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AN IMPROVED HARMONY SEARCH APPROACH TO ECONOMIC DISPATCH

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Abstract- In this paper an improved Harmony Search (HS) is applied to solve the Economic Dispatch (ED) problem with nonconvex cost functions. The proposed approach modifies the improvement of Novel Global Harmony Search (NGHS) reported in the literature where the resulting approach is known as NGHS-II. The practical ED problem have nonconvex cost functions with equality and inequality constraints that makes the problem of finding the global optimum difficult using any optimization approaches. In this paper, the NGHS-II is deal with the equality and inequality constraints in the ED problem. To validate the results obtained by proposed NGHS-II, NGHS and other improved version of harmony search (IHS) are applied for comparison. Also, the results obtained by the NGHS-II are compared with the previous approaches reported in the literature. The results show that the proposed NGHS-II produces better solutions for all study systems.

Keywords: Harmony Search, Economic Dispatch, Constrained Optimization, Heuristic Algorithm.

I. INTRODUCTION

In the traditional ED problem, the cost function for each generator has been approximately represented by a single quadratic function and is solved using mathematical programming based on the optimization techniques such as lambda-iteration method, gradient method, dynamic programming method and etc [1]. However many mathematical assumptions-such as convex, quadratic, differentiable objective, linear objective and constraints are required to simplify the problem.

The practical ED problem with ramp rate limits, prohibited operating zones, valve point effects, and multi fuel options is represented as a non-smooth or non-convex optimization problem with equality and inequality constraints and this makes the problem of finding the global optimum difficult and cannot be solved by the traditional methods easily.

Over the last decades there has been a growing interest in algorithms inspired from the observation of natural phenomenon. It has been shown by many researches that these algorithms are good replacement as tools to solve complex computational problems. A considerable amount of work has been adopted by researches to solve a practical ED problem by considering different nonconvex cost functions using various heuristic approaches such as genetic algorithm (GA) [2]-[6], simulated annealing [7], artificial neural network [8]-[10], tabu search [11], evolutionary programming [12]-[16], PSO [17-21], ant colony optimization [22]-[23] and differential evolutionary [24-25].

In this paper, a new heuristic approach is proposed and applied to economic dispatch problem. The proposed approach is based on the improvement of Novel Global Harmony Search (NGHS) reported in [26]. Thus the proposed approach in this paper is called second Novel Global Harmony Search (NGHS-II).

The proposed approach is applied on three test systems. Also, to show the effectiveness of the proposed approach, NGHS and another improvement of HS (IHS) proposed by Mahdavi [27] are applied on these systems. The results obtained by NGHS-II, not only are compared by NGHS and IHS but also are compared with those obtained by the previous approaches reported in the literature. To make a proper background, a brief description of HS, IHS and NGHS are given in the next section followed by the description of the proposed approach.

II. OVERVIEW OF HS, IHS AND NGHS

A. Harmony Search (HS)

HS is based on natural musical performance a process that searches for a perfect state of harmony. The harmony in music is analogous to the optimization solution vector, and the musician's improvisations are analogous to local and global search schemes in optimization techniques. The HS algorithm does not require initial values for the decision variables and uses a stochastic random search that is based on the harmony memory considering rate and the pitch adjusting rate. In general, the HS algorithm works as follows [28-29]:

Step 1. Define the objective function, the decision variables. Input the system parameters and the boundaries of the decision variables.

The optimization problem can be defined as:

Minimize $f(x)$ subject to $x_{iL} \le x_i \le x_{iU}$ $(i = 1, 2, \cdots, N)$

where x_{iL} and x_{iU} are the lower and upper bounds for decision variables.

The HS algorithm parameters are specified in this step. They are the harmony memory size (*HMS*) or the number of solution vectors in harmony memory, harmony memory considering rate (*HMCR*), distance bandwidth (*bw*), pitch adjusting rate (*PAR*), and the number of improvisations (*K*), or stopping criterion. *K* is the same as the total number of function evaluations.

Step 2. Initialize the harmony memory (HM). The harmony memory is a memory location where all the solution vectors (sets of decision variables) are stored. The initial harmony memory is randomly generated in the region $[x_{iL}, x_{iU}]$ $(i = 1, 2, \cdots, N)$. This is done based on the following equation:

$$x_i^j = x_{iL} + \text{rand}() \times (x_{iU} - x_{iL}) \quad j = 1, 2, \cdots, HMS \qquad (1)$$

where $\text{rand}()$ is a random from a uniform distribution of [0,1].

Step 3. Improvise a new harmony from the harmony memory. Generating a new harmony x_i^{new} is called improvisation where it is based on 3 rules: memory consideration, pitch adjustment and random selection. First of all, a uniform random number r_1 is generated in the range [0, 1]. If r_1 is less than HMCR, the decision variable x_i^{new} is generated by the memory consideration; otherwise, x_i^{new} is obtained by a random selection. Then, each decision variable x_i^{new} will undergo a pitch adjustment with a probability of PAR if it is produced by the memory consideration. The pitch adjustment rule is given as follows:

$$x_i^{new} = x_i^{new} \pm r \times bw \qquad (2)$$

where r is a uniform random number between 0 and 1.

Step 4. Update harmony memory. After a new harmony vector x^{new} is generated, the harmony memory will be updated. If the fitness of the improvised harmony vector $x^{new} = (x_1^{new}, x_2^{new}, \cdots, x_N^{new})$ is better than that of the worst harmony, the worst harmony in the HM will be replaced with x^{new} and become a new member of the HM.

Step 5. Repeat steps 3-4 until the stopping criterion (maximum number of improvisations *K*) is met.

B. The Improved Harmony Search (IHS)

An improved harmony search algorithm (IHS) is proposed in [27], in which the key modifications are about *PAR* and *bw*. In the HS, *PAR* and *bw* are all constants, but the IHS updated them dynamically as follows:

$$PAR(k) = PAR_{\min} + (\frac{PAR_{\max} - PAR_{\min}}{K})k \qquad (3)$$

$$bw(k) = bw_{\max} \exp(\frac{\ln\left(\frac{bw_{\min}}{bw_{\max}}\right)}{K})k \qquad (4)$$

where k is current number of improvisations, and K is maximum number of improvisations. IHS employs a novel method for generating new solution vectors that enhances accuracy and convergence rate of harmony search. The IHS has been successfully applied to various engineering optimization problems. Numerical results reveal that the IHS can find better solutions compared to the HS.

C. A Novel Global Harmony Search (NGHS)

The NGHS proposed by Zou [26] is different with HS in three aspects. Mutation operator is added and it modifies the improvisation step of the HS such that the new harmony mimics the global best harmony in the HM. The differences are as follows:

- Instead of *HMCR* and *PAR* a genetic mutation probability (p_m) is considered in the NGHS.
- The NGHS modifies the improvisation step of the HS, and it works as follows [26]:

----

for $i = 1 : N$ do

  $step_i = \left| x_i^{best} - x_i^{worst} \right|$ %calculating the adaptive step

  $x_i^{new} = x_i^{best} \pm r \times step_i$ %position updating (5)

  if $\text{rand}() \le p_m$

    $x_i^{new} = x_{iL} + \text{rand}() \times (x_{iU} - x_{iL})$ %genetic mutation

  end

endfor

----

where, "best" and "worst" are the indexes of the global best harmony and the worst harmony in HM, respectively. r and rand() are all uniformly generated random numbers in [0,1].

The reasonable design for $step_i$ can guarantee that the algorithm has strong global search ability in the early stage of optimization, and has strong local search ability in the late stage of optimization. Dynamically adjusted $step_i$ keeps a balance between the global search and the local search.

The genetic mutation operation is carried out for the worst harmony of harmony memory after updating position to prevent the premature convergence of the NGHS.

- After improvisation, the NGHS replaces the worst harmony x^{worst} in HM with the new harmony x^{new} even if x^{new} is worse than x^{worst}.

III. THE PROPOSED APPROACH: NGHS-II

In NGHS, the original structure of harmony search is changed by excluding the *HMCR* parameter and including a mutation probability. By a careful consideration, we can find that the role of p_m is the same as 1-*HMCR*. Therefore, in this paper *HMCR* is used to emphasize that the original structure of harmony search is held and the improvisation step becomes as following.

In NGHS, new harmony is inclined to mimic the global best harmony in HM. In NGHS-II, *1-HMCR* determines the randomness of new harmony. Therefore large *HMCR* results in premature convergence. To maintain the diversity of HM, *HMCR* must be small. But small *HMCR* decreases convergence velocity, also results in producing new harmonies which are infeasible.

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for $i = 1 : N$ do
  if $\text{rand}() \le HMCR$
    $step_i = \left| x_i^{best} - x_i^{worst} \right|$ %calculating the adaptive step
    $x_i^{new} = x_i^{best} \pm r \times step_i$ %position updating (6)
    $x_i^{new} = \max(x_{iL}, \min(x_{iU}, x_i^{new}))$
  else
    $x_i^{new} = x_{iL} + \text{rand}() \times (x_{iU} - x_{iL})$ %genetic mutation
  end
endfor

In this paper *HMCR* is adjusted close to one to produce feasible solutions and having a good exploitation. After some evaluations, the algorithm may reach to a local solution and *the adaptive step* ($step_i$) goes to zero. At this step the algorithm is stagnated. Therefore, to prevent the stagnation, we generate a few harmonies randomly and replace them by the worse harmonies in the HM. The number of new random harmonies depends on the problem and the size of the HM. The new random harmonies cause the *adaptive step* ($step_i$) is increased and the algorithm starts new exploration to find a better solution.

Furthermore, after improvisation in the NGHS, the worst harmony x^{worst} in HM will be replaced with the new harmony x^{new} even if x^{new} is worse than x^{worst}. This replacement is not good and it makes the algorithm not to converge. Therefore, in this paper, the worst harmony x^{worst} in HM will be replaced with the new harmony x^{new} if x^{new} is better than x^{worst}.

In many improved versions of harmony search such as IHS, the number of parameters is increased which is not good. It should be note that in order to get the optimum point by heuristic algorithms, the parameters of the algorithm must be tuned for the problem at hand. In NGHS the number of parameters is decreased, and NGHS-II does not add any parameters to NGHS. Therefore it can be used for any problem easily.

IV. FORMULATION OF ECONOMIC DISPATCH PROBLEM

For convenience in solving the ED problem, the unit generation output is usually assumed to be adjusted smoothly and instantaneously. Practically, the operating range of all online units is restricted by their ramp rate limits by forcing the units to operate continually between two adjacent specific operation zones. In addition, the prohibited operating zones, valve point effects and multi-fuel options must be taken into account. The traditional and practical ED is explained below.

A. Traditional ED Problem with Smooth Cost Functions

In the traditional ED problem, the cost function for each generator has been approximately represented by a single quadratic function. The primary objective of the ED problem is to determine the optimal combination of power outputs of all generating units so that the required load demand at minimum operating cost is met while satisfying system equality and inequality constraints. Therefore, the ED problem can be described as a minimization problem with the following objective:

$$\min F = \sum_{i=1}^{N_G} F_i(P_{Gi}) = \sum_{i=1}^{N_G} (a_i P_{Gi}^2 + b_i P_{Gi} + c_i) \tag{7}$$

subject to

$$\sum_{i=1}^{N_G} P_{Gi} = P_{load} + P_{loss} \tag{8}$$

$$P_{Gi\min} \le P_{Gi} \le P_{Gi\max} \quad \text{for} \quad j = 1, 2 \ldots, N_G \tag{9}$$

where F is the total generation cost ($/hr), F_i is the fuel-cost function of generator i ($/hr), N_G is the number of generators, P_{Gi} is the real power output of generator i (MW), and a_i, b_i and c_i are the fuel-cost coefficients of generator i, P_{load} is the total load in the system (MW), P_{loss} is the network loss (MW) that can be calculated by the *B*-matrix loss formula, $P_{Gi\min}$ and $P_{Gi\max}$ are the minimum and maximum power generation limits of generator *i*.

B. Practical ED Problem with Non-smooth Cost Functions

As it is mentioned, a practical ED must take ramp rate limits, prohibited operating zones, valve point effects, and multi-fuel options into consideration to provide the completeness for the ED formulation. The resulting ED is a nonconvex optimization problem that has multiple minima, which makes the problem of finding the global optimum difficult:

1) *Generator Ramp Rate Limits.* If the generator ramp rate limits are considered, the effective real power operating limits are modified as follows:

$$\max(P_{Gi\min}, P_{Gi}^0 - DR_i) \le P_{Gi} \le \min(P_{Gi\max}, P_{Gi}^0 + UR_i) \quad i = 1, 2, \cdots, N_G \tag{10}$$

where P_{Gi}^0 is the previous operating point of generator *i*, DR_i and UR_i are the down and up ramp limits of the generator *i*.

2) *Prohibited Operating Zones.* A generator with prohibited regions (zones) has discontinuous fuel-cost characteristics. The concept of prohibited operating zones is included as the following constraint in the ED:

$$P_{Gi} \in \begin{cases} P_{Gi\min} \le P_{Gi} \le P_{Gi}^{LB1} \\ P_{Gi}^{UB_{k-1}} \le P_{Gi} \le P_{Gi}^{LBk} & k = 2, 3, \cdots, N_{PZi} \\ P_{Gi}^{UBk} \le P_{Gi} \le P_{Gi\max} & k = N_{PZi} \end{cases} \quad j = 1, 2 \ldots, N_{GPZ} \tag{11}$$

where P_{Gi}^{LBk} and P_{Gi}^{UBk} are the lower and upper boundaries of prohibited operating zone k of generator i in (MW), respectively; N_{PZi} is the number of prohibited operating zones of generator *i*; and N_{GPZ} is the number of generators with prohibited operating zones. The discontinuous fuel-cost characteristics of the generators by considering prohibited zones are shown in Figure 1.

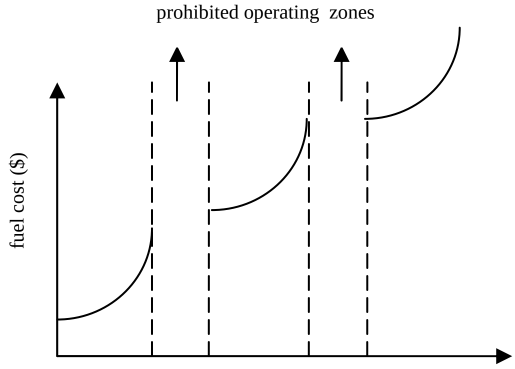

Figure 1. Input-output curve with prohibited operating zones

3) *Valve-Point Effects.* The generator with multi-valve steam turbines has very different input-output curve compared with the smooth cost function. As each steam valve starts to open, the valve point results in ripples as shown in Figure 2. To consider the valve-point effects, sinusoidal functions can be added to the quadratic cost functions as follows:

$$F_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i + \left| e_i \sin(f_{i(}(P_{Gi\min} - P_{Gi})) \right| \quad (12)$$

where e_i and f_i are the coefficients of generator reflecting valve-point effects.

4) *Multi-fuel options.* A piecewise quadratic function is used to represent the input-output curve of a generator with multiple fuels. The piecewise quadratic function is described as (13) and the cost and the incremental cost functions are illustrated in Figure 3:

$$F_i(P_{Gi}) = a_{ik} P_{Gi}^2 + b_{ik} P_{Gi} + c_{ik}$$
$$\text{if } P_{Gi,k}^{\min} \le P_{Gi} \le P_{Gi,k}^{\max} \quad \text{for} \quad j = 1, 2 \ldots, N_G \quad (13)$$
$$k = 1, 2, \ldots, N_F$$

For a power plant with N_G generators and N_F fuel options for each unit, the cost function of the generator with valve-point loading is expressed as:

$$F_i(P_{Gi}) = a_{ik} P_{Gi}^2 + b_{ik} P_{Gi} + c_{ik} + \left| e_{ik} \sin(f_{ik(}(P_{Gi\min} - P_{Gi})) \right|$$
$$\text{if } P_{Gi,k}^{\min} \le P_{Gi} \le P_{Gi,k}^{\max} \quad \text{for} \quad j = 1, 2 \ldots, N_G \quad (14)$$
$$k = 1, 2, \ldots, N_F$$

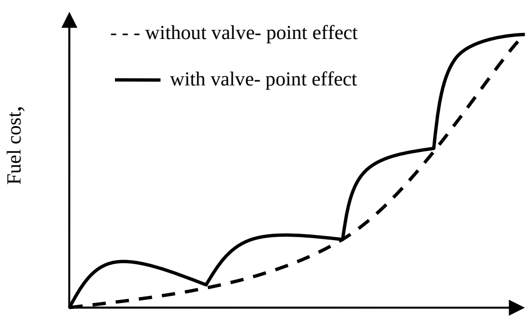

Figure 2. Piecewise Input-output curve under valve-point loading

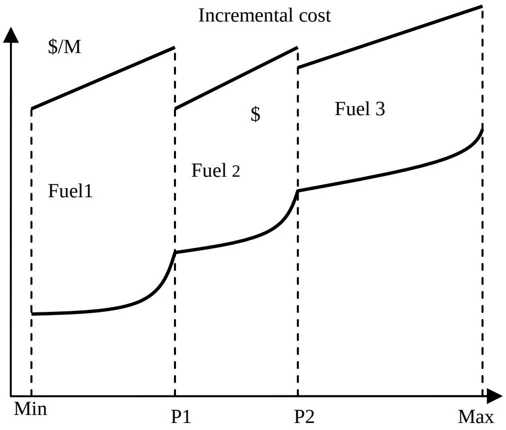

Figure 3. Piecewise quadratic and incremental cost functions of a generator

V. STUDY SYSTEMS

To assess the efficiency of the proposed approach, it has been applied to ED problem by considering three test systems having nonconvex solution spaces.

1) *The first study system*. This study system consists of six generators with ramp rate limit and prohibited operating zones. The input data for 6-generator system are given in [19] and the total demand is set as 1263 MW. All the generators are having ramp rate limits. The network losses are calculated by the *B*-matrix loss formula. It was reported in [21] that the best generation cost reported until now is 15443.0925 $/h.

2) *The second study system*. This study system consists of 15 generators with ramp rate limit and prohibited operating zones. The input data of this system are given in [18] and has a total load of 2630 MW. Also, the network losses are calculated by B matrix loss formula. The main difference of the study systems 1 and 2 is that the system 2 has many local minima compared to system 1. Thus, the ability of the proposed algorithms is investigated on a larger system. The best generation cost reported until now is 32738.4177 $/h [21].

3) *The third study system.* This study system consists of ten generators with multi-fuel options and valve-point effects [18]. The total demand for this system is set as 2700 MW. It was reported in [18] that the global optimum solution found for the 10-generator system is 624.1273.

VI. IMPLEMENTATION AND SIMULATION

The implementation of the NGHS-II is given below: For the study system 1 with six generators, the goal of the optimization is to find the best generation for the six generators. Therefore, each harmony is a d-dimensional vector in which $d = 6$. The HMS is selected to be 20. *HMCR* and evaluation number are set to be 0.9 and 1000, respectively.

Each harmony in the population is evaluated using the objective function defined by Equation (7) subject to Equations (8)-(14) searching for the harmony associated with F_{best}.

To find the minimum cost, the NGHS, IHS and NGHS-II are run for 50 independent runs under different random seeds. The results obtained by the algorithms are shown in Table 1, in the first three columns. The other columns of the table show the results obtained by MPSO reported in [21], binary version of GA, PSO, a modified (new) version of PSO having local random search (NPSO-LRS) reported in [19] and a self-organizing hierarchical PSO (SOH_PSO) reported in [20]. This table shows that the NGHS-II is performing better than other algorithms in terms of the best generation schedule with minimum network loss in addition to minimum generation cost.

The best-so-far of each run is recorded and averaged over 50 independent runs for the NGHS, IHS and NGHS-II. To have a better clarity, the convergence characteristics in finding the minimum cost are given in Figure 4. This figure shows that the NGHS-II algorithm performs better than others.

To investigate the ability of the NGHS-II in finding the solution and convergence characteristics of the algorithm, the same study is carried out on the second study system, which is a larger system. For this system, the evaluation number is set to be 12000 but other settings are the same as study system 1.

The results obtained by the NGHS, IHS and NGHS-II are given in Table 2, in the first three columns. The other columns of the table show the results obtained by MPSO reported in [21], binary version of GA and PSO reported in [18] and SOH_PSO reported in [20]. The results obtained by all algorithms (listed in Table 2) reveals that the best found solution by NGHS-II is better than the other algorithms. In other words, it is clear that dimensionality is not the key factor and the NGHS-II still outperforms other approaches significantly. The convergence characteristics in finding the minimum cost are given in Figure 5.

In the study system 3, the evaluation number is set to be 6000 but other settings are the same as previous study systems. The obtained result by NGHS-II shows that the global optimum solution for the 10-generator system is slightly better than those reported in the literature. The convergence characteristics in finding the minimum cost by NGHS, IHS and NGHS-II for the study system 3 are given in Figure 6.

The obtained solution is given in Table 3. The last three columns of the table show the results obtained by MPSO reported in [21], an improved GA with multiplier updating (IGA_MU) and NPSO_LRS reported in [19].

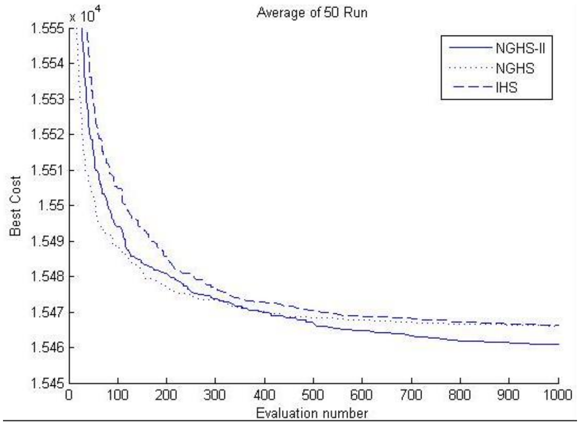

Figure 4. Convergence characteristics of NGHS-II, NGHS and IHS on the average best-so-far in finding the solution in study system 1

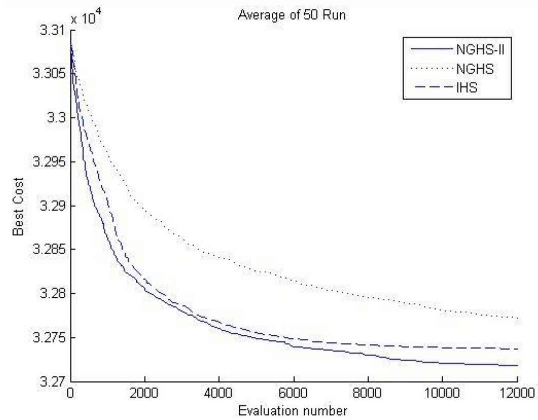

Figure 5. Convergence characteristics of NGHS-II, NGHS and IHS on the average best-so-far in finding the solution in study system 2

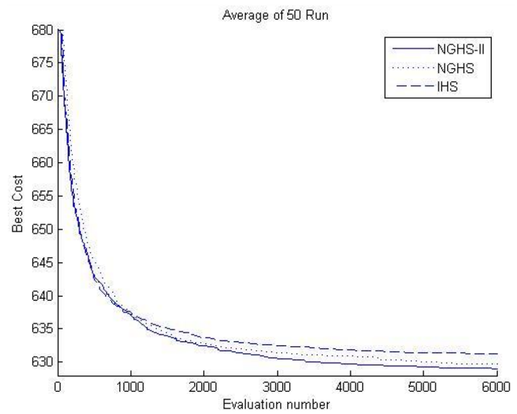

Figure 6. Convergence characteristics of NGHS-II, NGHS and IHS on the average best-so-far in finding the solution in study system 3

Table 1. Comparison of simulation results of each method (6-generator system)

unit	NGHS-II	NGHS	IHS	MPSO [21]	GA [19]	PSO [19]	NPSO-LRS [19]	SOH_PSO [20]
P1	446.51	447.56	445.60	446.48690	474.8066	447.4970	446.9600	438.21
P2	176.05	172.3	172.57	168.6612	178.6363	173.3221	173.3944	172.58
P3	262.46	256.28	261.44	265.0000	262.2089	263.4745	262.3436	257.42
P4	139.79	135.3	141.23	139.4927	134.2826	139.0594	139.5120	141.09
P5	163.48	171.64	166.50	164.0036	151.9039	165.4761	164.7089	179.37
P6	87.07	92.43	88.02	91.74655	74.1812	87.1280	89.0162	86.88
Total generation	1275.340	1275.5	1275.3600	1275.3911	1276.03	1276.01	1275.94	1275.55
Loss	12.3350	12.501	12.3590	12.37368	13.0217	12.9584	12.9361	12.5
Load demand	1263.000	1263	1263.0000	1263.01746	1263.0083	1263.0516	1263.0039	1263.05
Cost	15442.6642	15443.962	15442.6851	15443.0925	15459	15450	15450	15446.02

Table 2. Comparison of simulation results of each method (15-generator system)

Unit	NGHS-II	NGHS	IHS	MPSO [21]	GA [18]	PSO [18]	SOH_PSO [20]
P1	455.00	453.3500	455	455	415.3108	439.1162	455.000
P2	380.00	377.9100	380.0000	380	359.7206	407.9727	380.000
P3	130.00	128.1600	130	130	104.4250	119.6324	130.000
P4	130.00	128.9200	130	130	74.9853	129.9925	130.000
P5	170.00	169.5700	170.0000	170	380.2844	151.0681	170.000
P6	460.00	457.4300	460	460	426.7902	459.9978	459.96
P7	430.00	427.7800	430.0000	430	341.3164	425.5601	430.00
P8	72.670	77.0100	60.0000	92.7278	124.7867	98.5699	117.53
P9	58.20	83.3900	70.8400	43.0282	133.1445	113.4936	77.90
P10	160.00	142.3900	160.0000	140.1938	89.2567	101.1142	119.54
P11	80.00	78.9400	80.0000	80	60.0572	33.9116	54.50
P12	80.00	79.3600	80.0000	80	49.9998	79.9583	80.00
P13	25.00	25.4100	25.0000	27.6403	38.7713	25.0042	25.00
P14	15.00	15.8800	15.0000	20.7610	41.9425	41.4140	17.00
P15	15.00	15.7900	15.0000	22.2724	22.6445	35.6140	15.00
Total generation	2660.9000	2661.3	2660.8000	2661.6235	2668.4	2262.4	2662.29
Loss	30.8614	31.138	30.8290	29.978	38.2782	32.4306	32.28
Load demand	2630.0000	2630.0000	2630.0000	2631.6455	2630.1218	2230.03	2630.01
Cost	32706.7635	32734.6017	32707.1628	32738.41778	33113	32858	32751.39

Table 3. Comparison of simulation results of each method (10-generator system)

Unit	NGHS-II	NGHS	IHS	MPSO [21]	IGA_MU [19]	NPSO [19]
P1	217.0700	212.1329	215.2417	225.6469	219.1261	223.3352
P2	211.9100	211.8220	210.4310	212.5351	211.1645	212.1957
P3	280.6300	287.9033	282.8876	278.7109	280.6572	276.2167
P4	239.9600	243.8860	239.9599	244.1951	238.4770	239.4187
P5	286.5800	273.9292	286.8456	285.2029	276.4179	274.6470
P6	239.5300	237.3798	238.3166	232.7839	240.4672	239.7974
P7	282.8200	287.5214	286.3224	285.5217	287.7399	285.5388
P8	238.3400	242.0860	240.6280	241.0419	240.7614	240.6323
P9	428.4400	436.1787	425.5656	420.0863	429.3370	429.2637
P10	274.7300	267.2318	273.8228	274.3454	275.8518	278.9541
Sum	2700	2701	2700	2700.0706	2700	2700
Cost	**624.0081**	624.7894	**624.0835**	624.1285	624.5178	624.1273

VII. CONCLUSIONS

In this paper, a new heuristic approach is proposed and applied to economic dispatch problem. The proposed approach is based on the improvement of Novel Global Harmony Search (NGHS) reported in [26] which is called second Novel Global Harmony Search (NGHS-II). With the aid of comparisons of the results obtained by NGHS-II and the results of earlier methods available in the literature, it has been shown that the proposed NGHS-II is able to find a new optimum solution for the study systems.

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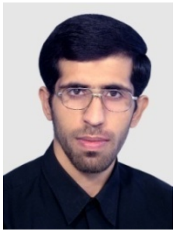
BIOGRAPHIES



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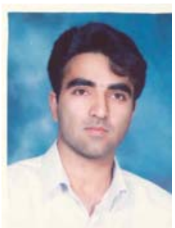

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