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# Economic Load Dispatch with Multiple Fuel Options by Watercycle Algorithm

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***Abstract:*** *This paper proposes the application of novel natural based algorithm called water cycle algorithm (WCA) on economic load dispatch (ELD) problem with multiple fuel types. In practical operation of power systems, the fuel cost function characteristics of generating units which are supplied with multiple fuel sources, have piecewise quadratic shapes which makes the problem of finding the global optimum more difficult when using any mathematical approaches. The proposed algorithm is based T is based on how the streams and rivers flow downhill toward the sea and change back and has been applied on a 10 unit system with multiple fuel options as two case studies, considering and neglecting valve point loading effect and also with various load demand values. This 10 unit system has also been duplicated to challenge the algorithm with large scale 30, 60 and 100 unit case studies. The results demonstrate the excellent convergence characteristics of the proposed method.*

***Keywords***: *Economic load dispatch, watercycle algorithm, multiple fuels, optimization*.

## 1. Introduction

Economic load dispatch (ELD) is one of the most important issues of power systems along by other power system planning and scheduling tasks such as unit commitment and power flow studies. In ELD, the main objective is to find the optimal outputs of all generating units so that the required load demand and other system load requirements like transmission loss , spinning reserve at minimum operating cost are met while satisfying system equality and inequality constraints. Over the years, massive number of approaches have been proposed for different objective functions of economic load dispatch considering variety of constraints and options like valve point loading effect, transmission loss, prohibited zones of generators, ramp rate limits etc. When considering multiple fuel options, the traditional ELD objective function which is a single quadratic equation, meets some changes, meaning every generation bound which have a specific fuel type have a separate objective function similar to the traditional ELD function.

For the ELD with multiple fuel options, some traditional approaches like the method in [1, 2] which linearize the cost functions but doesn't give good quality solutions and also meta heuristic methods have been proposed such as conventional Hopfield neural network (HNN) [3] which is based on the minimization of its energy function when there is a status change of neurons and has the disadvantages of difficulty in handling nonlinear constraints and its convergence to optimal solution is also sensitive to the choice of penalty factors associated with constraints, enhanced Lagrangian neural network (ELANN) [4] which has more convergence quality compared to HNN, but suffers from the large number of iterations, Adaptive Hopfield neural network [5, 6] which has better solutions which are obtained faster than the aforementioned approaches. Few attempts also made for solving ELD problem with the combination of multiple fuel option and valve point loading effects , such as improved genetic algorithm (IGA) [7] and as improved genetic algorithm with multiplier updating (IGA-MU) [7].

In this paper the application of novel watercycle algorithm (WCA) [8] has been proposed to solve various types of ELD problem with multiple fuel units option. First a 10 unit case study considering multiple fuel options and neglecting valve points, then same previous system while considering both multiple fuels and valve point effects and finally large scale 30, 60 and 100 unit case studies based on basic 10 unit system have been tested to completely challenge the algorithm. Also a brief sensitivity analysis has been applied on the algorithm to demonstrate the algorithms sensitivity to the changes it's important parameters.

## 2. ELD formulation

ELD as an optimization problem with the goal of minimizing the total power system generation cost, can be formulated as follows:

$$\min \sum_{i=1}^{N} F_i(P_i) \tag{1}$$

Where $N$ is the number of generator units, $P_i$ is the power output of each unit and $F_i$ is the production cost of the $ith$ unit given as:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \tag{2}$$

However, due to valve-point loading of fossil fuel plants higher order nonlinearities are visible in the real input-output characteristics of units. So the valve-point effect causes ripples in the heat rate curves. To take this effect into account, sinusoidal functions are usually added to the quadratic cost functions as given in Eq. (3).

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| e_i \sin(f_i (P_i^{\min} - P_i)) \right| \tag{3}$$

When considering multiple fuel options, a more complex objective function will be resulted. In some practical systems, the dispatching units are practically supplied with multi fuel sources and each unit has piecewise quadratic functions given below:

$$F_i(P_i) = \begin{cases} a_{i1} P_i^2 + b_{i1} P_i + c_{i1}, fuel1, P_i^{\min} < P_i < P_{i1} \\ a_{i2} P_i^2 + b_{i2} P_i + c_{i2}, fuel2, P_{i1} < P_i < P_{i2} \\ \dots \\ a_{ik} P_i^2 + b_{ik} P_i + c_{ik}, fuelk, P_{ik-1} < P_i < P_i^{\max} \end{cases} \tag{4}$$

where $a_{ij}, b_{ij}, c_{ij}$ are cost coefficients of unit i for the jth fuel type.

## 3. Water cycle algorithm

### 3.1. Basic Concept

This novel nature inspired algorithm introduced in [8], is based on how the streams and rivers flow downhill toward the sea and change back. Water moves downhill in the form of streams and rivers starting from high up in the mountains and ending up in the sea. Streams and rivers collect water from the rain and other streams on their way downhill. The rivers and lakes water is evaporated when plants give off water as transpire process. Then clouds are generated when the evaporated water is carried in the atmosphere. These clouds condense in the colder atmosphere and release the water back in the rain form, creating new streams and rivers.

### 3.2. The process of WCA

Like other meta heuristic algorithms, the method begins with an initial population called raindrops resulting from rain or precipitation. The best raindrop is chosen as sea, a number of good raindrops as rivers and the rest of them are considered as streams flowing to rivers or directly to the sea.

***Create an Initial Population***

In GA [9] and PSO [10] Algorithms, arrays called ‘‘Chromosome’’ and ‘‘Particle Position’’ form the individuals carrying values of problem variables. In WCA, each array is called ‘‘Raindrop’’, for a single solution and for a $N$ dimensional optimization problem is defined as follows:

$$\text{Raindrop} = \left[ \chi_1, \chi_2, \chi_3, \dots, \chi_N \right] \tag{5}$$

Considering $N_{pop}$ individuals, the Raindrops matrix extends as follows:

$$\text{Population of raindrops} = \begin{bmatrix} Raindrops_1 \\ Raindrops_2 \\ Raindrops_3 \\ \vdots \\ Raindrops_{N_{pop}} \end{bmatrix} = \begin{bmatrix} \chi_1^1 & \chi_2^1 & \chi_3^1 & \cdots & \chi_{N\,\text{var}}^1 \\ \chi_1^2 & \chi_2^2 & \chi_3^2 & \cdots & \chi_{N\,\text{var}}^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \chi_1^{Npop} & \chi_2^{Npop} & \chi_3^{Npop} & \cdots & \chi_{N\,\text{var}}^{Npop} \end{bmatrix} \tag{6}$$

Where $N_{pop}$ is the number of raindrops and $N_{\text{var}}$ defines number of variables. In a randomly generated matrix of raindrops with the size of $N_{pop} \times N_{\text{var}}$, Each of the decision variable values $\left( \chi_1, \chi_2, \chi_3, \dots, \chi_N \right)$ can be represented as real values or as a predefined set for continuous and discrete problems, respectively. The fitness or cost of each row is obtained using the Cost function $(C)$ given as:

$$C_i = Cost_i = f(x_1^i, x_2^i, \dots, x_{N\,\text{var}}^i) \tag{7}$$
$$i = 1, 2, 3, \dots, N_{pop}$$

After generating $N_{pop}$ raindrops, a number of $N_{sr}$ among the best of them (which have the best fitness or minimum cost values) are chosen as rivers and sea. The raindrop which has the best function value is considered as sea. The rest of raindrops are considered as streams that may flow to the rivers or directly to the sea.

$$N_{sr} = \text{Number of Rivers} + \underbrace{1}_{Sea} \tag{8}$$

$$N_{Streams} = N_{pop} - N_{sr} \tag{9}$$

Streams are assigned to the rivers and sea depending on the intensity of the flow calculated with the equation below:

$$NS_n = round\left\{\left|\frac{Cost_n}{\sum_{i=1}^{NS_r} Cost_i}\right| \times N_{Streams}\right\} \quad (10)$$

Where $NS_n$ is the number of streams which flow to a specific river or sea.

***How do streams flow to the rivers or sea?***

The movement of a stream's flow to a specific river is applied along the connecting line between them using a randomly chosen distance as follows:

$$X \in (0, C \times d) \quad (11)$$

Where $C$ is a user defined value between 1 and 2 and $d$ is the current distance between stream and river. The value X is a number between 0 and $C \times d$ with any distribution. If the value of $C$ be greater than 1, the streams gain ability to flow in different directions toward the rivers. So the best value for $C$ may be chosen as 2. This concept can also be used in flowing rivers to the sea. So new position for streams and rivers can be calculated using:

$$X_{Stream}^{i+1} = X_{Stream}^{i} + rand \times C \times \left(X_{River}^{i} - X_{Stream}^{i}\right) \quad (12)$$

$$X_{River}^{i+1} = X_{River}^{i} + rand \times C \times \left(X_{Sea}^{i} - X_{River}^{i}\right) \quad (13)$$

where $rand$ is a uniformly distributed random number between 0 and 1. If any streams solution value is better than its connecting river, their position is changed (the stream becomes river and the corresponding river is considered as a stream). Also the position of sea and a river is changed if the river has a better solution than the sea.

***Evaporation condition***

This process has an important role in the algorithm preventing the algorithm from getting trapped in local optima and rapid convergence. The concept of this process is taken from the evaporation of water from sea while plants transpire water during photosynthesis. Then clouds are formed from the evaporated water and release them back to the earth in the form of rain and make new streams and rivers flowing to the sea. The following Pseudo code represents the determination of whether or not the evaporation and raining process happens.

*If* $\left|X_{Sea}^{i} - X_{River}^{i}\right| < d_{\max} \quad i = 1,2,3,...N_{sr} - 1$ (14)

*Evaporation and raining process*
*end*

where, $d_{\max}$ is a small number close to zero and controls the search depth, near the sea. When a large value of $d_{\max}$ is selected the search intensity is being reduces but its small value encourages it. When the distance between the river and sea is less than $d_{\max}$ the river has joined the sea. So, the evaporation process is applied and then the raining process will happen which is described in the incoming section. The value of $d$ decreases at the end of each iteration with equation below:

$$d_{\max}^{i+1} = d_{\max}^{i} - \frac{d_{\max}^{i}}{\text{max iteration}} \quad (15)$$

***Raining process***

This process is similar to the mutation operator in GA. The new randomly generated raindrops form new streams in different locations. Again the raindrop with the best function value among other new raindrops is considered as a river flowing to the sea. The rest of them are considered as new streams which flow to the river or go directly to the sea. For the streams that directly flow to the sea a specific equation which increases the exploration near sea is used, resulting improvements in the convergence rate and computational performance of the algorithm for constrained problems.

$$X_{stream}^{new} = X_{sea} + \sqrt{U} \times randn(1, N_{\text{var}}) \quad (16)$$

Where represents the standard deviation and $U$ defines the concept of variance. In fact the value of $U$ shows the range of searching region near the sea and $randn$ is a normally distributed random number. The most suitable value found for $U$ is 0.1, while the higher values increases the possibility of quitting from feasible region and the lower values reduce the searching space and exploration near the sea.

***WCA Steps***

The summary of WCA steps is described as follows:

Step 1: Choose initial WCA parameters: $N_{pop}$, $NS_n$, $N_{sr}$, $d_{\max}$, $C$ and $U$.

Step 2: Initialize Raindrops matrix randomly and form the initial streams, rivers and sea.

Step 3: evaluate each raindrop using the Cost function in Eq. (7).

Step 4: Calculate the intensity of the flow for rivers and sea using Eq. (10).

Step 5: The streams flow to the rivers and the rivers flow to the sea using Eqs. (12) and (13) respectively.

Step 6: Exchange positions of river with a stream which gives the best solution, and positions of sea with a better answering river

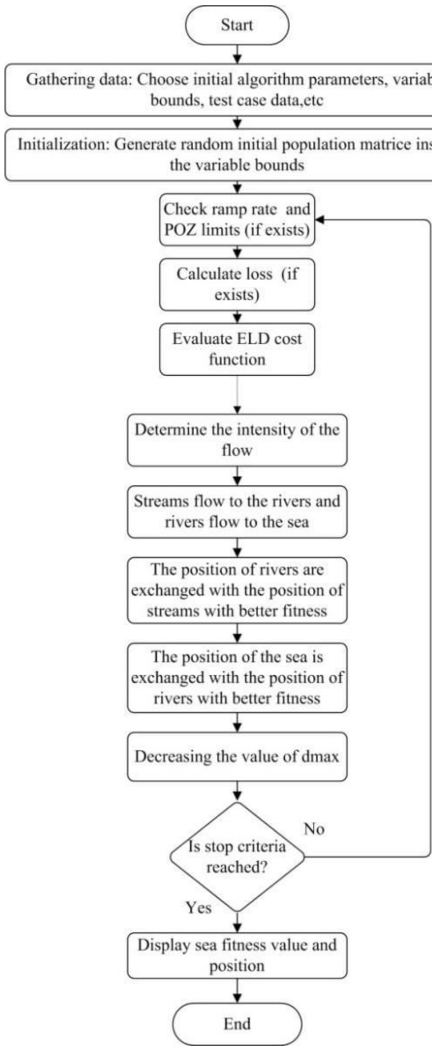


Fig.1: Flowchart of WCA applied on ELD problem.

Step 7: Check the evaporation condition using the Pseudocode in subsection 3.2.3 and the raining process will occur if it is satisfied using newly generated raindrops randomly or using Eq. (16).

Step 8: Reduce the value of $d_{\max}$ using Eq. (15).

Step 9: Check the stopping criteria. If the stopping criterion is satisfied, the algorithm will be stopped, otherwise return to Step 5. In this study the maximum number of iterations is considered as the stopping criteria. Figure 1 shows the flowchart of the proposed method.

## 4. Case studies

### 4.1. Test case I

A 10 unit system considering valve point loading effects and with load demands of 2400, 2500, 2300 and 2700 MW has been used to demonstrate the convergence and feasibility of the method. the system data is given in [7].The proposed method has been implemented in MATLAB 7.8 on a Pentium IV processor, 3 GHZ, with 3.0 GHZ of RAM. The algorithm parameters has been set to $N_{pop}$ =100, $N_{sr}$ =30, $d_{\max}$ =0.1, $C$ =2, U=0.1, $\beta$ =3 for all tests, the algorithm has been run for 20 times each time with 50 iterations. Table I represents the test results and figure2 show the convergence characteristics of the system for various load demands. Table II compares WCA best solution with results obtained by different previously applied methods.

### 4.2. Test case II

There are not much attempts made which consider both valve point effects and multiple fuels for ELD problem. So the second case has been concentrated on ELD problem with these specific characteristics. The system data is given in [7] also for this test case. For this test case only the load demand of 2700 MW has been considered and the algorithm parameters are set similar to the previous test case. Comparison results and convergence diagram are given in table III and figure 3 respectively.

### 4.3. Test case III

To completely challenge the algorithm, previous 10 unit system has been duplicated to create 30, 60 and 100 unit large scale test cases algorithm while the system load demand has also been increased proportionally.

TABLE I. Results by WCA for the load demand of 2400 to 2700 MW neglecting valve point effect

| Generator No | 2400(MW) | | 2500(MW) | | 2600(MW) | | 2700(MW) | |
|---|---|---|---|---|---|---|---|---|
| | Output | F | Output | F | Output | F | Output | F |
| 1(MW) | 189.73 | 1 | 206.52 | 2 | 216.58 | 2 | 218.27 | 2 |
| 2(MW) | 202.35 | 1 | 206.45 | 1 | 210.88 | 1 | 211.67 | 1 |
| 3(MW) | 253.89 | 1 | 265.74 | 1 | 278.51 | 1 | 280.72 | 1 |
| 4(MW) | 233.05 | 3 | 235.95 | 3 | 239.07 | 3 | 239.63 | 3 |
| 5(MW) | 241.85 | 1 | 258.01 | 1 | 275.53 | 1 | 278.49 | 1 |
| 6(MW) | 233.04 | 3 | 235.95 | 3 | 239.18 | 3 | 239.63 | 3 |
| 7(MW) | 253.26 | 1 | 268.87 | 1 | 285.70 | 1 | 288.60 | 1 |
| 8(MW) | 233.04 | 3 | 235.95 | 3 | 239.13 | 3 | 239.63 | 3 |
| 9(MW) | 320.38 | 1 | 331.49 | 1 | 343.52 | 3 | 428.47 | 3 |
| 10(MW) | 239.40 | 1 | 255.05 | 1 | 271.97 | 1 | 274.87 | 1 |
| $F_{total}$ ($/h) | 481.72 | | 526.22 | | 574.37 | | 623.79 | |

TABLE II. Comparison of the total fuel costs for the load demand of 2400 to 2700 MW neglecting valve point effect

| Methods | Total fuel cost | | | |
|---|---|---|---|---|
| | **2400(MW)** | **2500(MW)** | **2600(MW)** | **2700(MW)** |
| HNUM[2] | 488.50* | 526.70* | 574.03* | 625.18* |
| HNN[3] | 487.87* | 526.13* | 574.26* | 626.12* |
| AHNN[5] | 481.72 | 526.23 | 574.37 | 626.24 |
| ELANN[4] | 481.74 | 526.27 | 574.41 | 623.88 |
| IEP[11] | 481.779 | 526.304 | 574.473 | 623.851 |
| DE[12] | 481.723 | 526.239 | 574.381 | 623.809 |
| MPSO[13] | 481.723 | 526.239 | 574.381 | 623.809 |
| RCGA[14] | 481.723 | 526.239 | 574.396 | 623.809 |
| HRCGA[14] | 481.722 | 526.238 | 574.380 | 623.809 |
| AIS[15] | 481.723 | 526.240 | 574.381 | 623.809 |
| HICDEDP[16] | 481.723 | 526.239 | 574.381 | 623.809 |
| EALHN[17] | 481.723 | 526.239 | 574.381 | 623.809 |
| WCA | **481.7216** | **526.2279** | **574.3791** | **623.7980** |

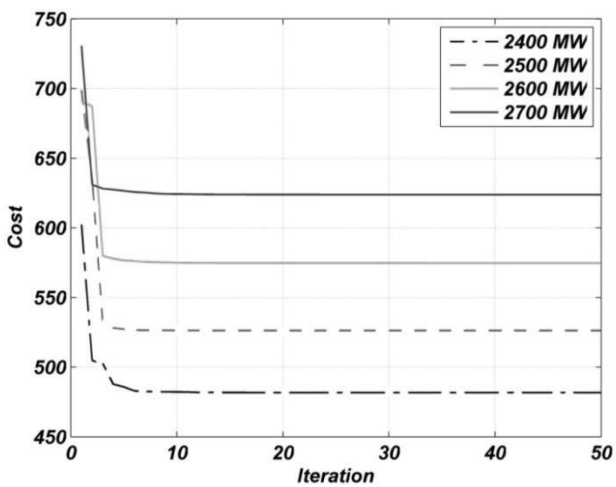


Fig. 2: Convergence characteristics of WCA for the load demands of 2400 to 2700 MW for test case I.

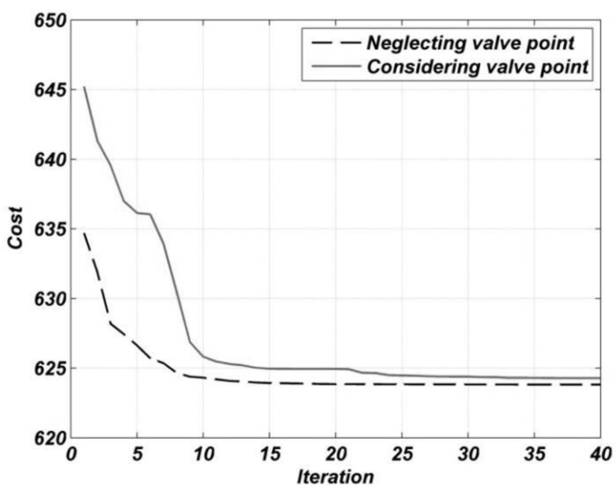


Fig. 3: Convergence characteristics of WCA for the load demands of 2700 MW for test case II.

TABLE III. Comparison of the total fuel costs for the load demand of 2700 MW considering valve point effect

| Generator No | CGA_MU[7] | | IGA_MU[7] | | WCA | |
|---|---|---|---|---|---|---|
| | Output | F | Output | F | Output | F |
| 1(MW) | 222.0108 | 2 | 219.1261 | 2 | 220.0550 | 2 |
| 2(MW) | 211.6352 | 1 | 211.1645 | 1 | 210.9169 | 1 |
| 3(MW) | 283.9455 | 1 | 280.6572 | 1 | 279.6702 | 1 |
| 4(MW) | 237.8052 | 3 | 238.4770 | 3 | 238.7458 | 3 |
| 5(MW) | 280.4480 | 1 | 276.4179 | 1 | 280.1485 | 1 |
| 6(MW) | 236.0330 | 3 | 240.4672 | 3 | 239.6610 | 3 |
| 7(MW) | 292.0499 | 1 | 287.7399 | 1 | 287.7073 | 1 |
| 8(MW) | 241.9708 | 3 | 240.7614 | 3 | 239.6864 | 3 |
| 9(MW) | 424.2011 | 3 | 429.3370 | 3 | 427.4088 | 3 |
| 10(MW) | 269.9005 | 1 | 275.8518 | 1 | 275.9998 | 1 |
| $F_{total}$ ($/h) | 624.7193 | | 624.5178 | | **623.8509** | |

TABLE IV. Comparison of total fuel cost for large scale 30, 60 and 100 unit systems

| Methods | No. of units (N) | Total cost ($) |
|---|---|---|
| WCA | 30 | **1871.0134** |
| | 60 | **3741.835** |
| | 100 | **6238.118** |
| CGA[18] | 30 | 1873.691 |
| | 60 | 3748.761 |
| | 100 | 6251.469 |
| IGA_AMUM[18] | 30 | 1872.047 |
| | 60 | 3744.722 |
| | 100 | 6242.787 |
| EALHN[17] | 30 | 1871.463 |
| | 60 | 3742.926 |
| | 100 | 6238.210 |

## 5. Discussion

Although WCA results are close to other previously applied methods especially on first two case studies but the execution time is much lower than others. For example in test case I, for RCGA [14] method, CPU time values of 49.92, 49.92, 33.57, 33.57 have been reported for the load demands of 2400, 2500, 2600 and 2700 MW respectively, While these values for WCA where 0.083, for all load demands, showing significant improvements similar to methods such as EALHN [17]. But unfortunately it may not directly and exactly comparable among the methods due to various computers and programming languages used. Even though this methods shows great convergence results with much low iterations which have lower costs than many other previously applied methods on this problem.

**Sensitivity analysis**

In order to observe the algorithm sensitivity to its parameters, additional studies have been done. First, WCA has been tested with different values of $d_{max}$. As mentioned in section 3.2.3 this parameter prevents the algorithm from getting trapped in local optima and rapid convergence which have a small decrease after each iteration. For the three different values of $d_{max}$, results and convergence characteristics are given in table V and figure 4, respectively.

Results show that if this parameter has much bigger value, the algorithm exploration ability will increase, but too much if this leads to a lower quality results compared to global minimum. Also if its value becomes much lower the search ability of the algorithm will decrease and the same lower quality results happen. The lower exploration ability for the low values of $d_{max}$ is obvious in the early iterations for the value of 0.01 in figure 4, which the algorithm cannot achieve much decrease in the first iterations. Finally the optimum value of 0.1, resulted the best solutions among multiple runs.

TABLE V. WCA results of different values of $d_{max}$

| Generator No | $d_{max}$=2 | | $d_{max}$=0.1 | | $d_{max}$=0.01 | |
|---|---|---|---|---|---|---|
| | Output | F | Output | F | Output | F |
| 1(MW) | 218.5807 | 2 | 220.0550 | 2 | 216.3999 | 2 |
| 2(MW) | 214.1351 | 1 | 210.9169 | 1 | 211.4120 | 1 |
| 3(MW) | 280.6462 | 1 | 279.6702 | 1 | 284.4471 | 1 |
| 4(MW) | 239.2832 | 3 | 238.7458 | 3 | 240.7613 | 3 |
| 5(MW) | 273.7120 | 1 | 280.1485 | 1 | 278.8212 | 1 |
| 6(MW) | 239.1236 | 3 | 239.6610 | 3 | 237.2423 | 3 |
| 7(MW) | 287.7891 | 1 | 287.7073 | 1 | 289.7176 | 1 |
| 8(MW) | 239.9551 | 3 | 239.6864 | 3 | 240.8957 | 3 |
| 9(MW) | 427.5427 | 3 | 427.4088 | 3 | 425.7371 | 3 |
| 10(MW) | 279.1428 | 1 | 275.9998 | 1 | 274.5656 | 1 |
| $F_{total}$ (\$/h) | 623.9863 | | **623.8509** | | 623.9657 | |

For the second analysis, the parameter of C has been considered. As mentioned in 3.2.2. This parameter controls how the streams flow to rivers or sea and gets a user defined value between 0 and 2. If the value of $C$ be greater than 1, the streams will gain ability to flow in different directions toward the rivers but for the values lower than 1 the streams just will get close in one direction. As mentioned in the main WCA article [8], the value of 2 usually gives the best solutions which have been demonstrated in table VI and fig 5.

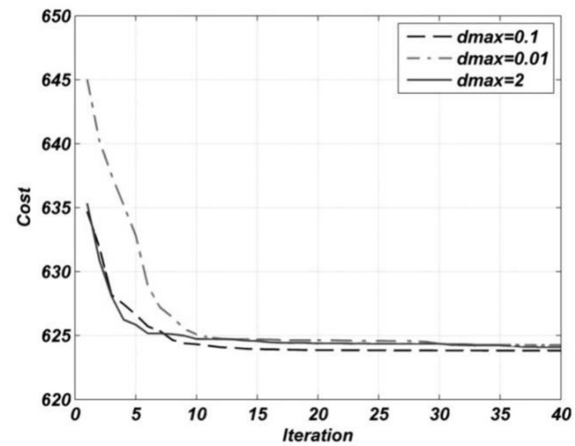


Fig. 4: Sensitivity analysis of the 10 unit system for the load demand of 2700 MW with different values of d $_{max}$

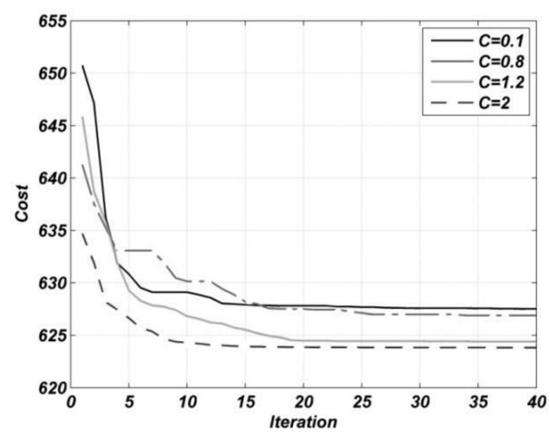


Fig. 5: Sensitivity analysis of the 10 unit system for the load demand of 2700 MW with different values of C.

TABLE VI. WCA results for different values of C

| Generator No | C=0.1 | | C=0.8 | | C=1.4 | | C=2 | |
|---|---|---|---|---|---|---|---|---|
| | Output | F | Output | F | Output | F | Output | F |
| 1(MW) | 219.5905 | 2 | 215.2694 | 2 | 212.0377 | 2 | 220.0550 | 2 |
| 2(MW) | 207.1839 | 1 | 222.9899 | 1 | 215.1524 | 1 | 210.9169 | 1 |
| 3(MW) | 297.7758 | 1 | 283.4461 | 1 | 279.4089 | 1 | 279.6702 | 1 |
| 4(MW) | 242.3708 | 3 | 241.0252 | 3 | 240.6257 | 3 | 238.7458 | 3 |
| 5(MW) | 311.3986 | 1 | 294.1461 | 1 | 279.5790 | 1 | 280.1485 | 1 |
| 6(MW) | 245.5736 | 3 | 244.8194 | 3 | 240.0692 | 3 | 239.6610 | 3 |
| 7(MW) | 302.0291 | 1 | 277.4023 | 1 | 285.1218 | 1 | 287.7073 | 1 |
| 8(MW) | 244.5238 | 3 | 243.4481 | 3 | 236.9990 | 3 | 239.6864 | 3 |
| 9(MW) | 350.3311 | 3 | 393.6467 | 3 | 424.3429 | 3 | 427.4088 | 3 |
| 10(MW) | 279.1511 | 1 | 283.6891 | 1 | 286.5712 | 1 | 275.9998 | 1 |
| $F_{total}$ (\$/h) | 627.4213 | | 626.3751 | | 624.3440 | | **623.8509** | |

## 6. Conclusion

In this paper, application of novel Watercycle algorithm on economic load dispatch problem with multiple fuel options has been studied. This novel nature inspired algorithm is based on how the streams and rivers flow downhill toward the sea and change back. A 10 unit system which is being used most in ELD with multiple fuel option studies has been used as the main case study. Additional case studies which simultaneously consider multiple fuels and valve point effects, and also large scale 30, 60 and 100 unit systems based on main 10 unit system have been used. Also a useful sensitivity analysis has been studied for two parameters of WCA, with results which can be useful for further usages of this algorithm in other studies.

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