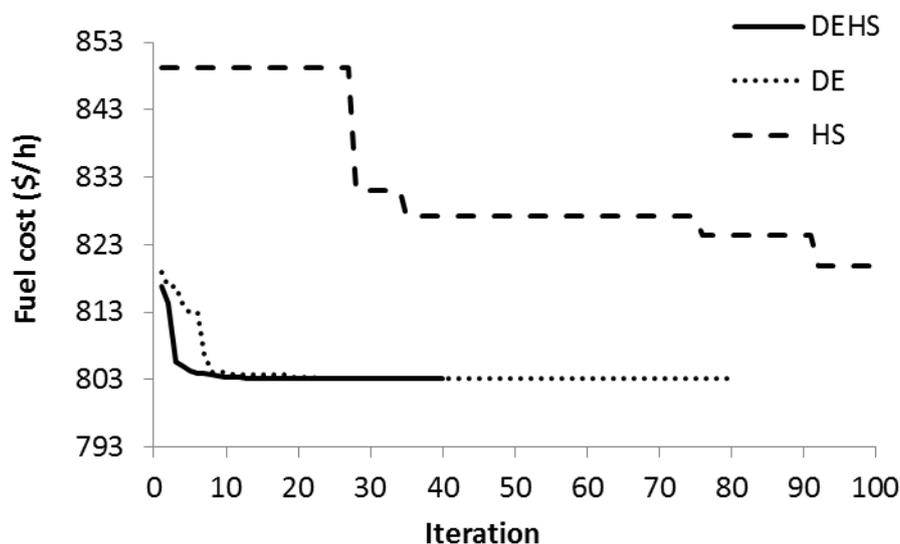


Figure 1. Comparison of the convergence curves of DE-HS, DE (Differential Evolution), and HS (Harmony Search) (case 1)

The results of the proposed approach were compared in Table 4 to those reported using Gradient Projection Method (GPM) [23], Nonlinear Programming (NLP) [25],

Evolutionary Programming (EP) [26], Improved Particle Swarm optimization (IPSO) [27], and Improved Evolutionary Programming (IEP) [28]. It can be seen that the results given by DE-HS are close to those reported in the literature. As a conclusion, we can say that the suggested DE-HS has the ability to find acceptable solutions in a reasonable time compared to other approaches which allow to an online implementation.

Table 4. Comparison of simulation results for the IEEE 30 bus system

Parameters	GPM [23]	NLP [25]	EP [26]	IPSO [27]	IEP [28]	HS	DE	DE-HS
P ₁ (MW)	187.22	176.26	173.85	179.37	176.24	168.46	177.51	177.70
P ₂ (MW)	53.78	48.84	49.99	44.24	49.01	47.16	48.43	48.43
P ₃ (MW)	16.95	21.51	21.39	24.61	21.50	19.91	20.86	20.99
P ₄ (MW)	11.29	22.15	22.63	19.90	21.811	27.23	21.78	21.46
P ₅ (MW)	11.29	12.14	12.93	10.71	12.34	13.68	12.59	12.60
P ₆ (MW)	13.35	12.00	12.00	14.09	12.01	16.09	12.00	12.00
Total Gen. (MW)	293.88	292.90	292.79	292.92	292.9105	292.53	293.17	293.19
Cost (\$/h)	804.85	802.40	802.62	803.69	802.465	804.58	803.10	803.10
Loss (MW)	10.49	9.48	-	9.52	-	9.13	9.78	9.80
CPU time (s)	4.32	-	51.4	7.00	594.08	0.10	0.20	0.14

GPM = Gradient Projection Method; NLP = Nonlinear Programming; EP = Evolutionary Programming; IPSO = Improved Particle Swarm optimization; IEP = Improved Evolutionary Programming; HS = Harmony Search; DE = Differential Evolution

Case 2: Results for the practical Algerian 59 bus system

The Algerian network consists of 59 buses and 10 generators supplying a total load of 684.10 MW [24]. Table 5 provides the parameters associated with the generating units (it is noting that the generator no. 5 at bus no. 13 is not operational).

The results found by DE-HS were compared in Table 6 with the results of DE and HS methods. From the comparative results of Table 6, it is evident that the hybrid DE-HS outperforms all other methods in terms of achieving successfully the best mean cost of 1712.12 \$/h with less iterations and less computation time than the original DE. It is also observed that the minimum and maximum costs achieved by DE-HS are very close, which gives a clear indication of stability of the results and robustness of the proposed strategy.

Table 5. Generator parameters of the Algerian network

Bus	Gen.	P_i^{\min} (MW)	P_i^{\max} (MW)	a (\$/MW ² h)	b (\$/MWh)	c (\$/h)
1	1	8	72	0.0085	1.50	0
2	2	10	70	0.0170	2.50	0
3	3	30	510	0.0085	1.50	0
4	4	20	400	0.0085	1.50	0
13	5	15	150	0.0170	2.50	0
27	6	10	100	0.0170	2.50	0
37	7	10	100	0.0030	2.00	0
41	8	15	140	0.0030	2.00	0
42	9	18	175	0.0030	2.00	0
53	10	30	450	0.0085	1.50	0

P_i^{\min} = Minimum power generation; P_i^{\max} = Maximum power generation; a, b and c = cost coefficients

Table 6. Comparison results of the three methods (DE-HS, DE and HS) for case 2

Method	Minimum cost (\$/h)	Maximum cost (\$/h)	Mean cost (\$/h)	Mean iteration	Average CPU Time (s)
HS	1712.17	1728.30	1713.94	986	0.09
DE	1712.18	1724.51	1714.32	208	0.35
DE-HS	1712.10	1712.20	1712.12	59	0.16

HS = Harmony Search; DE = Differential Evolution

The convergence characteristics of DE-HS, DE and HS are depicted in Fig. 2. It is quite clear that the proposed DE-HS approach has a faster convergence rate.

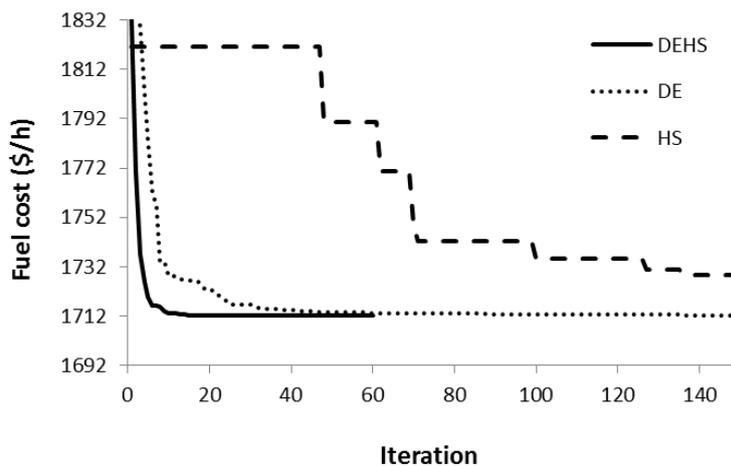


Figure 2. Convergence behaviour of DE-HS, DE (Differential Evolution) and HS (Harmony Search) algorithms (case 2)

The results of the proposed approach were compared to those reported using genetic algorithm (GA) [24] and ant colony optimization method (ACO) [29]. The comparison results are given in Table 7. From this table, it can be seen that the proposed approach gives better results with a very short computation time and the saving in fuel cost is significant. This demonstrates the potential and effectiveness of the proposed method to solve the nonlinear optimization problems.

Table 7. Comparison of simulation results for the Algerian network

Parameters	GA [13]	ACO [14]	HS	DE	DE-HS
P ₁ (MW)	70.57	64.01	55.64	54.45	54.80
P ₂ (MW)	56.57	22.75	24.13	24.18	25.01
P ₃ (MW)	89.27	82.37	104.62	103.51	104.69
P ₄ (MW)	78.22	46.21	112.32	114.77	112.72
P ₅ (MW)	0.00	0.00	0.00	0.00	0.00
P ₆ (MW)	57.93	47.05	27.39	26.36	27.24
P ₇ (MW)	39.55	65.56	57.47	57.42	57.11
P ₈ (MW)	46.40	39.55	91.84	89.79	89.83
P ₉ (MW)	63.58	154.23	139.57	140.36	140.01
P ₁₀ (MW)	211.58	202.36	105.80	107.19	106.60
Total Generation (MW)	713.67	724.09	718.78	718.02	718.02
Cost (\$/h)	1937.10	1815.70	1712.17	1712.18	1712.10
Loss (MW)	29.58	39.98	34.69	33.93	33.93
CPU time (s)	3.10	25.00	0.10	0.30	0.16

GA = Genetic Algorithm; ACO = Ant Colony Optimization; HS = Harmony Search; DE = Differential Evolution

Conclusions

Incorporating the HS-based new individual generation strategy into the DE can indeed enhance its local exploration in the search space and result in a superior optimization performance.

Computational results show that the proposed hybrid approach has the ability to converge to high quality solutions with stable convergence characteristic and good computation efficiency.

Considering the cases and comparative study presented in this paper, DE-HS algorithm appears to be very efficient in particular for its fast convergence to the global

optimum and its interesting financial profit. This method is highly appropriate for on-line applications in power systems.

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