

## **INVASIVE WEED OPTIMIZATION FOR ECONOMIC DISPATCH WITH VALVE POINT EFFECTS**

RAMA PRABHA D.\* , JAYABARATHI T., MAGESHVARAN R.,  
VUDUTALA RAHUL BHARADWAJ, GUNDLA SIDDHARTHA

School of Electrical Engineering, VIT University, Vellore-632 014, Tamilnadu India

\*Corresponding Author: dramaprabha@vit.ac.in

### **Abstract**

This paper proposes a novel optimization methodology aimed at solving economic dispatch (ED) problem considering valve point effects using invasive weed optimization (IWO) algorithm. IWO was recently proposed as a simple but powerful metaheuristic algorithm for real parameter optimization. IWO draws inspiration from the ecological process of weeds colonization and distribution and is capable of solving general multi-dimensional, linear and nonlinear optimization problems with appreciable efficiency. The proposed method has been applied to three test systems comprising 3, 13 and 40 units. These test systems are also solved using the catfish particle swarm optimisation (Catfish PSO) algorithm - an improved version of PSO - for the comparison and validation of the solutions. The obtained best values have been compared with different methods in literature and the results of them have been discussed. The result obtained proves that the IWO algorithm is efficient and can be used practically for solving economic dispatch problem. A comparative analysis with other settled nature-inspired solution algorithms demonstrates the superior performance of the proposed methodology in terms of both solution accuracy and convergence performances.

Keywords: Economic dispatch, Valve point effects, Invasive weed optimization, Metaheuristic algorithm, Particle swarm optimization.

### **1. Introduction**

Economic dispatch problem is allocating loads to plants for minimum cost while meeting the constraints. It is formulated as an optimization problem of minimizing the total fuel cost of all the committed plants while meeting the load demand and losses. In conventional ED, Lagrangian multipliers are employed to

**Nomenclatures**

$a_i, b_i, c_i$	Cost efficient of $i^{\text{th}}$ unit
$e_i, f_i$	
$c_1, c_2$	Cognitive and social acceleration coefficient
$C_i$	Total fuel cost of $i^{\text{th}}$ generator, \$/hr
$C_T$	Total generation cost, \$
$P_D$	Total demand
$P_G^t$	Best position of the group until iteration $t$
$P_i$	Real power at bus $i$
$P_i^{\max}$	Maximum power outputs of $i^{\text{th}}$ unit
$P_i^{\min}$	Minimum power outputs of $i^{\text{th}}$ unit
$P_i^t$	Best position of particle $i$ until iteration $t$
$P_L$	Total power loss
$r_1, r_2$	Random numbers between 0 and 1
$sd_{\max}$	Maximum deviation
$sd_{\min}$	Minimum deviation
$t_{\max}$	Maximum number of iterations
$V_i^t$	Velocity of particle $i$ at iteration $t$
$w_{\max}$	Initial weights
$w_{\min}$	final weights
$X_i^t$	Position of particle $i$ at iteration $t$

**Greek Symbols**

$\theta$ -PSO     $\theta$ -Particle Swarm Optimisation

**Abbreviations**

BBO	Biogeography Based Optimisation
Catfish	Catfish Particle Swarm Optimisation
PSO	
CEP	Classical Evolutionary Programming
DE	Differential Evolution
EA	Evolutionary Algorithm
ED	Economic Dispatch
FCASO	Fuzzy adaptive Chaotic Ant Swarm Optimisation
FEP	Fast Evolutionary Programming
GA	Genetic Algorithm
GAAPI	Genetic Algorithm and Ant Colony Optimization
HGA	Hybrid Genetic Algorithm
HGPSO	Hybrid Gradient descent PSO
HP-SOM	Hybrid Particle Swarm Optimizer with Mutation
HPSO	Hybrid Particle Swarm Optimisation with Wavelet Mutation
WM	
IABC	Incremental Artificial Bee Colony
IABC-LS	Incremental Artificial Bee Colony with Local Search

IFEP	Improved Fast Evolutionary Programming
IWO	Invasive Weed Optimisation
MFEP	Mean Fast Evolutionary Programming
MTS	Multiple Tabu Search
PSO	Particle Swarm Optimisation
PSO_T	PSO with Time Varying Acceleration Coefficients
VAC	
PSO-	PSO with Sequential Quadratic Programming
SQP	
QPSO	Quantum-inspired PSO
SA	Simulated Annealing
SDE	Shuffled Differential Evolution
SFLA	Shuffled Frog Leaping Algorithm
SPSO	Standard PSO
SQP	Sequential Quadratic Programming

solve the monotonically increasing incremental cost curves. Unfortunately, the input-output characteristics of modern units are highly nonlinear because of valve point loading effects, ramp rate limits, etc., and they lead to multiple local minimum points in the cost function.

An evolutionary programming is an useful tool for handling the nonlinear ED problems. Various modifications in the basic method have been proposed in [1] to enhance the speed of convergence. In [2], the incremental artificial bee colony (IABC) algorithm based on the incremental social learning framework has been proposed for ED problems. The hybrid particle swarm optimisation with wavelet mutation (HPSOWM) has been shown as a useful tool to solve optimisation problems. Due to the wavelet properties, the quality and the stability of the hybrid PSO is improved and it has been used for solving ED problems in [3].

An approach that combines the benefits of both PSO and anti-predatory nature has been proposed in [4]. In classical PSO, inertial, cognitive and social behaviours of the particle are considered. Here another activity which help the swarm to escape from predator called as anti-predatory nature has been considered. The result obtained by this algorithm has shown the superior performance in terms of both solution accuracy and convergence performance.

Due to swarm diversity loss the PSO may be trapped in local minima. In order to overcome this drawback, an efficient method has been developed by integrating PSO technique with the sequential quadratic programming (SQP) technique in [5]. Multiple tabu search (MTS) introduced in [6], shows that the proposed method is capable of obtaining higher quality solution efficiently at the lowest computational time. Biogeography-based optimization (BBO) algorithm which is considered to be a promising alternative approach is proposed in [7].

PSO with time varying acceleration coefficients (PSO\_TVAC) is applied for constrained ED problem in [8, 19]. Here the premature convergence is avoided and the global solutions are achieved using the TVAC. In [9] a quantum-inspired PSO (QPSO) based on the concepts and principles of quantum computing, which can strike the right balance between exploration and exploitation more easily when compared with conventional EAs are introduced. Meanwhile, the QPSO can explore the search space with a smaller number of individuals and exploit global solution within a short span of time.

Differential evolution (DE), a population-based stochastic search technique that works in the general framework of evolutionary algorithms is proposed to solve ED problems in [10]. An efficient hybrid genetic algorithm (HGA) approach for solving ED problems with valve point effects is proposed in [11].

A new numerical stochastic optimization algorithm, Invasive weed optimization (IWO) algorithm inspired from colonising weeds, is proposed for electromagnetic applications in [12]. In [13], the IWO algorithm is used for solving general multi-dimensional, linear and nonlinear optimization problems. IWO algorithm has been applied for various optimisation problems including design of a periodic antenna arrays [14], linear antenna array synthesis [15], design of non-uniform circular antenna array [16], analysis of pareto improvement model in electricity market [17] and so on.

PSO algorithm to solve various types of ED problems is proposed in [18]. An improved version of PSO namely the catfish particle swarm optimisation (Catfish PSO) is introduced in [20]. The catfish particles are introduced in PSO in order to move the whole swarm to promising new regions of the search space and accelerate convergence.

An innovative technique called shuffled differential evolution (SDE) characterized by a novel mutation operator that overcomes the intrinsic limitations of DE and SFLA is proposed in solving non-convex ED problems in [21]. A hybrid method integrating the fuzzy adaptive chaotic ant swarm optimisation (FCASO) algorithm and the sequential quadratic programming (SQP), named FCASO-SQP is used to solve the ED problem in [22]. In [23], the standard PSO is modified by replacing its velocity vector with a phase angle vector to decide the positions of particles and it is named as  $\theta$ -particle swarm optimisation ( $\theta$ -PSO).

In this paper, IWO algorithm is used for solving the economic dispatch problem with valve point effects. The IWO algorithm was proposed in 2006 by Mehrabian and Lucas and since then, it has already found many real-world applications such as optimal positioning of piezoelectric actuators on a smart fin [24], optimal locations of base stations and channel assignments in UMTS mobile networks [25], electric market dynamics [26] and antenna design and configuration [27], IWO is a derivative free algorithm, this property helps the algorithm to converge faster. It converges to the optimal solution thereby eliminate the possible sub optimal solutions. IWO algorithm also involves the simple coding [30]. In [31] the optimisation algorithm used for finding the real and complex roots of the systems have been discussed. Multi-objective optimisation problems and previous studies show that it is used as a global optimizer for solving numerical benchmark as well as real world problems [32].

The cost curves are highly nonlinear because of valve point effects, ramp rate limits, etc., and they lead to multiple local minimum points in the cost function. Since IWO is capable of escaping from these local minimum points its applicability has been shown in this paper. The results obtained from IWO are compared with those obtained from the Catfish PSO algorithm for authenticity. Comparison shows that the IWO gives better solutions than the Catfish PSO. The remainder of the paper is organised as follows. The ED model is described in section 2. The Catfish PSO is briefly discussed in section 3. Sections 4 and 5 include introduction to the IWO

algorithm and its implementation to ED problems. Numerical results are presented in section 6. Section 7 gives the conclusions.

## 2. Problem Formulation

The main objective of ED is to find the optimal generation values such that the total cost of generation is minimum while satisfying at the same time, both equality and inequality constraints. For a power plant containing  $N$  generation units and each generating  $P_i$  MW of power, the optimisation problem of classical ED can be formalized by a constrained nonlinear optimisation problem as

$$\text{Minimize } C_T = \text{Min. } \sum_{i=1}^N C_i(P_i) \tag{1}$$

where  $C_T$  is the total generation cost (\$) and  $C_i$  is the total fuel cost of  $i^{th}$  generator (\$/hour).

Usually, fuel cost of generating unit is expressed as a second order approximate function of its output power  $P_i$  as.

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

where  $a_i, b_i, c_i$  are fuel cost coefficients of unit. In order to account for valve point effects, a sinusoidal function is added to the fuel cost function and is represented as

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

where  $e_i$  and  $f_i$  are the coefficients of the generator  $i$  reflecting the valve point effect. This objective with sinusoidal term is a complex function with a multiple local optima.

*Subject to the constraints*

$$\sum_{i=1}^{NG} (P_{Gi}) - P_D - P_L = 0 \tag{4}$$

The losses,  $P_L$  can be calculated using B-loss coefficients. But this is neglected in this paper.

$$P_i^{min} \leq P_i \leq P_i^{max} \tag{5}$$

where  $P_i^{min}$  and  $P_i^{max}$  are minimum and maximum power outputs of  $i^{th}$  unit.

## 3. Catfish PSO for Economic Dispatch

PSO is a multi-point, random search technique which can easily handle any objective function irrespective of its shape. While the standard or basic PSO performs better than algorithms like the simple genetic algorithm (GA), Simulated Annealing (SA) and Tabu search, in terms of its ability to find global optima, it is still vulnerable to getting trapped in local optima in ED problems which have multiple local optima [20]. Several variants of PSO have been proposed to avoid this convergence to local optima. One such variant is the Catfish PSO, which differs from the basic PSO as follows. Unlike in the basic PSO, the catfish particles initialize a new search from the extreme points of the search space when the global best fitness value remains unchanged across a few iterations. In the

Catfish PSO, ten percent of the original particles are randomly selected and replaced with catfish particles. The catfish particles are those with generator outputs at extreme values, that is, the positions with (Min, Min), (Min, Max), (Max, Min), (Max, Max). In both the PSO and the catfish PSO, the velocity and position of each particle are updated as follows

$$V_i^t = w^t V_i^{t-1} + c_1 * r_1 * (P_i^{t-1} - X_i^{t-1}) + c_2 * r_2 * (P_G^{t-1} - X_i^{t-1}) \quad (6)$$

$$X_i^t = X_i^{t-1} + V_i^t \quad (7)$$

The weighing factor is modified by

$$w^t = w_{max} - \frac{(w_{max} - w_{min})}{t_{max}} t \quad (8)$$

#### 4. The Invasive weed optimization algorithm

The invasive weed optimization was developed by mehrabian and lucas in 2006. It is a bio- inspired algorithm that simulates the natural behavior of seeds in colonizing and finding suitable places for growth and reproduction. There are four steps of the algorithm as described below

- I. Initialisation: A search space is taken and a certain number of weeds are initialised randomly in the entire search space
- II. Reproduction: The randomly produced weeds are now allowed to produce seeds. The production of seeds by a weed is dependent on its own fitness and the fitness of its colony. The weed having more fitness produces maximum number of seeds whereas the weed with least fitness produces minimum number of seeds. The seeds produced by weeds increase linearly starting with worst fitness and ending with the best fitness.
- III. Spatial dispersion: The generated seeds are randomly distributed in the entire search space by normal distribution with zero mean and varying standard deviation. The constraint mean is maintained zero with varying variance. This step ensures that the seed is randomly distributed around the parent weed. The standard deviation (SD) decreases with increase in iterations in a nonlinear manner.

Let  $n$  be any real number (generally, we consider it as modulation index), the standard deviation of a particular iteration is given as

$$sd_{iter} = \frac{(iter_{max} - iter)^n}{iter_{max}} (sd_{max} - sd_{min}) + sd_{min} \quad (9)$$

This step ensures that the probability of dropping a seed in distant area decreases nonlinearly. By this we can group the fitter plants from that of the inappropriate plants.

- IV. Competitive Exclusion: There exists a competition between plants for survival. If a plant produces no offspring, it goes extinct. The initial plants in the colony reproduce plants very fast and all the plants will be considered in the colony. But the population cannot go more than  $pop_{max}$ . So the plants with more fitness are taken into the colony and the less fitter plants are neglected. Now, in this step the plants in the colony are considered as parent plants and steps 2-4 are repeated again until the maximum number of iterations is reached. This is the selection procedure of IWO.

One important property of the IWO algorithm is that it allows all of the plants to participate in the reproduction process. Fitter plants produce more seeds than less fit plants, which tends to improve the convergence of the algorithm. Furthermore, it is possible that some of the plants with the lower fitness carry more useful information compared to the fitter plants. This property of IWO gives a chance even to the lesser fit plants to reproduce and if the seeds produced by them have good fitnesses in the colony, they can survive to find the better solutions.

## 5. Implementation of IWO Algorithm for ED Problems

In IWO algorithm, each weed is a candidate solution to the ED problem. It is a vector of generator outputs. The fitness of each weed is calculated by using the cost function. The lowest cost function has the highest fitness in this cost minimisation problem. Depending on the fitness the seeds are produced linearly. As the number of seeds and weeds cannot exceed maximum population, the fitness of all seeds and weeds are calculated and ranked in descending order. The algorithm is as follows

1. A certain number of initial weeds are initialised in the entire search space using uniform distribution.
2. Each weed consists of N generators. The power values of the generators are made to be bounded in specified range.
3. The fitness value of each weed is calculated by substituting the generator values of corresponding weed in the cost function given by Eq. (3)
4. The weeds with the highest fitness produce the maximum number of seeds and those with lowest fitness produce minimum seeds. The seeds produced by a weed is calculated by using

$$s(i) = s_{max} - \left( abs \left( floor \left( s_{max} * \frac{g_{best} - rk(i)}{g_{best} - g_{worst}} \right) \right) \right) \quad (10)$$

5. The produced seeds are randomly distributed near the parent weed with zero mean and varying standard deviation. The standard deviation is calculated using Eq. (9).
6. Now the generated seeds are added to the solution set and the fitness values are calculated for the combined set of weeds and seeds.
7. The population is sorted in descending order of their fitness. Truncate the population with minimum fitness until the maximum population is reached and the fitness of the new solution set is calculated.
8. The process stops when the maximum number of iterations is reached.

## 6. Simulation Results

The proposed method has been tested on three test systems (3, 13 and 40 units) with valve point effects. For comparison, these test systems have also been solved by the Catfish PSO. The results have been compared with several previously published approaches and the Catfish PSO. The software was written in Matlab and executed on a PC with 2.4 GHz, Intel i5 processor with 4 GB RAM. In all these examples better solutions are obtained since the trajectory of the solutions

follows the path of high probability of improved solutions. This might have helped in avoiding local optima. The IWO algorithm appears to converge faster since by applying different initial or final standard deviation values, the convergence speed or the level of the cost function doesn't change too much.

In all the three examples solved by the proposed IWO method, the parameters used are modulation index = 2, maximum population of seeds = 40, maximum number of seeds = 5, minimum number of seeds = 1, sigma initial = 2 and sigma final = 0.001. The parameters of the Catfish PSO algorithm used for comparison are: population size = 40,  $c1 = 2$  and  $c2 = 2$ .

### 6.1. Three unit system with valve point effects

This is a small system consisting of three generating units with a demand of 850MW. The required data of the test system is given in [1].

The comparison of the generator outputs using the proposed method and QPSO [9], SPSO [3], PSO [19] and the Catfish PSO are presented in Table 1. To verify the performance of the proposed algorithm, this test case was repeatedly solved 100 times and the best solutions are presented in Table 2. This table also shows the comparison of the solutions obtained by several other methods. The optimal cost obtained by the proposed method is \$8234.07. The convergence characteristics for the IWO and the Catfish PSO methods are shown in Fig. 1. It is observed that the IWO method converges to a better solution than Catfish PSO.

**Table 1. Comparison of generated outputs of Three unit system using different methods.**

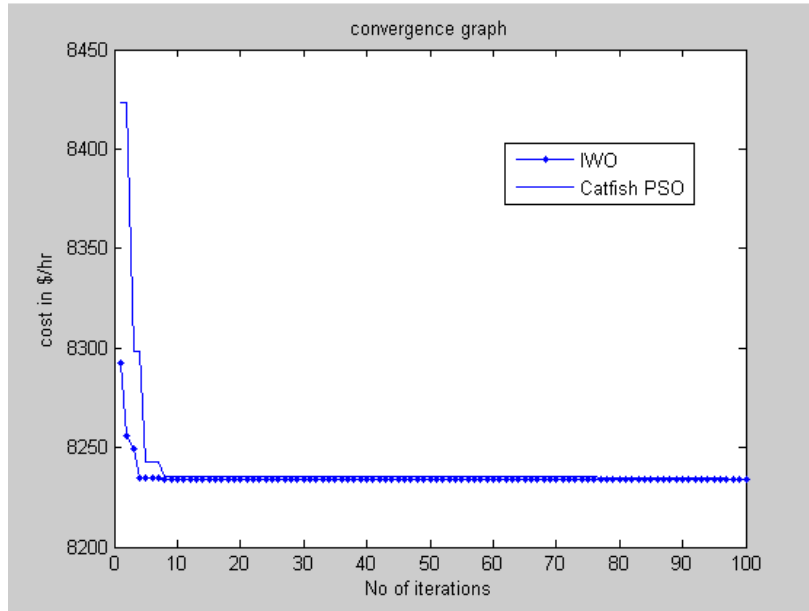
Method	P1(MW)	P2(MW)	P3(MW)
QPSO[9]	300.270	149.730	400.000
SPSO[3]	300.270	149.730	400.000
PSO[19]	300.267	149.733	400.000
GAAPI[28]	300.25	149.77	399.98
Catfish PSO	300.264	149.736	400.000
IWO	300.267	149.733	400.000

**Table 2. Comparison of total cost values of Three unit system using different methods.**

Method	Min Cost(\$/h)	Mean Cost(\$/h)	Max Cost(\$/h)
CEP[1]	8234.07	8235.97	8241.83
FEP[1]	8234.07	8234.24	8241.78
MFEP[1]	8234.08	8234.71	8241.80
IFEP[1]	8234.07	8234.16	8234.54
QPSO[9]	8234.07	8234.10	NA
SPSO[3]	8234.07	8234.18	NA
PSO[19]	8234.07	8234.07	NA
GAAPI[28]	8234.07	8234.07	NA
GSA[29]	8234.07	8234.11	8241.95
Catfish PSO	8234.07	8236.52	8241.4
IWO	8234.07	8236.97	8241.2

NA\* – not appeared in that paper





**Fig. 1. Convergence characteristics of IWO and the Catfish PSO for Three unit system.**

**6.2. Thirteen unit system with valve point effects**

This test system has a demand of 1800 MW. The data of the test system is given in [1]. The comparison of the generator outputs obtained using the proposed IWO and the Catfish PSO are presented in Table 3. Table 4 shows the comparison of the solutions obtained by IWO and several other methods such as the CEP [1], FEP [2], MEP [1], IFEP [1], PSO [19] and the Catfish PSO.

**Table 3. Comparison of generated outputs of Thirteen unit system using IWO and the Catfish PSO.**

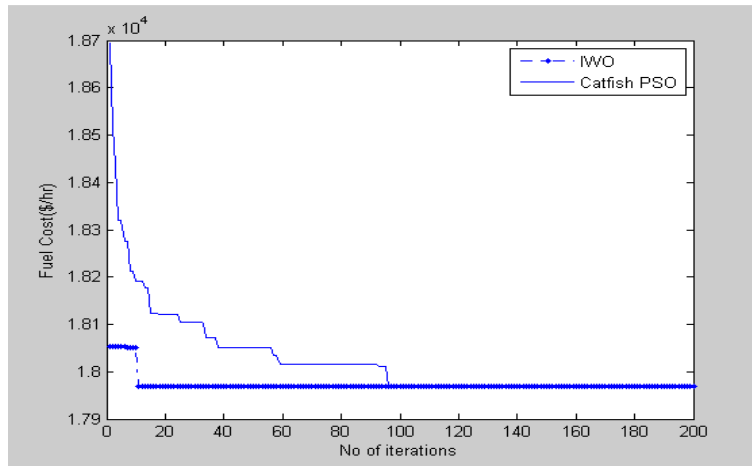
Gen. Output	Catfish PSO	IWO	Gen. Output	Catfish PSO	IWO
P1	538.5610	538.5555	P8	109.9090	109.8666
P2	149.9040	075.6399	P9	109.8750	159.7331
P3	224.8200	299.2008	P10	77.4230	040.0000
P4	109.8810	109.8666	P11	40.0000	040.0006
P5	109.8810	109.8668	P12	55.0000	092.4000
P6	109.8710	109.8667	P13	55.0000	055.0003
P7	109.8730	060.0000	<b>Total cost(\$/h)</b>	17969.0	17968.00

To verify the performance of the proposed method, this test case was repeatedly solved 100 times and the best solutions are presented in this table. The optimal cost obtained by the IWO is \$17,968.00, which compares favourably with the other results in the table. Figure 2 shows the convergence characteristics of

the Catfish PSO and IWO. The Catfish PSO converged to the optimum cost from 97<sup>th</sup> iteration onwards. Whereas IWO converges at less than 20 iterations.

**Table 4. Comparison of total cost values of Thirteen unit system using different methods.**

Method	Best cost(\$/h)
CEP[1]	18048.21
FEP[1]	18018.00
MEP[1]	18028.09
IFEP[1]	17994.07
PSO[19]	18075.28
Catfish PSO	17969.00
IWO	17968.00



**Fig. 2. Convergence characteristics of IWO and the Catfish PSO for Thirteen unit system.**

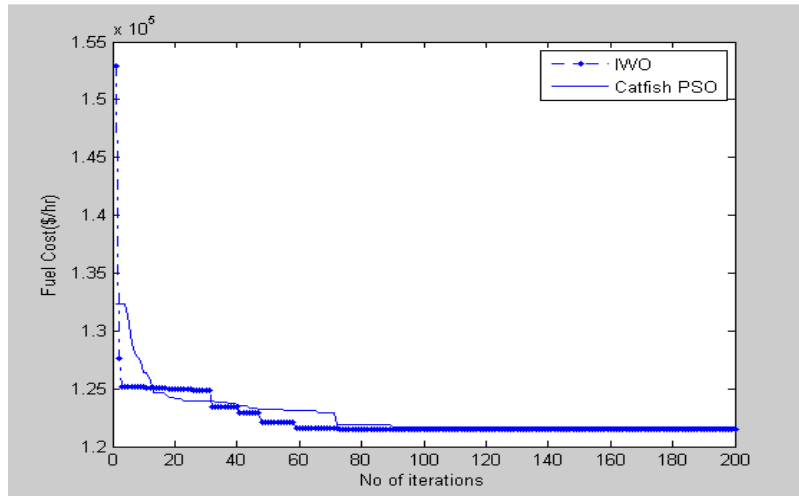
### 6.3. Forty unit system with valve point effects

This is a system consisting of forty generating units with a demand of 10500 MW. The required data of test system is given in [1].

The comparison of the generator outputs obtained using the proposed IWO and the Catfish PSO are presented in Table 5. Table 6 shows the comparison of the solutions obtained by IWO and several other methods such as the CEP [1], FEP [1], MFEP [1], IFEP [1], PSO [4], SPSO [3], HGPSO [3], HP-SOM [3], PSO-SQP [5], MTS [6], BBO [7], IABC [2], IABC-LS [2] and the Catfish PSO. The optimal cost obtained by the proposed IWO method is 121,485.90 \$/hr. This is the least value obtained when compared with the solutions reported by the other methods given in the table. Figure 3 depicts the convergence characteristics of the IWO and the Catfish PSO. It is seen that with the same initial solutions, the IWO converges at a lesser number of iterations as compared to the catfish PSO.

**Table 5. Comparison of generated outputs of Forty unit system using IWO and the Catfish PSO.**

Gen. Output	Catfish PSO	IWO	Gen. Output	Catfish PSO	IWO
P1	113.2600	110.8061	P21	540.4050	523.2799
P2	114.0000	110.8037	P22	533.3920	523.2797
P3	97.7940	097.4007	P23	521.4440	523.2795
P4	179.5570	179.7332	P24	528.9490	523.2794
P5	95.3180	096.3394	P25	550.0000	523.2798
P6	139.548	140.0000	P26	550.0000	523.2793
P7	299.984	300.0000	P27	10.4800	010.0000
P8	288.840	284.6003	P28	10.0850	010.0004
P9	291.817	284.6017	P29	14.7550	010.0000
P10	130.1960	130.0000	P30	95.5970	087.8020
P11	94.3670	094.0003	P31	189.8370	190.0000
P12	94.0320	094.0000	P32	189.8410	189.9997
P13	512.6290	214.7595	P33	190.0000	189.9997
P14	394.4170	304.5196	P34	200.0000	200.0000
P15	306.6790	394.2791	P35	198.9410	200.0000
P16	93.4180	394.2794	P36	192.6120	199.9987
P17	490.8500	489.2795	P37	110.0000	110.0000
P18	489.7540	489.2796	P38	110.0000	109.9998
P19	511.6600	511.2795	P39	110.0000	109.9998
P20	512.0280	511.2809	P40	214.7300	511.2797



**Fig. 3. Convergence characteristics of IWO and the Catfish PSO for Forty unit system.**

**Table 6. Comparison of total cost values of Forty unit system with valve point effects using different methods.**

Method	Best cost (\$/h)
CEP[1]	123488.29
FEP[1]	122679.71
MFEP[1]	122647.57
IFEP[1]	122624.35
PSO[4]	121735.47
SPSO[3]	124350.40
HGPSO[3]	124797.13
HP-SOM[3]	122112.40
PSO-SQP[5]	122094.67
MTS[6]	121532.10
SOHPSO[8]	121510.14
IABC[2]	121491.28
IABC-LS[2]	121488.76
Catfish PSO	121683.70
IWO	121485.90

## 7. Conclusion

In this paper, IWO method has been implemented for solving ED problems with valve point loading effects. The feasibility of the method is demonstrated using three test systems comprising 3, 13 and 40 units.

By applying the IWO algorithm the economic dispatch problem with valve point effects has been optimized, so that ultimately the cost is reduced with all the constraints satisfied. This in turn will help the utilities with economic operational benefits.

- It is shown that the method compares favourably against the Catfish PSO and several other methods.
- The solutions obtained in all the three test systems show the robustness and the convergence characteristics of the proposed method.
- It is surmised that the IWO method proposed in this paper performs better than the other methods since IWO is explorative initially and exploitative later on as the iteration progress, due to decreasing standard deviation in the spatial dispersion.
- The main advantage of the proposed technique is that it is easy to implement, needs less effort in tuning the parameters and capable of finding feasible, optimal or near optimal solutions with less time involved in computation compared to other algorithms.

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