Active power loss reduction by opposition based kidney search algorithm

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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.

Keywords: Opposition based kidney search algorithm, Optimal reactive power, Transmission loss

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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.

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2. PROBLEM FORMULATION

Objective of the problem is to reduce the true power loss

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

(1)

Voltage deviation given as follows

\[ F = P_L + \omega \times \text{Voltage Deviation} \]

(2)

Voltage deviation given by

\[ \text{Voltage Deviation} = \sum_{i=1}^{N_{pq}} |V_i - 1| \]

(3)

Constraint (Equality)

\[ P_G = P_D + P_L \]

(4)

Constraints (Inequality)

\[ p_{\text{gslack}}^{\text{min}} \leq P_{\text{gslack}} \leq p_{\text{gslack}}^{\text{max}} \]

(5)

\[ q_{gi}^{\text{min}} \leq Q_{gi} \leq q_{gi}^{\text{max}}, \quad i \in N_g \]

(6)

\[ v_i^{\text{min}} \leq V_i \leq v_i^{\text{max}}, \quad i \in N \]

(7)

\[ t_i^{\text{min}} \leq T_i \leq t_i^{\text{max}}, \quad i \in N_T \]

(8)

\[ q_c^{\text{min}} \leq Q_c \leq q_c^{\text{max}}, \quad i \in N_C \]

(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

\[ Z_{i+1} = Z_i + \text{rand}(Z_{\text{best}} - Z_i) \]

(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

\[ l_r = \beta \times \frac{\sum_{s=1}^{S_f} f(Y_i)}{S} \]

(11)

\( \beta \) 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 \( i \)th 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

\[
\text{Glomerular filtration rate}_{\text{minimum}} = 120 - \left( \frac{fr_{FB}^{\text{100}}}{fr} \right)
\]  
(12)

Define the Population
Calculate approximate solution in the population
Most excellent solution \( Z_{\text{best}} \), 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 \( Z_{\text{new}} \) by using (10)
If re-absorption is not fulfilled then \( Z_{\text{new}} \) 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 \( Z_{\text{worst in FB}} \)
\( Z_{\text{worst}} \) 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 \( Z_i \) from FB and modernize the \( Z_{\text{best}} \)
Merge W and FB
By (11) amend filtration rate \( l_r \)
End while
Return \( Z_{\text{best}} \)

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

\[
N^o = x + y - N
\]  
(13)

In the exploration space it has been extended as

\[
N_i^o = x_i + y_i - N_i
\]  
(14)

Where \( (N_1, N_2, .. N_d) \) is a point in the dimensional search space, \( N_i \in [x_i, y_i], i \rightarrow \{1,2,3, .. d\} \)
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,” based on mutual information based switching
e. Apply the filtration operator
f. Is “Z,” assigned as “W”? ; if “Yes” apply the reabsorption operator; or check is “Z,” better than the “Z_worst” – if yes then secrete “Z_worst” from FB or secrete “Z,”
g. Can “Z_new” be assigned as FB? If yes remove “Z” from W and insert a random “Z” into “W”
h. Have all “Z,” have been met?
i. If “yes” engender “Z̅_ϕ” or else go to step “d”
j. Is “Z̅_ϕ” better than the “Z_worst” in FB? if “yes” replace “Z_worst” with “Z̅_ϕ”
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 | Table 2. Constrains of reactive power generators |
|-------------------------------------------|-----------------------------------------------|
| System Variables | Minimum (PU) | Maximum (PU) | System | Q Minimum (PU) | Q Maximum (PU) |
| Generator Voltage | 0.95 | 1.1 | | | |
| IEEE 14 Bus Transformer Tap | 0.9 | 1.1 | | | |
| VAR Source | 0 | 0.20 | | | |

Table 3. Simulation results of IEEE –14 system

| Control variables | Base case | MPSO [18] | PSO [18] | EP [18] | SARGA [18] | OKS |
|-------------------|-----------|----------|---------|---------|-----------|-----|
| V_G−1 | 1.060 | 1.100 | 1.100 | NR* | NR* | 1.012 |
| V_G−2 | 1.045 | 1.085 | 1.086 | 1.029 | 1.060 | 1.028 |
| V_G−3 | 1.010 | 1.055 | 1.056 | 1.016 | 1.036 | 1.024 |
| V_G−6 | 1.070 | 1.069 | 1.087 | 1.097 | 1.099 | 1.016 |
| V_G−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 |
| Q_G−9 | 0.19 | 14.64 | 0.185 | 0.18 | 0.06 | 0.146 |
| Q_G (Mvar) | 82.44 | 75.79 | 76.79 | NR* | NR* | 71.09 |
| 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 | Table 5. Constrains of reactive power generators |
|-------------------------------------------|-----------------------------------------------|
| System Variables | Minimum (PU) | Maximum (PU) | System | Q Minimum (PU) | Q Maximum (PU) |
| IEEE 30 Bus Generator Voltage | 0.95 | 1.1 | IEEE 30 Bus | 1 | 0 | 10 |
| Transformer Tap | 0.9 | 1.1 | 2 | -40 | 50 |
| VAR Source | 0 | 0.20 | 5 | -40 | 40 |
| PG | 272.39 | 271.32 | 8 | -6 | 24 |
| 11 | -6 | 24 | 13 | -6 | 24 |
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            | 0.2          |

### Table 8. Constraints 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] | EP [18] | AGA [18] | CGA [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-3              | 1.017     | 1.047     | 1.038    | 1.049   | 1.053    | 1.017    |
| VG-5              | 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    | 1.072   | 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     | 0.199    |
| QC24              | 0.043     | 0.119     | 0.128    | 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   |
| Total 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 118 Bus system. Table 10 shows the constraints of control variables and the comparison results are presented in Table 11 as shown in appendix.

| System           | Variables      | Minimum (PU) | Maximum (PU) |
|------------------|----------------|--------------|--------------|
| IEEE 118 Bus     | Generator Voltage | 0.95         | 1.1          |
|                  | 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.

| 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  | MPPOSO [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 | 0.977 | 1.078 | 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 | 0.999 |
| VG 31 | 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 | 0.991 | 0.983 | 0.950 |
| VG 6 | 0.985 | 1.019 | 0.970 | 1.051 | 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 | 0.983 | 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 |
| VG 56 | 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 | 0.965 | 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 93 | 1.010 | 1.031 | 1.023 | 0.954 | 1.088 | 1.005 |
| VG 100 | 1.017 | 1.049 | 1.037 | 0.958 | 0.961 | 1.003 |
| VG 101 | 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 |

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

| VG 107  | MPSO [18] | PSO [18] | PSO [18] | CLPSO [18] | OKS   |
|---------|-----------|----------|----------|------------|-------|
| 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*        | 4358.02* |
| QG(MVAR)| 759.6     | 604.3    | 653.5    | 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.