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Water Evaporation Optimization Algorithm for Solving Dynamic Economic Dispatch

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Abstract: *This paper presents an efficient Water Evaporation Optimization algorithm (WEO) is proposed to solve a Dynamic Economic Dispatch problem (DED). The dynamic dispatch problem differs from the static economic dispatch problem by incorporating generator spinning reserve, ramp rate limits, and valve point loading and transmission losses. The proposed water evaporation optimization algorithm is based on the evaporation of a tiny amount of water molecules on the solid surfaces with different wettability which can be studied by molecular dynamics simulations. The performance of the WEO algorithm is tested on five unit system with spinning reserve and ten unit systems. The comparison of the simulation results prove that the proposed WEO algorithm have a better performance than the existing methods.*

Keywords: *Dynamic economic dispatch, water evaporation algorithm, molecular dynamics simulation, reserve constrain, ramp rate, valve-point loading effect.*

I. Introduction

Dynamic Economic Dispatch (DED) is used to resolve the optimal generation schedule of on-line generators, so as to meet the predicted load demand over certain problem period of time at minimum operating cost under different system and operational constraints. The dynamic optimization problem may need to consider the spinning reserve requirements (SRR_s) in order to incorporate the unit coupling of ramp rates at the unit level. Due to the ramp-rate constraints of a generator, the operational decision at an hour may affect the operational decision at a later hour. Traditionally valve point loading effects of the turbine were ignored and a convex quadratic fuel cost function was considered for the thermal units. However, a more realistic model must take into account the valve-point effects. It has a look-ahead ability which is necessary to schedule the load early so that the system can predict rapid load changes in near future. The DED problem can be formulated as a large-scale, optimization problem, which is quite difficult due to its intrinsic high dimensional, non-convex and nonlinear nature. The dimension of the problem increases rapidly with the system size and the scheduling horizon [1].

Several optimization methods including classical and heuristic algorithms were applied to solve DED problem. The conventional methods consist of Linear Programming (LP) [2], Non-Linear Programming (NLP) [3], Quadratic Programming (QP) [4], Lagrangian Programming (LP) [5] and Mixed Integer Quadratic Programming (MIQP) [6]. The main drawbacks of these methods are only need to run in linear problem and not applicable to large scale system. Unfortunately, DED with non smooth or non convex cost functions in valve point loading can fail to get global optimal solutions.

To overcome this deficiency, turn to various heuristic techniques such as Genetic Algorithm (GA) [7], Simulated Annealing (SA) [8], Artificial Immune System (AIS) [9], Evolutionary Programming (EP) [10], Differential Evolution (DE) [11], Harmony Search (HS) [12], Artificial Bee Colony (ABC) [13], Imperialist Competitive Algorithm (ICA) [14], Seeker Optimization Algorithm (SOA) [15], Teaching Learning Algorithm (TLA) [16], Improved Particle Swarm Optimization (IPSO) [17], Chaotic Differential Evolution (IDE) [18], Modified Teaching Learning Algorithm (MTLA) [19], Self-Adaptive Modified Firefly Algorithm (SAMFO) [20], Improve Pattern Search (IPS) [21], Enhanced Cross Entropy (ECE) [25], Adaptive Particle Swarm Optimization (APSO) [28], Enhanced Bee Swarm Optimization (EBSO) [35], Deterministic Guided Particle Swarm Optimization (DGPSO) [37]. The main drawback of these heuristic techniques gives the results but struck the local minima and lack of guarantee of convergence infinite time for large scale DED problems.

Hybrid techniques are used to solve the DED problem, such as Hybrid Immune-Genetic Algorithm (IGA) [22], hybridization of Artificial Immune System and Sequential Quadratic Programming (AIS-SQP) [23], modified hybrid Evolutionary Programming-Sequential Quadratic Programming (EP-SQP) [24], Hybrid Differential Evaluation (HDE) [29], Chaotic Differential Bee Colony Optimization (CDBCO) [30], Improved Chaotic Particle Swarm Optimization (ICPSO) [31], Chaotic Self Adaptive Particle Swarm Optimization (CSA-PSO) [32], Enhanced Adaptive Particle Swarm Optimization (EAPSO) [33], Time Varying Acceleration Coefficient – Improved Particle Swarm Optimization (TVAC-IPSO) [34], Adaptive Hybrid Differential Evolution (AHDE) [38], hybrid methods are consuming more time to compute the results. Because the structure of this methods are more complicated. Moreover, an appropriate integration point of two algorithms is very difficult to determine.

Recently, crisscross optimization (CSO) [26], Hybrid Quantum Particle Swarm Optimization (HQPSO) [36], Hybrid Immune Genetic Algorithm (HI-GA) [39] method is solving the DED problem. But the convergence stagnancy phenomena are very large to compute the result. The large system is not suitable for maintain the population of personal best solutions so as to greatly accelerate the convergence.

Newly, motivated by the shallow water theory, researchers have proposed Water Evaporation Optimization (WEO) algorithm for solving global optimization problem [27]. The WEO algorithm is conceptually simple and easy to implement. The WEO algorithmic search consists of both global and local search. This guarantees that the proposed algorithm is competitive with other efficient well-known meta-heuristics. The objective of this papers it to use WEO algorithm to obtain the optimal dispatches and compare the performances in terms of quality of solution with the recent reports.

The rest of this paper is organized as follows. Section II details the ELD problem formulation. Brief description of WEO algorithm and implementation of WEO for solving ELD problem are presented in Section III. The comparison of numerical simulation results and discussion with recent literature results are detailed in Section IV. Conclusions are presented in Section V followed by references.

II. Problem Formulation

2.1 Objective Function

The main objective of DED problem is to economically assign the power output over the operating perspective while fulfilling the demand, unit constrains and minimizes the total fuel cost.
The objective of DED is the total fuel cost equation as formulated as:

$$F_i(P_i) = \sum_{t=1}^{T}\sum_{i=1}^{N} a_i P_{i,t}^{\;2} + b_i P_{i,t} + c_i + \left|e_i \times \sin\left(f_i \times \left(P_{i,\min} - P_{i,t}\right)\right)\right| \tag{1}$$

Where F_i is the cost function of the i^{th} generator at time t. at, P_i is the real power generated by the i^{th} generator, N is the total number of online participating generating units, and a_i, b_i, c_i is the cost coefficients of i^{th} generator. e_i and f_i are the cost coefficients of i^{th} generator reflecting valve point loading effects and $P_{i,min}$ is the minimum output power of i^{th} generating unit. T is the total number of hours in the scheduling horizon.

2.2 Constraints

2.2.1 Power Balance

The total power generation must satisfy sum of the demand and losses.

$$P_{D,t} + P_{L,t} = \sum_{i=1}^{N} P_{i,t} \tag{2}$$

$$P_{L,t} = \sum_{i=1}^{T}\; \sum_{j=1}^{N} P_{i,t} B_{ij} P_{j,t} + \sum_{i=1}^{N} B_{oi} P_{i,t} + B_{oo} \tag{3}$$

Where P_D is the total load, P_L is the transmission loss, B_{ij}, B_{oi}, B_{oo} are the transmission loss coefficients.

2.2.2 Generator Power Limit

The generated power should be within its minimum and maximum limits.

$$P_{i,\min} \le P_i \le P_{i,\max} \tag{4}$$

$P_{i,min}$ and $P_{i,max}$ is the minimum and maximum output power of i^{th} generating unit.

2.2.3 Ramp Rate Limit

To avoid undue thermal stresses on the boiler and the combustion equipment, the rate of change of the output power of each thermal unit must not exceed a certain ramp limit rate during increasing or decreasing the power output of each unit. This can be mathematically as follows.

$$\max\left(P_{i,\min}, P_{i,t}^{0} - DR_i\right) \le P_{i,t} \le \min\left(P_{i,\max}, P_{i,t}^{0} + UR_i\right) \tag{5}$$

Such that max ($P_{i\ min}$, $P_{i,t}^{0}$-DR_i) = $P_{i,t\ min}$ and min($P_{i\ max}$, $P_{i,t}^{0}$+UR_i) = $P_{i,t\ max}$ where $P_{i,t\ min}$ and $P_{i,t\ max}$ are the minimum and maximum limit of the real power of the i^{th} unit at the t^{th} interval in MW and $P_{i,t}^{0}$ is the power generated by the i^{th} unit at the $(t-1)^{th}$ hour. UR_i and DR_i are the UP and DOWN ramp rate limits of the i^{th} unit in MW/h.

2.2.4 Spinning Reserve Requirements

The SRR_s should be measured as an additional constraint to stay away from an unpredicted large load to the system or a breakdown in a certain large unit. Hence SRR_s for the RCDED problem are formulated in three different ways.

$$\left(\Delta_T^{(1)} = \sum_{i=1}^{NU} P_i^{\max} - \left(P_D + P_{loss} + SR_T \right) \geq 0 \right) \tag{6}$$

$$\left(\Delta_T^{(2)} = \sum_{i=1}^{NU} \left(\min\left(P_i^{\max} - P_{i,t}, UR_i \right) \right) - SR_T \right) \geq 0 \tag{7}$$

$$\left(\Delta_T^{(3)} = \sum_{i=1}^{NU} \left(\min\left(P_i^{\max} - P_{i,t}, \frac{UR_i}{6} \right) \right) - SR_T^{'} \right) \geq 0 \tag{8}$$

Equations (6) and (7) are generally applied the DED problems within 60 min of being required. Equation (8) will exactly satisfy the 10 min of being required and its amount is related to the ramp up rate constraint of generating unit. For time interval of the ramp up rate of unit i is UR_i (MW/h), the equivalent amount for 10 min is $UR_i/6$.

III. Water Evaporation Optimization

The evaporation of water is very important in biological and environmental science. The water evaporation from bulk surface such as a lake or a river is different from evaporation of water restricted on the surface of solid materials. In this WEO algorithm water molecules are considered as algorithm individuals. Solid surface or substrate with variable wettability is reflected as the search space. Decreasing the surface wettability (substrate changed from hydrophility to hydrophobicity) reforms the water aggregation from a monolayer to a sessile droplet. Such a behavior is consistent with how the layout of individuals changes to each other as the algorithm progresses. And the decreasing wettability of surface can represent the decrease of objective function for a minimizing optimization problem. Evaporation flux rate of the water molecules is considered as the most appropriate measure for updating individuals which its pattern of change is in good agreement with the local and global search ability of the algorithm and make this algorithm have well converged behavior and simple algorithmic structure. The details of the water evaporation optimization algorithm are well presented in [27].

In the WEO algorithm, each cycle of the search consists of following three steps (i) Monolayer Evaporation Phase, this phase is considered as the global search ability of the algorithm (ii) Droplet Evaporation Phase, this phase can be considered as the local search ability of the algorithm and (iii) Updating Water Molecules, the updating mechanism of individuals.

3.1 Monolayer Evaporation Phase

In the monolayer evaporation phase the objective function of the each individuals Fit_i^t is scaled to the interval [-3.5, -0.5] and represented by the corresponding $E_{sub}(i)^t$ inserted to each individual (substrate energy vector), via the following scaling function.

$$E_{sub}(i)^t = \frac{\left(E_{\max} - E_{\min}\right) \times \left(Fit_i^t - Min(Fit)\right)}{\left(MaX(Fit) - Min(Fit)\right)} + E_{\min} \tag{9}$$

where E_{max} and E_{min} are the maximum and minimum values of E_{sub} respectively. After generating the substrate energy vector, the Monolayer Evaporation Matrix (MEP) is constructed by the following equation.

$$MEP_{ij}^t = \begin{cases} 1 & if\ rand_{ij} \leq \exp\left(E_{sub}(i)^t\right) \\ 0 & if\ rand_{ij} \geq \exp\left(E_{sub}(i)^t\right) \end{cases} \tag{10}$$

where MEP_t^{ij} isthe updating probability for the j^{th} variable of the i^{th} individual or water molecule in the t^{th} iteration of the algorithm. In this way an individual with better objective function is more likely to remain unchanged in the search space.

3.2 Droplet Evaporation Phase

In the droplet evaporation phase, the evaporation flux is calculated by the following equation.

$$J(\theta) = J_o P_o \left(\frac{2}{3} + \frac{\cos^3 \theta}{3} - \cos\theta \right)(1 - \cos\theta) \tag{11}$$

where J_o and P_o are constant values. The evaporation flux value is depends upon the contact angle Θ, whenever this angle is greater and as a result will have less evaporation. The contact angle vector is represented the following scaling function.

$$\theta(i)^t = \frac{(\theta_{\max} - \theta_{\min}) \times \left(Fit_i^t - Min(Fit)\right)}{\left(Max(Fit) - Min(Fit)\right)} + \theta_{\min} \tag{12}$$

where the min and max are the minimum and maximum functions. The Θ_{min} & Θ_{max} values are chosen between $-50^o < \Theta < -20^o$ is quite suitable for WEO. After generating contact angle vector $\Theta(i)^t$ the Droplet Probability Matrix (DEP) is constructed by the following equation.

$$DEP_{ij}^t = \begin{cases} 1 & if\ rand_{ij} < J\left(\theta_i^{(t)}\right) \\ 0 & if\ rand_{ij} \geq J\left(\theta_i^{(t)}\right) \end{cases} \tag{13}$$

where DEP^t_{ij} is the updating probability for the j^{th} variable of the i^{th} individual or water molecule in the t^{th} iteration of the algorithm.

3.3 Updating Water Molecules

In the WEO algorithm the number of algorithm individuals or number of water molecules (nWM) is considered constant in all t^{th} iterations, where t is the number of current iterations. Considering a maximum value for algorithm iterations (t_{max}) is essential for this algorithm to determine the evaporation phase and for stopping criterion. When a water molecule is evaporated it should be renewed. Updating or evaporation of the current water molecules is made with the aim of improving objective function. The best strategy for regenerating the evaporated water molecules is using the current set of water molecules ($WM^{(t)}$). In this way a random permutation based step size can be considered for possible modification of individual as:

$$S = rand.\left(WM^{(t)}\left[permute1(i)(j)\right] - WM^{(t)}\left[permute2(i)(j)\right]\right) \tag{14}$$

where rand is a random number in [0,1] range, permute1and permute 2 are different rows of permutation functions. i is the number of water molecule, j is the number of dimensions of the problem. The next set of molecules ($WM^{(t+1)}$) is generated by adding this random permutation based step size multiplied by the corresponding updating probability (monolayer evaporation and droplet evaporation probability) and can be stated mathematically as:

$$WM^{(t+1)} = WM^{(t)} + S \times \begin{cases} MEP^{(t)}\ t \leq t_{\max}/2 \\ DEP^{(t)}\ t > t_{\max}/2 \end{cases} \tag{15}$$

Each water molecule is compared and replaced by the corresponding renewed molecule based on objective function. It should be noted that random permutation based step size can help in two aspects. In the first phase, water molecules are more far from each other than the second phase. In this way the generated permutation based step size will guarantee global and local capability in each phase.

The WEO algorithm can be summarized as follows:

Step1: Initialize all the algorithm and problem parameters, randomly initialize all water molecules.

Step2: Generating water evaporation matrix

Every water molecule follow the evaporation probability rules specified for each phase of the algorithm based on the Eqs. (10) and (13). For $t \leq t_{max}/2$, water molecules are globally evaporated based on monolayer evaporation probability MEP by using Eq (10). For $t > t_{max}/2$, evaporation occurs based on the droplet evaporation probability DEP by using Eq (13). It should be noted that for generating monolayer and droplet evaporation probability matrices, it is necessary to generate the correspondent substrate energy vector and contact angle vector by using Eqs (9) and (12) respectively.

Step 3: Generating random permutation based step size matrix

A random permutation based step size matrix is generated according to Eq. (14)

Step 4: Generating evaporated water molecules and updating the matrix of water molecules

The evaporated set of water molecules $WM^{(t+1)}$ is generated by adding the product of step size matrix and evaporation matrix to the current set of molecules $WM^{(t)}$ by using Eq. (15). These molecules are evaluated

based on the objective function. For the molecule i (i = 1, 2,....nWM) if the newly generated molecule is better than the current one, the latter should be replaced. Return the best water molecule as the output of the algorithm
Step 5: Terminating condition check
If the number of iteration of the algorithm (t) becomes larger than the maximum number of iterations (t_{max}), the algorithm terminates. Otherwise go to step 2.
The detailed flowchart for the implementation of WEO algorithm for DED problem is shown in Fig 1.

IV. Examples And Simulation Results

The proposed methodology has been tested with three test systems and the proposed algorithm is developed in Matlab environment and is implemented using Intel(R) Core(TM) i5-4200U CPU@1.60 GHz 2.30 GHz processor. The effectiveness of the proposed WEO algorithm for ELD problem has been validated by comparing the simulation results obtained from the other method which is available in literature. The WEO algorithm parameters for all test systems are chosen as the number of water molecules (nWM) = 10, maximum number of algorithm iteration (t_{max}) = 100, MEP_{min} = 0.03, MEP_{max} = 0.6, DEP_{min} = 0.6, DEP_{max} = 1.

4.1 Test System 1

This test system consist of 5 generating units is consider to validate the proposed method. Here spinning reserve, valve point loading and transmission losses are included. The test system particulars are available in the literature [8]. The best generation schedule obtained by the proposed WEO algorithm for a 5 generating units system is given in the Table 1. From the simulation results it is clear that the proposed WEO algorithm meet the load demand for entire planning period of 24 hr and obtain the minimized fuel cost of 422993.6318($) with a loss of 195.1953(MW) with satisfying system constraints power balance, generator power limit.

Table 1. The best generation schedule using WEO algorithm for 5 unit system

Unit	Load	P_1(MW)	P_2(MW)	P_3(MW)	P_4(MW)	P_5(MW)	P_{loss}(MW)	Generation	$\Delta_t^{(1)}$	$\Delta_t^{(2)}$	$\Delta_t^{(3)}$
1	410	20.6014	98.5423	30.0000	124.9100	139.7583	3.8120	1249.5795	490.6880	175.9577	26.5000
2	435	10.0000	97.9621	66.4957	124.9048	139.7598	4.1224	1422.7021	464.1276	175.2879	26.0833
3	475	10.0354	98.5257	106.4960	124.9517	139.7722	4.7810	1339.8280	421.4690	172.7243	25.4168
4	530	10.0013	98.5810	112.7087	174.9513	139.7706	6.0129	1659.2123	362.4871	169.9190	24.5000
5	558	10.0000	92.9923	112.6655	209.8147	139.9279	7.4004	1587.8947	331.6996	162.2853	24.0333
6	608	10.0000	98.5409	112.6710	209.8153	184.9576	7.9848	1872.0504	278.6152	156.3338	23.2000
7	626	10.0000	72.4515	112.6740	209.8158	229.5193	8.4606	1840.6093	259.2394	158.8842	22.9000
8	654	12.7044	98.5437	112.6727	209.8160	229.5192	9.2560	1797.2305	229.0494	153.9403	22.4333
9	690	42.7044	105.4542	112.6735	209.8160	229.5191	10.1672	2012.1289	190.3328	145.2300	21.8333
10	704	64.0108	98.5398	112.6735	209.8158	229.5196	10.5595	1996.5951	175.2405	132.4336	21.6000
11	720	75.0000	104.0359	112.6735	209.8158	229.5196	11.0448	2037.9302	157.9552	115.1483	16.3333
12	740	75.0000	124.7111	112.6735	209.8158	229.5196	11.7200	2180.0222	136.2800	93.4731	11.2889
13	704	64.0108	98.5398	112.6735	209.8158	229.5196	10.5595	1996.5951	175.2405	132.4336	21.6000
14	690	49.6196	98.5398	112.6735	209.8158	229.5196	10.1683	1977.6613	190.3317	147.5248	21.8333
15	654	19.6187	91.5860	112.6734	209.8158	229.5200	9.2139	1862.7466	229.0861	157.4842	22.4333
16	580	10.0000	75.1565	112.6734	159.8087	229.5200	7.1886	1892.8463	308.8114	171.0000	23.6667
17	558	10.0000	87.7145	112.6735	124.9078	229.5323	6.8290	1615.0520	332.2710	172.1000	24.0333
18	608	10.0000	98.5403	112.6759	165.0898	229.5200	7.8260	1853.1315	278.7740	166.0597	23.2000
19	654	12.7080	98.5407	112.6735	209.8160	229.5196	9.2578	1797.2251	229.0422	153.9433	22.4333
20	704	42.7078	119.9405	112.6735	209.8158	229.5196	10.6572	2115.5135	175.1428	130.0437	21.6000
21	680	39.3528	98.5399	112.6735	209.8158	229.5196	9.9016	1944.5975	201.0984	152.6443	22.0000
22	605	10.0001	98.5399	112.6735	162.1377	229.5196	7.8708	1843.5182	281.8792	166.2101	23.2500
23	527	10.0000	98.5398	112.6733	124.9081	186.7828	5.9040	1677.5493	365.7460	170.1102	24.5500
24	463	10.0000	80.1559	112.6731	124.9082	139.7598	4.4970	1421.4122	434.3530	176.8500	25.6167
							195.1953	**422993.6318**			

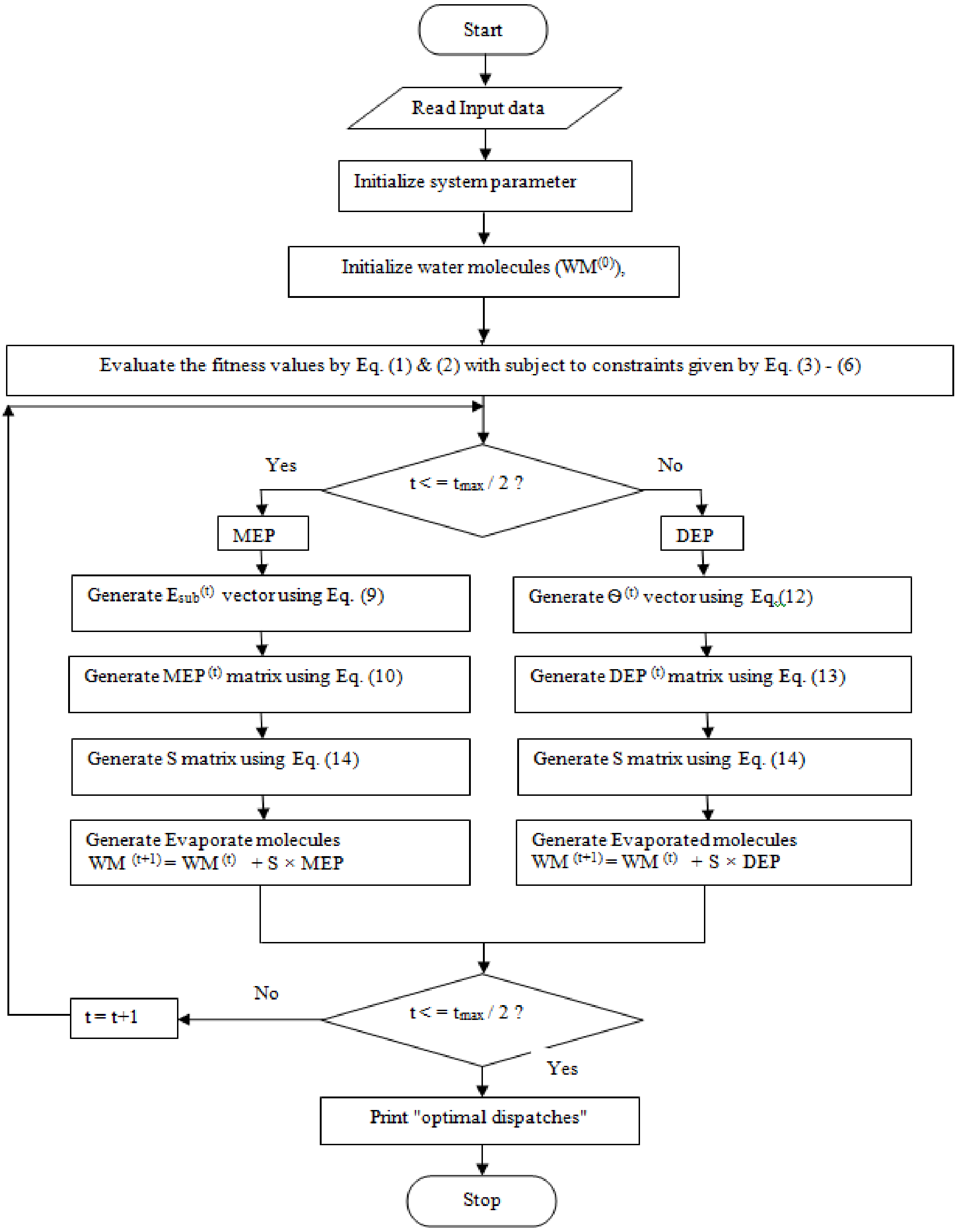

Fig. 1 Flowchart for the proposed WEO algorithm to solve DED

The results also imply that every hour the ramp rate limit has to be maintained. The comparison of best, worst and the mean value of the total fuel cost is presented in Table 2. The proposed WEO algorithm achieve the best cost of 42993.6318($), worst cost of 43089.63($), and mean cost of 43009.74($). From the comparison it is clear that the proposed algorithm achieve the best results in comparison with SA [8], APSO [28], AIS [9], TLA [19] and MTLA [19]. The cost convergence characteristic curve is depicting in Fig 2. The convergence curve demonstrate that the cost is converged from larger value to smaller value ensure that the WEO algorithm is capable of producing better results than existing algorithms.

The spinning reserve requirements are set to 5% of load demand in each hour for this test system with time period of 24 – hour. Here the SRRs are formulated in three different ways, $\Delta_T^{(1)}$, $\Delta_T^{(2)}$, $\Delta_T^{(3)}$ and are computed by WEO algorithm is also presented in Table1. All the SRRs values are positive ensure that the proposed algorithm maintained sufficient SRR in each hour.

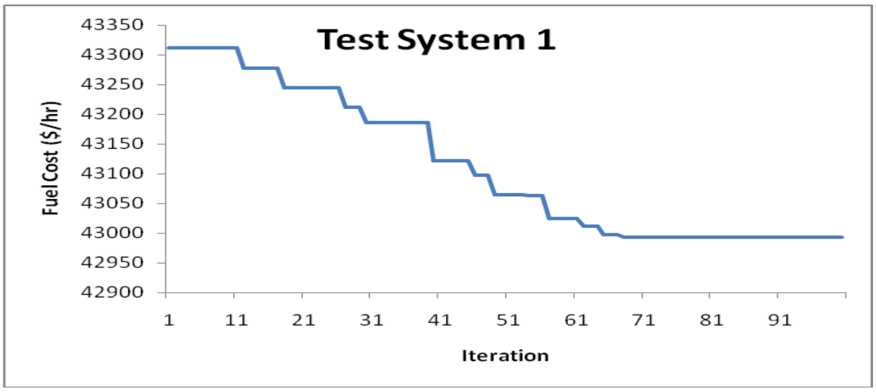

Fig. 2 Convergence curve of the Test system 1

Table 2. The best generation schedule using WEO algorithm for 5 unit system

Solution Techniques	Total Fuel cost ($)			Time (Min)
	Best Value	Mean Value	Worst Value	
SA[8]	47356	NA	NA	4.395
APSO[28]	44678	NA	NA	NA
AIS[9]	44385.4	44758.8	45553.8	5.333
TLA[19]	43132.9	43209.4	43897.4	0.060
MTLA[19]	43048.4	43077.9	43128.5	0.071
WEO	**42993.6318**	**43009.74**	**43089.63**	**0.0078**

NA: Not available in the literature

4.1 Test System 2

To demonstrate the validity of the proposed WEO algorithm a ten unit test system is considered with valve point loading effect and ramp rate limit. In this test system losses are neglected. The test system particulars are available in the literature [26]. The simulation results of 10 unit test system for a planning period of 24 hour obtained by the proposed WEO algorithm is presented in Table 3. The simulated results make sure that the proposed algorithm reaches the least cost with satisfying system constraints out and out. The comparison of total fuel cost in comparison with existing algorithms is presented in Table 4. It is evident from the comparison the proposed algorithm alone achieve the minimized cost than earlier reported algorithms. The objective value versus iteration curve is plotted in Fig. 3. From the convergence curve it is clear that the proposed WEO algorithm is efficient in handling system constraints and obtains the competitive results than existing algorithms.

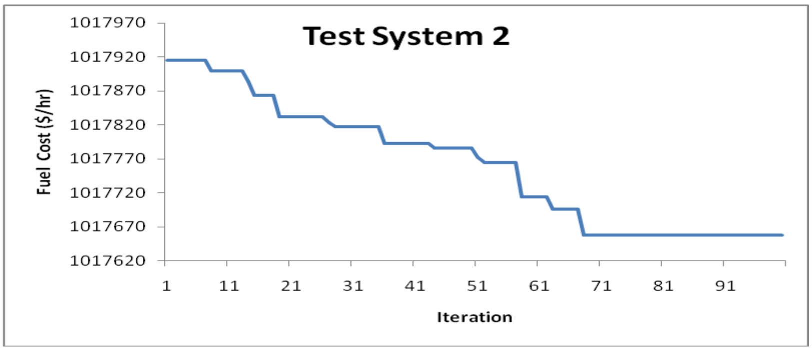

Fig. 3 Convergence curve of the Test system 2

4.3 Test System 3

In this case, the same 10 unit test system is considered along with network loss. The result obtained by the proposed WEO is present in table 5. The simulation results shows that the WEO algorithm meet the load demand in each hour and fulfill the system constraints. The proposed algorithm achieve the best optimal total cost of 1,038,313 $ with total loss of 801.87 MW. The total fuel cost comparison of 10 unit test system with loss is presented in Table 6. The comparisons imply that proposed WEO algorithm alone reach the minimized cost than existing algorithms. The Fig. 4 shows the cost convergence curve of test system 3. The convergence curves make clear that the results converged from larger values guarantee that the proposed WEO algorithm is efficient and obtain better results than earlier reported techniques.

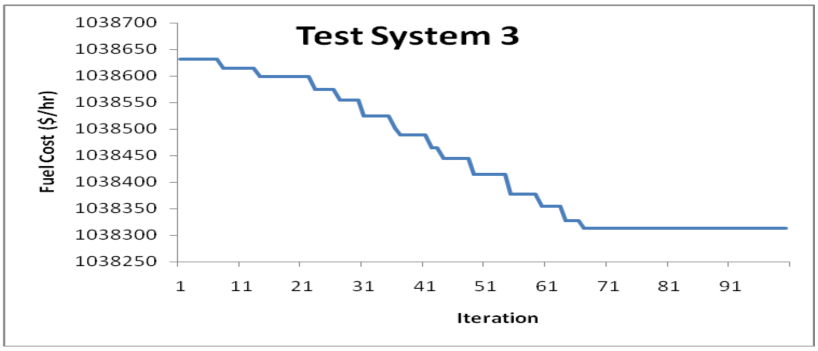

Fig 4: Convergence curve of the Test system 3

Table 3. The best generation schedule using WEO algorithm for 10 unit system without loss

Hour	Load	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	Cost ($)
1	1036	150	135	194.08	60	122.87	122.46	129.59	47	20	50	28238.48
2	1110	150	135	268.08	60	122.87	122.46	129.59	47	20	55	29946.84
3	1258	226.63	215	309.32	60	73	122.46	129.59	47	20	55	33123.67
4	1406	303.26	222.28	323.56	60	122.85	122.46	129.59	47	20	55	36290.84
5	1480	379.87	302.27	290.82	60	73.00	122.45	129.59	47	20	55	37903.48
6	1628	456.50	309.53	305.06	60	122.87	122.45	129.59	47	20	55	40981.77
7	1702	456.50	309.53	308.06	80	172.73	123.58	129.59	47	20	55	42902.12
8	1776	456.50	309.53	308.06	126	172.73	151.58	129.59	47	20	55	44651.6
9	1924	456.50	389.54	305.34	176	222.60	122.43	129.59	47	20	55	47903.64
10	2072	456.50	396.80	298.50	226.01	222.60	160	129.59	47	50	55	51808.93
11	2146	456.50	396.80	340	248.13	122.63	160	129.59	85.29	52.06	55	53407.02
12	2220	456.50	460.00	300.80	298.14	222.60	160	129.59	85.31	52.06	55	55306.5
13	2072	456.50	396.80	297.40	248.14	222.60	158.60	129.59	85.31	22.06	55	51415.72
14	1924	456.50	396.80	287.47	198.14	172.73	122.45	129.59	85.31	20	55	48041.52
15	1776	379.88	396.80	283.27	180.82	122.86	122.45	129.59	85.31	20	55	44594.07
16	1554	302.88	396.80	283.27	180.82	122.86	122.45	129.59	85.31	20	55	39969.23
17	1480	222.62	309.53	288.21	120.42	122.81	122.45	129.59	85.31	20	55	37973.28
18	1628	303.25	316.80	317.79	130.83	73	122.45	129.59	85.31	20	55	41215.03
19	1776	379.87	389.53	301.09	120.42	172.73	122.45	129.59	85.31	20	55	44510.52
20	2072	456.50	460.00	312.59	170.42	222.60	160.00	129.59	85.31	20	55	51768.67
21	1924	456.50	396.80	315.33	120.42	222.60	122.45	129.59	85.31	20	55	47708.92
22	1628	379.87	316.80	275.83	70.42	172.73	122.45	129.59	85.31	20	55	41496.69
23	1332	303.23	236.80	196.74	60	122.88	122.45	129.59	85.31	20	55	35037.12
24	1184	226.61	222.26	189.78	60	73	122.45	129.59	85.31	20	55	31461.86
Total Cost												**1,017,657.52**

Table 4. Comparison of total fuel cost for 10 unit system without loss

Method	**Total Fuel cost ($)**			**Time (min)**
	BEST	**MEAN**	**WORST**	
SQP [10]	1,051,163	NA	NA	0.421
EP [10]	1,048,638	NA	NA	15.049
HS [12]	1,046,726	NA	NA	NA
DE [11]	1,036,756	1,040,586	1,452,558	0.20
GA [7]	1,033,481	1,038,014	1,042,606	NA
SOA [15]	1,023,946	1,026,289	1,029,213	NA
AIS [9]	1,021,980	1,023,156	1,024,973	25.346
ABC [13]	1,021,576	1,022,686	1,024,316	2.603
TLA [16]	1,019,925	1,020,411	1,021,118	0.049
ICA [14]	1,018,467	1,019,291	1,021,796	NA
HDE [29]	1,031,077	NA	NA	NA
IPSO [17]	1,023,807	1,026,863	NA	0.060

CDBCO [30]	1,021,500	1,024,300	NA	0.67
CDE [18]	1,019,123	1,020,870	1,023,115	0.32
ICPSO [31]	1,019,072	1,020,027	NA	0.350
CSAPSO [32]	1,018,767	1,019,874	NA	0.350
EAPSO [33]	1,018,510	1,018,710	1,019,302	0.625
TVAC-IPSO [34]	1,018,217	1,018,965	1,020,417	2.718
EBSO [35]	1,017,147	1,017,526	1,017,891	0.205
HQPSO [36]	1,031,559	1,033,837	1,036,681	0.773
AIS-SQP [23]	1,029,900	NA	NA	NA
DGPSO [37]	1,028,835	1,030,183	NA	4.809
ECE [25]	1,022,271	1,023,334	NA	0.329
SOA-SQP [15]	1,021,460	1,023,840	1,026,852	NA
AHDE [38]	1,020,082	1,022,476	NA	1.10
HHS [12]	1,019,091	NA	NA	10.194
HIGA [39]	1,018,473	1,019,328	1,022,284	3.53
CSO[26]	1,017,660	1,018,120	1,019,286	0.961
WEO	**1,017,657.52**	**1,018,109**	**1,019,116**	**1.130**

Table 5. The best generation schedule using WEO algorithm for 10 unit system with loss

Hour	Load	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	Loss (MW)	Cost ($)
1	1036	150	135	206.21	60	122.88	122.45	129.59	47	20	55	12.13	28591.83
2	1110	150	135	282.76	60	122.87	122.45	129.59	47	20	55	14.67	30148.99
3	1258	226.62	135	307.50	60	172.73	122.45	129.59	47	20	55	17.89	33388.38
4	1406	303.25	215.00	304.38	60	172.73	122.45	129.59	47	20	55	23.40	36824.88
5	1480	379.87	222.27	297.40	60	172.73	122.45	129.59	47	20	55	26.31	38293.21
6	1628	456.50	222.27	305.09	80	222.60	122.45	129.59	47	20	55	32.50	42004.14
7	1702	456.50	302.27	312.13	120.42	172.73	122.45	129.59	47	20	55	36.08	43731.35
8	1776	456.50	309.53	299.42	170.42	172.73	122.45	129.59	77	20	55	36.64	45622.45
9	1924	456.50	389.53	299.42	189.55	222.60	122.45	129.59	85.31	20	55	45.95	49017.74
10	2072	456.50	396.80	325.60	239.51	222.60	160	129.59	115.31	20	55	48.91	52817.04
11	2146	458.45	396.78	340	239.51	222.60	160	129.59	120	20	55	50.93	54809.25
12	2220	456.50	459.97	325.05	300	222.60	160	129.59	120	50	55	58.71	56961.01
13	2072	456.50	396.76	298.44	300	222.60	122.44	129.59	85.30	20	55	49.33	52515.69
14	1924	456.50	316.80	302.34	250.00	222.60	122.45	129.59	90	20	55	41.28	49246.06
15	1776	379.86	309.51	294.61	241.18	172.72	122.45	129.59	85.31	20	55	34.22	45409.30
16	1554	303.24	229.52	318.36	191.15	122.84	122.45	129.59	85.31	20	55	23.46	40658.66
17	1480	226.62	222.26	287.67	180.79	172.73	122.44	129.59	85.31	20	55	22.42	38646.77
18	1628	303.25	222.27	312.74	180.83	222.60	123.35	129.59	85.31	20	55	26.93	42017.57
19	1776	379.84	302.27	313	180.83	222.60	122.44	129.59	85.31	20	55	34.88	45538.72
20	2072	456.50	382.21	340	230.83	230.44	160	129.59	115.30	20	55	47.87	53382.49
21	1924	456.50	396.80	301.35	180.83	222.60	122.45	129.59	85.31	20	55	46.42	48752.43
22	1628	379.86	316.81	278.30	130.84	172.69	122.45	129.59	55.29	20	55	32.83	42479.09
23	1332	303.25	236.80	198.33	118.34	122.87	122.45	129.59	47	20	55	21.20	35599.61
24	1184	226.60	222.24	184.62	120.41	73	122.45	129.59	47	20	55	16.91	31856.02
												801.87	**1,038,313.49**

Table 6. The total fuel cost comparison of 10 unit system with loss

Method	Total Fuel cost ($)			Loss (MW)	Time (min)
	BEST	**MEAN**	**WORST**		
MIQP [6]	1,038,550	NA	NA	NA	NA
EP [10]	1,054,685	1,057,323	NA	NA	47.23
GA [7]	1,052,251	1,058,041	1,062,511	NA	3.444
AIS [9]	1,045,715	1,047,050	1,04 8,431	835.62	30.973
ABC [13]	1,043,381	1,044,963	1,046,805	817.80	3.408
ICA [14]	1,040,758	1,041,664	1,043,173	848.797	NA
IPSO [17]	1,046,275	1,048,154	NA	NA	0.180
CDBCO [30]	1,042,900	1,044,700	NA	839.31	1.53
TVAC-IPSO [34]	1,041,066	1,042,118	1,043,626	854.033	3.155
EBSO [35]	1,038,915	1,039,188	1,039,272	NA	0.22
EP-SQP [10]	1,052,668	1,053,771	NA	NA	27.53
MHEP-SQP [10]	1,050,054	1,052,349	NA	NA	24.33
DGPSO [37]	1,049,167	1,051,725	NA	NA	5.99

ECE [25]	1,043,989	1,044,470	NA	NA	0.644
HIGA [39]	1,041,088	1,042,980	1,044,927	853.53	3.8
CSO[26]	1,038,320	1,039,374	1,042,518	802.62	1.481
Proposed WEO	**1,038,313**	**1,039,003**	**1,042,186**	**801.87**	**1.764**

V. Conclusion

A heuristic optimization method called WEO was developed for the purpose of optimal solution for the DED problem. The practical operational constraints of generators such as spinning reserve, ramp rate limits and valve point effect along with transmission loss were considered in the analysis. The feasibility and efficiency of the proposed method were demonstrated on five and ten unit test systems. The numerical results were compared with the recent optimization approaches. The numerical results revealed that the dispatch solution obtained by the proposed WEO approach led to a smaller operating cost than those found by other methods, which showed the capability of the algorithm to determine the global or near global solutions for the DED problem.

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