International Journal of Advances in Applied Sciences (IJAAS)
Vol. 8, No. 3, September 2019, pp. 217~224
ISSN: 2252-8814, DOI: 10.11591/ijaas.v8.i3.pp217-224

Active power loss reduction by opposition based kidney search algorithm

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Article Info

Article history:

Received Apr 30, 2019
Revised Jul 11, 2019
Accepted Jul 27, 2019

Keywords:

Opposition based kidney search algorithm
Optimal reactive power
Transmission loss

ABSTRACT

In this work Opposition based Kidney Search Algorithm (OKS) is used to solve the optimal reactive power problem. Kidney search algorithm imitates the various sequences of functions done by biological kidney. Opposition based learning (OBL) stratagem is engaged to commence the algorithm. This is to make certain high-quality of preliminary population and to expand the exploration steps in case of stagnation of the most excellent solutions. Opposition based learning (OBL) is one of the influential optimization tools to boost the convergence speed of different optimization techniques. The thriving implementation of the OBL engages evaluation of opposite population and existing population in the similar generation to discover the superior candidate solution of a given reactive power problem. Proposed Opposition based Kidney Search Algorithm (OKS) has been tested in standard IEEE 14, 30, 57,118,300 bus test systems and simulation results show that the proposed algorithm reduced the real power loss efficiently.

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1. INTRODUCTION

Reactive power problem plays a key role in secure and economic operations of power system. Optimal reactive power problem has been solved by variety of types of methods [1-6]. Nevertheless, numerous scientific difficulties are found while solving problem due to an assortment of constraints. Evolutionary techniques [7-15] are applied to solve the reactive power problem, but the main problem is many algorithms get stuck in local optimal solution & failed to balance the Exploration & Exploitation during the search of global solution. In this work Opposition based Kidney Search Algorithm (OKS) is used to solve the optimal reactive power problem. Kidney search algorithm imitates the various sequences of functions done by biological kidney. In preliminary segment, a capricious population of feasible solutions is formed and re-absorption, secretion, excretion are replicated in the exploration procedure to verify different conditions well-established to the algorithm. Opposition based learning (OBL) stratagem is engaged to commence the algorithm. This is to make certain high-quality of preliminary population and to expand the exploration steps in case of stagnation of the most excellent solutions. Opposition based learning (OBL) is one of the influential optimization tools to boost the convergence speed of different optimization techniques. The thriving implementation of the OBL engages evaluation of opposite population and existing population in the similar generation to discover the superior candidate solution of a given reactive power problem. In all oppositional based optimization; the conception of OBL is used in the initialization procedure and as well as in each iteration using the generation jumping rate, Jr. Proposed Opposition based Kidney Search Algorithm (OKS) has been tested in standard IEEE 14, 30, 57,118,300 bus test systems and simulation results show the projected algorithm reduced the real power loss comprehensively.

2. PROBLEM FORMULATION

Objective of the problem is to reduce the true power loss

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

Voltage deviation given as follows

$$F = P_L + \omega_v \times \text{Voltage Deviation} \quad (2)$$

Voltage deviation given by

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

Constraint (Equality)

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

Constraints (Inequality)

$$P_{gslack}^{min} \le P_{gslack} \le P_{gslack}^{max} \quad (5)$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}, i \in N_g \quad (6)$$

$$V_i^{min} \le V_i \le V_i^{max}, i \in N \quad (7)$$

$$T_i^{min} \le T_i \le T_i^{max}, i \in N_T \quad (8)$$

$$Q_c^{min} \le Q_c \le Q_C^{max}, i \in N_C \quad (9)$$

3. OPPOSITION BASED KIDNEY SEARCH ALGORITHM

Kidney search algorithm imitates the various sequences of functions done by biological kidney. Filtration, Re-absorption, Secretion, Excretion plays key function in the function of the kidney. In preliminary segment, a capricious population of feasible solutions is formed and re-absorption, secretion, excretion are replicated in the exploration procedure to verify different conditions well-established to the algorithm. Algorithm is built to perk up the exploration even a potential solution stirred to waste (W) and it will be fetch back to the filtered blood (FB). Glomerular filtration rate (GFR) test is employed to authenticate the robustness of kidney. The test roughly gives the capability of blood that pass all the way through the glomeruli every minute. Depending on the GFR test outcome which is less than 15 or falls between 15 and 60 or is more than 60 a meticulous action will be accomplished. This process executed to perk up the rate of exploration and to discover the optimal solution. The GFR testing process is added at the ending of iterations. When GFR level is less than 15, the method is recurring with the population in Filtered Blood. When GFR level is between 15 and 60, development of realistic solutions in Filtered blood is applied as a treatment for abridged kidney function. This sequence augments the searching capability and is designed to assist the algorithm in detection of improved solution. If the GFR level is larger than 60, then kidney function is ordinary, in which case no extra development is added to algorithm.

Movement equation as follows

$$Z_{i+1} = Z_i + rand(Z_{best} - Z_i) \quad (10)$$

Filtering of the solutions is done with a filtration rate and Calculation of the filtration rate (l_r) is done using the following equation

$$l_r = \beta \times \frac{\sum_{i=1}^{s} f(y_i)}{s} \quad (11)$$

β is a constant value between 0 and 1 and is attuned in advance. s represents the size of the population. $f(y_i)$ represents an objective function of solution y at ith iteration [16]. In every iteration, previous to integration the Filtration of blood (FB) and waste (W) will be population for the subsequent iteration, the algorithm compute the GFR level based on the fr in FB

$$\text{Glomerular filtration rate}_{minimum} = 120 - \left(\frac{fr_{FB}*100}{fr}\right) \tag{12}$$

Define the Population
Calculate approximate solution in the population
Most excellent solution Z_{best} , is found
By (11) find the Filtration rate- l_r,
Define waste (W)
Define filtered blood (FB)
Number of iteration will be found
Do while (iteration $< number\ of\ iterations$)
For Z_i ; compute new Z_i by using (10)
Check the value of Z_i using l_r
If Z_i allocated to W then place on re-absorption and produce Z_{new} by using (10)
If re-absorption is not fulfilled then Z_{new} will not be part of FB
Eradicate Z_i from W (excretion)
Place randomly Z into W to exchange Z_i
End if
Z_i is reabsorbed
Else
If it is superior than the Z_{worst} $in\ FB$
Z_{worst} is secreted
Calculate the GFR level solutions in FB by using (12)
$if\ 15 < GFR\ level < 60\ ; then\ implement\ movement\ of\ solutions\ in\ FB$
End if
$if\ GFR\ level < 15\ ; then\ algorithm\ proceeded\ with\ the\ same\ population\ in\ FB$
End if
End if
End for
Rank the Z_s from FB and modernize the Z_{best}
Merge W and FB
By (11) amend filtration rate l_r
End while
Return Z_{best}

In this work Opposition based Kidney Search Algorithm (OKS) is used to solve the problem. Opposition based learning (OBL) stratagem is engaged to commence the algorithm. This is to make certain high-quality of preliminary population and to expand the exploration steps in case of stagnation of the most excellent solutions. Opposition based learning (OBL) is one of the influential optimization tools to boost the convergence speed of different optimization techniques [17]. The thriving implementation of the OBL engages evaluation of opposite population and existing population in the similar generation to discover the superior candidate solution of a given reactive power problem. The conception of opposite number requirements is to be defined to explain OBL.

Let N ($N \in [x, y]$) be a real number and the N^o (opposite number) can be defined as follows

$$N^o = x + y - N \tag{13}$$

In the exploration space it has been extended as

$$N_i^o = x_i + y_i - N_i \tag{14}$$

Where $(N_1, N_2, .. N_d)$ is a point in the dimensional search space, $N_i \in [x_i, y_i]$, $i \to \{1,2,3, .. d\}$

In all oppositional based optimization; the conception of OBL is used in the initialization procedure and as well as in each iteration using the generation jumping rate, Jr.

a. Begin
b. Engender OBL based population
c. Calculate each "Z" in the population and fix the "Z_{best}"
d. Produce new-fangled "Z" for "Z_i" based on mutual information based switching
e. Apply the filtration operator
f. Is "Z_i" assigned as "W"? ; if "Yes" apply the reabsorption operator; or check is "Z_i" better than the "Z_{worst}" – if yes then secrete "Z_{worst}" from FB or secrete "Z_i"
g. Can "Z_{new}" be assigned as FB? If yes remove "Z_i" from W and insert a random "Z" into "W"
h. Have all "Z_s" have been met?
i. If "yes" engender $\bar{Z}_{best}$ or else go to step "d"
j. Is "$\bar{Z}_{best}$" better than the "Z_{worst}" in FB? if "yes" replace "Z_{worst}" with "$\bar{Z}_{best}$"
k. Or else update "Z_{best}" , merge W ,FB modernize the filtration rate
l. Is end criterion reached? if yes stop or else go to step "d"

4. SIMULATION STUDY

At first in standard IEEE 14 bus system the validity of the proposed Opposition based Kidney Search Algorithm (OKS) has been tested, Table 1 shows the constraints of control variables Table 2 shows the limits of reactive power generators and comparison results are presented in Table 3.

Table 1. Constraints of control variables

System	Variables	Minimum (PU)	Maximum (PU)
IEEE 14 Bus	Generator Voltage	0.95	1.1
	Transformer Tap	o.9	1.1
	VAR Source	0	0.20

Table 2. Constrains of reactive power generators

System	Variables	Q Minimum (PU)	Q Maximum (PU)
IEEE 14 Bus	1	0	10
	2	-40	50
	3	0	40
	6	-6	24
	8	-6	24

Table 3. Simulation results of IEEE −14 system

Control variables	Base case	MPSO [18]	PSO [18]	EP [18]	SARGA [18]	OKS
$VG{-}1$	1.060	1.100	1.100	NR*	NR*	1.012
$VG{-}2$	1.045	1.085	1.086	1.029	1.060	1.028
$VG{-}3$	1.010	1.055	1.056	1.016	1.036	1.024
$VG{-}6$	1.070	1.069	1.067	1.097	1.099	1.016
$VG{-}8$	1.090	1.074	1.060	1.053	1.078	1.019
Tap 8	0.978	1.018	1.019	1.04	0.95	0.910
Tap 9	0.969	0.975	0.988	0.94	0.95	0.902
Tap 10	0.932	1.024	1.008	1.03	0.96	0.915
$QC{-}9$	0.19	14.64	0.185	0.18	0.06	0.146
PG	272.39	271.32	271.32	NR*	NR*	271.09
QG (Mvar)	82.44	75.79	76.79	NR*	NR*	75.17
Reduction in PLoss (%)	0	9.2	9.1	1.5	2.5	18.75
Total PLoss (Mw)	13.550	12.293	12.315	13.346	13.216	11.009

NR* - Not reported.

Then the proposed Opposition based Kidney Search Algorithm (OKS) has been tested, in IEEE 30 Bus system. Table 4 shows the constraints of control variables, Table 5 shows the limits of reactive power generators and comparison results are presented in Table 6.

Table 4. Constraints of control variables

System	Variables	Minimum (PU)	Maximum (PU)
IEEE 30 Bus	Generator Voltage	0.95	1.1
	Transformer Tap	o.9	1.1
	VAR Source	0	0.20

Table 5. Constrains of reactive power generators

System	Variables	Q Minimum (PU)	Q Maximum (PU)
IEEE 30 Bus	1	0	10
	2	-40	50
	5	-40	40
	8	-10	40
	11	-6	24
	13	-6	24

Table 6. Simulation results of IEEE −30 system

Control variables	Base case	MPSO [18]	PSO [18]	EP [18]	SARGA [18]	OKS
$VG{-}1$	1.060	1.101	1.100	NR*	NR*	1.028
$VG{-}2$	1.045	1.086	1.072	1.097	1.094	1.029
$VG{-}5$	1.010	1.047	1.038	1.049	1.053	1.017
$VG{-}8$	1.010	1.057	1.048	1.033	1.059	1.028
$VG{-}12$	1.082	1.048	1.058	1.092	1.099	1.019
VG-13	1.071	1.068	1.080	1.091	1.099	1.026
Tap11	0.978	0.983	0.987	1.01	0.99	0.920
Tap12	0.969	1.023	1.015	1.03	1.03	0.921
Tap15	0.932	1.020	1.020	1.07	0.98	0.922
Tap36	0.968	0.988	1.012	0.99	0.96	0.929
QC10	0.19	0.077	0.077	0.19	0.19	0.094
QC24	0.043	0.119	0.128	0.04	0.04	0.107
PG (MW)	300.9	299.54	299.54	NR*	NR*	297.08
QG (Mvar)	133.9	130.83	130.94	NR*	NR*	131.78
Reduction in PLoss (%)	0	8.4	7.4	6.6	8.3	14.46
Total PLoss (Mw)	17.55	16.07	16.25	16.38	16.09	15.012

NR* - Not reported.

Then the proposed Opposition based Kidney Search Algorithm (OKS) has been tested, in IEEE 57 Bus system. Table 7 shows the constraints of control variables, Table 8 shows the limits of reactive power generators and comparison results are presented in Table 9.

Table 7. Constraints of control variables

System	Variables	Minimum (PU)	Maximum (PU)
IEEE 57 Bus	Generator Voltage	0.95	1.1
	Transformer Tap	0.9	1.1
	VAR Source	0	0.20

Table 8. Constrains of reactive power generators

System	Variables	Q Minimum (PU)	Q Maximum (PU)
IEEE 57 Bus	1	-140	200
	2	-17	50
	3	-10	60
	6	-8	25
	8	-140	200
	9	-3	9
	12	-150	155

Table 9. Simulation results of IEEE −57 system

Control variables	Base case	MPSO [18]	PSO [18]	CGA [18]	AGA [18]	OKS
VG 1	1.040	1.093	1.083	0.968	1.027	1.012
VG 2	1.010	1.086	1.071	1.049	1.011	1.018
VG 3	0.985	1.056	1.055	1.056	1.033	1.028
VG 6	0.980	1.038	1.036	0.987	1.001	1.027
VG 8	1.005	1.066	1.059	1.022	1.051	1.029
VG 9	0.980	1.054	1.048	0.991	1.051	1.030
VG 12	1.015	1.054	1.046	1.004	1.057	1.040
Tap 19	0.970	0.975	0.987	0.920	1.030	0.900
Tap 20	0.978	0.982	0.983	0.920	1.020	0.909
Tap 31	1.043	0.975	0.981	0.970	1.060	0.906
Tap 35	1.000	1.025	1.003	NR*	NR*	1.018
Tap 36	1.000	1.002	0.985	NR*	NR*	1.014
Tap 37	1.043	1.007	1.009	0.900	0.990	1.008
Tap 41	0.967	0.994	1.007	0.910	1.100	0.940
Tap 46	0.975	1.013	1.018	1.100	0.980	1.010
Tap 54	0.955	0.988	0.986	0.940	1.010	0.920
Tap 58	0.955	0.979	0.992	0.950	1.080	0.930
Tap 59	0.900	0.983	0.990	1.030	0.940	0.921
Tap 65	0.930	1.015	0.997	1.090	0.950	1.005
Tap 66	0.895	0.975	0.984	0.900	1.050	0.931
Tap 71	0.958	1.020	0.990	0.900	0.950	1.008
Tap 73	0.958	1.001	0.988	1.000	1.010	1.010
Tap 76	0.980	0.979	0.980	0.960	0.940	0.942
Tap 80	0.940	1.002	1.017	1.000	1.000	1.004
QC 18	0.1	0.179	0.131	0.084	0.016	0.152
QC 25	0.059	0.176	0.144	0.008	0.015	0.141
QC 53	0.063	0.141	0.162	0.053	0.038	0.120
PG (MW)	1278.6	1274.4	1274.8	1276	1275	1272.92
QG (Mvar)	321.08	272.27	276.58	309.1	304.4	272.01
Reduction in PLoss (%)	0	15.4	14.1	9.2	11.6	24.12
Total PLoss (Mw)	27.8	23.51	23.86	25.24	24.56	21.092

NR* - Not reported.

Then the proposed Opposition based Kidney Search Algorithm (OKS) has been tested, in IEEE 118 Bus system. Table 10 shows the constraints of control variables and the comparison results are presented in Table 11 as shown in appendix.

Table 10. Constraints of control variables

System	Variables	Minimum (PU)	Maximum (PU)
	Generator Voltage	0.95	1.1
IEEE 118 Bus	Transformer Tap	0.9	1.1
	VAR Source	0	0.20

Then IEEE 300 bus system [19] is used as test system to validate the performance of the Opposition based Kidney Search Algorithm (OKS). Table 12 shows the comparison of real power loss obtained after optimization.

Table 12. Comparison of real power loss

Parameter	Method EGA [20]	Method EEA [20]	Method CSA [21]	OKS
PLOSS (MW)	646.2998	650.6027	635.8942	613.0974

5. CONCLUSION

In this work Opposition based Kidney Search Algorithm (OKS) has been successfully applied for solving optimal reactive power problem. Opposition based learning (OBL) stratagem is engaged to commence the algorithm. The prosperous execution of the OBL employ assessment of opposite population and existing population in the analogous generation to find out the better candidate solution of a given reactive power problem. In all oppositional based optimization; the conception of OBL is used in the initialization procedure and as well as in each iteration using the generation jumping rate. Proposed Opposition based Kidney Search Algorithm (OKS) has been tested in standard IEEE 14, 30, 57,118,300 bus test systems and simulation results show that the proposed algorithm reduced the real power loss efficiently.

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APPENDIX

Table 11. Simulation results of IEEE −118 system

	Base case	MPSO [18]	PSO [18]	PSO [18]	CLPSO [18]	OKS
VG 1	0.955	1.021	1.019	1.085	1.033	1.012
VG 4	0.998	1.044	1.038	1.042	1.055	1.016
VG 6	0.990	1.044	1.044	1.080	0.975	1.028
VG 8	1.015	1.063	1.039	0.968	0.966	1.019
VG 10	1.050	1.084	1.040	1.075	0.981	1.012
VG 12	0.990	1.032	1.029	1.022	1.009	1.028
VG 15	0.970	1.024	1.020	1.078	0.978	1.019
VG 18	0.973	1.042	1.016	1.049	1.079	1.006
VG 19	0.962	1.031	1.015	1.077	1.080	1.015
VG 24	0.992	1.058	1.033	1.082	1.028	1.014
VG 25	1.050	1.064	1.059	0.956	1.030	1.013
VG 26	1.015	1.033	1.049	1.080	0.987	1.022
VG 27	0.968	1.020	1.021	1.087	1.015	0.909
VG31	0.967	1.023	1.012	0.960	0.961	0.906
VG 32	0.963	1.023	1.018	1.100	0.985	0.905
VG 34	0.984	1.034	1.023	0.961	1.015	1.014
VG 36	0.980	1.035	1.014	1.036	1.084	1.003
VG 40	0.970	1.016	1.015	1.091	0.983	0.950
VG 42	0.985	1.019	1.015	0.970	1.051	1.008
VG 46	1.005	1.010	1.017	1.039	0.975	1.010
VG 49	1.025	1.045	1.030	1.083	0.983	1.011
VG 54	0.955	1.029	1.020	0.976	0.963	0.912
VG 55	0.952	1.031	1.017	1.010	0.971	0.929
VG56	0.954	1.029	1.018	0.953	1.025	0.944
VG 59	0.985	1.052	1.042	0.967	1.000	0.932
VG 61	0.995	1.042	1.029	1.093	1.077	0.910
VG 62	0.998	1.029	1.029	1.097	1.048	0.922
VG 65	1.005	1.054	1.042	1.089	0.968	1.006
VG 66	1.050	1.056	1.054	1.086	0.964	1.049
VG 69	1.035	1.072	1.058	0.966	0.957	1.012
VG 70	0.984	1.040	1.031	1.078	0.976	1.010
VG 72	0.980	1.039	1.039	0.950	1.024	1.008
VG 73	0.991	1.028	1.015	0.972	0.965	1.009
VG 74	0.958	1.032	1.029	0.971	1.073	1.002
VG 76	0.943	1.005	1.021	0.960	1.030	1.006
VG 77	1.006	1.038	1.026	1.078	1.027	1.008
VG 80	1.040	1.049	1.038	1.078	0.985	1.004
VG 85	0.985	1.024	1.024	0.956	0.983	1.010
VG 87	1.015	1.019	1.022	0.964	1.088	1.002
VG 89	1.000	1.074	1.061	0.974	0.989	1.031
VG 90	1.005	1.045	1.032	1.024	0.990	1.010
VG 91	0.980	1.052	1.033	0.961	1.028	1.009
VG 92	0.990	1.058	1.038	0.956	0.976	1.018
VG 99	1.010	1.023	1.037	0.954	1.088	1.005
VG 100	1.017	1.049	1.037	0.958	0.961	1.003
VG 103	1.010	1.045	1.031	1.016	0.961	1.009
VG 104	0.971	1.035	1.031	1.099	1.012	1.017
VG 105	0.965	1.043	1.029	0.969	1.068	1.028

Table 11. Simulation results of IEEE −118 system (*continued*)

	Base case	MPSO [18]	PSO [18]	PSO [18]	CLPSO [18]	OKS
VG 107	0.952	1.023	1.008	0.965	0.976	1.012
VG 110	0.973	1.032	1.028	1.087	1.041	1.016
VG 111	0.980	1.035	1.039	1.037	0.979	1.019
VG 112	0.975	1.018	1.019	1.092	0.976	1.092
VG 113	0.993	1.043	1.027	1.075	0.972	1.016
VG 116	1.005	1.011	1.031	0.959	1.033	1.018
Tap 8	0.985	0.999	0.994	1.011	1.004	0.932
Tap 32	0.960	1.017	1.013	1.090	1.060	1.004
Tap 36	0.960	0.994	0.997	1.003	1.000	0.949
Tap 51	0.935	0.998	1.000	1.000	1.000	0.912
Tap 93	0.960	1.000	0.997	1.008	0.992	1.018
Tap 95	0.985	0.995	1.020	1.032	1.007	0.930
Tap 102	0.935	1.024	1.004	0.944	1.061	1.012
Tap 107	0.935	0.989	1.008	0.906	0.930	0.930
Tap 127	0.935	1.010	1.009	0.967	0.957	1.014
QC 34	0.140	0.049	0.048	0.093	0.117	0.010
QC 44	0.100	0.026	0.026	0.093	0.098	0.024
QC 45	0.100	0.196	0.197	0.086	0.094	0.110
QC 46	0.100	0.117	0.118	0.089	0.026	0.109
QC 48	0.150	0.056	0.056	0.118	0.028	0.020
QC 74	0.120	0.120	0.120	0.046	0.005	0.112
QC 79	0.200	0.139	0.140	0.105	0. 148	0.109
QC 82	0.200	0.180	0.180	0.164	0.194	0.140
QC 83	0.100	0.166	0.166	0.096	0.069	0.106
QC 105	0.200	0.189	0.190	0.089	0.090	0.110
QC 107	0.060	0.128	0.129	0.050	0.049	0.121
QC 110	0.060	0.014	0.014	0.055	0.022	0.015
PG(MW)	4374.8	4359.3	4361.4	NR*	NR*	4358.02
QG(MVAR)	795.6	604.3	653.5	* NR*	NR*	605.97
Reduction in PLOSS (%)	0	11.7	10.1	0.6	1.3	13.38
Total PLOSS (Mw)	132.8	117.19	119.34	131.99	130.96	115.02

NR* - Not reported.