Economic Dispatch with Multiple Fuel Options using Water Evaporation Optimization

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ABSTRACT
This paper presents Water Evaporation Optimization (WEO) algorithm for solving Economic Dispatch (ED) problem with multiple fuel options. The objective of the problem is to identify the most economical fuel for each generating unit in order to minimize the total fuel cost while satisfying system constraints. The valve point loading effects should also be considered to obtain a realistic and more accurate ED solution. The proposed WEO 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 proposed algorithm is implemented and tested on ten generating unit test system. The obtained results have shown that the proposed method is efficient for solving ED problem with multiple fuel options and favorable for implementation in large scale problems.

Keywords
Economic Load Dispatch, Multiple Fuel Options, Piecewise Quadratic Cost Function, Water Evaporation Optimization, Valve Point Loading Effects.

1. INTRODUCTION
In certain fossil fire systems, the generation cost function is represented as a segmented piecewise quadratic cost function. The generating unit, supplied with multi – fuel sources like coal, natural gas or oil suffers with the problem of determining the most economic fuel to burn. The multi – fuel effects with valve point loading effects add non – linearity to the traditional ED problem. In order to solve non – smooth and non – convex ED problem an analytical method named Quadratically Constrained Programming (QAP) has been proposed [1]. Due to the huge constraints and nonlinear characteristics of the ED problem, the calculus based methods cannot perform satisfactorily and are trapped to local optimum. Therefore conventional mathematical approaches are difficult to handle such a non – linearities hence a new numerical approaches are needed to cope with these difficulties [2-3].

The Hierarchical Method (HM) of Lagrangian multipliers to find the incremental fuel cost for subsystems comprising set units for solving ED with multiple fuel options has been proposed [4]. The solution searches for the optimal for various choices of fuel and generation range of the units iteratively. The major disadvantage of this method is assumption of initial lambda value. A Hopfield Neural Networks (HNN) [5], an improved adaptive HNN [6] has also been proposed to solve the ED with multiple fuel effects. The drawback of HNN method is slow convergence rate and more number of iterations. The Enhanced Augmented Lagrange Hopfield Network (EALHN) for solving economic dispatch with piecewise quadratic cost functions have been presented [7].

Economic dispatch solutions with piecewise quadratic cost functions solved by an Improved Genetic Algorithm (IGA) has been discussed [8]. In order to improve the effectiveness of GA multi-stage algorithm and directional crossover methods are proposed and projection method is introduced to satisfy a linear equality constraint from power balance. An improved GA with multiplier updating (IGA-MU) have been proposed to solve ED problem considering both valve – point loading effects and multiple fuels [9]. A real – coded version of GA has also been proposed to solve ED with non-smooth cost functions [10].

In recent years several artificial intelligence techniques like Particle Swarm Optimization (PSO) [11], Taguchi Method (TM) [12], Evolutionary Programming (EP) and their improved version [13-14], Bio – Geography Based Optimization (BBO) [15], Artificial Bee Colony (ABC) algorithm[16], Backtracking Search Algorithm (BSA) [17], Grey Wolf Optimization (GWO) [18], Opposition – based Greedy Heuristic Search (OGHS) [19], Synergic Predator – Prey Optimization (SPPO) [20] has been applied to solve the ED with non-smooth cost functions.

The algorithm based on the human understanding and searching capability for finding an optimum solution named Seeker Optimization Algorithm (SOA) developed and implemented to solve constrained economic load dispatch problem [21]. In this SOA, the search direction is based on empirical gradient by evaluating the response to the position changes and the step length is based on uncertainty reasoning by using simple fuzzy rule. An efficient Crisscross Optimization (CSO) solution to large – scale non – convex economic load dispatch with multiple fuel types and valve – point has been proposed [22]. The algorithm based on kinetic energy and the natural motions of gas molecules called Kinetic Gas Molecule Optimization (KGMO) have been presented to solve non convex economic dispatch problem [23].

The hybridized algorithm between Differential Evolution (DE) and PSO for solving economic load dispatch with multiple fuel effects has been discussed [24]. Recently, motivated by the shallow water theory, researchers have proposed Water Evaporation Optimization (WEO) algorithm for solving global optimization problem [25]. 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 WEO algorithm is used for selection of fuel and economic dispatch for the selected fuels.

2. PROBLEM FORMULATION

The objective of the ED problem with multiple fuel options is to find a suitable fuel for each generating unit so as their total cost is minimized while satisfying different constraints including power balance and generation limits.

$$Min\ F = \sum_{i=1}^{N} F_i(P_i) \tag{2.1}$$

Where

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i1}P_i + c_{i1}P_i^2,\ fuel\ 1; & P_{i,\min} \le P_i \le P_{i1} \\ a_{i2} + b_{i2}P_i + c_{i2}P_i^2,\ fuel\ 2; & P_{i1} \le P_i \le P_{i2} \\ ..... & \\ a_{ik} + b_{ik}P_i + c_{ik}P_i^2,\ fuel\ k; & P_{ik-1} \le P_i \le P_{i,\max} \end{cases} \tag{2.2}$$

Where a_{ik}, b_{ik} and c_{ik} are the cost coefficients of the i^{th} generator using the fuel type k.

Subject to

(a) Power balance constraint

$$\sum_{i=1}^{N} P_i - P_L - P_D = 0 \tag{2.3}$$

Where P_i is the output power of unit i (MW), P_L is the total network loss of the system (MW) and P_D is the total load demand of the system (MW), N is the number of online generating units.

The power loss is approximately calculated by

$$PL = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{oi}P_i + B_{oo} \tag{2.4}$$

Where B_{ij}, B_{oi}, B_{oo} are the transmission loss coefficients.

(b) Generator operating limits

$$P_{i,\min} \le P_i \le P_{i,\max};\ i = 1,2,.....N \tag{2.5}$$

Where $P_{i,min}$ and $P_{i,max}$ are the lower and upper generation limits of unit i (MW).

To obtain an accurate and practical economic dispatch solution, the realistic operation of the ELD problem should consider the valve – point effects in the cost model. Therefore a sinusoidal function is incorporated in to the quadratic function.

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i1}P_i + c_{i1}P_i^2 + \left|e_{i1} \times \sin\left(f_{i1} \times (P_{i1}^{\min} - P_{i1})\right)\right|,\ fuel\ 1; & P_{i,\min} \le P_i \le P_{i1} \\ a_{i2} + b_{i2}P_i + c_{i2}P_i^2 + \left|e_{i2} \times \sin\left(f_{i2} \times (P_{i2}^{\min} - P_{i2})\right)\right|,\ fuel\ 2; & P_{i1} \le P_i \le P_{i2} \\ ..... & \\ a_{ik} + b_{ik}P_i + c_{ik}P_i^2 + \left|e_{ik} \times \sin\left(f_{ik} \times (P_{ik}^{\min} - P_{ik})\right)\right|,\ fuel\ k; & P_{ik-1} \le P_i \le P_{i,\max} \end{cases} \tag{2.6}$$

3. 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 [25].

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.

$$E_{sub}(i)^t = \frac{(E_{\max} - E_{\min}) \times (Fit_i^t - Min(Fit))}{(MaX(Fit) - Min(Fit))} + E_{\min} \tag{3.1}$$

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.

$$MEP_{ij}^t = \begin{cases} 1 if\ rand_{ij} \le \exp\left(E_{sub}(i)^t\right) \\ 0 if\ rand_{ij} \ge \exp\left(E_{sub}(i)^t\right) \end{cases} \tag{3.2}$$

Where MEP_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. 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.

$$J(\theta) = J_o P_o \left(\frac{2}{3} + \frac{\cos^3\theta}{3} - \cos\theta\right)(1 - \cos\theta) \tag{3.3}$$

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.

$$\theta(i)^t = \frac{(\theta_{\max} - \theta_{\min}) \times (Fit_i^t - Min(Fit))}{(Max(Fit) - Min(Fit))} + \theta_{\min} \quad (3.4)$$

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.

$$DEP_{ij}^t = \begin{cases} 1 if\ rand_{ij} < J(\theta_i^{(t)}) \\ 0 if\ rand_{ij} \geq J(\theta_i^{(t)}) \end{cases} \quad (3.5)$$

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:

$$S = rand. \begin{pmatrix} WM^{(t)}[permute1(i)(j)] \\ -WM^{(t)}[permute2(i)(j)] \end{pmatrix} \quad (3.6)$$

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:

$$WM^{(t+1)} = WM^{(t)} + S \times \begin{cases} MEP^{(t)}\ t \leq t_{\max}/2 \\ DEP^{(t)}\ t > t_{\max}/2 \end{cases} \quad (3.7)$$

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 (3.2) & (3.5). For $t \leq t_{max}/2$, water molecules are globally evaporated based on monolayer evaporation probability MEP by using Eq (3.2). For $t > t_{max}/2$, evaporation occurs based on the droplet evaporation probability DEP by using Eq (3.5). 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 (3.1) and (3.4) respectively.

Step 3: Generating random permutation based step size matrix

A random permutation based step size matrix is generated according to Eq. (3.6)

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. (3.7). 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 with multiple fuel options is shown in Figure 1.

4. EXAMPLES AND SIMULATION RESULTS

The proposed methodology has been tested with 10 generating unit system with multiple fuel options 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 with multiple fuel effects has been validated by comparing the simulation results obtained from the other methods which are 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 Case 1

In this case the sample system consists of 10 generating units with multiple fuel options and valve point loading effect is not considered. The system particulars are available in the literature [9]. The load demand of 2700 MW is considered. The optimum fuel of each generating unit and economic dispatch of selected fuel obtained by the proposed WEO algorithm in comparison with existing algorithms are presented in Table 1. The simulation results shows that all algorithms are satisfies the generator

limit constraint and except HNN all other algorithms are satisfies the load demand. The simulation results indicates that the optimum fuel selection obtained by the proposed WEO algorithm is similar to the existing algorithms OGHS [19], CGA – MU [10], IGA – MU [9]. From the comparison it is also clear that the proposed WEO algorithm alone achieve the minimum fuel cost of 623.8079 ($/h) than HNN [5], AHNN [6], EP [4], CGA – MU [10], IGA – MU [9] and OGHS [19] algorithms. The objective value versus iterations curve is presented in Figure 2. The convergence curve implies that the objective value is minimized from larger value and it ensures that the proposed WEO algorithm is efficient and outperforms the existing algorithms in terms of achieve better results.

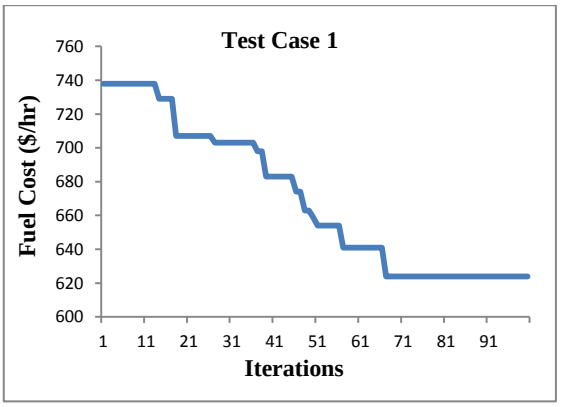

Fig 2: Objective value versus iterations of test case 1

4.2 Test Case 2

In this case the electric power test system consists of 10 – generating units considering multiple fuel options with valve point loading effect is studied for a load demand of 2700 MW. The system particulars are available in the literature [9]. The simulation results obtained by the proposed WEO and existing algorithms are presented in Table 2. In this case a proposed as well as other algorithm satisfies the load demand and generator limit constraint. The most economic fuel for each generation plant obtained by the proposed as well as existing algorithms are same. The total fuel costs obtained by the proposed WEO algorithm are compared with new particle swarm optimization-local random search (NPSO-LRS) [19], constraint treatment particle swarm optimization (CTPSO) [19], chaotic sequences particle swarm optimization (CSPSO) [19], crossover operation particle swarm optimization (COPSO) [19], both chaotic sequences and crossover operation particle swarm optimization (CCPSO) [19] and opposition-based greedy heuristic search (OGHS) [19]. The comparison make clear that the proposed algorithm alone reach the minimum fuel cost of 623.8238 ($/h). The cost convergence characteristic curve is depicted in Figure 3. The converged results indicate that the proposed algorithm is highly competitive with recent techniques.

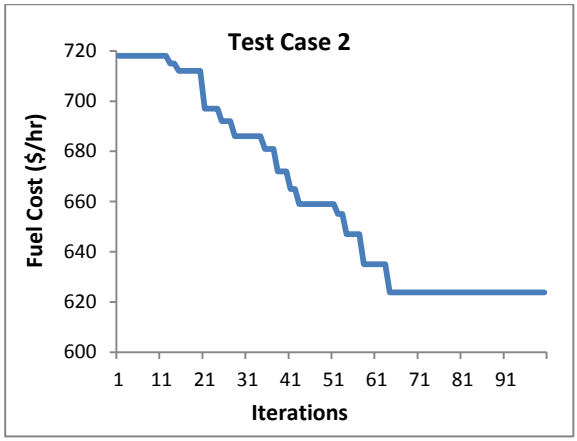

Fig 3: Cost convergence characteristic of test case 2

Table: 1 Simulation results obtained by the proposed WEO as well as existing algorithms for test case 1

Unit	HNN[5]		AHNN[6]		EP[4]		CGA-MU[10]		IGA-MU[9]		OGHS[19]		**WEO**	
	FT	P_{gi}	FT	P_{gi}	FT	P_{gi}	FT	P_{gi}	FT	P_{gi}	FT	P_{gi}	**FT**	**P_{gi}**
1	2	224.5	2	228.2	2	225.2	2	218.4572	2	218.1248	2	218.2648	**2**	**218.4162**
2	1	215.0	1	214.8	1	215.6	1	211.5140	1	211.6826	1	211.7042	**1**	**211.5543**
3	3	291.8	1	291.7	1	291.8	1	280.8987	1	280.8630	1	280.7813	**1**	**280.8774**
4	3	242.2	3	242.3	3	242.1	3	239.6241	3	239.6533	3	239.6363	**3**	**239.6242**
5	1	293.3	1	293.3	1	293.7	1	278.5036	1	278.6304	1	278.5239	**1**	**278.5238**
6	3	242.2	3	242.2	3	241.9	3	239.6390	3	239.6140	3	239.6266	**3**	**239.5261**
7	1	303.1	1	302.3	1	301.6	1	288.6201	1	288.5725	1	288.5204	**1**	**288.4176**
8	3	242.2	3	242.3	3	242.8	3	239.6211	3	239.7057	3	239.6341	**3**	**239.6840**
9	1	335.7	1	354.2	1	356.6	3	428.5760	3	428.4542	3	428.3894	**3**	**428.3894**
10	1	289.5	1	288.9	1	288.7	1	274.5462	1	274.6995	1	274.9174	**1**	**274.9840**
P_D	2699.7		2700		2700		2700		2700		2700		**2700**	
F_t	626.12		626.24		626.26		623.8095		623.8093		623.8082		**623.8079**	

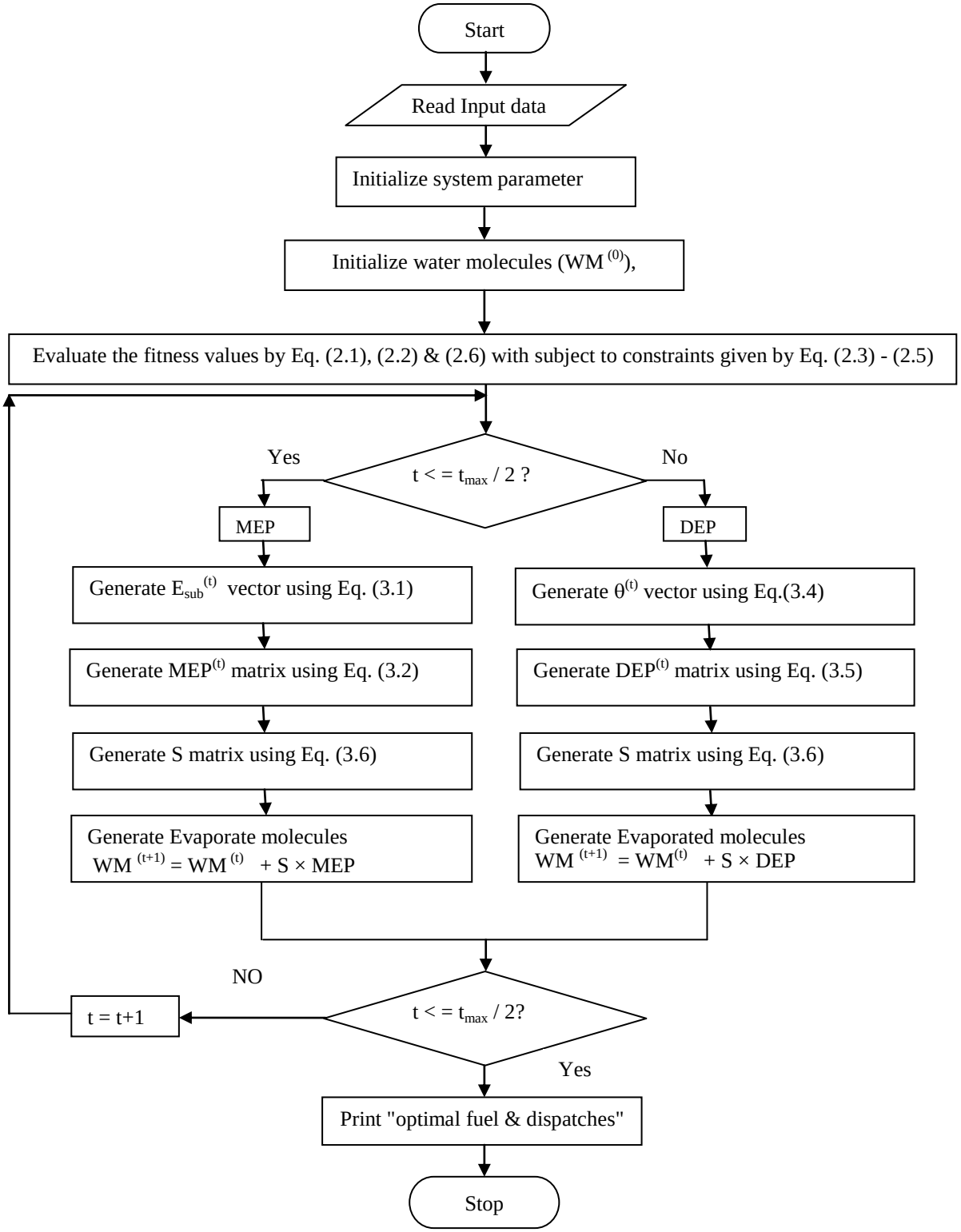

Fig 1: Flowchart for the proposed WEO algorithm to solve ELD with multiple fuel effects

Table: 2 Simulation results obtained by the proposed WEO as well as existing algorithms for test case 2

Unit	NPSO-LRS[19]		CTPSO[19]		CSPSO[19]		COPSO[19]		CCPSO[19]		OGHS[19]		**WEO**	
	FT	Pgi	FT	Pgi	FT	Pgi	FT	Pgi	FT	Pgi	FT	Pgi	**FT**	**Pgi**
1	2	223.3352	2	218.6807	2	219.6210	2	218.5940	2	218.5940	2	218.1046	**2**	**218.5939**
2	1	212.1957	1	211.4642	1	210.9690	1	211.7117	1	211.7117	1	212.1547	**1**	**211.7117**
3	1	276.2161	1	280.6545	1	279.6489	1	280.6571	1	280.6571	1	280.6580	**1**	**280.6572**
4	3	239.4187	3	240.4457	3	239.5051	3	239.6394	3	239.6394	3	239.6864	**3**	**239.6393**
5	1	274.6470	1	276.4034	1	279.8834	1	279.9345	1	279.9346	1	279.9067	**1**	**279.9369**
6	3	239.7974	3	240.1769	3	239.6394	3	239.6394	3	239.5051	3	239.6610	**3**	**239.6394**
7	1	285.5388	1	287.8657	1	289.9623	1	287.7275	1	287.7275	1	287.7285	**1**	**287.7150**
8	3	240.6323	3	240.5800	3	239.9082	3	239.6394	3	239.6394	3	239.8208	**3**	**239.6395**
9	3	429.2637	3	428.5886	3	425.0471	3	426.5883	3	426.7226	3	426.3710	**3**	**426.5863**
10	1	278.9541	1	275.1403	1	275.8157	1	275.8686	1	275.8686	1	275.9072	**1**	**275.8685**
PD	2700		2700		2700		2700		2700		2700		**2700**	
Ft($/h)	624.1273		623.8588		623.8420		623.8266		623.8266		623.8240		**623.8238**	

5. CONCLUSION

In practical conditions of power system operation, the fuel cost function of thermal generating units those are supplied with multiple fuel sources like coal, natural gas and oil may be segmented as piecewise quadratic cost function for representing different fuel types. The combined action of multiple fuel effects and valve point loading effects increases the degree of difficulty to solve the ELD problem. In this paper a new meta-heuristic technique named Water Evaporation Optimization algorithm is presented to solve an economic load dispatch problem considering multiple fuel effects, with and without considering valve point loading effects. To show the validity of the proposed WEO algorithm it has been implemented to solve an economic dispatch problem with piece wise quadratic cost function for a ten generating unit test system with load demand of 2700 MW with and without considering valve point loading effects. The simulation results are compared with many other methods available in the literature. The result comparison has indicated that the proposed WEO algorithm is efficient and effective than many other methods in terms of total cost. In future studies, the proposed WEO method can also be applied in other power system optimization problem such as unit commitment and generator maintenance scheduling in regulated and deregulated market.

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