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Real Power Loss Reduction by Cultivation of Soil Optimization Algorithm

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Abstract. In this paper, the optimal reactive power problem has been solved by the cultivation of soil optimization (CSO) algorithm. The reduction of real power loss is a key objective of this work. The projected CSO algorithm has been modeled based on the quality of soil which has been used in the cultivation of various crops season to season. With respect to the quality of the soil in the cultivation land, there will be a change in the poor-quality soil since there will up the gradation of the poor soil is done through by adding the nutrient contents. Depend upon the needs and about the type of cultivation farmers will improve the quality of the soil by adding valuable and various types of fertilizers (natural and artificial) such that it will enhance the fertile and growth (green) of the crops. Time to time farmers will choose appropriate nutrient contents that will be mixed with the soil in order to enhance the fertility of the soil. In standard IEEE 14, 30, 57 bus test systems Cultivation of Soil Optimization (CSO) algorithm has been tested. The CSO algorithm reduced the real power loss and control variables are within the limits.

Keywords: optimal reactive power, transmission loss, cultivation soil optimization algorithm.

1 Introduction

The reactive power problem plays a key role in power system operation and control. Real power loss reduction is the main objective of this work. Methods like Newton, interior point, successive quadratic programming [1–6] are already utilized to solve the optimal reactive power problem. Still, many scientific difficulties are found due to the assortment of constraints in conventional methods. A gravitational search algorithm, particle swarm optimization, symbiotic organism search algorithm [7–14] are applied to solve the reactive power problem. Yet proper balance between exploration and exploitation is needed to reach the global optimal solution. Few evolutionary algorithms good in exploration but lack in exploitation and some algorithms will good in exploitation but lacks in exploration. In order to balance properly in this work, a new algorithm has been projected to solve the problem. This paper proposes the cultivation of soil optimization algorithm to solve the optimal reactive power problem. The designed algorithm has been modeled based on the quality of soil which has been used in the cultivation of various crops season to season.

As a division of the farmland the exploration space will be divided into sections k and n indicates the available number of solutions in the farmland. Normally farmers will analyze all the parts of the cultivation land which has been partitioned as sections. The analysis will be done by the framers in each section about the nutrients' content in the cultivation soil [15–17]. Then accordingly they will enhance the quality of the cultivation soil by adding materials like fertilizers (natural and artificial). There will difference in adding the nutrient content materials to the cultivation soil with respect to the quality of the land. These actions are all imitated to model the CSO algorithm. Naturally, all the soil which has been used for cultivation will not same with respect to fertility, water content. Farmers will use fertilizers (natural and artificial) in order to improve the fertility of the soil such that the nutrient content of the soil will be improved efficiently. The proposed CSO algorithm has been tested in standard IEEE 14, 30, 57 bus test systems and simulation results show the projected algorithm reduced the real power loss comprehensively.

2 Research Methodology

2.1 Problem formulation

The 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 is given as follows:

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

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

Constraint (equality):

$$P_G = P_D + P_L$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}, i \in N_g$$

$$V_i^{min} \le V_i \le V_i^{max}, i \in N \quad (3)$$

$$T_i^{min} \le T_i \le T_i^{max}, i \in N_T$$

$$Q_c^{min} \le Q_c \le Q_C^{max}, i \in N_C$$

2.2 Cultivation of soil optimization algorithm

This work projects the CSO algorithm for solving the optimal reactive power problem. The designed algorithm has been modeled based on the quality of soil which has been used in the cultivation of various crops season to season.

Naturally, all the soil which has been used for cultivation will not same with respect to fertility, water content. Farmers will use fertilizers (natural and artificial) in order to improve the fertility of the soil such that the nutrient content of the soil will be improved efficiently. Depend upon the needs and about the type of cultivation farmers will improve the quality of the soil by adding valuable and various types of fertilizers (natural and artificial) such that it will enhance the fertile and growth (green) of the crops. Time to time farmers will choose appropriate nutrient contents that will be mixed with the soil in order to enhance the fertility of the soil.

Normally farmers will analyze all the parts of the cultivation land which has been partitioned as sections. The analysis will be done by the framers in each section about the nutrients' content in the cultivation soil. Then accordingly they will enhance the quality of the cultivation soil by adding materials like fertilizers (natural and artificial). There will difference in adding the nutrient content materials to the cultivation soil with respect to the quality of the land. These actions are all imitated to model the CSO algorithm.

Initialization of the population with respect to the fertility of the cultivation soil is given by

$$Total\ number\ of\ population\ (tnp) = k * n \quad (4)$$

As a division of the farmland the exploration space will be divided into sections *k* and *n* indicates the available number of solutions (present) in the farmland.

Exploration space will be created arbitrarily by

$$y_{ij} = Lower_j + random\ (0,1) \times \left(Upper_j - Lower_j\right) \quad (5)$$

With respect to the objective function fitness value, available solutions in the exploration space will be evaluated in common without considering the division at this stage.

As to how the farmers divide the cultivation land into various sections here in the projected algorithm division of the exploration space is done through *k*. Many assumptions for choosing the value *k* has been maintained as; *k* = 1, *k* = 2, *k* – the maximum number of population possible, maximum *k* = 8, *k* = *y*. In the projected algorithm the value of *k* has been chosen carefully with respect to problem and to balance the exploration and exploitation effectively.

Through each division of the cultivation land's available solution (average) is utilized to get the quality of the cultivation land

$$\begin{gathered} Divison's\ (D) = y(aj); \\ a = n^*(D-1); n * DD = \{1,2,\ldots,k\}; \\ j = \{1,2..,4\} \end{gathered} \quad (6)$$

$$\begin{gathered} fitness - Division's = \\ = Mean\left(all\ fitness\ (y_{ij})in\ Division's\right); \\ D = \{1,2..,k\}; i = \{1,2..,n\} \end{gathered} \quad (7)$$

Updating the local and global memory of the solution average of divided cultivation land is done by

$$\begin{gathered} memory_{local} = round\,(t * n);\ 0.1 < t < 1 \\ memory_{global} = round\,(t * tnp);\ 0.1 < t < 1 \end{gathered} \quad (8)$$

With respect to the quality of the soil in the cultivation land, there will be a change in the poor quality soil since there will up gradation of the poor soil is done through by adding the nutrient contents and defined by

$$\begin{gathered} c = \beta * random(0.1) \\ y_{new} = c * \left(y_{ij} - y_{uj}\right) + y_{ij} \end{gathered} \quad (9)$$

The "$global_{best} - local_{best}$" combination is obtained by

$$C = \begin{cases} y_{new} = y_{ij} + \omega_1 * \left(y_{ij} - global_{best}(gb)\right) \\ \quad .Q > random \\ y_{new} = y_{ij} + random\ (0.1) \\ \quad * \left(y_{ij} - local_{best}(lb)\right) \ .else \end{cases} \quad (10)$$
$$\omega_1 = \omega_1 * r_v,\ 0 < r_v\ 1$$

The corresponding algorithm is presented below:

1) begin;

2) initial parameters are determined;

3) number of the division's in the cultivation land is defined;

4) quality of the cultivation soil is determined with respect to the division;

5) average quality of the soil computed;

6) with respect to each division update the local and global memory:

6.1) in poor quality soil division – changes will be amended through the most excellent solutions which have been available in the external memory;

6.2) in all other divisions (except poor quality division) – changes will be amended through all solutions which available in all division;

7) new-fangled solutions are computed if they are excellent it will replace the previous solution;

8) is the value not less than random?

8.1) if "yes", the solutions are changed with respect to the most excellent solutions in the global memory;

8.2) if "no", the solutions are changed with respect to the most excellent solutions in the local memory;

9) new-fangled solutions are computed if they are excellent it will replace the previous solution;

10) if the end criterion satisfied the stop, or else – go to step 4);

11) output the results.

3 Results

The validity of the CSO algorithm has been tested in the standard IEEE 14 bus system. 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

Variables	Minimum PU	Maximum PU
Generator Voltage	0.95	1.10
Transformer Tap	0.90	1.10
VAR Source	0.00	0.20

Table 2 – Constrains of reactive power generators

Variable	Q Minimum PU	Q Maximum PU
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]	CSO
VG−1	1.060	1.100	1.100	N/R*	N/R	1.002
VG−2	1.045	1.085	1.086	1.029	1.060	1.023
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	1.032
VG−8	1.090	1.074	1.060	1.053	1.078	1.013
Tap 8	0.978	1.018	1.019	1.040	0.950	0.904
Tap 9	0.969	0.975	0.988	0.940	0.950	0.920
Tap 10	0.932	1.024	1.008	1.030	0.960	0.941
QC−9	0.190	14.640	0.185	0.180	0.060	0.153
PG	272.390	271.32	271.320	N/R	N/R	270.62
QG, Mvar	82.440	75.79	76.790	N/R	N/R	75.110
Reduction in PLoss, %	0.000	9.200	9.100	1.500	2.500	23.180
Total PLoss, MWt	13.550	12.290	12.315	13.346	13.216	10.409

* N/R – not reported.

Then the CSO algorithm evaluated, in IEEE 30 and 57 Bus systems. Table 1 shows the constraints of control variables.

Tables 4, 5 show the limits of reactive power generators and comparison results are presented in Tables 6, 7.

Table 4 – Constrains of reactive power generators

Variables	Q Minimum PU	Q Maximum PU
1	0	10
2	–40	50
5	–40	40
8	–10	40
11	–6	24
13	–6	24

Table 5 – Constrains of reactive power generators

Variables	Q Minimum PU	Q Maximum PU
1	–140	200
2	–17	50
3	–10	60
6	–8	25
8	–140	200
9	–3	9

Table 6 – Simulation results of IEEE − 30 system

Control variables	Base case	MPSO [18]	PSO [18]	EP [18]	SARGA [18]	CSO
$VG{-}1$	1.060	1.101	1.100	N/R	N/R	1.032
$VG{-}2$	1.045	1.086	1.072	1.097	1.094	1.024
$VG{-}5$	1.010	1.047	1.038	1.049	1.053	1.050
$VG{-}8$	1.010	1.057	1.048	1.033	1.059	1.023
$VG{-}12$	1.082	1.048	1.058	1.092	1.099	1.060
VG-13	1.071	1.068	1.080	1.091	1.099	1.052
Tap11	0.978	0.983	0.987	1.010	0.990	0.912
Tap12	0.969	1.023	1.015	1.030	1.030	0.921
Tap15	0.932	1.020	1.020	1.070	0.980	0.912
Tap36	0.968	0.988	1.012	0.990	0.960	0.903
QC10	0.19	0.077	0.077	0.190	0.190	0.093
QC24	0.043	0.119	0.128	0.040	0.040	0.124
PG (MW)	300.900	299.540	299.540	N/R	N/R	297.100
QG (Mvar)	133.900	130.830	130.940	N/R	N/R	131.230
Reduction in PLoss, %	0.000	8.400	7.400	6.600	8.300	18.000
Total PLoss, MWt	17.550	16.070	16.250	16.380	16.090	14.390

Table 7 – Simulation results of IEEE −57 system

Control variables	Base case	MPSO [18]	PSO [18]	CGA [18]	AGA [18]	CSO
VG 1	1.040	1.093	1.083	0.968	1.027	1.023
VG 2	1.010	1.086	1.071	1.049	1.011	1.014
VG 3	0.985	1.056	1.055	1.056	1.033	1.032
VG 6	0.980	1.038	1.036	0.987	1.001	1.010
VG 8	1.005	1.066	1.059	1.022	1.051	1.031
VG 9	0.980	1.054	1.048	0.991	1.051	1.013
VG 12	1.015	1.054	1.046	1.004	1.057	1.042
Tap 19	0.970	0.975	0.987	0.920	1.030	0.951
Tap 20	0.978	0.982	0.983	0.920	1.020	0.934
Tap 31	1.043	0.975	0.981	0.970	1.060	0.920
Tap 35	1.000	1.025	1.003	N/R	N/R	1.013
Tap 36	1.000	1.002	0.985	N/R	N/R	1.002
Tap 37	1.043	1.007	1.009	0.900	0.990	1.000
Tap 41	0.967	0.994	1.007	0.910	1.100	0.993
Tap 46	0.975	1.013	1.018	1.100	0.980	1.012
Tap 54	0.955	0.988	0.986	0.940	1.010	0.970
Tap 58	0.955	0.979	0.992	0.950	1.080	0.963
Tap 59	0.900	0.983	0.990	1.030	0.940	0.962
Tap 65	0.930	1.015	0.997	1.090	0.950	1.003
Tap 66	0.895	0.975	0.984	0.900	1.050	0.951
Tap 71	0.958	1.020	0.990	0.900	0.950	1.003
Tap 73	0.958	1.001	0.988	1.000	1.010	1.004
Tap 76	0.980	0.979	0.980	0.960	0.940	0.964
Tap 80	0.940	1.002	1.017	1.000	1.000	1.003
QC 18	0.100	0.179	0.131	0.084	0.016	0.172
QC 25	0.059	0.176	0.144	0.008	0.015	0.161
QC 53	0.063	0.141	0.162	0.053	0.038	0.142
$PG,$ MWt	1278.600	1274.400	1274.800	1276.000	1275.000	1270.110
$QG,$ Mvar	321.080	272.270	276.580	309.100	304.400	272.310
Reduction in PLoss, %	0.000	15.400	14.100	9.200	11.600	22.960
Total PLoss, MWt	27.800	23.510	23.860	25.240	24.560	21.417

4 Conclusions

In this CSO algorithm, the optimal reactive power problem was successfully solved. As a division of the farmland the exploration space will be divided into sections *k* and *n* indicates the available number of solutions (present) in the farmland. Alike how the farmers divide the cultivation land into various sections here in the projected algorithm division of the exploration space is done through *k*. In the projected algorithm the value of *k* has been chosen carefully with respect to problem and to balance the exploration and exploitation effectively. In standard IEEE 14, 30, 57 bus test systems proposed the CSO algorithm has been tested. Power loss reduced and the percentage of real power loss reduction has been enhanced.

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