[Lenin *, Vol.5 (Iss.11): November, 2017]
ISSN- 2350-0530(O), ISSN- 2394-3629(P)
DOI: 10.5281/zenodo.1069332

INTERNATIONAL JOURNAL OF RESEARCH – GRANTHAALAYAH
A knowledge Repository

Science

REDUCTION OF ACTIVE POWER LOSS BY IMPROVED INTELLIGENT WATER DROP ALGORITHM

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Abstract

In this paper, Improved Intelligent Water Drop (IIW) algorithm has been proposed to solve the optimal reactive power problem. In this work firefly and water drop algorithm has been combined to improve the exploration & exploitation. Fire fly algorithm imitates the firefly light flashing behaviour is an astonishing signal in the sky, usually found in tropical and temperate regions. Water drop algorithm contains a few necessary elements of natural water drops and action and reaction that occur between river bed & the water drops that flow within. Proposed Improved Intelligent Water Drop (IIW) algorithm has been tested in Standard IEEE 57,118 bus systems & real power loss has been comparatively reduced with voltage profiles are within the limits.

Keywords: Improved Intelligent Water Drop Algorithm; Firefly Algorithm; Reactive Power Problem; Optimization.

Cite This Article: Dr.K.Lenin. (2017). "REDUCTION OF ACTIVE POWER LOSS BY IMPROVED INTELLIGENT WATER DROP ALGORITHM." *International Journal of Research - Granthaalayah*, 5(11), 116-125. https://doi.org/10.5281/zenodo.1069332.

1. Introduction

Optimal reactive power problem plays most important role in the stability of power system operation and control. In this paper the main aspect is to diminish the real power loss and to keep the voltage variables within the limits. Previously many mathematical techniques like gradient method, Newton method, linear programming [4-7] has been utilized to solve the optimal reactive power dispatch problem and those methods have many difficulties in handling inequality constraints. Voltage stability and voltage collapse play an imperative role in power system planning and operation [8]. Recently Evolutionary algorithms like genetic algorithm have been already utilized to solve the reactive power flow problem [9,10].In [11-20] Genetic algorithm, Hybrid differential evolution algorithm, Biogeography Based algorithm, fuzzy based methodology, improved evolutionary programming has been used to solve optimal reactive power flow problem and all the algorithm successfully handled the reactive power problem. The Artificial Bee Colony (ABC) algorithm was introduced by Karaboga [21] as a technical report, and then its performance was measured using benchmark optimization functions [22-33]. In this paper, Improved Intelligent Water Drop (IIW) algorithm has been proposed to solve the optimal reactive power problem. In this work firefly and water drop algorithm has been combined to improve the exploration & exploitation. Fire fly algorithm imitates the firefly light flashing behaviour is an astonishing signal in the sky, usually found in tropical and temperate regions. Water drop algorithm contains a few necessary elements of natural water drops and action and reaction that occur between river bed & the water drops that flow within. Proposed Improved Intelligent Water Drop (IIW) algorithm has been tested in Standard IEEE 57,118 bus systems & real power loss has been comparatively reduced with voltage profiles are within the limits.

2. Objective Function

2.1. Active Power Loss

The objective of the reactive power dispatch problem is to minimize the active power loss and can be defined in equations as follows:

$$F = PL = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}\right) \quad (1)$$

Where g_k : is the conductance of branch between nodes i and j, Nbr: is the total number of transmission lines in power systems.

2.2. Voltage Profile Improvement

To minimize the voltage deviation in PQ buses, the objective function can be written as:

$$F = PL + \omega_v \times VD \quad (2)$$

Whereω_v: is a weighting factor of voltage deviation.
VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \quad (3)$$

2.3. Equality Constraint

The equality constraint of the problem is indicated by the power balance equation as follows:

$$P_G = P_D + P_L \quad (4)$$

Where the total power generation PG has to cover the total power demand PD and the power losses PL.

2.4. Inequality Constraints

The inequality constraint implies the limits on components in the power system in addition to the limits created to make sure system security. Upper and lower bounds on the active power of slack bus, and reactive power of generators are written as follows:

$$\mathrm{P}_{\mathrm{gslack}}^{\mathrm{min}} \leq \mathrm{P}_{\mathrm{gslack}} \leq \mathrm{P}_{\mathrm{gslack}}^{\mathrm{max}} \quad (5)$$

$$\mathrm{Q}_{\mathrm{gi}}^{\mathrm{min}} \leq \mathrm{Q}_{\mathrm{gi}} \leq \mathrm{Q}_{\mathrm{gi}}^{\mathrm{max}}, \mathrm{i} \in \mathrm{N}_{\mathrm{g}} \quad (6)$$

Upper and lower bounds on the bus voltage magnitudes:

$$\mathrm{V}_{\mathrm{i}}^{\mathrm{min}} \leq \mathrm{V}_{\mathrm{i}} \leq \mathrm{V}_{\mathrm{i}}^{\mathrm{max}}, \mathrm{i} \in \mathrm{N} \quad (7)$$

Upper and lower bounds on the transformers tap ratios:

$$\mathrm{T}_{\mathrm{i}}^{\mathrm{min}} \leq \mathrm{T}_{\mathrm{i}} \leq \mathrm{T}_{\mathrm{i}}^{\mathrm{max}}, \mathrm{i} \in \mathrm{N}_{\mathrm{T}} \quad (8)$$

Upper and lower bounds on the compensators

$$\mathrm{Q}_{\mathrm{c}}^{\mathrm{min}} \leq \mathrm{Q}_{\mathrm{c}} \leq \mathrm{Q}_{\mathrm{C}}^{\mathrm{max}}, \mathrm{i} \in \mathrm{N}_{\mathrm{C}} \quad (9)$$

Where N is the total number of buses, NT is the total number of Transformers; Nc is the total number of shunt reactive compensators.

3. Firefly Algorithm

The firefly light flashing behaviour is an astonishing signal in the sky, usually found in tropical and temperate regions. There are about 2000 species of firefly algorithm and most fire beetle acquire unique and rhythmic scour. These flashes are used are fundamental function such as attracting mating parts as well as potential prays. In additions, the flashing behaviour may also save as a vindicatory admonition mechanism. These rhythmic flashes are different from each other on the basis of rate of flashing. A female firefly responds to peerless pattern of flashing of a male firefly which brings both sexes together. We know that, when a light source emits light intensity at a Euclidian distance r from the light source it obeys the inverse square low. The intensity I decrease with increase in the Euclidian distance r which is term of,

$$I \infty \frac{1}{r^2} \quad (10)$$

1) Fireflies are attracted toward each other regardless of gender. 2) The attractiveness of the fireflies is correlative with their brightness. Thus the less attractive firefly will move forward to the more attractive one. 3) The brightness of fireflies depends on the objective function.
For two fireflies x_i & x_j, they can be updated as follows:

$$x_j = x_i + \beta_o e^{-\gamma r_{ij}^2}\left(x_j - x_i\right) + \alpha\epsilon \quad (11)$$

Whereα represents the movement of firefly,β_o represents the attractiveness of the firefly.

γ represent the intensity of firefly. In our work, the intensity of firefly represents the cost function of software, and r represents the Euclidian distance of the firefly.

Firefly algorithm

```
Step a: Objective function
Step b: Generate initial population of fireflies;
Step c: Formulate light intensity I;
Step d: Define absorption coefficient γ;
Step e: While (t Ii), move firefly i towards j; end if Evaluate new solutions and update light intensity;
        End for j;
        End for i;
        Rank the fireflies and find the current best;
Step f: End while; Post process results and visualization;
Step g: End procedure;
```

4. Intelligent Water Drop Algorithm

The Intelligent Water Drop (IWD) algorithm is based on swarm nature inspired optimization algorithm. This algorithm contains a few necessary elements of natural water drops and action and reaction that occur between river bed & the water drops that flow within. It flows in two categories like metaheuristic and swarm intelligence. Intrinsically, Intelligent Water Drop algorithm can be used for combinatorial optimization. It was firstly introduced for the travelling salesman problem in 2007. Since then, multitudes of researchers have focused on improving the algorithm for different problems.

The IWD algorithms update the soil for the edges by

$$soil(k) = 1.1. soil(k) - 0.01 \cdot \Delta soil(k) \tag{12}$$

$$soil^{IWD} = soil^{IWD} + \Delta soil(k) \tag{13}$$

Water Drop algorithm

```
Step a: Static parameter initialization
        aa. Problem representation in the form of a graph
        aaa. Setting values for static parameters
Step b: Dynamic parameter initialization: soil and velocity of IWDs
Step c: Distribution of IWDs on the problem's graph
Step d: Solution construction by IWDs along with soil and velocity updating
        dd. Local soil updating on the graph
        ddd. Soil and velocity updating on the IWDs
Step e: Local search over each IWD's solution (optional)
Step f: Global soil updating
Step g: Total-best solution updating
Step h: Go to step b unless termination condition is satisfied
```

5. Improved Intelligent Water Drop (IIW) Algorithm

Proposed methodology updates the poor solutions to accelerate its convergence speed. In this work firefly and water drop algorithm has been combined to improve the exploration & exploitation. It improves the accuracy of the effort estimation of software testing and reduces the magnitude relative errors. In this algorithm, the firefly algorithm however tuned using the parameters of test effort estimation techniques i.e. UCP (use case Point) and TPA (test point analysis). However there is an issue with the algorithm. The problem is that the firefly algorithm has some tuning parameters which need to be optimized.

Improved Intelligent Water Drop (IIW) algorithm for solving reactive power problem

```
Begin Initialize parameters of fireflies: $\alpha$, $\beta$ and $\gamma$
Calculate river velocity If (number of paths>1)
Select the minimum soil path
Run loop of Intelligent Water Drop algorithm for all $\alpha$, $\beta$ and $\gamma$
Initialize parameters of TPA and UCP
J:position x of fireflies
 MaxGen: the maximal number of generations
$\gamma$: the light absorption coefficient
r: the particular distance from the light source
d: the domain space
f(x):objective function as a combination of throughput, efficiency and average waiting time
Define the objective function of f(x)=Calculated Effort, where $x=(x_1,........,x_d)$
Generate the initial population of fireflies or $x_i$ $(i=1,2 ,..., n)$
Determine the light intensity of $I_i$ at $x_i$ via $f(x_i)$
While $(t < MaxGen)$
For i = 1 to n (all n fireflies);
For j=1 to n (n fireflies)
If $I_j > I_i$
 Move firefly i towards j
End if
Attractiveness varies with distance r via Exp [- $\gamma r^2$ ];
Evaluate new solutions and update light intensity;
End for j;
End for i;
Rank the fireflies and find the current best;
End while;
Calculate the best parameters and store.
Update river velocities and select optimal path
Go to Water Drop algorithm loop again
Calculate and store the estimated effort
End Procedure
```

6. Simulation Results

At first Improved Intelligent Water Drop (IIW) algorithm has been tested in standard IEEE-57 bus power system. The reactive power compensation buses are 18, 25 and 53. Bus 2, 3, 6, 8, 9 and 12 are PV buses and bus 1 is selected as slack-bus. The system variable limits are given in Table 1.

The preliminary conditions for the IEEE-57 bus power system are given as follows:

P_{load} = 12.134 p.u. Q_{load} = 3.052 p.u.

The total initial generations and power losses are obtained as follows:

$\sum P_G$ = 12.374 p.u. $\sum Q_G$ = 3.3278 p.u.

P_{loss} = 0.25626 p.u. Q_{loss} = -1.2108 p.u.

Table 2 shows the various system control variables i.e. generator bus voltages, shunt capacitances and transformer tap settings obtained after optimization which are within the acceptable limits. In Table 3, shows the comparison of optimum results obtained from proposed methods with other optimization techniques. These results indicate the robustness of proposed approaches for providing better optimal solution in case of IEEE-57 bus system.

Table 1: Variable Limits

Reactive Power Generation Limits							
Bus no	1	2	3	6	8	9	12
Qgmin	-1.4	-.015	-.02	-0.04	-1.3	-0.03	-0.4
Qgmax	1	0.3	0.4	0.21	1	0.04	1.50

Voltage And Tap Setting Limits					
vgmin	**Vgmax**	**vpqmin**	**Vpqmax**	**tkmin**	**tkmax**
0.9	1.0	0.91	1.05	0.9	1.0

Shunt Capacitor Limits			
Bus no	18	25	53
Qcmin	0	0	0
Qcmax	10	5.2	6.1

Table 2: Control variables obtained after optimization

Control Variables	**IIW**
V1	1.10
V2	1.029
V3	1.022
V6	1.020
V8	1.021
V9	1.000
V12	1.000
Qc18	0.0502
Qc25	0.199
Qc53	0.0243
T4-18	1.000
T21-20	1.032
T24-25	0.712

T24-26	0.728
T7-29	1.034
T34-32	0.746
T11-41	1.009
T15-45	1.029
T14-46	0.892
T10-51	1.009
T13-49	1.039
T11-43	0.900
T40-56	0.900
T39-57	0.950
T9-55	0.950

Table 3: Comparison results

S.No.	Optimization Algorithm	Finest Solution	Poorest Solution	Normal Solution
1	NLP [34]	0.25902	0.30854	0.27858
2	CGA [34]	0.25244	0.27507	0.26293
3	AGA [34]	0.24564	0.26671	0.25127
4	PSO-w [34]	0.24270	0.26152	0.24725
5	PSO-cf [34]	0.24280	0.26032	0.24698
6	CLPSO [34]	0.24515	0.24780	0.24673
7	SPSO-07 [34]	0.24430	0.25457	0.24752
8	L-DE [34]	0.27812	0.41909	0.33177
9	L-SACP-DE [34]	0.27915	0.36978	0.31032
10	L-SaDE [34]	0.24267	0.24391	0.24311
11	SOA [34]	0.24265	0.24280	0.24270
12	LM [35]	0.2484	0.2922	0.2641
13	MBEP1 [35]	0.2474	0.2848	0.2643
14	MBEP2 [35]	0.2482	0.283	0.2592
15	BES100 [35]	0.2438	0.263	0.2541
16	BES200 [35]	0.3417	0.2486	0.2443
17	Proposed IIW	0.22010	0.23048	0.22162

Then Improved Intelligent Water Drop (IIW) algorithm has been tested in standard IEEE 118-bus test system [36].The system has 54 generator buses, 64 load buses, 186 branches and 9 of them are with the tap setting transformers. The limits of voltage on generator buses are 0.95 -1.1 per-unit., and on load buses are 0.95 -1.05 per-unit. The limit of transformer rate is 0.9 -1.1, with the changes step of 0.025. The limitations of reactive power source are listed in Table 4, with the change in step of 0.01

Table 4: Limitation of reactive power sources

BUS	5	34	37	44	45	46	48
QCMAX	0	14	0	10	10	10	15
QCMIN	-40	0	-25	0	0	0	0
BUS	74	79	82	83	105	107	110
QCMAX	12	20	20	10	20	6	6
QCMIN	0	0	0	0	0	0	0

The statistical comparison results have been listed in Table 5 and the results clearly show the better performance of proposed Improved Intelligent Water Drop (IIW) algorithm in reducing the real power loss.

Table 5: Comparison results

Active power loss (MW)	**BBO [37]**	**ILSBBO/ strategy1 [37]**	**ILSBBO/ strategy1 [37]**	**Proposed IIW**
Min	128.77	126.98	124.78	115.18
Max	132.64	137.34	132.39	123.04
Average	130.21	130.37	129.22	119.26

7. Conclusion

In this paper, Improved Intelligent Water Drop (IIW) algorithm successfully solved the optimal reactive power problem. In this work firefly and water drop algorithm has been combined to improve the exploration & exploitation. Fire fly algorithm imitates the firefly light flashing behaviour is an astonishing signal in the sky, usually found in tropical and temperate regions. Water drop algorithm contains a few necessary elements of natural water drops and action and reaction that occur between river bed & the water drops that flow within. Proposed Improved Intelligent Water Drop (IIW) algorithm has been tested in Standard IEEE 57,118 bus systems & real power loss has been comparatively reduced with voltage profiles are within the limits.

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