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Tournament-based harmony search algorithm for non-convex economic load dispatch problem

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ABSTRACT

This paper proposes a tournament-based harmony search (THS) algorithm for economic load dispatch (ELD) problem. The THS is an efficient modified version of the harmony search (HS) algorithm where the random selection process in the memory consideration operator is replaced by the tournament selection process to activate the natural selection of the survival-of-the-fittest principle and thus improve the convergence properties of HS. The performance THS is evaluated with ELD problem using five different test systems: 3-units generator system; two versions of 13-units generator system; 40-units generator system; and large-scaled 80-units generator system. The effect of tournament size (t) on the performance of THS is studied. A comparative evaluation between THS and other existing methods reported in the literature are carried out. The simulation results show that the THS algorithm is capable of achieving better quality solutions than many of the well-popular optimization methods.

1. Introduction

In power system, economic load dispatch (ELD) problem is an important optimization and operations task. The main aim of solving ELD is to distribute the required generation among the generating units in such a way to minimize the fuel costs of each unit subject to satisfying equality constraints related to the power balance and inequality constraints related to the power output [27,65]. Therefore, ELD problem is considered as a non-convex and highly non-linear optimization problem which can not be easily tackled using traditional calculus-based optimization methods [65,28]. Indeed, the calculus-based methods require smoothing and differentiable objective function when applied to tackle the ELD problems [34].

Recently, the emergence of the approximation methods for ELD revealed very successful stories in the operations and planning of the power system. These approximation methods can be grouped into (i) swarm-based algorithms such as shuffled frog leaping algorithm [70], firefly algorithm [28,87], artificial bee colony [43,44], bacterial foraging algorithm [35], cuckoo search [17,84], particle swarm optimization [73], ant colony optimization [45,24,68], honey bee mating optimization [61], chemical reaction optimization [71], (ii) evolutionary-based algorithms such as genetic algorithm [29,80], harmony search algorithm [27], biogeography-based optimization [69,21,19], and (iii) trajectory-based algorithms such as simulated annealing [66], tabu search [67]. The approximation methods have the ability to find potential solutions when employed to tackle the problem of high dimensionality such as ELD.

However, due to the complexity nature of ELD search space, recent studies modified or hybridized the approximation methods in order to improve their performance. For example, the evolutionary programming and genetic algorithm are incorporated for the ELD in [77,29] while the performance of particle swarm optimization is enhanced with sequential quadratic programming (PSO-SQP) in [83]. And many other improvements related to ELD can be found in [73,20,48,51,18,15,42].

The most important issue related to adaptation of any optimization algorithm to constrained problems is how the algorithm handles the constraints relating to the problem. Over the years, several methods are proposed to handle the problem constraints. These methods include those that preserve the feasibility of solutions, penalty-based methods, methods that clearly distinguish between feasible and infeasible solutions, and hybrid methods [32]. When ELD-based methods handle the equality and inequality

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constraints, they choose to work in a feasible search space region or infeasible one. In case, if the method is employed to search the feasible region of the search space (like the one adapted in this paper), the feasibility of each generated solution is maintained using a special repair strategy that guaranteed the satisfactions of all constraints [33,54]. In contrast, when the method is utilized to search the infeasible region of the search space, an error rate that reflects the violation in the constraints is incorporated in the fitness function (which penalizes infeasible solutions). Thus, this converts the constrained to unconstrained optimization problem. By means of modifying the fitness function to include the constraint violations (normally with high penalty value), the method obtains a solution with no constraint violations as well as with a minimum fuel cost at the final stage of run [23,47].

In the recent years, several harmony search (HS) algorithms have been proposed to tackle ELD problems [30,27,47,65,63]. The HS, which is the recent evolutionary algorithm proposed in [40], is considered to be an efficient approximation technique due to its derivative-free characteristics [53]. Literatures have shown the usability of HS algorithm have been increasing over the year to address a wide range of optimization problems [76,12,39,37,38,46]. Similarly, the HS algorithm has been modified and hybridized with other efficient methods to cope with the combinatorial nature of highly constrained optimization problems [4,7,1,10,11,14]. Furthermore, the parameter-free HS [41] and population structured of HS are proposed to improve the theoretical aspects of the algorithm [2,5].

Procedurally, HS as an evolutionary algorithm begins with a population of individuals generated randomly. At each generation, a new individual called "new harmony" is generated in accordance with three operations: "memory consideration" concerned with a recombination process; "random consideration" concerned with diversification aspects; and "pitch adjustment" concerned with local intensification. The new individual is evaluated and replaced the worst individual in the entire population, if superior. This generation process is repeated until a certain stop criterion is reached.

One of the main shortcomings of the HS algorithm raised is in the area of memory consideration selection process where the natural selection of survival-of-the-fittest principle is omitted [3]. Thus, the investigations of novel selection methods in the memory consideration for the HS algorithm are proposed in [3,13] and analyzed in [6], where five selection schemes were investigated: proportional, tournament, global best, linear rank, and exponential rank. Interestingly, the tournament-based HS algorithm achieved the best performance for the global optimization problems and adopted by other researchers as an efficient variant of the HS algorithm [25,75,49].

In this paper, the tournament-based HS (THS) algorithm is investigated for the ELD problem. The performance of THS is better than HS because it utilized the survival-of-the-fittest principle of the natural selection in memory consideration process. Note that the memory consideration is the main operator of THS which responsible for constructing the new solutions from the accumulative search and therefore, improving its selection process will improve the convergence property directly. However, time complexity in each iteration of the THS algorithm might be marginally affected because new data structure will be added to operate the tournament concepts in memory consideration. The THS algorithm is experimented with five ELD test systems with valve point loading effect instances for diverse power systems and different cost curve natures. These include 3-units generator system; two versions of 13-units generator system; 40-units generator system; and a large-scaled 80-units generator system. In all experimented ELD cases, the proposed THS competitively produced comparable results.

The remainder of this paper is organized as follows: Section 2 provides the formulations of ELD problem. The description of THS algorithm for ELD is given in Section 3. Experimental results and analysis of the findings are presented in Section 4 while the conclusion and possible future research directions are provided in Section 5.

2. Economic load dispatch problem

The economic load dispatch problem could be traditionally formulated as a minimization of the fuel costs summation of the individual dispatchable generating power units subject to the balance of real power with the total load demand in addition to limits on power generating system outputs. Mathematically, the objective function of ELD problem can be formulated in Eq. (1) as:

$$F(\boldsymbol{P}) = \sum_{i=1}^{N} F_i(P_i). \tag{1}$$

where $F(\boldsymbol{P})$ is a system-wide total cost functions of N generating units; F_i is generating cost function of generating unit i; and P_i is the generation output of the active generating unit i. The incremental cost functions of the power generating systems with valve-point loading effects are represented using Eq. (2) as follows:

$$F_i(P_i) = \lfloor a_i P_i^2 + b_i P_i + c_i + |e_i \sin(f_i(P_i^{(\min)} - P_i))| \rfloor. \tag{2}$$

Subject to

$$\sum_{i=1}^{N} P_i - P_D - P_L = 0 \tag{3}$$

$$P_i^{(\min)} \leq P_i \leq P_i^{(\max)}, \quad i \in N_s \tag{4}$$

In Eq. (2), (a_i, b_i, c_i) and (e_i, f_i) are the smooth and non-smooth cost fuel coefficients of generating unit i respectively. Note that Eq. (3) represents the equilibrium state between total system generation $(\sum_{i=1}^{N} P_i)$ and the summation of total system loads (P_D) with losses (P_L). Finally, the lower and upper bound $(P_i \in [(P_i^{(\min)}), (P_i^{(\max)})])$ of the output of each active generating unit is inequality constrained in Eq. (4).

The total transmission losses of the system is expressed as a quadratic function of outputs of the power generating system as shown in Eq. (5)

$$P_L = \sum_{k=1}^{N} \sum_{i=1}^{N} P_k B_{ki} P_i + \sum_{k=1}^{N} B_{0k} P_k + B_{00} \tag{5}$$

where B_{ki} is the $k$ith component of the loss coefficient square matrix while B_{0k} and B_{00} are the ith component of the loss coefficient vector and the constant of the loss coefficient respectively.

The fuel cost function together with sinusoidal function which models the effect of valve-point generates waves in the heat-rate curve creates additional local optima to the solution search space [8]. As experimented by other comparative studies reported in Table 1 [23,8,22,54,82,58], the total transmission losses are ignored for all the test arrangements for sake of simplicity sought in this paper(i.e., $P_L = 0$).

3. Tournament harmony search for ELD

Procedurally, the THS has five main steps pseudo-coded in Algorithm 1 and described as follows:

Table 1
Key to comparative methods.

Key	Method name	Test system	Reference
ABOMDE	Accelerated biogeography based optimization modified differential evolution	2, 4	[55]
ARCGA	Adaptive real coded genetic algorithm	4	[72]
ACO	Ant colony optimization	3, 4	[68]
ABC	Artificial bee colony	4	[43]
BGO	Biogeography based optimization	4	[21]
CBPSO-RVM	Particle swarm optimization (constriction factor and inertia weight)-real valued mutation	4	[56]
CE-SQP	Cross-entropy method and sequential quadratic programming	5	[79]
CSOMA	Cultural self organizing migrating algorithm	4	[31]
CSO	Civilized swarm optimization	5	[74]
DE-BGO	Differential evolution-biogeography based optimization	4	[20]
DVL-MILP	Discrete value loading mixed integer linear programming	4	[36]
FAPSO	Fuzzy adaptive particle swarm optimization	4	[61]
FAPSO-NM	Fuzzy adaptive particle swarm optimization-Nelder Mead	4	[61]
FCASO-SQP	Fuzzy chaotic ant swarm optimization-sequential quadratic programming	1, 2, 3, 4	[23]
FFA	Fire fly algorithm	4	[77]
GA-API	Genetic algorithm-ant colony optimization (special class)	1	[78]
GA-PS-SQP	Genetic algorithm-pattern search-sequential quadratic programming	1, 2, 4	[8]
GSO	Group search optimizer	4	[60]
HS	Harmony search	2	[30]
DHS	Differential harmony search	2	[86]
IHS	Improved harmony search	2	[30]
HHS	Hybrid Harmony Search	2, 4	[64]
HCASO	Hybrid chaotic ant swarm optimization	1, 2, 3, 4	[23]
HCPSO	Hybrid chaotic particle swarm optimization	1, 3, 4	[22]
HCPSO-SQP	Hybrid chaotic particle swarm optimization-sequential quadratic programming	1, 3, 4	[22]
HMAPSO	Hybrid multi agent based particle swarm optimization	2, 4	[52]
HQIPSO	Hybrid quantum inspired particle swarm optimization	2, 4	[26]
KHA	Krill herd algorithm	5	[57]
MDE	Modified differential evolution	1, 4	[9]
MSL	Maclaurin series based Lagrangian method	2	[59]
NDS	Novel direct search method	1, 2, 4	[54]
NSS	Novel stochastic search method	1, 2, 4	[82]
PSO	Particle swarm optimization	5	[74]
PSO-MSAF	Particle swarm optimization-modified stochastic acceleration factor	4	[81]
QIPSO	Quantum inspired particle swarm optimization	1, 2, 4	[58]
RCGA	Real coded genetic algorithm	2, 4	[26]
SOMA	Self organizing migrating algorithm	4	[31]
SDE	Shuffled differential evolution	1	[78]
SCA	Society civilized algorithm	5	[74]
TLA	Teacher learning algorithm	4	[16]
TS	Tabu search	3, 4	[68]
TSA	Taguchi algorithm	3	[50]
TSARGA	Taguchi self adaptive real genetic algorithm	4	[80]

Algorithm 1. Tournament harmony search algorithm

```
Set HMCR, PAR, NI, HMS, FW.
for j = 1, ..., HMS do
  for i = 1, ..., N do
    P_i^j = P_i^(min) + (P_i^(max) − P_i^(min)) × U(0, 1) {generate HM individuals}
  end for
  Calculate(F(P^j))
end for
itr = 1
while (itr ≤ NI) do
  P′ = φ
  for i = 1, ..., N do
    if (U(0, 1) ≤ HMCR) then
      best=Tournament Memory Consideration() {see Algorithm 3}
      P′_i = P_i^best
      if (U(0, 1) ≤ PAR) then
        P′_i = P′_i + U(−1, 1) × FW {pitch adjustment}
      end if
    else
      P′_i = P_i^(min) + (P_i^(max) − P_i^(min)) × U(0, 1) {random consideration}
    end if
  end for
  if (F(P′) < F(P^worst)) then
    Include P′ to the HM.
    Exclude P^worst from HM.
  end if
  itr = itr + 1
end while
```

Step 1: Initialize the parameters. In this step, the ELD search space definitions are initialized which include the individual representation as well as the system-wide total cost function with a value range for each generation output of the active generating units discussed in Section 2. Furthermore, the parameters of the THS algorithm required to solve the ELD problem are specified in this step: the harmony memory consideration rate (HMCR) which determines the rate of selecting the value from the memory; the harmony memory size (HMS) is similar to the population size in other EAs; pitch adjustment rate (PAR) that determines the probability of local improvement; the fret width (FW), which determines the distance of adjustment, number of improvisations (NI) or number of generations, and finally the tournament size t are initialized.

Step 2: Initialize the harmony memory. The harmony memory (HM) is a repository of the individuals in the population, $\mathbf{HM} = [\boldsymbol{P}^1, \boldsymbol{P}^2, \ldots, \boldsymbol{P}^{\text{HMS}}]^{\mathbf{T}}$, of size HMS. In this step, these individuals are randomly generated as follows:

$$P_i^j = P_i^{(\min)} + (P_i^{(\max)} - P_i^{(\min)}) \times U(0, 1),$$

where $\forall i = 1, b, \ldots, N$ and $\forall j = 1, 2, \ldots, \text{HMS}$, and $U(0, 1)$ generate a uniform random number between 0 and 1. Note that the equality constraints in Eq. (3) and inequality constraints for Eq. (4) are fulfilled for each individual stored in **HM** using a simple repair process to ensure the feasibility (see Algorithm 2).

In Algorithm 2, the method of constraint handling used in this paper does not include the load balance constraint and the minimum and maximum power units constraints in the objective function. These two types of constraints are handled for each generated solution using repair strategy that grantee the satisfactions of these constraints. Therefore, the feasibility of each generated solution is addressed before the fuel cost of that solution is evaluated by the objective function. Note that the method presented in this paper handled the constraints similar to some previous methods introduced for ELD problem like in [33,54]. The Repair_process(.) proposed here is pseudo-coded where the power of each generated unit P_i in the repaired solution is adjusted to meet the optimal range of that unit (i.e., $P_i \in [P_i^{(\min)}, P_i^{(\max)}]$) as well as to narrow the distance of the total system loads (P_D) represented by *diff* variable in the algorithm. Note that the Repair_process(.) is looped until the *diff* equal zero.

Algorithm 2. Repair_Process().

```
for i = 1, . . ., N do
  Total = Total + P_i
end for
diff = Total - P_D
while diff ≠ 0 do
  temp = rand(0, diff)
  i = rand (1, N) {i is the index of the active generation unit}
  if (P_i ± temp) ≥ P_i^(min) and (P_i ± temp) ≤ P_i^(max) then
    P_i = P_i ± temp
    diff = diff ± temp
  end if
end while
```

Step 3: Improvise a new harmony. A new harmony individual, $\mathbf{P}' = (P'_1, P'_2, \ldots, P'_N)$, is generated based on three operators with respect to a probability (w.p.) of such parameter rates: (i) memory consideration (MC), (ii) pitch adjustment (PA), and (iii) random consideration (RC). If the new harmony individual is unfeasibly generated, the repair process in Algorithm 2 is invoked. The three operators assign a value for each generation output of the active generating unit P'_i in the new harmony as formulated in Eq. (6).

$$P'_i \leftarrow \begin{cases} \in \{P_i^1, P_i^2, \ldots, P_i^{\mathrm{HMS}}\} & \text{w.p.} \quad \mathrm{HMCR} \times (1 - \mathrm{PAR}) \quad \{\mathrm{MC}\} \\ = P'_i + U(-1, 1) \times \mathrm{FW} & \text{w.p.} \quad \mathrm{HMCR} \times \mathrm{PAR} \quad \{\mathrm{PA}\} \\ \in [(P_i^{(\min)}, (P_i^{(\max)}] & \text{w.p.} \quad 1 - \mathrm{HMCR} \quad \{\mathrm{RC}\} \end{cases} \tag{6}$$

As shown in Eq. (6), the memory consideration (MC) initially selects an individual $\mathbf{P}^j$ stored in HM where $j \in (1, 2, \ldots, \mathrm{HMS})$ at random to assign a value for the generation output of the active generating unit P'_i where $P'_i = P_i^j$. Note that the process is repeated for all generation output of the active generating units with a probability of HMCR. Indeed, this selection process does not considered the natural selection of the survival-of-the-fittest principle. Therefore, the main focus of this paper is to replace the random selection process in the memory consideration with the tournament selection process to improve the convergence rate.

Tournament memory consideration: In order to employ the natural selection of the survival-of-the-fittest principle in THS, the tournament selection process is adapted where a set of individuals, $\zeta = \{\mathbf{P}^j | j \in (1, 2, \ldots, t)\}$, $\zeta \subseteq \mathbf{HM}$ and t is the tournament size, is randomly filled from the **HM**. Then the individual $P^{best} \subseteq \zeta$ is selected as in Eq. (7):

$$best = arg \min_{(j=1,\ldots,t)} F(\mathbf{P}^j) \tag{7}$$

Note that in Eq. (7), the individual $\mathbf{P}^{best}$ with the minimum objective function in ζ is selected and used in the improvisation process

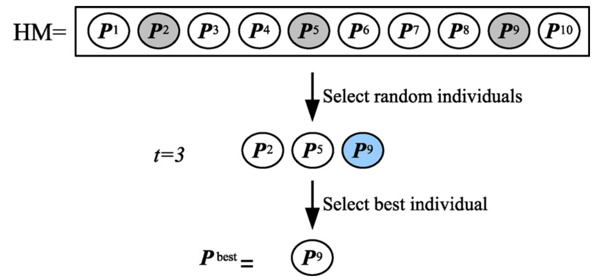

Fig. 1. Example of THS.

where $P'_i = P_i^{best}$. To elaborate, Algorithm 3 pseudo-coded the tournament selection process of THS. The algorithm is looped t times where at each step, a random individual is randomly chosen and kept in case if better. Furthermore, as an example of the tournament memory consideration, Fig. 1 shows a HM with HMS = 10. In tournament memory consideration, t = 3 random individuals are chosen and the best among them is used in the improvisation process.

Algorithm 3. Tournament Memory Consideration().

```
best = rand(1,HMS)
j = 1
while j < t do
  temp = rand(1,HMS)
  if (F(P^temp) < F(P^best)) then
    best = temp
  end if
  j++
end while
return best
```

Indeed, the tournament size t affect the performance of the THS. The bigger value of the tournament size t is, the higher the selection pressure will be and thus leads to increase the intensification capability of the THS. However, when tournament size t takes a small value, the behavior of the THS algorithm will tend to behave similar to the original version of HS algorithm.

Step 4: Update the harmony memory. The new harmony individual, $\mathbf{P}' = (P'_1, P'_2, \ldots, P'_N)$, replaces the worst harmony $\mathbf{P}^{\mathrm{worst}}$ stored in HM, if better.

Step 5: Check the stop criterion. Step 3 and step 4 of THS algorithm are repeated until the stop criterion (NI) is met.

4. Numerical examples and experimental results

The process of evaluating the convergence behaviors of THS algorithm is studied and analyzed with varying tournament size t using five different test systems of real-world ELD problems and compared with other comparative methods:

1. 3-units generator system for a load demand of 850 MW.
2. 13-units generator system for a load demand of 1800 MW.
3. 13-units generator system for a load demand of 2520 MW.
4. 40-units generator system for a load demand of 10,500 MW.
5. 80-units generator system for a load demand of 21,000 MW.

The keys to the comparative methods are provided in Table 1. Note that the third column shows which test system used for comparison. In the experiments carried out below, each method runs 30 independent replications. All the experiments are run using a computer with 2.66 Intel Core 2 Quad with 4GB of RAM. The operating system used is Microsoft Windows Vista Enterprize Service Pack 1. The source code is implemented using MATLAB Version 7.6.0.324(R2008a).

Table 2
Results for 3-units generator system for a demand of 850 MW.

Generator	THS (t = 2)	THS (t = 5)	THS (t = 8)
pg1	300.2669	300.2669	300.2669
pg2	400	400	400
pg3	149.7331	149.7331	149.7331
MW	850	850	850
Total cost ($)	**8234.07**	**8234.07**	**8234.07**
Mean cost	8234.55	8234.31	8234.07
Stdev	1.8020	1.2968	0

It is worth mentioning that the parameter settings are one of the main factors for optimization methods to yield a desired outcome for constraint optimization problems. With that in mind, the THS parameters are set as follows: HMS = 10, HMCR = 0.90, PAR = 0.30, FW = 0.03, and NI = 5 × 10^6. The optimal values of these parameters are selected in a way similar to what is done in [62].

The tournament size (t) is experimented with different values to show its effect on the convergence behavior of THS. The three values of t are selected: t = 2 which is small, t = 5 that represents medium, and t = 8 which is large. Note that t = 8 is close to HMS. These various values of t are used for all experimented cases in order to determine the optimal value to be used for THS.

4.1. Case I: 3-units generator system with load demand of 850 MW

The characteristics of the problem tackled in Case I include three generating units with the total expected load demand of 850 MW. All data of this problem (upper and lower bounds for the units and fuel cost coefficients a, b, c, e, and f) are provided in [85,77].

The comparative results among the three versions of THS algorithm based on various tournament size values (i.e., t = 2, t = 5, and t = 8) are summarized in Table 2. The optimal individual with its total fuel cost is recorded in addition to the mean cost and the standard deviation (stdev) over 30 runs for each THS versions which are all summarized in Table 2. Apparently, the three versions of THS are able to achieve individuals with the same optimal fuel cost. However, the THS (t = 8) algorithm is the most robust algorithm among the three proposed THS algorithms, where it achieved the optimal fuel cost for all the 30 runs. It is worth mentioning that the higher the value of t is, the better the results for the 3-units generating system will be. This is because the chance of selecting the individual with the least fuel cost is increased by increasing the t value and therefore improve the convergence capability of THS.

Fig. 2 illustrates the behavior of the three THS algorithms visualized in terms of fuel cost against 5 × 10^3 iterations. The figure shows that the THS (t = 2) algorithm had a faster convergence, while the version of THS with t = 5 had a slower convergence speed. Apparently, the THS (t = 8) algorithm maintained the balance between intensification and diversification as much as possible, where the value of fuel cost decreases as the number of iterations increases. Similarly, Fig. 3 shows the distribution results of the three THS algorithms in box plot format. As shown in this figure, the box plot of the THS (t = 8) algorithm is the more stable than the other versions of the THS algorithms, where it obtained results does not include outliers '+'.

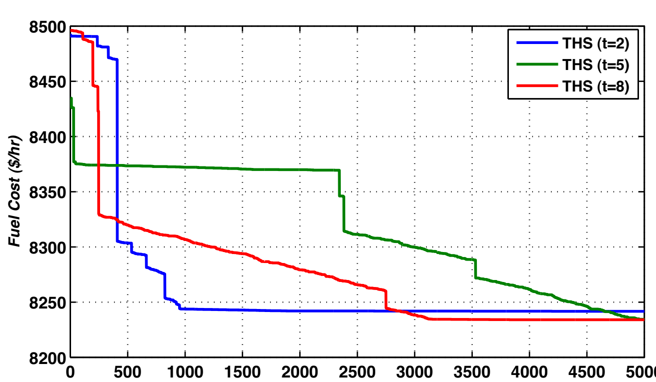

Fig. 2. Convergence characteristic of 3-units generator system with 850 MW obtained by THS algorithms.

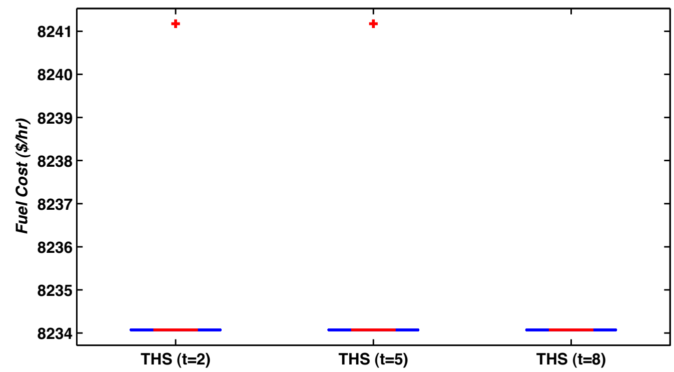

Fig. 3. Boxplot for the results of THS with varying values of t on Case I.

Table 3 provides the best experimental results produced by the proposed THS algorithms against the results of the state-of-art methods that worked on the same 3-units generating system. The key of the state-of-art methods are provided in Table 1. The best results are highlighted in bold font. It is worth mentioning that almost all comparative methods were able to obtain a solutions with the minimum fuel costs as achieved by the three THS algorithms. Apparently, in THS (t = 8) algorithm, the mean of the 30 runs is equal to the minimum fuel cost. This is indicate excellent success rate, equal to 100% of the version of THS with t = 8 which signifies robustness and superiority of the algorithm compared to other existing approaches.

4.2. Case II: 13-units generator system with load demand of 1800 MW

Thirteen generating units are included in Case II, and the data (upper and lower bounds for the units and fuel cost coefficients a, b, c, e, and f) are selected from [85]. In this system, the total load dispatch of all generation units is 1800 MW. The achieved results of the three THS (i.e., THS (t = 2), THS (t = 5), and THS (t = 8)) algorithms are given in Table 4. As shown in this table, the best individual achieved among the 30 replication runs is recorded for each THS

Table 3
Comparison for 3-units generator system for a demand of 850 MW.

Method	Best	Mean
THS (t = 2)	**8234.07**	8234.55
THS (t = 5)	**8234.07**	8234.31
THS (t = 8)	**8234.07**	8234.07
FCASO-SQP	**8234.07**	8234.07
GA-API	**8234.07**	NA
GA-PS-SQP	8234.10	8234.10
HCASO	**8234.07**	8234.07
HCPSO	**8234.07**	NA
HCPSO-SQP	**8234.07**	8234.07
MDE	**8234.07**	NA
NDS	**8234.07**	8234.07
NSS	8234.08	8234.08
QIPSO	**8234.07**	8234.10
SDE	**8234.07**	NA

Table 4
Results for 13-units generator system for a demand of 1800 MW.

Generator	THS (t = 2)	THS (t = 5)	THS (t = 8)
pg1	628.3185	628.3185	628.3185
pg2	149.5984	149.5993	149.5990
pg3	222.7517	222.7516	222.7514
pg4	109.8662	60	109.8665
pg5	60.0000	109.8660	60.0000
pg6	109.8662	109.8662	109.8661
pg7	109.8664	109.8660	109.8665
pg8	109.8661	109.8658	109.8657
pg9	109.8664	109.8665	109.8662
pg10	40	40	40
pg11	40	40	40
pg12	55	55	55
pg13	55	55	55
MW	1800	1800	1800
Total cost ($)	**17,960.37**	**17,960.37**	**17,960.37**
Mean cost	17,982.98	17,985.15	17,977.60
Stdev	21.2438	25.6739	17.0560

algorithm. Furthermore, the total fuel cost for each best individual, and the mean fuel cost together with the standard deviation (stdev) for all replication runs are also recorded. The results show that the minimum fuel cost achieved for the Case II is 17,960.37$, where this cost is obtained by the three THS algorithms. Once again the stability of the results produced are affected by the t in which higher value of t empower the THS algorithm to achieve better results in each run thus improve the convergence. This is borne out by the mean and stdev of each THS version.

The convergence characteristics for the three THS algorithms over the Case II are shown in Fig. 4. The fastest convergence speed is achieved by the THS (t = 2) algorithm. Furthermore, the distribution results of the three THS algorithms in box plot format are provided in Fig. 5. Once again, the version of the THS with t = 8 is the robust among the three versions of THS due to almost all individuals achieved close to the best individual.

The best and mean fuel costs of the test system produced by the proposed THS algorithms and 16 other comparative methods for Case II are reported in Table 5. The key of the comparative methods are abbreviated in Table 1. The best results are highlighted in bold font. It is observed from the results that the best results with the minimum fuel cost is achieved by the proposed THS algorithms as obtained by other two comparative methods (i.e., DHS and IHS). The harmony search algorithm with tournament selection method in the memory consideration operator is an efficient version in tackling ELD problem of 13-units generator system which is able to achieve a superior results with an easy structured algorithm.

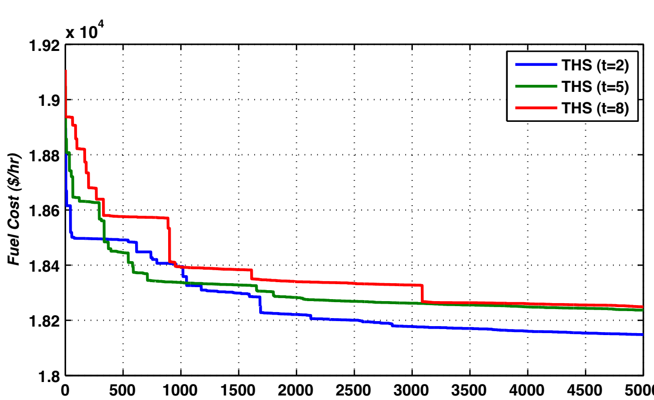

Fig. 4. Convergence characteristic of 13-units generator system with 1800 MW obtained by THS algorithms.

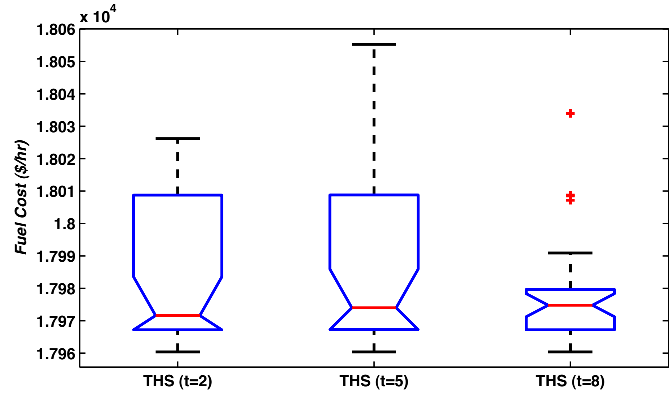

Fig. 5. Boxplot for the results of THS with varying values of t on Case II.

Table 5
Comparison results for 13-units generator system for a demand of 1800 MW.

Method	Best	Mean
THS (t = 2)	**17,960.37**	17,982.98
THS (t = 5)	**17,960.37**	17,985.15
THS (t = 8)	**17,960.37**	17,977.60
ABOMDE	17,963.85	17,967.36
DHS	**17,960.37**	17,961.12
FCASO-SQP	17,964.08	18,001.96
GA-PS-SQP	17,964.00	18,199.00
HCASO	17,965.15	18,022.04
HHS	17,963.83	17,972.48
HMAPSO	17,969.31	17,969.31
HQIPSO	17,966.37	18,081.05
HS	17,965.62	17,986.56
IHS	**17,960.37**	17,965.42
MSL	18,158.68	NA
NDS	17,976.95	17,976.95
NSS	17,976.95	17,976.95
QBPSO	17,964.00	NA
QIPSO	17,969.01	18,075.11
RCGA	17,963.86	NA

4.3. Case III: 13-units generator system with load demand of 2520 MW

This test system comprises of 13 generating units with a load demand of 2520 MW. The same data used in Case II are also used in Case III. The best individual obtained by the different variants of THS are reported in Table 6. Furthermore, the total fuel cost for each best individual as well as the mean fuel cost together with the standard

Table 6
Results for 13-units generator system for a demand of 2520 MW.

Generator	THS (t = 2)	THS (t = 5)	THS (t = 8)
pg1	628.3185	628.3185	628.3185
pg2	299.1991	299.1992	299.1983
pg3	294.4890	294.4903	294.4887
pg4	159.7331	159.7325	159.7329
pg5	159.7329	159.7330	159.7331
pg6	159.7329	159.7329	159.7326
pg7	159.7330	159.7325	159.7329
pg8	159.7330	159.7324	159.7330
pg9	159.7328	159.7326	159.7326
pg10	77.3997	77.3988	77.3992
pg11	77.3990	77.3983	77.3998
pg12	92.3998	92.3992	92.3997
pg13	92.3972	92.3999	92.3989
MW	2520	2520	2520
Total cost ($)	**24,164.06**	**24,164.06**	**24,164.06**
Mean cost	24,196.51	24,202.37	24,195.21
Stdev	31.7872	32.1173	30.2068

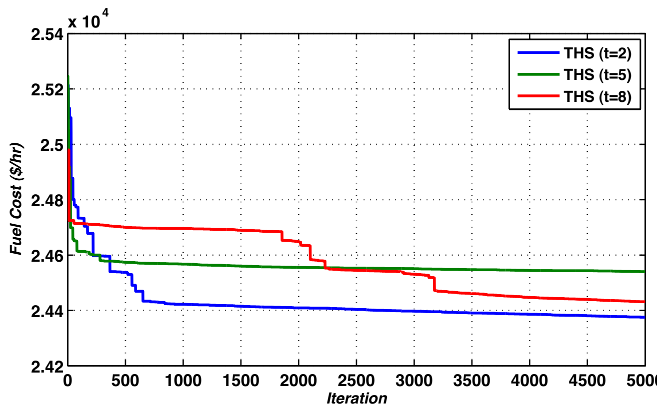

Fig. 6. Convergence characteristic of 13-units generator system with 2520 MW obtained by THS algorithms.

deviation (stdev) among the 30 replication runs are summarized in the same table. It is noteworthy that the three THS algorithms are able to achieve the individual with the total demand constraint (i.e., 24,164.06$). However, the mean fuel cost of THS version of $t = 8$ is the best among the three versions. This is because the best individual stored in HM has high probability to be a member of the tournament at each generation. Therefore, the new harmony inherits the features of the best individual.

In the Fig. 6, the convergence properties of the THS algorithms are visualized in terms of fuel cost and iterations. As shown in this figure, the THS ($t = 2$) had a faster convergence, while the THS ($t = 8$) yield more robust convergence where the results improved as the iterations increased. Furthermore, the distribution results of the three THS algorithms are box-plotted in Fig. 7. Clearly, the three versions of THS algorithms almost achieved same distribution with a small favor to THS ($t = 8$).

The results of the proposed THS algorithms for Case III are compared with seven comparative methods abbreviated in Table 1. Interestingly, the results obtained by the proposed algorithms are much better than those produced by other methods as shown in Table 7. Notably, in this case, the three THS versions yielded new results for the ELD research communities.

4.4. Case IV: 40-units generator system with load demand of 10,500 MW

The proposed THS algorithms are further evaluated using forty generating units with valve point loading effects and the total expected load demand is 10,500 MW. The ELD data (i.e., upper and lower bounds for the units and fuel cost coefficients a, b, c, e, and

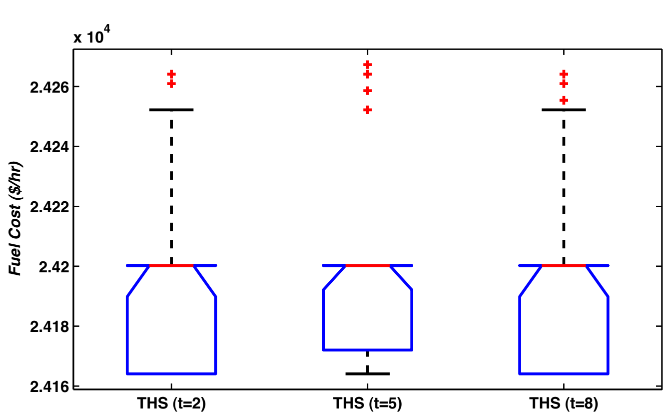

Fig. 7. Boxplot for the results of THS with varying values of t on Case III.

Table 7
Comparison of results for 13-units generator system for a demand of 2520 MW.

Method	Best	Mean
THS ($t = 2$)	**24,164.06**	24,196.51
THS ($t = 5$)	**24,164.06**	24,202.37
THS ($t = 8$)	**24,164.06**	24,195.21
ACO	24,174.39	24,211.09
FCASO-SQP	24,190.63	NA
HCASO	24,212.93	NA
HCPSO	24,211.56	NA
HCPSO-SQP	24,190.97	NA
TS	24,180.31	24,243.37
TSA	24,171.21	24,184.06

f) is selected from [77]. Again, each THS algorithm is run 30 times with various random seeds.

The best individual achieved by each THS algorithm (i.e., THS ($t = 2$), THS ($t = 5$), and THS ($t = 8$)) is recorded in Table 8. Furthermore, the total cost for that best individual and the mean fuel cost together with stdev are also provided in the same table. It should be noted that the THS ($t = 8$) algorithm is obtained the best individual, where the total fuel cost of this individual is highlighted in bold font. Whereas, the second-best individual is achieved by the THS ($t = 2$) algorithm.

Table 8
Results for 40-units generator system for a demand of 10,500 MW.

Generator	THS ($t = 2$)	THS ($t = 5$)	THS ($t = 8$)
pg1	114	114	110.8104
pg2	113.3808	113.4809	111.3803
pg3	97.4102	97.4019	97.4036
pg4	179.7357	179.7418	179.7344
pg5	96.9973	97	87.8331
pg6	140.0000	139.9998	140
pg7	259.6047	259.5998	259.6201
pg8	284.6041	284.5999	284.6089
pg9	284.6018	284.6121	284.6072
pg10	130	130	130
pg11	168.8034	168.8013	168.7990
pg12	168.8027	168.8010	94.0014
pg13	214.7619	214.7599	214.7608
pg14	394.2794	394.2762	394.2831
pg15	304.5215	304.5195	304.5142
pg16	304.5209	304.5190	394.2784
pg17	489.2841	489.2821	489.2764
pg18	489.2891	489.2801	489.2789
pg19	511.2813	511.2790	511.2863
pg20	511.2790	511.2813	511.2802
pg21	523.2838	523.2795	523.2813
pg22	523.2819	523.2795	523.2793
pg23	523.2779	523.2822	523.2822
pg24	523.2801	523.2808	523.2834
pg25	523.2824	523.2794	523.2831
pg26	523.2799	523.2821	523.2801
pg27	10	10	10.0036
pg28	10	10.0004	10
pg29	10	10	10
pg30	96.9928	97	97
pg31	190	190	190
pg32	190	190	190
pg33	190	190	190
pg34	164.8838	164.8015	164.8039
pg35	200	200	200
pg36	200	200	199.4622
pg37	110	110	110
pg38	110	110	110
pg39	110	110	110
pg40	511.2795	511.2790	511.2844
MW	10,500	10,500	10,500
Total cost ($)	121,467.44	121,467.25	**121,425.15**
Mean cost	121,524.26	121,530.77	121,528.65
Stdev	36.7026	47.0247	50.4751

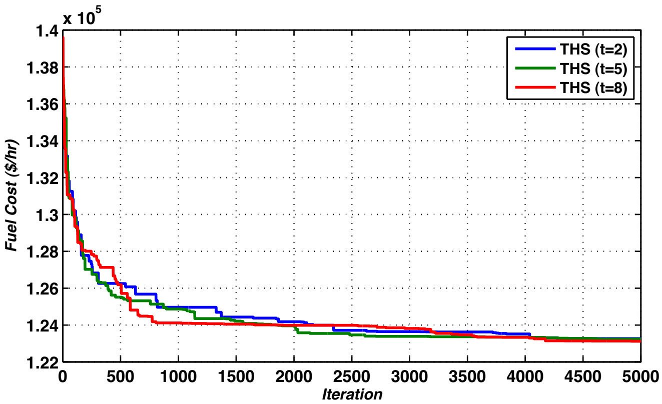

Fig. 8. Convergence characteristic of 40-units generator system with 10,500 MW obtained by THS algorithms.

The convergence of the proposed THS algorithms on Case IV is visualized in Fig. 8. Apparently, the convergence speed of the three versions of THS is almost the same, where the distribution results of the three algorithms are box-plotted in Fig. 9.

The best fuel costs of the three THS algorithms are compared with those obtained by the other comparative methods and summarized in Table 9. As shown in this table, the performance of the proposed THS algorithms are comparable with the performance of the other methods. Indeed, the proposed THS algorithms are able to produced fuel cost very close to the best fuel cost recorded by DVL-MILP. This proves that the proposed THS algorithm has powerful approach on exploring and exploiting the ELD search space and thus leads to good results.

Table 9
Comparisons of 40-units generator system for a demand of 10,500 MW.

Method	Best	Mean
THS (t = 2)	121,467.44	121,524.26
THS (t = 5)	121,467.25	121,530.77
THS (t = 8)	121,425.15	121,528.65
ABC	121,441.03	121,995.82
ABOMDE	121,414.87	121,487.85
ACO	121,811.37	121,930.58
ARCGA	121,415.50	121,462.15
BGO	121,479.50	121,512.06
CBPSO-RVM	121,555.32	122,281.14
CSOMA	121,414.70	121,415.05
DE-BGO	121,420.89	121,420.90
DVL-MILP	**121,413.00**	NA
FAPSO	121,712.40	121,778.25
FAPSO-NM	121,418.30	121,418.80
FCASO-SQP	121,456.98	122,026.21
FFA	121,415.05	121,416.57
GA-PS-SQP	121,458.00	122,039.00
GSO	124,265.40	124,609.18
HCASO	121,865.63	122,100.74
HCPSO	121,865.23	122,100.87
HCPSO-SQP	121,458.54	122,028.16
HHS	121,415.59	121,615.85
HMAPSO	121,586.90	121,586.90
HQIPSO	121,418.60	121,427.47
MDE	121,414.79	121,418.44
NDS	121,647.40	121,647.40
NSS	122,186.90	0.00
PSO-GM	121,845.98	122,398.38
PSO-MSAF	121,423.23	NA
QIPSO	121,448.21	122,225.07
RCGA	121,418.72	NA
SOMA	121,418.79	121,449.88
TLA	122,009.77	122,074.90
TS	122,288.38	122,424.81
TSARGA	121,463.07	122,928.31

4.5. *Case V: 80-units generator system with load demand of 21,000 MW*

In order to verify the efficiency of the proposed THS versions over a larger-scaled and highly complex solution space, the same data of Case IV are duplicated to form an 80-unit generator system as used in [74] and the total expected load demand is 21,000 MW. Again, each THS algorithm (THS(t = 2), THS(t = 5), THS(t = 8)) is run 30 replications with different random seeds.

In Table 10, the best produced results that realized the minimum fuel costs are recorded for each THS version. Furthermore, the total cost for that best individual and the mean fuel cost together with stdev are also provided in the same table. Notably, the best result in bold font produced for 80-units generator system is obtained when the value of t = 8 where the *Totalcost*($) = 243, 192.69. The second best solution is again obtained when the value of t = 2. A good justification of this result can be expressed based on the exploration and exploitation of ELD search space. When the value of t is small, a less consideration to the best solutions is achieved during the search and thus the search tends toward the exploration stage rather than the exploitation stage. In contrast, when t is large in its value, the search will consider the best solutions found during the search more rigorously and thus the search trend will move toward the exploitation rather than exploration. Therefore, the value of t = 8 might strike the right balance between the exploration and exploitation of ELD search space in all experimented cases.

The convergence behavior of the proposed THS algorithms on 80-unit generator system is plotted in Fig. 10. Apparently, the convergence speed of the three versions of THS is almost the same

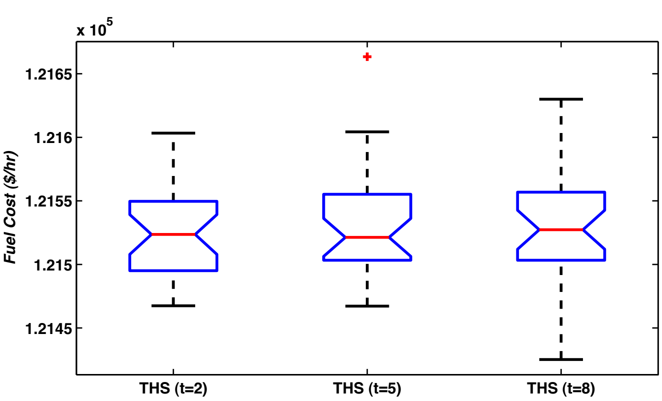

Fig. 9. Boxplot for the results of THS with varying values of t on Case IV.

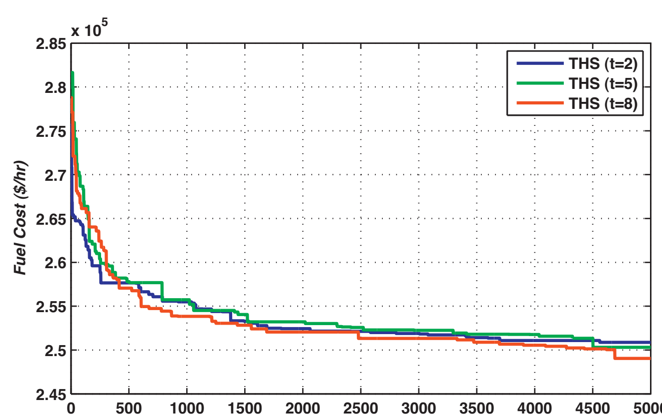

Fig. 10. Convergence characteristic of 80-units generator system with 21,000 MW obtained by THS algorithms.

Table 10
Results for 80-units generator system for a demand of 21,000 MW.

Generator	THS (t = 2)	THS (t = 5)	THS (t = 8)
pg1	114	113.9872268	114
pg2	111.8014988	114	111.2531465
pg3	97.50332084	120	99.09786721
pg4	179.506327	179.7767293	180.7932456
pg5	87.94717005	97	89.86186871
pg6	139.9731566	140	140
pg7	299.9823678	299.9687376	259.8077391
pg8	285.0358673	287.9632278	284.9844773
pg9	285.2029972	285.0796173	284.6915967
pg10	204.7926773	132.6745408	130.2937929
pg11	167.7524131	168.9983874	163.9720671
pg12	169.3683414	168.8248922	169.0359056
pg13	215.3275596	214.7045048	215.4177398
pg14	394.5503884	395.0749532	395.2625026
pg15	393.6932194	394.4557926	393.4388136
pg16	304.4228904	305.5816544	304.5334852
pg17	490.0146037	488.8486895	490.1590039
pg18	489.3519361	490.4769973	489.4715817
pg19	511.2823319	510.3778561	511.615092
pg20	511.6679937	513.5102051	511.3310859
pg21	521.8005378	524.0737305	525.4454794
pg22	525.839486	526.4009319	523.3910061
pg23	524.0790097	524.5745737	524.0322868
pg24	523.2384043	525.3828336	524.7217105
pg25	523.3053595	523.3306017	523.2715057
pg26	524.2500896	524.2725438	524.0219474
pg27	11.36502954	10.08233911	11.29863504
pg28	10.57857684	10.02724503	10
pg29	10.59251159	10.00474498	10
pg30	96.00728084	89.57572292	97
pg31	189.5228432	189.9797695	189.1039742
pg32	190	190	190
pg33	189.989175	189.992088	188.7423938
pg34	167.0512478	198.9988812	166.2018685
pg35	199.9740512	199.944225	166.0304934
pg36	165.7259728	199.8916248	196.144832
pg37	110	109.9771318	109.9713119
pg38	109.9219643	109.5689057	110
pg39	109.9975199	110	109.6182111
pg40	511.2755391	511.5386164	512.5653855
pg41	110.9062603	111.3602375	113.3150548
pg42	111.9979901	110.9845971	113.343713
pg43	97.70808125	97.46887606	97.53717205
pg44	179.722904	179.738149	179.7569001
pg45	96.38003813	93.86162612	96.32949633
pg46	139.8759999	139.9969221	139.9900922
pg47	259.582014	260.4104503	259.6039082
pg48	285.2488624	284.8681652	284.5967742
pg49	285.580317	285.194906	286.2053343
pg50	130	131.2407953	130.2915868
pg51	94.07810412	94	95.36059543
pg52	168.9857009	169.4239544	168.9311659
pg53	215.7961166	125.5585341	214.7713019
pg54	305.2786383	304.5994938	394.3400049
pg55	306.9295797	393.0295097	394.2268647
pg56	306.2932289	304.5557439	304.5383062
pg57	489.8726538	489.7173792	490.2844244
pg58	491.2114791	489.7084967	489.3321568
pg59	511.2818149	511.319585	511.2577788
pg60	511.3736612	511.6857762	512.062229
pg61	523.4615241	523.3476875	524.486095
pg62	524.1331685	523.2409682	523.4743906
pg63	525.6841245	524.4446514	523.2974871
pg64	524.9904382	523.6912293	523.9148666
pg65	524.8761702	527.0425217	523.4196828
pg66	523.2735086	524.6233539	523.3664147
pg67	10.01808064	10.07722519	10.15809612
pg68	10.26350289	11.57996685	10.00286467
pg69	10.08179072	10.02701766	10.05676741
pg70	88.73875319	91.51760254	95.92352235
pg71	189.4098132	190	190
pg72	189.8177453	189.9989	189.9103033
pg73	189.2799128	189.7260475	188.4565746
pg74	165.3993618	166.2846843	165.9607199
pg75	196.1401327	199.5972461	167.1145384
pg76	198.9997487	166.7621985	165.2948862
pg77	109.7712399	109.9778629	110
pg78	109.4528026	109.5451042	106.9307341
pg79	109.362664	109.573773	109.6373521
pg80	511.0504131	511.29824	511.9377908
MW	21,000	21,000	21,000
Total cost ($)	243,286.30	243,288.32	**243,192.69**
Mean cost	243,499.54	243,465.47	243,457.36
Stdev	116.3257	101.4403	120.9889

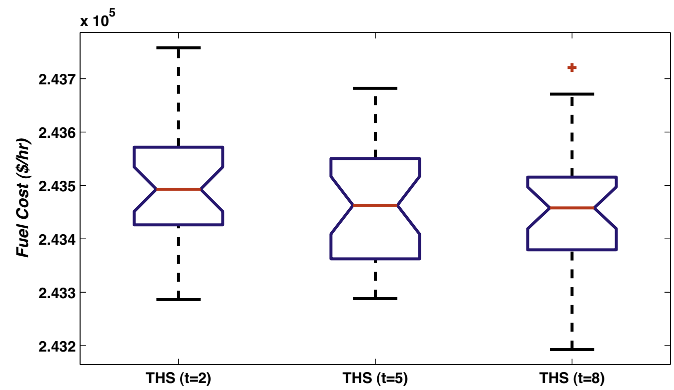

Fig. 11. Boxplot for the results of THS with varying values of t on Case V.

Table 11
Comparisons of 80-units generator system for a demand of 21,000 MW.

Method	Best	Mean
THS (t = 2)	243,286.30	243,499.54
THS (t = 5)	243,288.32	243,465.47
THS (t = 8)	243,192.69	243,457.36
CSO	243,195.38	243,546.63
PSO	244,188.35	246,375.87
KHA	**242,825.21**	242,826.93
SCA	250,864.05	254,579.79
CE-SQP	242,883.04	242,945.25

in small favor to THS version $t = 8$. Note that the distribution results of the three algorithms are represented as box-plots drawn in Fig. 11.

To comparatively evaluate the performance of the three THS algorithms, the best obtained results of five comparative methods are summarized in Table 11. Although the best recorded result was yielded by KHA algorithm, the proposed THS ($t = 8$) achieved the third best results in comparison with other results obtained by others. Therefore, the THS can be efficiently worked under the problem with large-scaled and highly complex ELD problems.

5. Conclusion and future work

This paper proposes a tournament-based harmony search (THS) algorithm for economic load dispatch (ELD) problem. The idea of THS is based on natural selection of the survival-of-the-fittest principle in the memory consideration to improve convergence properties. In THS, the selection process of memory consideration initially generates a tournament of randomly selected individuals stored in HM with size t. Thereafter, the individual with the best objective function value in the tournament is used in the improvisation process. Thus, the THS can be capable of accelerating the convergence rate by means of concentrating on the better individuals during the improvisation of the new harmony at each generation.

The convergence characteristics of the THS is evaluated using five different ELD problems. These ELD problems are widely circulated in the literature: 3-units generator system; two versions of ELD with 13-units generator system; 40-units generator system; and large-scaled ELD with 80-units generator system. At the initial stage of evaluations, the effect of the tournament size *t* with varying values is studied. Conclusively, the results in almost all test systems show that the higher the value of "*t*" is, the better the outcomes will be. Thereafter, to comparably evaluate the outcomes of the proposed THS for ELD, 43 comparative methods known and available for the authors were used for all test systems. The results shows that the THS algorithm is able to achieve the best results for 3-units generator system as obtained by other comparative methods. For the two versions of the 13-units generator system, the performance of THS is superior by means of achieving better results than those achieved by other comparative methods. For the 40-units generator system, the results of THS algorithm is ranked eighth out of 35 comparative methods. Lastly, the THS is ranked third in comparison with five comparative methods for solving the ELD with large-scaled 80-units generator system. Practically, the THS could be claimed to be a very efficient algorithm to solve ELD problem in the power system domain.

As THS produced very fruitful outcomes for the ELD problems, future research can be directed to investigate the efficiency of THS using other versions of ELD problems. The tournament size *t* has a very significant influence in the performance. Therefore, the effect of *t* on the convergence behavior of the THS can be analyzed to reveal the connection between the problem combinatoric nature and the performance of THS.

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