Middle-East Journal of Scientific Research 24 (12): 3678-3687, 2016
ISSN 1990-9233

DOI: 10.5829/idosi.mejsr.2016.3678.3687

Water Evaporation Optimization Algorithm to Solve Economic Load Dispatch with Valve Point Effect and Considering Transmission Losses

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Abstract: This paper presents a new physically inspired population based metaheuristic algorithm, named Water Evaporation Optimization (WEO) algorithm has been applied to solve the Economic Load Dispatch (ELD) problem in power systems with valve point effect and considering transmission losses. This 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 local and global search ability of this proposed WEO algorithm has well converged behavior and simple algorithmic structure. The proposed algorithm have been successfully tested in the middle and large scale test systems which consists of forty generating unit systems with loss considering valve point loading effects and one hundred forty generating unit systems with valve point loading and ramp rate limits. The comparison of simulation result obtained by the proposed WEO algorithm as well as existing algorithms for 40 units and 140 units test systems demonstrates superior performance of the proposed methodology by achieving minimum fuel cost.

Key words: Economic load dispatch · Water evaporation optimization · Molecular dynamics simulation · Valve point loading effects

INTRODUCTION

In power system operation, the Economic Load Dispatch (ELD) problem is an important optimization problem. The goal of ELD is to find a best feasible power generation schedule with a minimal fuel cost with satisfying system constraints [1]. Traditionally in ELD problems, the cost function for generating units has been approximated as a quadratic function. A wide variety of optimization techniques have been applied to solve ELD problems. Some of these techniques are based on classical optimization methods, while others use artificial intelligence and hybrid methods. Many references present the application of classical optimization methods such as lambda iteration, gradient search (GS), dynamic programming (DP), linear programming (LP), nonlinear programming (NLP), quadratic programming (QP), base point (BP) method, interior point (IP) method, etc. have been employed [2-9].

The modern power system, many thermal generating units are supplied with valve point loading effect and ramp rate limit which makes the ELD problem highly non-linear due to that these classical optimization methods mat not be applicable. Furthermore, for a large-scale system, the conventional methods have oscillatory problems, resulting in a local minimum solution or a longer computational time.

In the past decade, random search optimization methods simulated annealing (SA), genetic algorithm (GA), evolutionary programming (EP), tabu search (TS)], multiple tabu search (MTS), particle swarm optimization (PSO) and their versions, clonal algorithm, bacterial foraging algorithm (BFO), biogeography based optimization (BBO), differential evolution (DE), modified artificial bee colony (MABC) and so on has been applied to solve ELD problems [10-26]. Though, most of the methods mentioned above often provide fast and reasonable solutions but do not guarantee obtaining the global optimal solution.

Thus, developing a reliable, fast and efficient algorithm is still an active area for research in power systems. Various investigations on ELD have been explored till date, as better solutions would result in significant economical benefits. The modern meta-

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heuristic algorithm which mimics the herding behavior of ocean krill individuals [27] and an opposition based krill herd algorithm have been proposed to solve the ELD problems [28]. The teaching learning based optimization (TLBO) algorithm [29] and quasi – oppositional based TLBO [30] has been developed to solve the economic load dispatch problem. This evolutionary algorithm based on two basic concepts of education namely teaching phase and learning phase. Initially, learners improve their knowledge through the teaching methodology of teacher and finally learners increase their knowledge by interactions among them.

The root tree optimization algorithm [31], which mimics a plant roots in looking for water under the ground has been applied to ELD problems. The grey wolf optimization technique which is based on the behavior of grey wolfs has been applied to solve the economic load problems [32]. A new meta-heuristic method that requires a little tuning by the user, called chaotic bat algorithm [33] for solving economic dispatch problems of various levels of complexity has been discussed. Recently, a modified social spider algorithm for solving the economic dispatch has been addressed [34]. In this algorithm the spider web represents the search space of the optimization problem and the spider position on the web represents the possible solution to the problem.

In recent years, researchers have focused much attention on hybrid solution techniques combining exact and heuristic methods to attempt a wide range of complex ELD problems. The harmony search (HS) algorithm combined with swarm intelligence concepts to improve the quality of the HS solutions and to speed up the convergence rate of the HS algorithm, a hybrid strategy which integrates HS with a gradient based method named sequential quadratic programming (SQP) has been presented [35]. The genetic algorithm (GA) combined with ant colony approach to solve the ELD problems has been discussed [36]. This algorithm combines the downhill behavior of ant colony and a good spreading in the solution space of the GA strategy. The shuffled differential evolution (SDE) which combines the benefits of shuffled frog leaping algorithm and differential evolution has been presented [37].

The chemical reaction optimization (CRO) based hybrid method has been applied to solve the ELD problems. This algorithm imitates the interaction of molecules in a chemical reaction to reach from a higher energy unstable state to low energy stable state. A real coded version of it, known as an oppositional based real coded chemical reaction optimization for solving various ELD problems has been proposed [38]. In this quasi - opposite numbers have been utilized instead of pseudo random numbers to improve the convergence rate of the proposed algorithm.

Recently, motivated by the shallow water theory, researchers have proposed Water Evaporation Optimization (WEO) algorithm for solving global optimization problem [39]. 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. ELD problem is formulated in Section "Problem Formulation". The next section "Water Evaporation Optimization" briefly describes the algorithm. The numerical simulation results and discussion is presented in the Section "Examples and Simulation Results". The final Section outlines the "Conclusion" followed by references.

Problem Formulation

Economic Dispatch: The objective of the ELD problem is to find out the optimal combination of power generation units that minimize the overall generation cost subject to meet out system constraints fully. It is mathematically formulated as follows.

$$\text{minimize } F_T = \sum_{i=1}^{N} F_i\left(P_i\right) = \sum_{i=1}^{N} a_i P_i^2 + b_i P_i + c_i \tag{1}$$

where F_T is the overall generation cost, F_i is the cost function of the i^{th} generator , 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 are the cost coefficients of i^{th} generator.

Economic Dispatch with Valve Point Loading Effects: The addition of valve point increases the non-linearity of search space as well as number of local minima. In large steam turbine generators will have a number of steam valves that are opened in sequence to control the power output of generating units. Any increase in unit load makes the unit input to be increased and incremental heat rate will be decreased between the openings of any two valves. In general, the valve – point express ripples when every steam valves begins to open.

The valve – point loading is taken in consideration by adding a sine component to the cost of the generating units.

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

where 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.

Constraints

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

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

$$P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{oi} P_i + B_{oo} \quad (4)$$

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

Generator Power Limit: The generated power should be within its minimum and maximum limits.

$$P_{i,\min} \le P_i \le P_{i,\max} \quad (5)$$

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

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.

$$RDR_i \le P_i \le RUR_i \quad (6)$$

where RDR_i and RUR_i are the maximum and minimum allowable ramp – down and ramp – up rate of the i^{th} generator in MW.

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 [39].

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.

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.

$$E_{sub}(i)^t = \frac{(E_{\max} - E_{\min}) \times \left(Fit_i^t - Min(Fit) \right)}{\left(MaX(Fit) - Min(Fit) \right)} + E_{\min} \quad (7)$$

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

$$MEP_{ij}^t = \begin{cases} 1 \, if \; rand_{ij} \le \exp\left(E_{sub}(i)^t \right) \\ 0 \, if \; rand_{ij} \ge \exp\left(E_{sub}(i)^t \right) \end{cases} \quad (8)$$

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

Droplet Evaporation Phase: In the droplet evaporation phase, the evaporation flux is calculated by the following equation.

$$J(\theta) = J_o P_o \left(\frac{2}{3} + \frac{\cos^3\theta}{3} - \cos\theta \right)(1 - \cos\theta) \tag{9}$$

where Jo and Po 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.

$$\theta(i)^t = \frac{(\theta_{\max} - \theta_{\min}) \times \left(Fit_i^t - Min(Fit) \right)}{\left(Max(Fit) - Min(Fit) \right)} + \theta_{\min} \tag{10}$$

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

$$DEP_{ij}^t = \begin{cases} 1\, if\ rand_{ij} < J\left(\theta_i^{(t)}\right) \\ 0\, if\ rand_{ij} \geq J\left(\theta_i^{(t)}\right) \end{cases} \tag{11}$$

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.

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:

$$S = rand.\left(WM^{(t)}\left[permute1(i)(j) \right] - WM^{(t)}\left[permute2(i)(j) \right] \right) \tag{12}$$

where rand is a random number in [0, 1] range, permute 1 and 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:

$$WM^{(t+1)} = WM^{(t)} + S \times \begin{cases} MEP^{(t)}\ t \leq t_{\max}/2 \\ DEP^{(t)}\ t > t_{\max}/2 \end{cases} \tag{13}$$

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:

Step 1: Initialize all the algorithm and problem parameters, randomly initialize all water molecules.

Step 2: Generating water evaporation matrix

Every water molecule follow the evaporation probability rules specified for each phase of the algorithm based on the Eqs. (8) and (11). For $t \leq t_{max}/2$, water molecules are globally evaporated based on monolayer evaporation probability MEP by using Eq. (9). for $t > t_{max}/2$, evaporation occurs based on the droplet evaporation probability DEP by using Eq. (12). 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. (7) and (10) respectively.

Step 3: Generating random permutation based step size matrix.

A random permutation based step size matrix is generated according to Eq. (12).

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

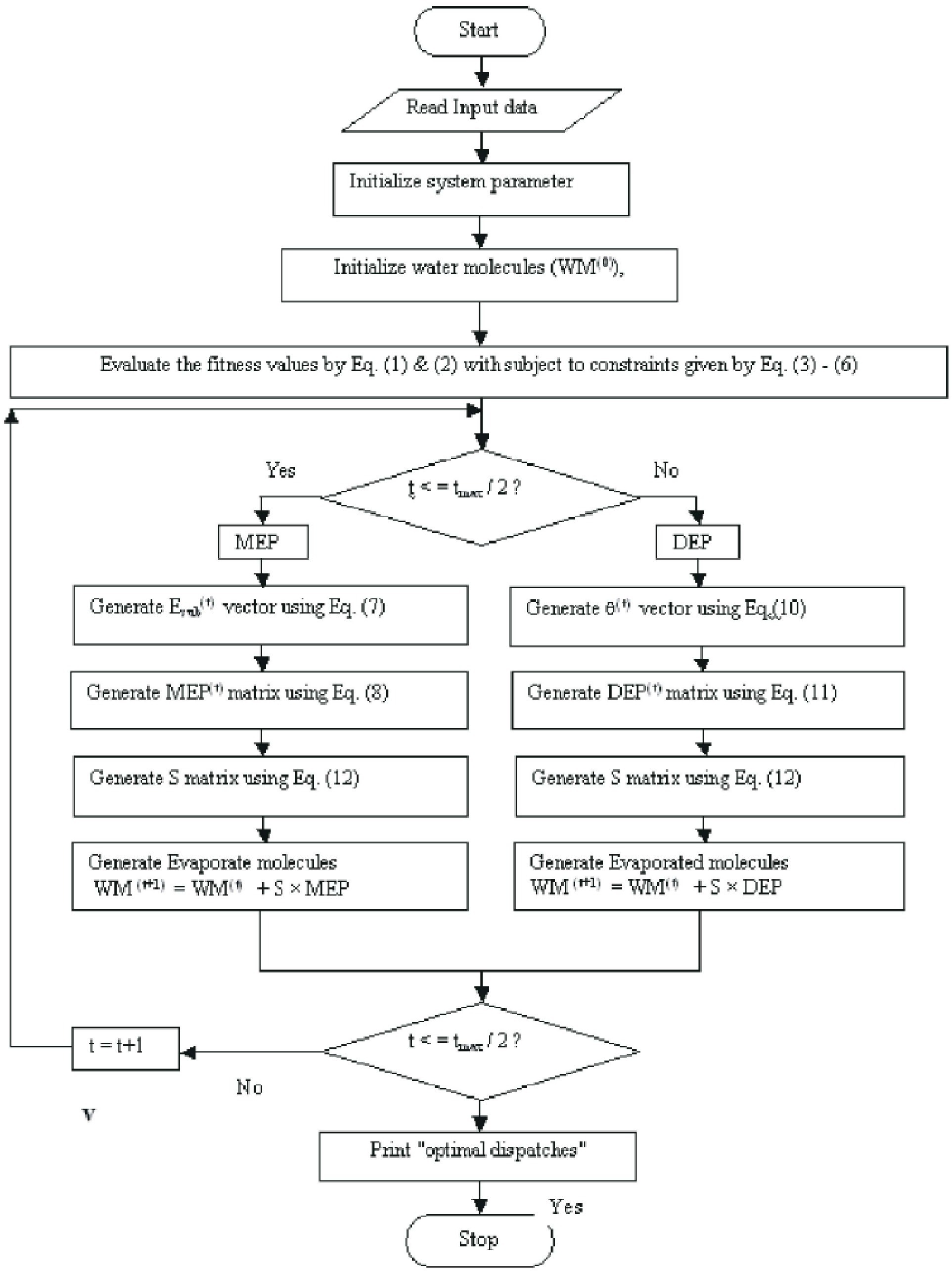

Fig. 1: Flowchart for the proposed WEO algorithm to solve ELD

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. (13). 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 solving ELD problem is shown in Fig. 1.

Table 1: The best generation schedule using WEO algorithm for 40 unit test system

Unit no	GA-API [36]	SDE [37]	TLBO [30]	QOTLBO [30]	KHA-IV [27]	OKHA [28]	GWO [32]	WEO
P_1	114	110.06	114	114	114	114	114	114
P_2	114	112.41	114	114	114	114	114.0000	114
P_3	120	120.00	120	107.8221	120.0000	120.0000	120	120
P_4	190	188.72	182.4448	190	190	182.5880	181.0490	182.0698
P_5	97	85.91	90.6923	88.3702	88.5944	88.3011	87.8351	88.8988
P_6	140	140.00	140	140	105.5166	140	140	140
P_7	300	250.19	300	300	300	300	300	300
P_8	300	290.68	296.0682	300	300	300	300	300
P_9	300	300.00	288.8518	300	300	300	300	300
P_{10}	205.25	282.01	281.9520	211.2071	280.6777	279.5994	279.9786	280.3235
P_{11}	226.30	180.82	238.1293	317.2766	243.5399	243.6246	243.6274	243.1211
P_{12}	204.72	168.74	251.0120	163.7603	168.8017	168.7592	94.1436	94.3562
P_{13}	346.48	469.96	483.1175	481.5709	484.1198	484.0490	484.4562	484.7569
P_{14}	434.32	484.17	481.9042	480.5462	484.1662	484.0362	484.2306	484.6565
P_{15}	431.34	487.73	488.2883	483.7683	485.2375	484.0367	484.2463	485.0897
P_{16}	440.22	482.30	396.3448	480.2998	485.0698	484.0704	484.0333	485.8703
P_{17}	500	499.64	494.2577	489.2488	489.4539	489.2827	489.6295	489.9899
P_{18}	500	411.32	408.3826	489.5524	489.3035	489.4094	489.3228	489.9876
P_{19}	550	510.47	510.5206	512.5482	510.7127	511.3137	511.4616	512.3658
P_{20}	550	542.04	521.2217	514.2914	511.3040	511.3323	511.4932	519.7744
P_{21}	550	544.81	540.5700	527.0877	524.4678	523.3375	523.4767	523.3364
P_{22}	550	550.00	522.1852	530.1025	535.5799	526.8873	547.6868	522.1236
P_{23}	550	550.00	526.1804	524.2912	523.3795	523.3242	523.3738	523.8975
P_{24}	550	528.16	521.1967	524.6512	523.15527	523.2762	523.1350	523.3634
P_{25}	550	524.16	525.8010	525.0586	524.1916	523.2985	523.3472	523.4875
P_{26}	550	539.10	526.0022	524.4654	523.5453	523.4107	523.3578	523.7613
P_{27}	11.44	10.00	13.0804	10.8929	10.1245	10.0129	10.0678	10.0678
P_{28}	11.56	10.37	11.0397	17.4312	10.1815	10.0020	10.6337	10.0369
P_{29}	11.42	10.00	12.9373	12.7839	10.0229	10.0215	10.5181	10.2658
P_{30}	97	96.10	89.7412	88.8119	87.8154	87.8017	87.8029	87.2365
P_{31}	190	185.85	190	190	190	190	190	190
P_{32}	190	189.54	190	190	190	190	190	190
P_{33}	190	189.96	190	190	190	190	190	190
P_{34}	200	199.90	200	200	200	200	200	200
P_{35}	200	196.25	200	168.0873	164.9199	164.8057	200	200
P_{36}	200	185.85	164.7435	165.5072	164.9787	164.8113	164.8334	164.8974
P_{37}	110	109.72	110	110	110	110	110	110
P_{38}	110	110.00	110	110	110	110	11	110
P_{39}	110	95.71	110	110	110	110	110	110
P_{40}	550	532.47	547.9677	511.5313	512.06775	511.2844	511.5471	515.9867
TL(MW)	1045.06	974.43	1002.63	1008.9	978.9251	990.68	973.2875	967.72
TC($/hr)	139864.96	138157.46	137814.17	137329.86	136670.37	136575.968	136446.85	136439.60

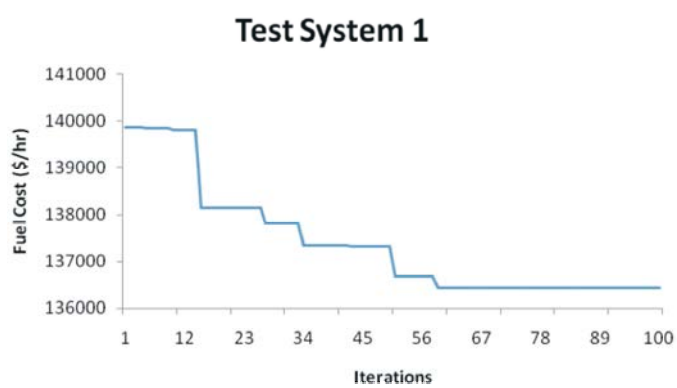

Fig. 2. Convergence characteristic of 40 unit test system

Examples and Simulation Results: The proposed methodology has been tested with different sample 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.

Test System 1: This sample system is a medium typed consist of 40 generating units is taken to validate the proposed approach. Here valve point loading and transmission losses are included. The demand for this test system is 10,500MW.

The test system particulars are available in the literature [25]. The best generation schedule obtained by the proposed WEO algorithm in comparison with GA-API [36], SDE [37], TLBO [30], QOTLBO [30], KHA-IV [27], OKHA [28] and GWO [32] for a 40 generating units system is given in the Table 1.

From the comparison results it is clear that the proposed WEO algorithm achieve the minimum fuel cost of 136439.60 (\$/hr) and transmission loss of 967.72 (MW) with satisfying system as well as the other practical constraints. From the discussion it is observed that the WEO algorithm provide better results than earlier reported methods in the literature. The cost convergence characteristics of 40 unit test system are presented in Figure 2. The figure shows that the converged result clearly indicates the minimization of objective function and for more effective generation dispatches.

Test System 2: In order to demonstrate the performance of the proposed WEO algorithm, a realistic large scale system namely Korean power system consists of 140 generating units is considered. Among 140 generating units forty are thermal generating units, fifty one gas units, twenty nuclear units and remaining twenty nine units are oil units. Unit data has been adopted from [28]. In this test system prohibited operating zone and transmission loss are not considered. The demand for this test system is 49,342MW. Out of 140 units, 6 thermal units, 4 gas units and two oil units have non - convex fuel cost function addressing valve loading effects.

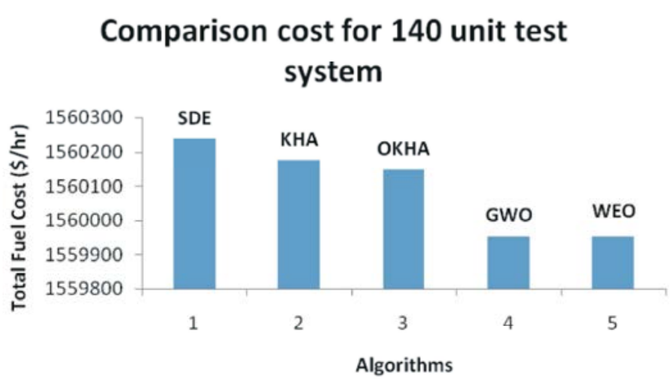

Fig. 3: Comparison of total fuel cost for 140 unit test system

Fig. 4: Objective values versus iterations of 140 unit test system

Table 2: The simulation results obtained by WEO algorithm for 140 unit test system

	GEN (MW)						GEN (MW)						GEN (MW)				
Unit no	SDE[37]	KHA[27]	OKHA[28]	GWO[32]	WEO	Unit no	SDE[37]	KHA[27]	OKHA[28]	GWO[32]	WEO	Unit no	SDE[37]	KHA[27]	OKHA[28]	GWO[32]	WEO
P_{1}	116.1654	118.3326	119	119	119	P_{48}	250	249	250	250	250	P_{95}	978	978	978	978	978
P_{2}	189	188.9995	189	189	189	P_{49}	250	250	250	250	250	P_{96}	682	682	682	682	682
P_{3}	190	189.9912	189.0012	190	190	P_{50}	250	250	250	250	250	P_{97}	720	719.6	720	720	720
P_{4}	190	189.2245	188.4245	190	190	P_{51}	165	165	165	165	165	P_{98}	718	717.8	718	718	718
P_{5}	168.5398	169.0012	169.1249	168.5397	168.5396	P_{52}	165	165	165	165	165	P_{99}	720	720	720	720	720
P_{6}	190	189.9832	189.9998	190	190	P_{53}	165	166	165	165	165	P_{100}	964	964	964	964	964
P_{7}	490	489.9968	490	490	490	P_{54}	165	165	165	165	165	P_{101}	958	958	958	958	958
P_{8}	490	489.9996	490	490	490	P_{55}	180	180	180	180	180	P_{102}	1007	1006.6667	1007	1007	1007
P_{9}	496	495.9902	496	496	496	P_{56}	180	180	180	180	180	P_{103}	1006	1005.998	1006	1006	1006
P_{10}	496	496	496	496	496	P_{57}	103	103.9942	103	103	103	P_{104}	1013	1013	1013	1013	1013
P_{11}	496	495.9993	496	496	496	P_{58}	198	199.0001	198	198	198	P_{105}	1020	1020	1020	1020	1020
P_{12}	496	496	496	496	496	P_{59}	312	311.99	312	312	312	P_{106}	954	954	954	954	954
P_{13}	506	505.965	506	506	506	P_{60}	281.8008	280.9912	281.9129	282.8903	282.9978	P_{107}	952	951	952	952	952
P_{14}	509	509	509	509	509	P_{61}	163	163	163	163	163	P_{108}	1006	1006	1006	1006	1006
P_{15}	506	505.9234	506	506	506	P_{62}	95	95	95	95	95	P_{109}	1013	1013	1013	1013	1013
P_{16}	505	504.9946	505	505	505	P_{63}	160.0001	160	160.2321	160.8840	160.9468	P_{110}	1021	1020.8998	1021	1021	1021
P_{17}	506	506	506	506	506	P_{64}	160	160	160	160	160	P_{111}	1015	1014.9989	1015	1015	1015
P_{18}	506	506	506	506	506	P_{65}	490	490	490	490	490	P_{112}	94	94.0001	94	94	94
P_{19}	505	504.9966	505	505	505	P_{66}	196.0001	201.2341	201.2341	196.2621	196.6122	P_{113}	94	94.1	94	94	94
P_{20}	505	504.9093	505	505	505	P_{67}	490	490	490	490	490	P_{114}	94	94	94	94	94
P_{21}	505	505	505	505	505	P_{68}	489.9999	488.1256	488.1256	489.6013	489.2746	P_{115}	244	244	244	244	244
P_{22}	505	504.9992	505	505	505	P_{69}	130	130	130	130	130	P_{116}	244	244.9	244	244	244
P_{23}	505	504.8982	505	505	505	P_{70}	234.7198	234.9838	233.9938	234.7006	234.7189	P_{117}	244	244	244	244	244
P_{24}	505	504.9668	505	505	505	P_{71}	137	137	137	137	137	P_{118}	95	95.6	95	95	95
P_{25}	537	536.9000	537	537	537	P_{72}	325.4956	325.9969	326.9969	325.8216	325.3296	P_{119}	95	95.0011	95	95	95
P_{26}	537	537	537	537	537	P_{73}	195	195	195	195	195	P_{120}	116	116.001	116	116	116
P_{27}	549	549	549	549	549	P_{74}	175	175	175	175.3892	175.2143	P_{121}	175	175.0032	175	175	175
P_{28}	549	549	549	549	549	P_{75}	175	175	175	175	175	P_{122}	2	2	2	2	2
P_{29}	501	501	501	501	501	P_{76}	175.0001	180	176	175.9936	175.2039	P_{123}	4	4	4	4	4
P_{30}	501	501	501	501	501	P_{77}	175	175	175	175.4087	175.4829	P_{124}	15	15.0002	15	15	15
P_{31}	506	506	506	506	506	P_{78}	330	330	330	330	330	P_{125}	9	9.2001	9	9	9
P_{32}	506	506	506	506	506	P_{79}	531	531	531	531	531	P_{126}	12	12.1001	12	12	12
P_{33}	506	506	506	506	506	P_{80}	531	531	531	531	531	P_{127}	10	10	10	10	10
P_{34}	506	506	506	506	506	P_{81}	368.6177	366.6179	367.6176	366.4013	366.5867	P_{128}	112	112.0042	112	112	112
P_{35}	500	500	500	500	500	P_{82}	56	56.2212	56	56	56	P_{129}	4	4.4262	4	4	4
P_{36}	500	500	500	500	500	P_{83}	115	115.2236	115	115	115	P_{130}	5	5.0022	5	5	5
P_{37}	241	241	241	241	241	P_{84}	115	115	115	115	115	P_{131}	5	5.0012	5	5	5
P_{38}	241	241	241	241	241	P_{85}	115	115	115	115	115	P_{132}	50	51.998	50	50	50
P_{39}	774	774	774	774	774	P_{86}	207	207	207	207	207	P_{133}	5	5.9942	5.5666	5	5.0689
P_{40}	769	769	769	769	769	P_{87}	207	207	207	207	207	P_{134}	42	42.9922	43.3363	42	42
P_{41}	3	3	3	3	3	P_{88}	175	175	175	175	175	P_{135}	42	42.9942	43.1223	42	42
P_{42}	3	3	3	3	3	P_{89}	175	175	175	175	175	P_{136}	41	41	41	41	41
P_{43}	249.9989	250	250	250	249.989	P_{90}	175	175	175	175	175	P_{137}	17	17	17	17	17
P_{44}	247.1855	249.9922	249.9911	249.9988	249.9978	P_{91}	175	175	175	175	175	P_{138}	18.9992	7.6659	12.7652	17	17
P_{45}	250	250	250	250	250	P_{92}	580	580	580	580	580	P_{139}	7	7.0042	8.112	7	7
P_{46}	250	250	250	250	250	P_{93}	645	645	645	645	645	P_{140}	39.1813	26.0486	27.1470	26.1302	27.0389
P_{47}	242.2959	248.7789	248.2960	249.9785	249.9983	P_{94}	984	984	984	984	984						

Table 3: Comparison of statistical results of earlier techniques for 140 unit test system

Methods	Best Cost ($/hr)	Mean Cost ($/hr)	Worst Cost ($/hr)
SDE [37]	1560236.85	NA	NA
KHA [27]	1560173.88	1560176.7448	1560177.8061
OKHA [28]	1560146.95	1560148.9264	1560149.9764
GWO [32]	1559953.18	1560132.93	1560228.40
WEO	1559952.90	1560128.67	1560589.34

The simulation is performed for 100 trials and obtained best generation scheduling for 140 unit test system in comparison with earlier methods is presented in Table 3. From the comparison results the proposed WEO as well as existing algorithms meet the load demand and satisfying system constraints fully. The total fuel cost obtained by the proposed WEO algorithm in comparison w ith recent techniques SDE [37], KHA [27], OKHA [28] and GWO [32] is shown in Figure 3. From the figure it is noticed that the proposed WEO algorithm obtain the minimum fuel cost of 1559952.9 ($/hr).

The Table 3 shows that statistical comparison total fuel cost obtained by the proposed WEO algorithm with earlier techniques. The objective value versus iterations for the 140 unit test system is shown in Figure 4. The converged results indicate that the proposed WEO algorithm is highly competitive with recent techniques.

CONCLUSION

The method economic load dispatch determines the most efficient, reliable and low cost operation of a power system by dispatching the power generation resources to supply the load on scheme and meet the other system constraints. A new physically inspired non - gradient algorithm named Water Evaporation Optimization (WEO) was successfully applied to solve ELD problems of various levels of complexity. The performance of the proposed WEO algorithm was tested for medium and large scale test systems and the results are compared with recent reports in the literature. In all cases the proposed algorithm achieves the competitive solution. The advantage of the proposed methodology are simple, easy to implement and applicable for large - scale practical systems. This study clearly indicates that the proposed WEO algorithm based methodology is a quite promising alternative for solving ELD problems.

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