Solution of Economic Load Dispatch Problems Using Novel Improved Harmony Search Algorithm

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Abstract: In this work, an efficient modified harmony search algorithm namely self-adaptive improved harmony search algorithm (SIHS) is proposed to solve economic load dispatch (ELD) problem with considering valve-point loading effects (VPE). The bandwidth parameter within the proposed approach varying dynamically at each new iteration to enhance the accuracy and the convergence velocity of the conventional HSA. To prove the effectiveness and the robustness of the proposed technique, the SIHS is tested on three ELD test systems including VPE: 3-units systems, 13-units system with two different levels of load demand, and 40-units system. Obtained results from SIHS are comparatively measured using 36 comparative algorithms including conventional HS algorithm. The numerical results have proved that the SIHS is more efficient for solving the ED with VPE than many other methods published recently.

Keywords: Non-convex economic dispatch, harmony search optimization, valve-point effects

1. Introduction

The ELD problem is among the most crucial decisions, making in power system operation, to return a profit on the capital invested. The aims of ELD is to meet the system load, at the minimum operating cost needed to satisfy the transmission and operational constraints [1]. ELD is applied to optimize each generating level in the system, in order to decrease the total fuel cost of thermal units while still covering power demand and power losses [2].

The fuel cost in classical ED problems is generally presented by a quadratic function without considering the power loss and operating limits constraints. Practically, some operational constraints such as the active power losses, valve-point effects, unit-ramp rate limits (RRL), prohibited operating zones (POZ), multifuel effects, becomes the dispatch problem more complex and non-differentiable [3].

There are many classical optimization approaches available in the literature to solve the based ELD problem together with, Lagrangian relaxation method (LR) [4], Lambda-iterations method [5], quadratic programming (QP) algorithm [6], linear programming (LP) technique [7], dynamic programming (DP) method [8], etc. Not all these traditional methods can be employed to resolve the complicated ELD problems for global optimum scheduling as they regularly entice at a local minimum [9].

To overcome these deficiencies, a lot of researchers focus on many modern metaheuristic techniques due to their efficiency in finding the local minimum at a reasonable simulation time such as, evolutionary programming techniques (EP) [10], ant colony optimization (ACO) [11], or genetic algorithm (GA) [12]. These methods have been employed to solving ED problem in particular with VPE.

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In the last five years, a lot of swarm intelligence algorithms have been applied to deal with the ELD problem such as, $MVMO^{S}$ in [13], a DPSO-Sine algorithm is used in [14], chaos-enhanced cuckoo search (CS-A)[15], invasive weed optimization (IWO)[16], grey wolf optimization (GWO)[17]. These metaheuristic techniques mentioned above have the potential to improve the computation accuracy and convergence to the optimal solution.

Researchers have established several hybrid optimization techniques to improve the behavior and the effectiveness of the population-based algorithms by combining multiple metaheuristic algorithms or algorithm components to solving ELD problem with VPE. A hybrid (DSPSO-TSA) approach is applied in [12], PSO algorithm hybrid with sequential quadratic programming (PSO-SQP) in [18], fuzzy adaptive PSO integrating variable differential evolution (FAPSO-VDE)[19], a (VCF-PSO) strategy is utilized in [20], and hybrid differential evolution with BBO algorithm (DE-BBO) is used in [21]. Combination between continuous GRASP and self-adaptive DE algorithm (C-GRASP-SaDE) in [22] and hybrid β-hill climbing optimizer with GWO (β-GWO) in [23] are recently applied to deal with large-scale ED of power systems.

In the latest years, various modern approaches based on metaheuristic algorithms were broadly implemented for the complex ELD problems with non-convex fuel cost functions due to (VPE) and practical constraints taking into account (RRL), (POZ), multi-fuel options, and power spinning reserve. For example, in the literature [24], a granular computing method (GrC) has been proposed to increase the resolution accuracy, a multi-behavior combination (MBC-DE) is implemented in [25]. An across neighborhood search (ANS) is suggested in [26]. In reference [27], an improved artificial cooperative search algorithm (IACS) is addressed to solving non-convex ED problems with VPL effects. A new variant of JAYA algorithm named (MP-CJAYA) is developed in [28]. Chaotic bat algorithm (CBA) in literature [29], is successfully implemented for solving ED problems with highly levels of complexity. Hybrid CRO technique with DE algorithm (HCRO-DE) proposed in literature [30], is applied to deal with large-scale economic dispatch.

Various metaheuristic approaches have been effectively employed to solve multi-objective ED such as, (IS) algorithm in [31], flower pollination algorithm (FPA) implemented in [32] and (OGS) algorithm suggested in literature [33].

Harmony search (HS) algorithm is one of the most famous metaheuristic approaches, originally invented by Geem et al [34], which draws inspiration from the musical process to attain an agreeable harmony. HS technique, takes some major advantages compared with other metaheuristics, such as EP, GA, DE, PSO and TS, which is simple in concept and structure, converges quickly to the optimum and easy to implement on optimization problems [35]. Thus, there are several monographs [36]–[38] addressed the advances of HS method and its variants.

A plenty of variants HSA, have been studied to improving algorithm-optimizing performance. Research works presented in literature [39]–[48], give some major variants of the basic HS algorithm published in the past decade. An updated review and analysis of the latest developments of the HSA and its application into engineering optimization have been discussed in [49]–[54].

Many variants techniques based HS algorithm to solve ED problems with VPE are available in the literature [55]–[58]. ED problem with considering operational limits constraints such as POZ, power loss and RRL, was solving by some hybrid metaheuristic methods with original HSA such as mentioned in literature [59]–[62].

The objectif of this article is to propose a simplified, robust, and effective modified HSA, which may be more effective than the ELD-based metaheuristic methods described within the recent published literature. In the initialization phase of HSA, all parameters are fixed value and cannot be varied during the generation process. Thus, in the proposed SIHS, the bandwidth is dynamically updating at each iteration. The proper selection of SIHS parameters values for all cases studied is considered as one of the challenging tasks, because parameter-setting strategy is problem dependent and size of test systems, one parameter setting strategy is suitable for one problem but may perform badly for another. To affirm the effectiveness, accuracy, and scalability of the suggested method, SIHS it is apply for the first time to solve the ED problem in three test systems having 3, 13 and 40 generators considering VPE. The statistical results are as compared with 35 algorithms existing in the recent literature.

The rest of this article is structured as follows: the definition and mathematically formulation of the ELD problem are offered in section 2, while section 3 addresses a brief description of the HSA. Section 4, describes the process of the proposed SIHS for ELD in depth. The obtained results are carefully studied and analyzed in section 5. Finally, conclusion and future suggestions are given in section 6.

2. Economic Load Dispatch Formulation

The aim of the usual ED problem is to dispatch the power output of each generator to meet the load demand at a specified time [10]. Generally, the fuel cost function similar to the scheduling results may be expressed as a quadratic function of the outputs from the generators [1], [2], which may be commonly formulated as follows:

$$\min F_t = \sum_{i=1}^{N} F_i(P_i) \tag{1}$$

where N is the number of generating units s, F_t is the total fuel cost (\$/h) while meeting the load demand, $F_i(P_i)$ is the fuel cost (\$/h) of ith generator with output P_i.

Approximately, the fuel cost curve of a thermal generating unit may be formulated as a quadratic polynomial by the following equation:

$$F_i(P_i) = a_i . P_i^2 + b_i . P_i + c_i \tag{2}$$

Where, a_i, b_i, c_i, are the coefficients of the fuel cost corresponding of generator i. Eq. (2) is subject to the following constraints [1], [2]:

a. Power balance constraint

$$\sum_{i=1}^{N} P_i = P_D + P_L \tag{3}$$

where P_D and P_l is the value of the demanded power and the whole power loss respectively. P_{Loss} is approximately calculated by Kron's formula [28]:

$$P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{0i} P_i + B_{00} \tag{4}$$

where P_i and P_j are the active power injections at i^{th} and j^{th} buses and B_{ij}, B_{i0}, B_{00} are the loss coefficients.

In the studies [14], [15], [18], [19], [62], power losses are ignored to gain simplicity. Therefore, transmission losses are neglected in this work ($P_{Loss} = 0$).

b. Generator operating limits

$$P_i^{\min} \le P_i \le P_i^{\max}, \quad i = 1,2,\ldots,N \tag{5}$$

where $P_i^{\min}$ and $P_i^{\max}$ are the lower and upper boundary power of i^{th} generator.

In reality, the ripple effects induced by modern steam turbines with multi-valve, create nonlinearity and no convexity in the fuel cost function [24], [32] as proven in Figure.1. So its function can be expressed by a sinusoidal term to the quadratic cost function as follows [20]:

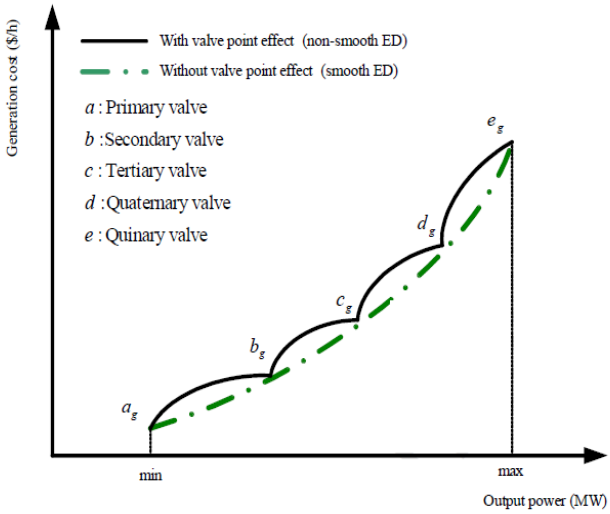
$$F_i'(P_i) = a_i . P_i^2 + b_i . P_i + c_i + \left| e_i \sin\left(f_i\left(P_i^{\min} - P_i\right)\right)\right| \tag{6}$$

where e_i, and f_i are cost coefficients of *ith* generator due to VPE. In this case, the objective function of the ELD problem can be expressed as [18], [23]:

$$\min F_t = \sum_{i=1}^{N} F_i'(P_i) = \sum_{i=1}^{N} \left(a_i . P_i^2 + b_i . P_i + c_i + \left| e_i \sin\left(f_i\left(P_i^{\min} - P_i\right)\right)\right|\right) \tag{7}$$

Table 1. Abbreviations of the comparative methods.

Key	Year	Description	Ref
ACHS	2014	Hybrid Harmony Search with Arithmetic Crossover Operation	[61]
ACO	2010	Ant Colony Optimization	[11]
ANS	2018	Across Neighborhood Search	[26]
CBA	2016	Chaotic Bat Algorithm	[29]
C-GRASP–SaDE	2017	Hybrid Continuous GRASP with Self-Adaptive Differential Evolution	[22]
CIHSA	2019	Chaotic Improved Harmony Search Algorithm	[62]
CS-A	2016	Chaos-Enhanced Cuckoo Search (A)	[15]
DE-BBO	2010	Differential Evolution-Biogeography Based Optimization	[21]
DHSPM	2015	Dynamic Harmony Search with Polynomial Mutation Algorithm	[58]
DPSO-Sine	2015	Democratic PSO algorithm Endowed with Sine Chaotic Map	[14]
DSPSO–TSA	2010	Hybrid Distributed Sobol PSO-TSA	[12]
FAPSO–VDE	2011	Fuzzy Adaptive PSO integrating-Variable Differential Evolution	[19]
FPA	2016	Flower Pollination Algorithm	[32]
GA	2010	Genetic Algorithm	[12]
GrC	2019	Granular Computing Method	[24]
β-GWO	2019	Hybrid β-hill climbing optimizer with Grey Wolf Optimization	[23]
GWO	2015	Grey Wolf Optimization	[17]
HCRO-DE	2014	Hybrid Chemical Reaction Optimization with Differential Evolution	[30]
HS-BLO	2015	Harmony Search Algorithm with Opposition-Based Learning Techniques	[59]
IACS	2018	Improved Artificial Cooperative Search Algorithm	[27]
IFEP	2003	Improved Fast Evolutionary Programming	[10]
ISA	2018	Interior Search Algorithm	[31]
ITHS	2013	Intelligent Tuned Harmony Search Algorithm	[56]
IWO	2016	Invasive Weed Optimization	[16]
MBC-DE	2019	Multi-Behavior Combination with DE	[25]
MP-CJAYA	2018	Multi-Population based Chaotic JAYA algorithm	[28]
MVMOS	2015	Mean–Variance Mapping Optimization Swarm	[13]
NGHS	2016	Natural Global-worst Harmony Search	[55]
NPHS	2016	Natural Proportional Harmony Search	[55]
NTHS	2016	Natural Tournament Harmony Search	[55]
OGSA	2012	Opposition-based Gravitational Search Algorithm	[33]
PSO-SQP	2004	Particle Swarm Optimization-Sequential Quadractic Programming	[18]
PSF-HS	2013	Parameter-Setting-Free Harmony Search Algorithm	[60]
PVHS	2011	Population-Variance Harmony Search Algorithm	[57]
VCF_PSO	2015	Varying Constriction Factor based Particle Swarm Optimization	[20]



Figureure 1. Fuel cost curve of single fuel option considering five-valve steam turbine unit.

3. Brief description of HS algorithm

HSA is a metaheuristic technique that is given great ideas from the process of music players to accomplish better harmony, originally proposed by Geem et al in 2001 [35].

The HS method's key steps can be described as [35]:

Step 1: Initialization. Set parameters of HS, The main parameters of the HSA include [48]:

- Harmony memory size (HMS), where the population is memorized.
- Pitch adjusting rate (PAR) for a new generated harmony, with PAR $\in$ [0, 1],
- Harmony memory considering rate (HMCR), with HMCR $\in$ [0, 1],
- Bandwidth (BW) for pitch adjustment, number of improvisations (NI) and number of maximum iterations (Nmax).

$$Minimize \quad f(x), \tag{8}$$

S. t

$$LB_i \le x_i \le UB_i \ , \quad i \in [1, N]. \tag{9}$$

Where, $f(x)$ is the objective function, x_i is the solution vector of the HMS, LB_i and UB_i are the minimum and maximum values of x_i.

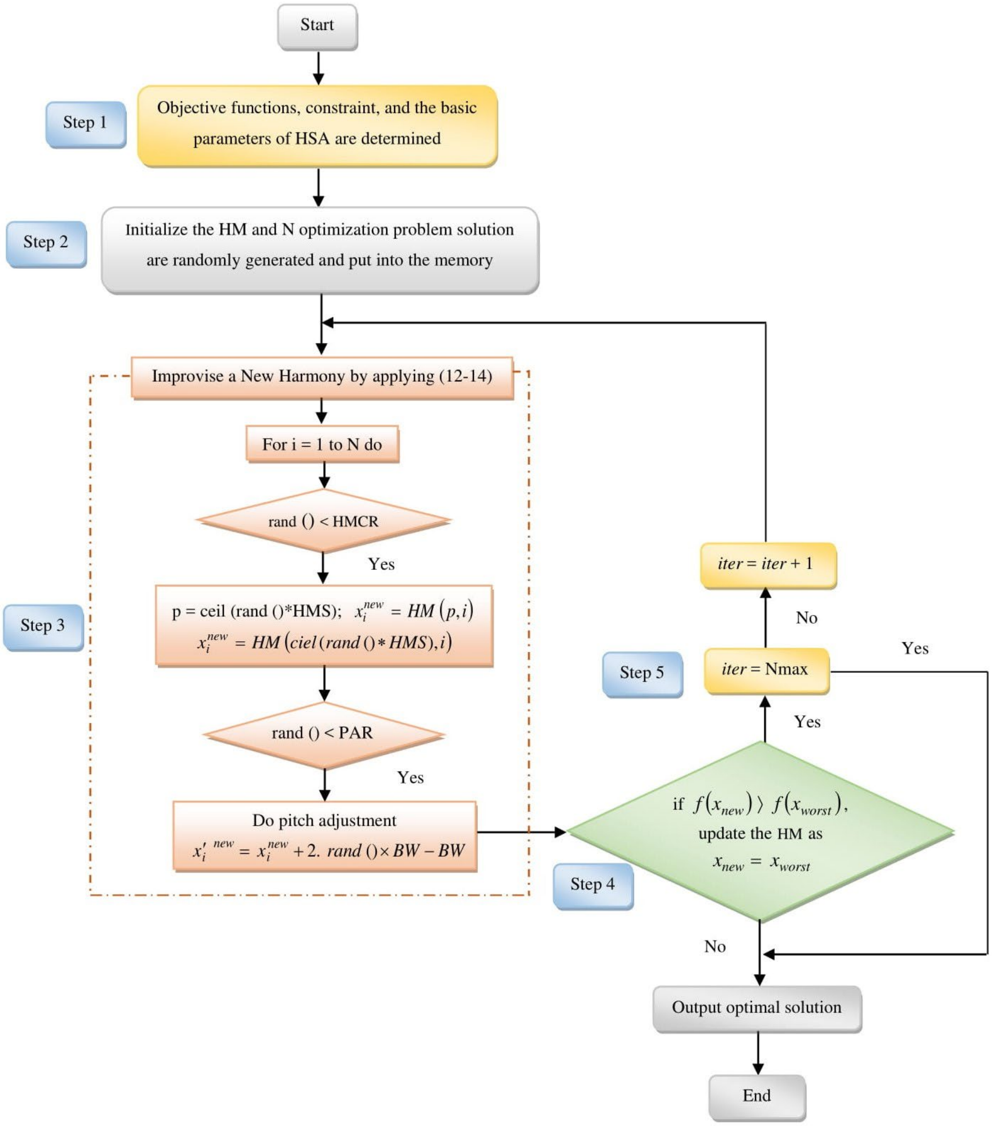
Step 2. Initialization of the HM matrix

HM is initialized by randomly produced harmony vectors considering HMS [52] by using Eq. (10) :

$$x_i^j = LB_i + rand\,() \times (UB_i - LB_i). \tag{10}$$

where j= 1, 2,..., HMS and $rand\ ()$ is random number, uniformly distributed between 0 and 1. The HM matrix can be expressed as follow:

$$HM = \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_{N-1}^1 & x_N^1 \\ x_1^2 & x_2^2 & \cdots & x_{N-1}^2 & x_N^2 \\ . & . & \cdots & . & . \\ . & . & \cdots & . & . \\ . & . & \cdots & . & . \\ x_1^{HMS-1} & x_2^{HMS-1} & \cdots & x_{N-1}^{HMS-1} & x_N^{HMS-1} \\ x_1^{HMS} & x_2^{HMS} & \cdots & x_{N-1}^{HMS} & x_N^{HMS} \end{bmatrix} \begin{matrix} \to f\left(x^{(1)}\right) \\ \to f\left(x^{(2)}\right) \\ . \\ . \\ . \\ \to f\left(x^{(HMS-1)}\right) \\ \to f\left(x^{(HMS)}\right) \end{matrix} \tag{11}$$



Figureure 2. A simplified flowchart of the HS algorithm.

Step 3. Improvise of a new harmony.

A novel solution vector $x_i^{new} = (x_1^{new}, {}_2^{new}, \ldots, {}_N^{new})$, is generated based on the main HS operators HMCR, PAR and BW. These operators are introduized in production of a new solution as the following [34]:

HMCR,

$$x_i^{new} \leftarrow \begin{cases} x_i^{new} \in \left\{ x_i^1, x_i^2, \ldots, x_i^{HMS} \right\}, & with\ probability\ HMCR \\ x_i^{new} \in X_i, & otherwise: i = 1, 2, \ldots, N. \end{cases} \tag{12}$$

PAR,

$$x_i^{new} \leftarrow \begin{cases} Yes\ \ with\ probability\ \ PAR \\ No\ \ with\ probability\ \ (1 - PAR) \end{cases} \tag{13}$$

A new solution vector x_i based on the disturbance principle can be generated as follows [63]:

$$x_i'^{\,new} = x_i^{new} + 2.\,rand\,() \times BW - BW \tag{14}$$

$x_i'^{\,new}$ is the i^{th} new solutions after disturbance.

Step 4. Updating the new harmony. The new harmony will replace the worst if *$f(x_{new}) < f(x_{worst})$*.
Step 5. (Checking the stopping criterion). Repeat Step 3 and 4 until the Nmax is reached.
A simplified flowchart of the HS method is demonstrated in Figure.2.

4. Self-Adaptative Improved Harmony Search (SIHS) algorithm

A. The motivation of the SIHS algorithm

Parameter settings have a massive effect at the performance of the HS algorithm. The PAR and BW operators, determining the accuracy of the solution. A small BW and low PAR values, becomes the convergence velocity of HSA very slowly and the first-rate-tuning of solution vectors could be increasing [49]. What's more, a bigger PAR and extensive BW values in the early iteration, HSA will converge fast to the satisfactory solution. Hence, may be very vital that PAR and BW had been dynamically adjusting at each new generation.

In SIHS algorithm, the precept concept is to use a wider BW to search in the whole domain and dynamically regulate the BW towards the best solution [44].

B. Novel parameter of BW

In this subsection, the self-adaptative improved HS algorithm with a changing bandwidth (BW) will be studied. Dynamic BW (DBW) is represented as a decreasing function of the current generation (iter) and of maximum iteration number (Nmax) specified for the problem, i.e. in the beginning phases of SIHS algorithm, BW is dynamically updating by maintaining a higher value and progressively reducing through a low value to ensure near convergence of the best solution [44].

The choice of the termination condition depends on the desired high quality level of the solution [44]. According to the criteria mentioned above, we find that the equation of a low-pass filter is approximately close to the requirement.

The new BW equation can be formulated as follows:

$$BW(i) = \frac{h}{1 + \gamma.\left(\dfrac{iter}{N_{\max}}\right)^{\alpha}} \tag{15}$$

where *h* and γ are constant values depend on the limit of BW values. To satisfy the above-mentioned criteria, generally *h* takes the value of BWmax and the exponent α must be greater than 1.

if $\sum_{i}^{N} P_i \langle P_D$, Add an amount ε

$\varepsilon \leftarrow \left| \sum_{i}^{N} P_i - P_D \right|$ to P_i^{new} that doesn't violate $P_i^{\max}$, such as $P_i^{new} \leftarrow \min\left(P_i^{new} + \varepsilon,\ P_i^{\max}\right)$

else if $\sum_{i}^{N} P_i \rangle P_D$, Subtract an amount ε

$\varepsilon \leftarrow \left| \sum_{i}^{N} P_i - P_D \right|$ to P_i^{new} that doesn't violate $P_i^{\min}$, such as $P_i^{new} \leftarrow \max\left(P_i^{new} - \varepsilon,\ P_i^{\min}\right)$

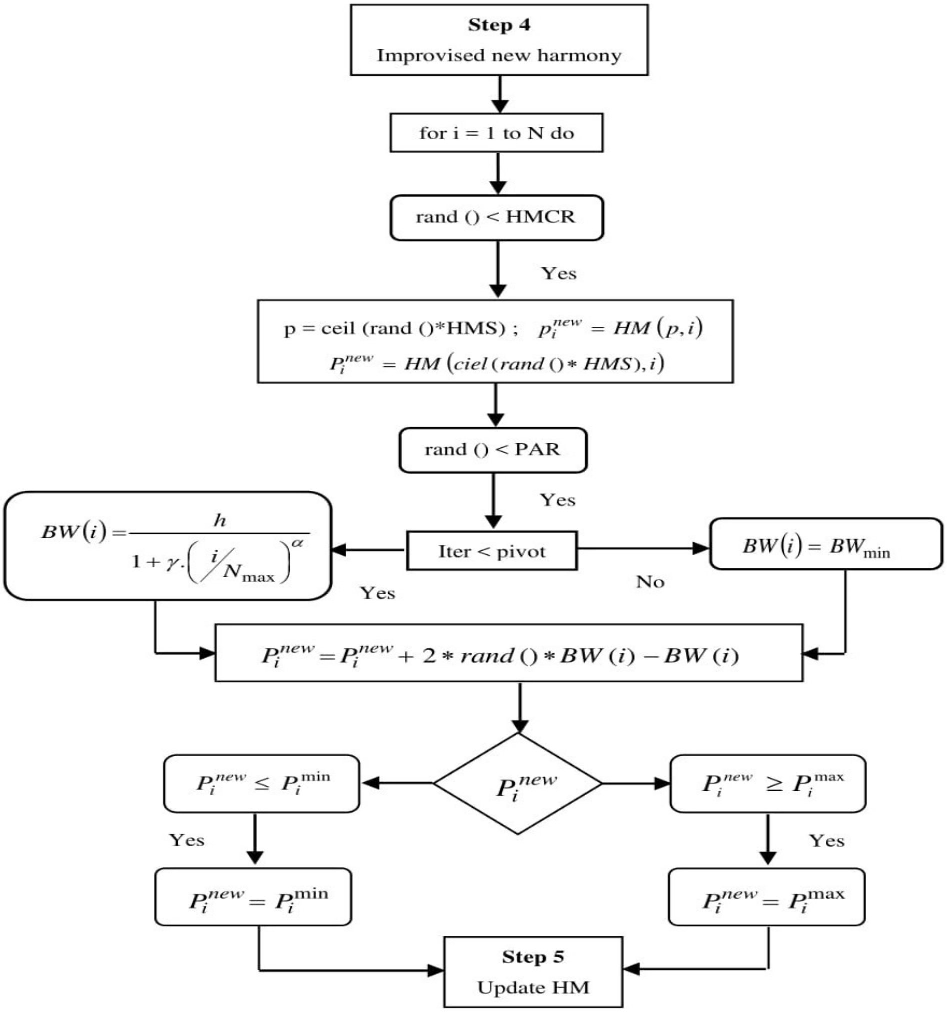
Figureure 3. Flowchart of constraints handling used HS and SIHS algorithms.

According to [44], a fairly truthful result may be obtained whilst BWmin value must be very small, normally ~ 0.1% of the range of decision variables. While BWmax is assumed to

5~10% of the variety of dimension problem. The value of γ, is evaluated with the logarithmic decremental equation as follow:

$$\gamma = b_1 \times \ln\left(\frac{BW_{\max}}{b_2 \times BW_{\min}}\right) \tag{16}$$

where b_1 and b_2 are constants and their values are experimentally determined in [44], [64], the best values of b_1 and b_2 that gives a minimum BW value ensures precise and fast convergence towards the optimal solution are chosen at 50 and 100, respectively.

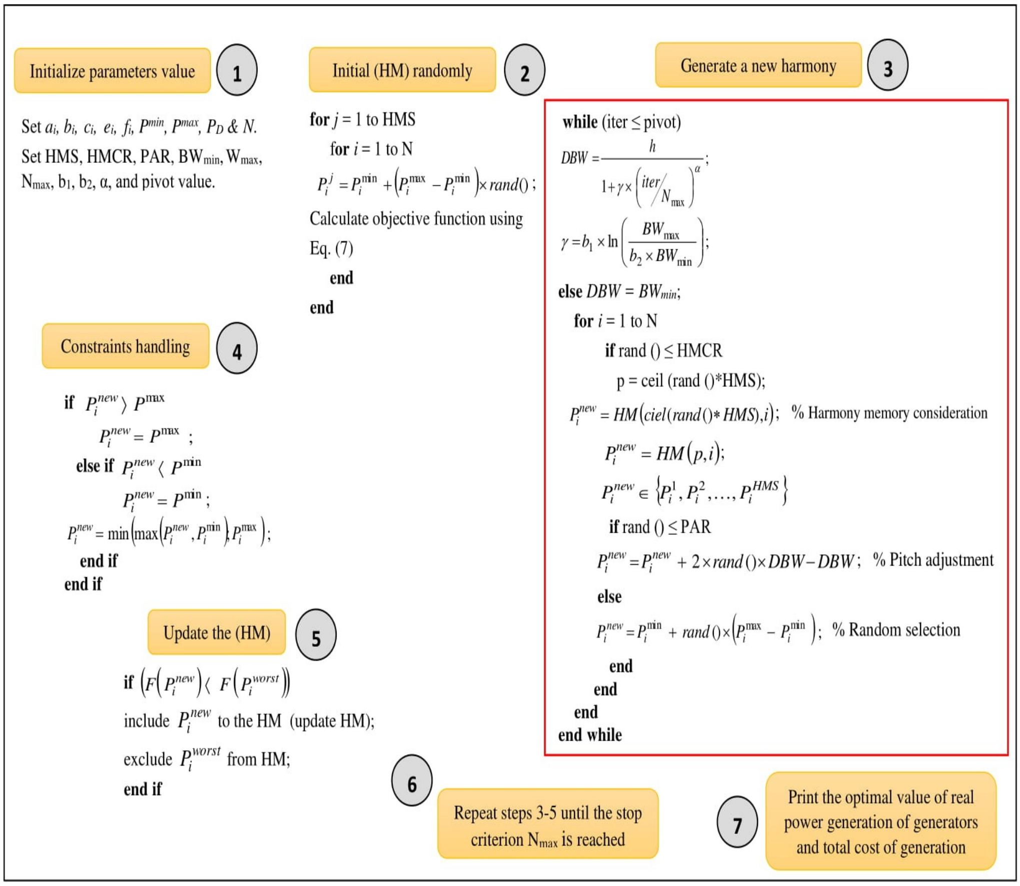


Figureure 4. Process of improvisation new harmony in SIHS algorithm

For the problems having low decision variables, Eq. (15) is more efficient to compute dynamic BW. For highly complex optimization problems, the best solution is found by modified Eq. (15) to a discontinuous adaptative dynamic BW function [44]. The proposed DADBW function is expressed as:

$$BW(i) = \begin{cases} BW(i) = \dfrac{h}{1+\gamma\left(\frac{iter}{N_{\max}}\right)^{\alpha}}; & i \langle \ pivot \\ BW_{\min} & ; \quad i \ge pivot \end{cases} \tag{17}$$

Where, 'pivot' decides the optimum point where the BW changes (generally $N_{max}/2$).



Figureure 5: Pseudo code of SIHS algorithm to ED problem

C. *Implementation of SIHS algorithm to solved ED problems*

In this part, the SIHS algorithm is used for solving ELD problems with thinking about load demand effect (VPE). Based on the similar improvement techniques, the proposed SIHS process is demonstrate under:

Step 1. Specify the generator cost coefficients (a_i, b_i, c_i, e_i and f_i), total number of generator units (N), set P_{max} and P_{min} of all units and load demand P_D. Set the parameters values of SIHS algorithm (HMS, HMCR, PAR, BW_{max}, BW_{min}, NI, N_{max} and Pivot).

Step 2. Initialize HM matrix with size (HMS × N). The initial HM is randomly generating as follow:

$$HM\ (i,j) = P_i^j = P_i^{\min} + rand() \times \left(P_i^{\max} - P_i^{\min}\right) \tag{18}$$

Index of j determines the j^{th} generation unit. In order, to not violate the generator limits and not to operate at prohibited zone after each generation, the total power produced by all units is compared to power demand.

Figure. 3 present the process to checking equality constraint used in HS and SIHS algorithms. This process is iterated for other units until the (ε = 0).

Step 3. Calculate the fitness value for each solution vector in the HM matrix using Eq. (6). The HM matrix is represented by Eq. (11).

Step 4. Generate a new solution by using Eq. (14) as mentioned in section (3) by changing BW value utilized Eq. (16). The process of a new harmony improvisation is depicted by the flowchart shown in Figure 4.

Step 5. Update the HM vector and calculate the fitness value $f(P_G)$, $P_i^{new} = (P_1^{new}, P_2^{new}, \ldots, P_N^{new})$. The new real power generation of units will replace the worst ($P_i^{new} = P_i^{worst}$) if $f(P_i^{new}) < f(P_i^{worst})$.

Step 6. If N_{max} is attained, go to Step 7; otherwise, repeat steps 4-5.

Step 7. Print the optimal value of active power generation of generators, thus the best total cost of production.

5. Simulation results and discussion

In order to evaluate the robustness of the proposed SIHS algorithm in solving ELD problems, four case studies with VPE have been taken into consideration. The constraints involved are power balance constraint without considering transmission losses and generator operating limits constraint. The obtained results are compared with the optimization approaches cited in Table 1. ELD cases include:

- Case I: 3-unit system with P_D = 850 MW;
- Case II: 13-unit system with P_D = 1800 MW;
- Case III: 13-unit system with P_D = 2520 MW;
- Case IV: 40-unit system with P_D = 10500 MW;

Table 2. Parameters of HS and SIHS for ELD cases.

	Case I		Case II		Case III		Case IV	
Parameters	HS	SIHS	HS	SIHS	HS	SIHS	HS	SIHS
HMS	5	5	10	10	20	20	20	20
HMCR	0.85	0.95	0.85	0.95	0.85	0.95	0.85	0.95
PAR	0.30	0.45	0.30	0.85	0.30	0.85	0.30	0.99
BW	0.01	-	0.01	-	0.01	-	0.01	-
BW_{min}	-	0.003	-	0.001	-	0.001	-	0.001
BW_{max}	-	0.15	-	0.5	-	0.5	-	0.5
NI	30	30	50	50	50	50	100	100

All the cases studies are execute in MATLAB 2017 under windows 8.1 on Intel Core(TM) i3-3110 CPU 2.40 GHz, with 4 GB RAM. The parameters values of HS and SIHS for all cases are indicate in Table 2. α, N_{max}, and pivot values of SIHS algorithms are 3, 10000, and 45%.N_{max} respectively. The pseudo-code of SIHS algorithm to solve ELD problem is shown in Figure.5. The values of these parameters are determined after performing various experiments, which provide more exploratory power. Due to the stochastic characteristic of both HS and SIHS algorithms, 60 trial runs have been performed.

Table 3. Optimal output power for three-unit system with different algorithms

Output (MW)	ITHS	MVMO^S	IWO	DHSPM	MP-CJAYA	HS	**Proposed SIHS**
Pg1	300.2668	300.2669	300.267	300.12	350.2464	300.2668	300.2668
Pg2	149.7331	400.0000	149.733	149.88	400.0000	400.000	400.0000
Pg3	400.000	149.7331	400.000	400	99.7576	149.7331	149.7331
TP (MW)	850	850	850	850	850.004	850	850
TC ($/hr)	8234.0717	8234.0717	8234.07	8234.07	**8223.29**	8234.0717	8234.07173

TP presents the total active power output.
TC presents the total cost of production.

A. Case I

The first case study covers of three thermal units with an overall load demand of 850 MW. The required data of the test system are available in literature [10].

The optimal generation schedule of 3-units system along with the total fuel cost obtained by HS and SIHS over 60 runs, are compared with ITHS, MVMO^S, IWO, DHSPM and MP-CJAYA in Table 3. The best results are highlighted in bold font.

Obviously, almost all the comparative methods get the same minimum fuel cost of 8234.07 ($/h), except for MP-CJAYA, which generated the best solution of 8223.29 ($/h).

The best, mean, max fuel cost, standard deviation and computational time achieved by HS and SIHS are depicts in Table 4. We can see that the proposed SIHS algorithm is better in terms of computation efficiency (0.0661s) than other methods recently published in the literature. In addition, the standard deviation of HS (1.946 $/hr) is less than SIHS (2.331 $/hr). The best standard deviation of 0.00 $/hr is provided by MVMO^S.

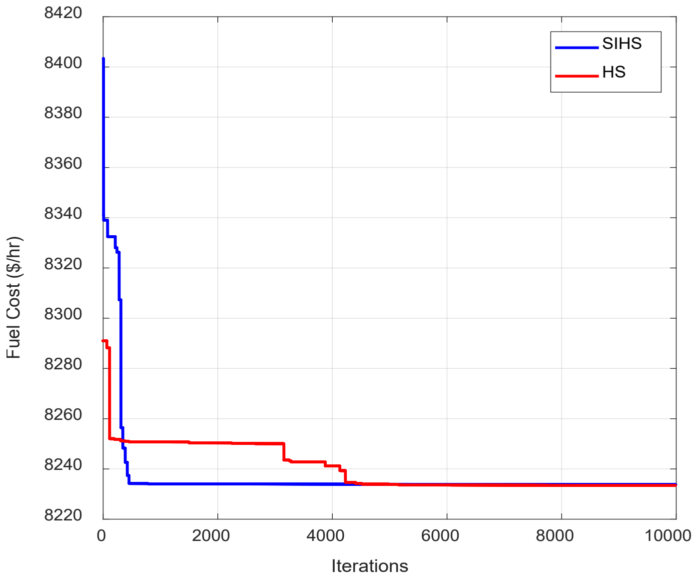


Figure 6. Fuel cost convergence behavior of case I.

Table 4. Comparison of simulation results of 3-units system with different algorithms

Method	Best Fuel Cost ($/hr)	Mean Fuel Cost ($/hr)	Max Fuel Cost ($/hr)	Std. dev ($/hr)	CPU time (s)
MP-CJAYA	**8223.29**	**8232.06**	NA	NA	NA
SIHS	8234.07173	8234.9243	8241.1769	2.331	**0.0661**
DHSPM	8234.07	8234.09	NA	NA	NA
HS	8234.07173	8234.6399	8241.17437	1.946	0.0672
ITHS	8234.07175	NA	NA	NA	NA
MVMOS	8234.0717	8234.0717	8234.0717	**0.0000**	3.65
IWO	8234.07	8236.97	8241.2	NA	NA
PSO-SQP	8234.07	8234.07	NA	NA	3.37
NTHS	8234.07	8234.07	NA	NA	NA
NGHS	8234.07	8234.22	NA	NA	NA
NPHS	8234.07	8234.08	NA	NA	NA
VCF_PSO	8234.072	8258.727	8343.945	38.863	0.146

NA means not available in the corresponding literature.

The fuel cost convergence obtained by HS and SIHS algorithms for 3-unit ELD problems is depict in Figure. 6. We see that SIHS has an incredible fast convergence ability compared to HS. SIHS has been trapped into local optimum at about 1201 iterations and HS at about 4526 iterations. Figure. 7 displays the overall cost of fuel per algorithm.

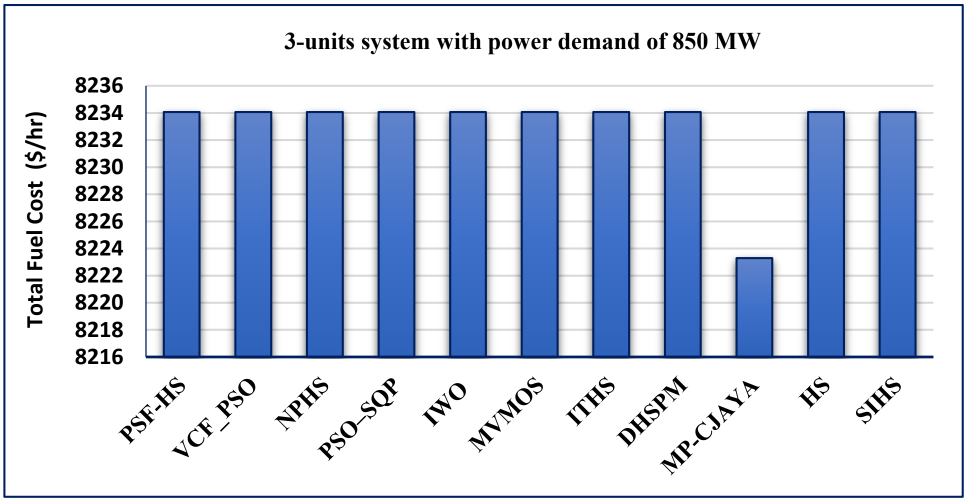


Figure 7. Total fuel cost for various methods for case study 1

B. Case II

The second case is a slightly wider system, comprising of 13 generators with a load demand of 1800 MW. The system data are extracted from [65].

The optimal real power dispatch and total cost obtained by various techniques such as DPSO-Sine, CBA, DHSPM, C-GRASP-SaDE, HS, and proposed SIHS are cited in Table 5. The best results are highlighted in bold font. The minimum value of TC achieved by HS and SIHS is 17960.442 $/hr and 17961.576 $/hr respectively. In this case study, the best TC is generated by C-GRASP–SaDE of 17960.393 $/hr.

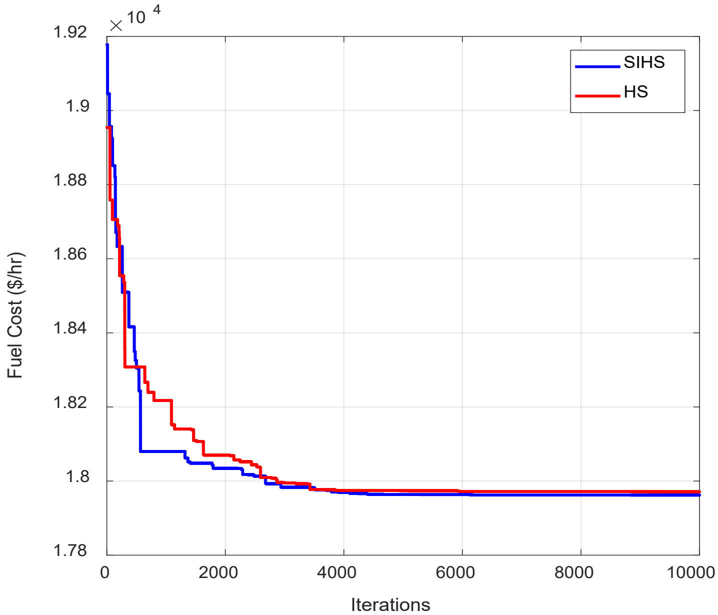


Figure 8. Fuel cost convergence behavior of 13-units system (P_D = 1800 MW)

Table 5. Best output power for 13-generator system with different algorithms (P_D = 1800 MW)

Output (MW)	DPSO-Sine	CBA	DHSPM	C-GRASP–SaDE	HS	**Proposed SIHS**
Pg1	628.31826	628.3185	628.3205	628.3185	628.231	628.318
Pg2	223.86847	149.5997	149.6024	149.5949	224.356	149.589
Pg3	148.98806	222.7491	222.7751	222.7571	148.292	222.775
Pg4	60.0000	109.8666	109.8655	109.8660	109.804	109.864
Pg5	109.42881	109.8666	109.8620	60.0000	109.780	109.865
Pg6	109.83620	109.8666	109.8582	109.8661	109.820	60.000
Pg7	109.83059	109.8666	60.0008	109.8662	109.862	109.858
Pg8	109.86588	60.0000	109.8614	109.8665	109.855	109.863
Pg9	109.86372	109.8663	109.8663	109.8665	60.000	109.865
Pg10	40.000	40.000	39.9997	40.0000	40.000	40.000
Pg11	40.000	40.000	39.9877	40.0000	40.000	40.000
Pg12	55.000	55.000	55.0001	55.0000	55.000	55.000
Pg13	55.000	55.000	55.0003	55.0000	55.000	55.000
TP (MW)	1800	1800	1800	1800	1800	1800
TC ($/hr)	17964.372	17963.83	17960.54	**17960.393**	17961.576	17960.442

Figure. 8 shows the best convergence behaviors of SIHS and HS. From Figure. 8, it is observed that SIHS converged to the optimum cost from 4390 iteration; it is quickly faster than HS (5982 iteration). The minimum cost of production obtained by each approach is offered in Figure. 9. Results of HS and SIHS have been compared with fifteen (15) methods reported in the literature, the results in terms of the maximum, mean, and best cost, standard deviation and mean computation time are summarized in Table 6.

Table 6. Comparison of simulation results for 13-generator system with different algorithms

Method	Best Fuel Cost ($/hr)	Mean Fuel Cost ($/hr)	Max Fuel Cost ($/hr)	Std. dev ($/hr)	CPU time (s)
C-GRASP–SaDE	**17960.393**	17966.106	17968.868	2.701	NA
Proposed SIHS	17960.442	17 986.506	18 066.928	36.205	**0.0883**
DHSPM	17960.54	17994.16	NA	NA	NA
HS-BLO	17960.6578	17969	18003	13.3525	NA
HS	17961.576	18042.389	18134.100	36.199	0.0999
FAPSO–VDE	17963.82	**17963.82484**	**17963.832**	NA	NA
GrC	17963.8292	17963.8292	17963.8292	**0.000**	6
ACHS	17963.8292	17973.7434	17978.1501	2.4877	0.93
CS-A	17963.83	17965.05	17968.99	2.15	NA
CBA	17963.83	17965.4889	17995.2256	6.8473	0.97
ANS	17963.9031	17969.1487	17973.4437	3.0015	NA
MVMOS	17964.1226	18011.0370	18070.7615	26.7448	34.02
DPSO- Sine	17964.372	17973.049	17978.919	2.571	NA
IWO	17968.00	NA	NA	NA	NA
PSO-SQP	17969.93	18029.99	NA	NA	33.97
GWO	17974.73	18085.49	18213.62	NA	NA
IFEP	17994.07	18192.00	18416.89	NA	156.81

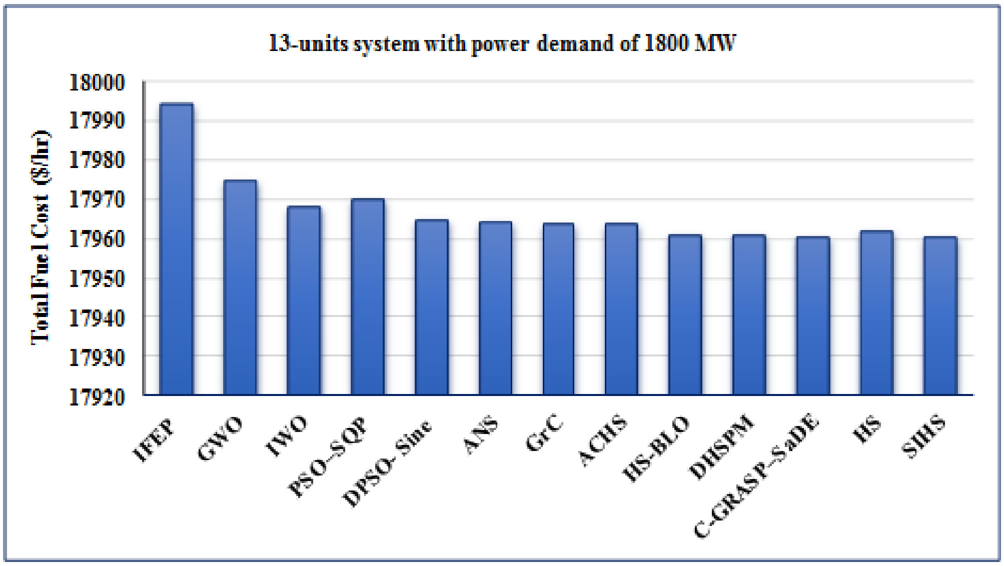


Figure 9. Total fuel cost for various methods for case study 2

C. Case III

The third case has the same number of generators and data as second case, expected different load demand of 2520 MW. All detailed data are available in [61].

The best power dispatch and best fuel cost solution obtained by SIHS and HS, are compared with those given by DPSO-Sine, MVMO^S, VCF-PSO, and IACS in Table 7. Notably, the optimal solution obtained is 24164.046 $/hr, it is achieved by IACS method, while the best cost obtained by the proposed SIHS is 24166.012 ($/hr), which is comparatively less than other algorithms.

Table 7. Best output power for 13-generator system with different algorithms (P_D = 2520 MW)

Output (MW)	DPSO-Sine	MVMO^S	VCF_PSO	IACS	HS	**Proposed SIHS**
Pg1	628.317	628.345	628.319	628.318	628.320	628.278
Pg2	299.184	299.190	299.199	299.199	299.168	299.163
Pg3	299.190	299.192	299.199	294.482	295.507	295.000
Pg4	159.728	159.731	159.733	159.733	159.679	159.727
Pg5	159.732	159.729	159.733	159.733	159.743	159.722
Pg6	159.665	159.732	159.733	159.733	159.603	159.672
Pg7	159.727	159.731	159.733	159.733	159.649	159.625
Pg8	159.725	159.732	159.733	159.733	159.713	159.710
Pg9	159.728	159.707	159.733	159.733	159.707	159.741
Pg10	77.365	77.368	77.4	77.3999	114.333	77.347
Pg11	77.378	77.373	77.4	77.399	77.174	77.286
Pg12	87.905	92.362	92.394	92.399	55.000	92.435
Pg13	92.368	87.802	87.691	92.399	92.400	92.288
TP (MW)	2520	2520	2520	2520	2520	2520
TC ($/hr)	24170.015	24170.013	24169.934	**24164.046**	24170.980	24166.012

The best convergence characteristics of proposed SIHS and original HS compared with thirteen methods in the literature are included in Table 8.

Table 8. Comparison of simulation results for 13-generator system with different algorithms

Method	Best Fuel Cost ($/hr)	Mean Fuel Cost ($/hr)	Max Fuel Cost ($/hr)	Std. dev ($/hr)	CPU time (s)
IACS	**24164.046**	**24164.046**	**24164.046**	**2.45E-8**	NA
β-GWO	24164.10	24164.20	NA	0.0492	NA
HCRO-DE	24164.8260	24164.9837	24165.3402	0.058	5.04
Proposed SIHS	24166.012	24308.278	24803.829	130.637	**0.119**
FAPSO–VDE	24169.9176	24169.9176	24169.9176	NA	NA
ITHS	24169.9218	NA	NA	NA	NA
DSPSO–TSA	24169.923	24173.137	24230.803	7.72	2.92
VCF_PSO	24169.934	24306.784	24460.246	81.101	3.035
MVMO^S	24170.0137	24193.4933	24226.8256	23.6363	34.32
DPSO- Sine	24170.015	24172.885	24176.515	1.994	NA
GA	24170.804	24188.394	24567.974	59.53	19.39
HS	24170.980	24288.556	24638.500	1.084	0.125
MP-CJAYA	24175.5444	24228.1331	NA	NA	NA
ACO	24195.91	24182.79	24169.63	7.86	14.35
PSO-SQP	24261.05	NA	NA	NA	NA

We can see from Table 8 that the minimum fuel cost of the proposed SIHS is comparatively lower than any other methods except for the IACS, β-GWO, and HCRO-DE performs significantly better than SIHS, but the results are competitive.

However, ICAS outperform all the other techniques in terms of best, mean, max fuel cost and standard deviation. The best computation time is provided by SIHS of 0.119 s. Figure.10 demonstrates the convergence behavior of the best total fuel cost obtained by the proposed SIHS and HS. It is clear that SIHS algorithm converge slowly to the best cost value; at about 8292 iteration and HS converge at about 9496 iteration. The best fuel cost obtained by every algorithm is illustrated in Figure. 11.

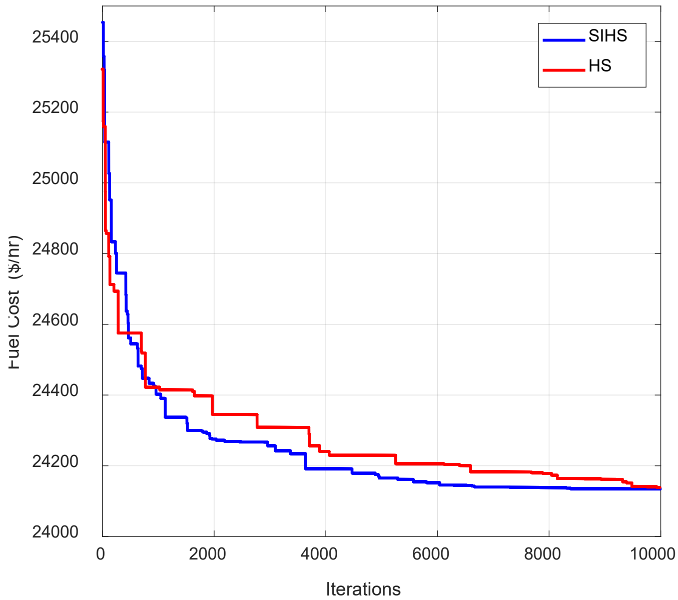


Figure 10. Fuel cost convergence behavior of 13-units system (P_D = 2520 MW)

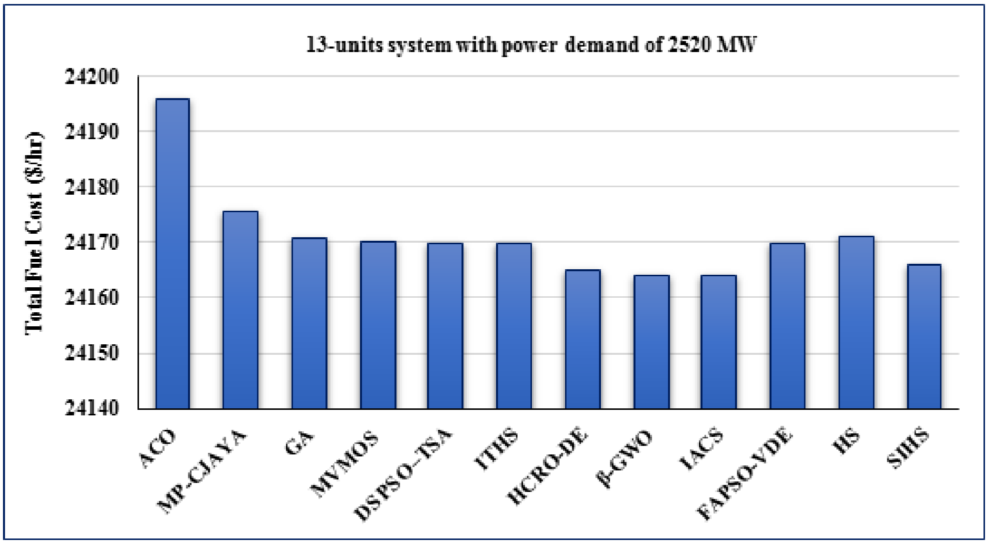


Figure 11. Total fuel cost for various methods for case study 3

D. Case IV

Due to 40 units with load demand of 10500 MW, and non-linearity of fuel cost functions due to VPE, test case 4 becomes more complex than the three cases studied above. The required data of case 4 are mainly derived from [10], [61].

To prove the efficiency of SIHS algorithm for large-scale economic dispatch of power systems, comparison results from methods ISA, OGSA, IACS, CIHSA, HS, and SIHS are illustrate in Table 9.

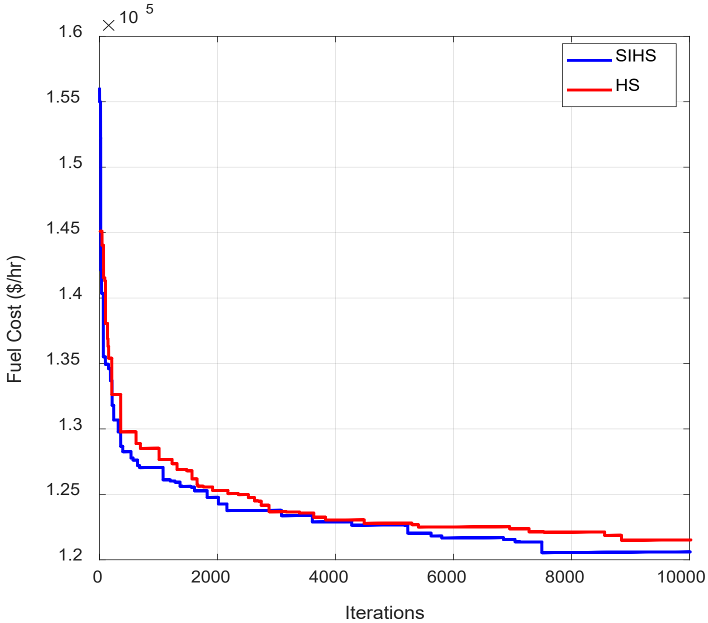


Figure 12. Fuel cost convergence behavior of 40-units system

The best statistical results of SIHS and HS algorithms compared with six HS variants technique and 19 methods mentioned in the literature, are recorded in Table 10. According to Table 10, the smallest fuel cost is obtained by the proposed SIHS of 120276.6778 $/hr. what is more, the lowest values of mean fuel cost and max fuel cost, are also achieved by SIHS, which is 120317.1410 $/hr, 120340.0490 $/hr respectively. The convergence curve of SIHS and HS are shown in Figure. 12. It is observed that the fuel cost function converges smoothly to the optimal solution without any abrupt oscillations, this proving the accuracy of the suggested algorithm.

Table 9. Best output power for 40-generator system with different algorithms

Output (MW)	IACS	CIHSA	OGSA	ISA	HS	**SIHS**
Pg1	110.8687	110.7998	114.0000	114.0004	114.0000	114.0000
Pg2	110.0013	110.7998	114.0000	111.1742	110.8045	114.0000
Pg3	97.3999	97.3999	120.0000	120.0000	97.4002	120.0000
Pg4	179.7331	179.7330	189.6786	188.5674	179.7335	189.7823
Pg5	92.4706	87.7999	97.0000	96.6566	87.8374	97.0000
Pg6	139.9999	140.0000	140.0000	139.9567	140.0000	139.8792
Pg7	259.5996	259.5996	259.2637	259.2432	259.5994	259.2633
Pg8	284.5996	284.5996	283.0360	282.9832	284.6007	282.9224
Pg9	284.5996	284.5996	290.0689	290.0129	284.6001	290.0191
Pg10	130.0000	130.0000	130.0000	129.8653	130.0000	129.8827
Pg11	168.7998	94.0000	101.2163	100.1766	168.7995	102.3883
Pg12	168.7998	94.0000	153.6064	153.6031	168.7997	153.5809
Pg13	214.7597	214.7597	210.1281	209.8476	214.7594	210.0005
Pg14	394.2793	394.2793	305.2207	305.1765	304.9195	305.2086
Pg15	394.2793	394.2793	297.6248	297.5324	394.2584	297.6197
Pg16	304.5195	394.2793	212.8865	211.8546	394.2791	212.8017
Pg17	489.2793	489.2793	499.7336	198.7546	489.2793	499.7881
Pg18	489.2793	489.2793	489.4927	488.8563	489.2793	488.9471
Pg19	511.2793	511.2793	511.9556	511.5464	511.3765	511.2171

Output (MW)	IACS	CIHSA	OGSA	ISA	HS	**SIHS**
Pg20	511.2793	511.2793	515.1468	514.1376	511.3765	514.9398
Pg21	523.2793	523.2793	524.8624	523.7647	523.5194	524.7284
Pg22	523.2793	523.2793	516.3822	515.9546	522.3888	515.8311
Pg23	523.2793	523.2793	522.0437	522.0176	523.2796	522.1840
Pg24	523.2793	523.2793	526.5253	526.5187	523.2794	526.2376
Pg25	523.2793	523.2793	512.1440	512.1322	523.2795	512.1179
Pg26	523.2793	523.2793	523.0461	523.0263	523.2795	523.1047
Pg27	10.0000	10.0000	131.8133	130.8563	10.0000	131.8415
Pg28	10.0000	10.0000	150.0000	149.8672	10.0000	149.9635
Pg29	10.0000	10.0000	133.4239	133.3567	10.0000	133.4329
Pg30	87.8169	87.7999	97.0000	97.0000	89.5070	97.0000
Pg31	189.9999	190.0000	187.6443	187.5767	190.0000	187.7540
Pg32	189.9999	190.0000	190.0000	190.0000	190.0000	190.0000
Pg33	189.9999	190.0000	169.7297	169.6498	189.9998	169.7165
Pg34	164.7998	164.7998	190.9535	190.8456	164.7514	190.9541
Pg35	164.7998	194.3978	176.4784	176.4638	164.9037	176.4723
Pg36	164.7998	199.9999	164.6995	164.4847	164.8296	164.6438
Pg37	109.9999	109.9999	99.1969	99.1254	110.0000	99.1597
Pg38	109.9999	110.0000	34.8100	32.4353	110.0000	34.8852
Pg39	109.9999	109.9999	85.8264	85.3543	109.9999	85.7163
Pg40	511.2793	511.2793	532.0793	530.7646	511.2794	531.0150
TP (MW)	10500	10500	10500	10500	10500	10500
TC ($/hr)	121371.56	121412.53	120390.00	120 385.47	121075.941	**120276.67**

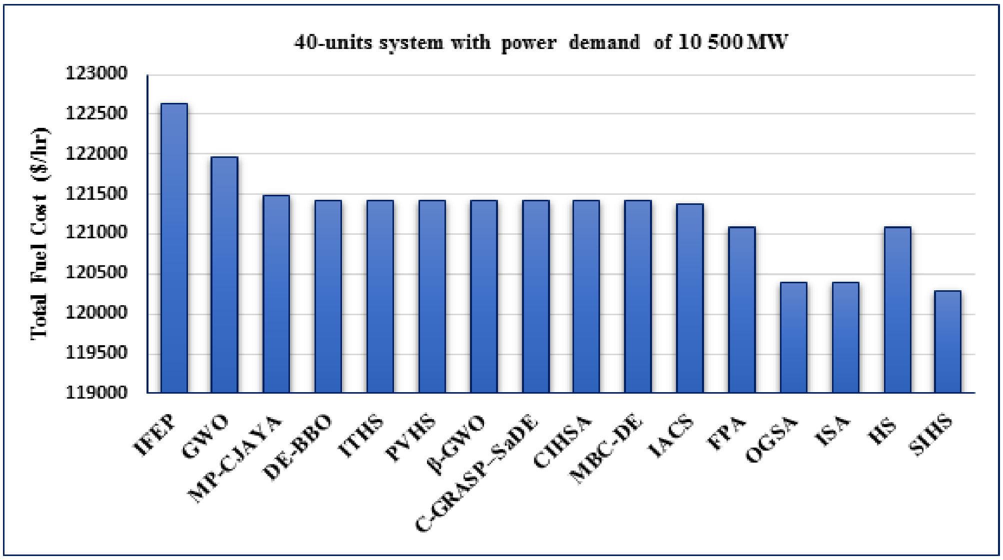


Figure 13. Total fuel cost for various methods for case study 4.

The minimum standard deviation of 0.0018 $/hr is obtained by GrC in [24]. The smallest computation time is 0.06 (s), obtained by DE-BBO in [21]. SIHS has higher standard deviation of 486.8694 $/hr and smaller CPU time of 0.2373(s).

Table 10. Comparison of simulation results for 13-generator system with different algorithms

Method	Best Fuel Cost ($/hr)	Mean Fuel Cost ($/hr)	Max Fuel Cost ($/hr)	Std. dev ($/hr)	CPU time (s)
Proposed SIHS	**120276.6778**	**120317.1410**	**120340.0490**	486.8694	0.237336
ISA	120385.47	120403.21	120478.62	NA	NA
OGSA	120390.00	NA	NA	NA	NA
FPA	121074.500	121 095.7	121 196.3	NA	0.89
HS	121075.941	121126.824	1211475.729	5.22012	0.2431
IACS	121371.5603	121,423.33	121,450.32	NA	NA
GrC	121412.5355	121412.5360	121412.5380	**0.0018**	43
MBC-DE	121412.5355	121450.32	121481.33	21.658087	NA
CIHSA	121412.5365	121413.3736	121420.8962	2.5725	NA
CBA	121412.5468	121418.9826	121436.15	1.611	1.55
HCRO-DE	121412.55	121413.11	121415.68	0.13	7.64
ANS	121412.6226	121427.7107	121472.9213	13.6539	NA
DHSPM	121412.66	121423.57	NA	NA	NA
NTHS	121412.7374	121549.95	NA	NA	NA
C-GRASP–SaDE	121414.621	121736.025	122245.696	166.896	NA
ACHS	121414.8587	121510.50	121655.66	54.28	2.18
β-GWO	121415.09	121417.79	NA	3.9476	NA
$MVMO^S$	121415.2346	121652.7238	121,913.4278	115.3685	107.98
PVHS	121415.4560	121567.0292	NA	94.1498	NA
ITHS	121416.6526	121416.7196	121417.025	0.1087	NA
DE-BBO	121420.8948	121420.8952	121420.8963	NA	**0.06**
DPSO- Sine	121424.0947	121459.909	121508.002	21.097	NA
MP-CJAYA	121480.10	121861.08	NA	NA	NA
IWO	121485.90	NA	NA	NA	NA
GWO	121963.721	122731.166	123884.827	NA	NA

The superiority of the proposed SIHS algorithm in reducing the total fuel cost value compared to other algorithms in literature can be confirmed as shown in Figure. 13.

As observed from Tables 3, 5, 7, and 9, the power output of each unit lies within the minimum and maximum generator capacity limits and satisfies the power balance constraint.

6. CONCLUSIONS

In this paper, solutions of ELD problem with VPE have been found by introduce an effective SIHS algorithm, which is developed based on conventional HS by generate a new harmony solution with dynamically varying bandwidth.

In order, to examine the efficacy and the robustness of the suggested SIHS algorithm, four typical ELD cases are employed without considering transmission losses. The numerical findings confirm that the SIHS can provide better solutions with lowest computation time than other different metaheuristic optimization, and successfully improve the efficiency of the ELD problems. However, the SIHS algorithm also has the weakness, that it requires "proper and appropriate" value setting for algorithm parameters.

From the evaluation above, it can be conclude that SIHS algorithm has the strongest ability of handling larger scale of ELD with several constraint. SIHS algorithm has demonstrate its superiority over all comparative methods in literature.

To ensure good results, in the future, we will endeavor to find a parameter-free developed technique combined with the SIHS algorithm and introduce it to other kinds of optimization issues, such as multi-objective ED problems with many complex constraints, dynamic ED problems and large-scale ELD problems integrated renewable energy sources.

7. acknowledgment

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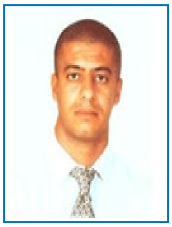

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