Chaotic theory incorporated with PSO algorithm for solving optimal reactive power dispatch problem of power system

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ABSTRACT

In this paper, the chaotic particle swarm optimization (CPSO) algorithm is combined with MATPOWER toolbox and used as an optimization tool for attaining solving the optimal reactive power dispatch (RPD) problem, by finding the optimal adjustment of reactive power control variables like a voltage of generator buses (VG), capacitor banks (QC) and transformer taps (Tap) while satisfying some of equality and inequality constraints at the same time. CPSO and Simple PSO algorithms will be checked in a large system such as IEEE node -118. CPSO and Simple PSO algorithms have been implemented and simulated in the MATLAB program, version (R2013b/m-file). Then compassion these results with the results obtained in the other algorithms in the literature like the comprehensive learning particle swarm optimization (CLPSO) algorithm. The simulation results confirm that the CPSO algorithm has high efficiency and ability in terms of decrease real power losses (P_{Loss}), and improve voltage profile compared with the obtained by using the simple (PSO) algorithm and (CLPSO) at light load.

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1. INTRODUCTION

Optimal reactive power dispatch (RPD) problem is considered as a complex, non-continous problem. The power system involves of generation, transmission and distribution system to provide the electric power to the consumers. It is an essential modern problem in the power system operating and control. The objective of (RPD) problem is to find the best value of reactive power independent (control) variables so as to minimize a certain objective function such as power loss and voltage deviation. The main goals in this work are to get minimum power loss, and enhance voltage profile for the system and this goals can be achieved through an optimal alteration of the reactive power control variables like, generator voltages value (V_G), the amount of (VAR) that injected from the capacitor banks (Q_C) and transformer taps (Tap) settings while dealing with equality and inequality constrains at the same time [1]. The electrical loads are not constant and vary from hour to hour. Any varying in power demands can lead to higher or lower voltages in the system, so it must keep the reactive power devices like (viz. V_G, Tap and Q_C) varying simultaneously with the changing in the electric load and voltage [2]. Undeniably, over the last decades, RPD problem plays a vital role in the power system operation and control and has recorded an ever-intense interest of the authors because of remarkable and great effect on the economic, safe and security operation problem.

This problem is considered as a branch problem of the optimal power flow (OPF) calculation. Carpentier was the first to introduce the model and concept of (OPF) in the early 1960s [3]. Then, many researchers has been working on solving OPF problem by utilizing multi methods and like ant lion optimizer (ALO) and integration of the invasive weed optimization (IWO) and Powell's pattern search (PPS) method [4], [5]. Ariantara *et al*. Using differential evolution (DE) Algorithm for the solution of OPF [6].

In the past, researchers were presented a lot of researches on (RPD) problem, and presented a number of optimization algorithms. These algorithms are classified into two types: conventional optimization algorithms and computational optimization algorithms. The concept of conventional algorithm is beginning from an initial point. These algorithms contain interior point methods (IPM) [7], linear programing (LP) [8], non-linear programming [9] and dynamic programming (DP) [10]. These algorithms have several disadvantages such as unable to dealing with complex optimization problem, unable to dealing with problem that include very large number of variables, huge calculations, big implementation time and convergence to the nearby local optima. So, it becomes essential for finding and developing methods able to avoid these disadvantages.

So, several optimization techniques have been presented in order to avoid these disadvantages of the conventional optimization algorithms and these algorithms called computational optimization algorithms and the basic concept of these algorithms are beginning from an initial solution swarm like, genetic algorithm (GA) [11], gentoo penguin algorithm (GPA) [12], hybrid GA-IPM [13], meleagris gallopavo algorithm (MGA) [14], chaotic predator-prey brain storm optimization (CPB) algorithm [15], Gravitational search algorithm (GSA) and sine cosine algorithm (SCA) [16], enhanced fruit fly optimization algorithm (EFF) and status of material algorithm (SMA) [17] and polar wolf optimization (PWO) algorithm [18] and particle swarm optimization (PSO) [19], have been presented for the solution of RPD problem in the literature. From all these algorithms, PSO shown great reliability to overcome the drawbacks of the conventional algorithms and can easily be applied to multi problems, but it doesn't mean that PSO algorithm doesn't involve any disadvantages. Therefore, in solving the non-continuous and complex problems this algorithm is declining to the local minima at the premature convergence, on the other hand, also it depends on its parameter settings.
So, many researchers working for enhance PSO algorithm and prevent that disadvantages by using sundry methods and techniques compact with PSO algorithm. Zhang *et al*. have proposed a two-phase HPSO technique to solved the RPD problem [20]. Vlachogiannis *et al*. have applied (PSO, GPAC-PSO, and LPAC-PSO) algorithms for reactive power and voltage control [21].

In the presented work, simple PSO has been developed to solve the RPD problem for minimizing power losses and voltage profile enhancement. So as to enhance the searching quality of the simple PSO algorithm and to avoid falling into the local minima and to decrease the calculation time, Chaotic PSO (CPSO) is utilized so as to overcome these disadvantages. The chaos greatly helps the CPSO algorithm for slip more easily from the local minima because of the special behavior, and strong ability for the chaotic theory. Simple PSO and CPSO are applied for solving the RPD problem on IEEE Node-118 system, then the simulation results were compared with other algorithm in the literature, like comprehensive learning particle swarm optimization (CLPSO).

2. PROBLEM FORMULATION

In this section, the main goal in this study is to find the best combinations of reactive power independent variables so as to decrease the power losses (P_{Loss}) for the system while dealing with numbers of equality and inequality constrains at the same time. So, the objective function in this work can be expressed as shown in (1) [22], [23].

$$\text{Min } P_{Loss} = \sum_{K=1}^{Ntl} G_K (V_i^2 + V_j^2 - 2V_iV_i \cos(\phi_i - \phi_j) \tag{1}$$

where, P_{Loss} is the active power loss function. Ntl depict the number of branches. G_K is the conductance of branch K. V_i, V_j are the voltage magnitudes at node i and j. ϕ_i, ϕ_j are the difference angles voltage at node i and j. (i and j) are the sending and receiving nodes of branch K.

2.1. System constrains

Equality constrains are the load flow equation and defined [24]:

$$\begin{cases} P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j \left(G_{ij}\cos(\phi_{ij}) + B_{ij}\sin(\phi_{ij}) \right) = 0 \\ Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j \left(G_{ij}\sin(\phi_{ij}) - B_{ij}\cos(\phi_{ij}) \right) = 0 \end{cases} \tag{2}$$

where P_{Gi}, Q_{Gi} are the real (MW) and reactive power (VAR) output from the generators at node i. P_{Di}, Q_{Di} are the real (MW) and reactive power (VAR) load demand at node i. G_{ij}, B_{ij} are the mutual and susceptance conductance among i node and j node. ϕ_{ij} depict the voltage angle magnitude in node i and j. Inequality constrains involves independent (control) variables like, generator voltages (V_G), injected reactive power from capacitor (Q_C) and transformer positions (Tap) [25]:

$$\begin{cases} V_{Gi}{}^{min} \le V_{Gi} \le V_{Gi}{}^{max}, i \in N_G \\ Tap_K{}^{min} \le Tap_K \le Tap_K{}^{max}, K \in N_T \\ Q_{Ci}{}^{min} \le Q_{Ci} \le Q_{Ci}{}^{max}, i \in N_C \end{cases} \tag{3}$$

where N_G depict the number of generator nodes. $V_{Gi}{}^{min}$, $V_{Gi}{}^{max}$ are the Minimum limit and maximum limit of generator voltage magnitude at i-node. N_T depict the total number of transformers. $Tap_k{}^{min}, Tap_k{}^{max}$ are the Minimum limit and Maximum limit of transformer ratio at branch K . N_C depict the total number of injected VAR source. $Q_{Ci}{}^{min}$, $Q_{Ci}{}^{max}$: are the Minimum limit and Maximum limit of injected VAR source from shunt capacitor at node i. And also involves dependent (state) variables such as voltage at load bus (V_l) and reactive power output from the generators (Q_G) [25]:

$$\begin{cases} Q_{Gi}{}^{min} \le Q_{Gi} \le Q_{Gi}{}^{max}, i \in N_G \\ V_{li}{}^{min} \le V_{li} \le V_{li}{}^{max}, i \in N_{PQ} \end{cases} \tag{4}$$

where, N_G depict the number of generator nodes. $Q_{Gi}{}^{min}$, $Q_{Gi}{}^{max}$ are the minimum (lower) limit and maximum (upper) limit of reactive power output of generator at $i -$ node. N_{PQ} depict the number of load nodes. $V_{li}{}^{min}$, $V_{li}{}^{max}$: are the Minimum (lower) limit and Maximum (upper) limit of voltage magnitude at i-node.

2.2. The generalized objective function

In this problem, the dependent variables can be added to (1) by utilizing penalty factors to constrain, so (1) can be written as shown in (5) [25]:

$$\text{Min F} = P_{Loss} + \lambda_V \sum_{i=1}^{NL} (v_{Li} - v_{Li}{}^{lim})^2 + \lambda_Q \sum_{i=1}^{NG} (Q_{Gi} - Q_{Gi}{}^{lim})^2 \tag{5}$$

where λ_V and λ_Q are penalty terms; X^{lim} is the limit value of inequality constrains; NL is the total number of load nodes; NG is the numbers of generation station and P_{Loss} is given in (1).

2.3. Concept of average voltage

In this study, the new average voltage index is suggested to deal with all voltage nodes as well as satisfy most of the electrical utility limits. The equation of this concept can be written as shown in (6):

$$V_{av} = \frac{\sum_{i=1}^{Nn} V_i}{N_n} \tag{6}$$

where V_{av} depict the average voltage of all system; V_i depict the voltage in node i. N_n depict the total number of nodes.

3. OPTIMIZATION PROCESS

3.1. Simple PSO algorithm

PSO algorithm is a best type for artificial intelligence, which mimics the social behavior of the animals which does not have any leader when searching for food like, bird flocking and fish schooling. It has several advantages such as simple, fast, can applied for solving optimization problem and guarantees best solution within lesser calculation time and the convergence characteristic have very stable than other stochastic algorithms and capable of dealing with continuous and discrete variables and does not have mutation and crossover operation like genetic algorithm. An individual represents the probable solution and every group of individuals represents a swarm. This theory was first put forward in 1995 [26]. Each individual has best position discover by the individual it self and it is stored in a memory called local best position (P_{best}), and the best position discovered among all individuals (P_{best}) in the swarm also stored in a memory called global best position (G_{best}), at every step the location of P_{best} and G_{best} are changing. Then, the velocity and position of every individual in the swarm are changed by employing the calculation of the present individual velocity and the location from P_{best} position and G_{best} position. The velocity and distance from P_{best} location and G_{best} location of the agents will be changed by utilizing (7) and (8) [27].

$$V_i^{k+1}=K*[W_{PSO}*V_i^k + C_1 * R_1*(P_{best(i)}{}^k - X_i^k) + C_2 * R_2*(G_{best(i)}{}^k - X_i^k)] \quad (7)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (8)$$

where, W_{PSO} is the inertia coefficient of PSO technique. V_i represents the velocity of individual. C_1, C_2 are the two learning factors that utilized to pull each agent to P_{best} location and G_{best} location within range [0 to 2.05]. R_1, R_2 are the two random numbers within limit [0 to 1]. $P_{best(i)}$ depicts the local best position. $G_{best(i)}$ represents the global best position. X_i represents the position of the individual and K is the constriction factor and it is utilize to improve the performance of the simple PSO algorithm and it was introduced by Shi indicate that using of this factor may be necessary and can be expressed [28].

$$K = \frac{2}{\left|2-\phi-\sqrt{\phi^2-4\phi}\right|}, \phi = C_1 + C_2, \phi \geq 4 \quad (9)$$

A proper choice of the inertia weight (W) can achieve a balance between global location and local location. So, in this work, W_{PSO} was reduced linearly from (0.4-0.9) for each iteration (step) to search in a big area at the start of the simulation and to attains balance between global position (G_{best}) and local position (P_{best}) [28]:

$$W_{PSO} = W_{max} - \left(\frac{W_{max} - W_{min}}{max_{iteration}}\right) * iter \quad (10)$$

where W_{max} is the max (upper) value of weight. W_{min} is the min (lower) value of weight. $iter$ is the current iteration and $max_{iteration}$ is the max (upper) iteration.

3.2. CPSO algorithm

Despite the advantages of the simple PSO algorithm, but it has several limitations such as highly depend on its parameter and decline to the local optimal at the premature convergence especially when the problem is very complex.In this work, so as to prevent these limitations and to boost the quality and performance, and the searching ability of the simple PSO algorithm, chaotic theory with Simple PSO are merged to form a hybrid algorithm called the CPSO algorithm. and undeniably, this merge is a very helpful to slip from the local optimal because of the special behavior and great ability of the chaotic CPSO algorithm [29]. In this work, the logistic map equation of the hybrid CPSO algorithm was described by the (11) [30].

$$\beta^{k+1} = \mu\beta^k\big((1-\beta^k)\big), 0 \leq \beta^1 \leq 1 \quad (11)$$

Where, k is the number of the iteration (steps), and the control parameter μ was set within a range (0.0 to 4.0). The magnitude of μ decides whether β stabilizes at a constant area, oscillates within restricted limits, or behaves chaotically in an unpredictable form. And (11) was shows chaotic dynamics when μ = 4.0 and β^1 ∈{0,0.25,0.5,0.75,1}, it shows the sensitive depend on its initial conditions, which is the basic features of chaotic. The new inertia weight factor (W_{CPSO}) was calculated by multiplying the (W_{PSO}) for (10) and logistic map for (11) to form (12).

$$W_{CPSO} = W_{PSO} * \beta^{k+1} \quad (12)$$

To enhance the behavior of the simple PSO, this work presents a novel velocity update by blending inertia weight factor WPSO with the logistic map equation (β). Finally, by blending (12) with (7), the following velocity changed equation to the proposed CPSO algorithm was obtained:

$$V_i^{k+1} = W_{CPSO} * V_i^k + C_1*R_1*(P_{best(i)}{}^k - X_i^k) + C_2*R_2*(G_{best(i)}{}^k - X_i^k) \quad (13)$$

In the CPSO algorithm, W_{CPSO} was oscillates and decrease simultaneously from (0.9-0.4) for total iteration, but in traditional PSO was decrease linearly. Table 1 shows a final choice of the control parameters CPSO and simple PSO algorithms that is considered the optimal choice in this study.

Table 1. Parameters used for CPSO and PSO algorithms

Parameters of CPSO and PSO algorithms	CPSO	PSO
n	100	100
c_1	2	2
c_2	2	2
r_1	1	1
r_2	1	1
w_{max}	0.9	0.9
w_{min}	0.4	0.4
μ	4	-
B^1	0.75	-
max_{iter}	300	300
numbers of particles	100	100

4. CASE STUDY AND SIMULATION RESULTS

To verify and test the performance and ability for the proposed methods (i.e. simple PSO and CPSO) for solving RPD problem in a complex power system, IEEE node-118 systems is employed. This system is involve, 12 injected reactive power sources (Q_C) from shunt capacitors, 186 branches, 54 generator voltages (V_G) and 9 transformer tap ratios (Tap) at branches 8, 32, 36, 51, 93, 95, 102, 107 and 127, the limits of these variables are illustrated in Table 2. Branch, bus, generator, the upper and lower limits of the reactive power in Mvar for the generators and other operating data are given in [31]. So, this system has 75 control (independent) variables as displayed given in Table 3 (see appendix), and at base case the initial active and reactive power generations are P_G=4374.86 Mw and Q_G=795.68 Mvar, the initial active and reactive power loads are P_{Load}=4242.00 Mw and Q_{Load}=1438.00 Mvar, the initial active and reactive power losses are P_{Loss}=132.86 Mw and Q_{Loss}=783.69 Mvar and they are 3 voltages outside the limits in the base placed at bus 53, 76 and 118 and the value of these voltages in p.u are V_{53}=0.946, V_{76}=0.943 and V_{118}= 0.949. The simulation results are given in Table 3 (see appendix) for the goal of minimization of P_{Loss} for the system and according to these results, found the results that yielded from the CPSO algorithm are the best for solving large power system compared to the results that obtained in the simple PSO and other algorithms in the literature like comprehensive learning particle swarm optimization CLPSO [32] algorithms. Figure 1 shows the comparison among the percentage reduction of power losses for the used algorithms, and Figure 2 shows the comparison among the real power loss value (P_{Loss}) for the used algorithms. The convergence characteristics of P_{Loss} in MW for the simple PSO and CPSO algorithms are expose in Figures 3 and 4, and from these figures, it can be seen that CPSO algorithm performs best and reaching to the global solution in less time than simple PSO for the solution of RPD problem. The voltage profile are given in Figure 5 and from this figure it is clear that the voltage average at initial is about **0.986,** at PSO is about 1.024, and at CPSO is about 1.045 and also all buses voltages are inside the limits after CPSO algorithm but in the simple PSO algorithm V_{32} and V_{33} are still outside the limits. The power loss reduction (P_{Loss}) is 15.1% (from 132.8 Mw to 112.65 Mw) achieved by utilizing CPSO algorithm, which is consider the largest reduction in P_L than that accomplished in the simple PSO, CLPSO [32] algorithms.

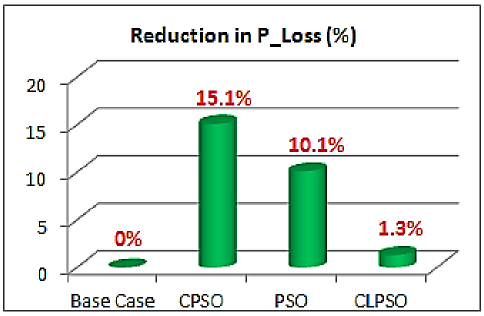

Figure 1. Real power loss reduction in percentage

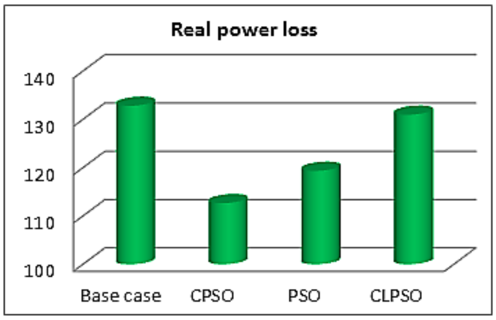

Figure 2. Comparison of real power loss (P_{Loss})

Table 2. Control variables limits

System Type	Variables	Min	Max
118 Bus	Generator voltage (V_G)	0.95	1.1
	Transformer position (Tap)	0.9	1.1
	VAR source compensation (Q_C)	0	0.20

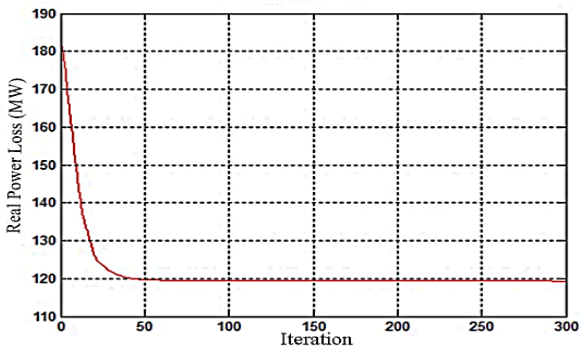

Figure 3. Convergence for IEEE 118 node power system with simple PSO algorithm

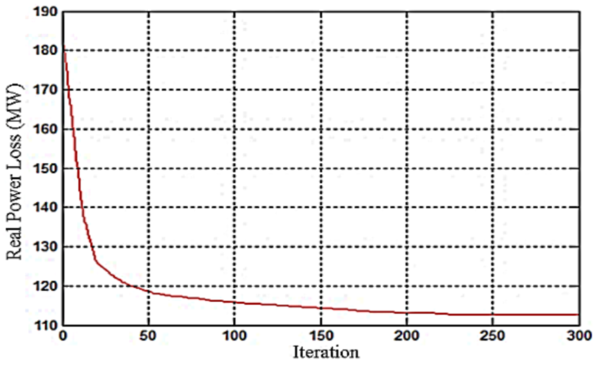

Figure 4. Convergence for IEEE 118 node power system with CPSO algorithm

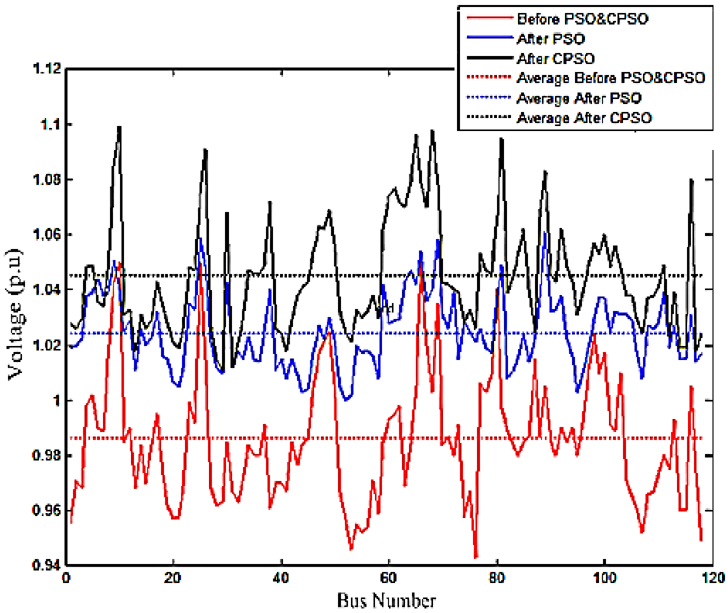

Figure 5. Voltage profile of IEEE 118-node system

5. CONCLUSIONS

In this study, two types of algorithms are utilized they simple PSO and CPSO. The chaotic particle swarm optimization algorithm is combined with MATPOWER toolbox and used as an optimization tool for attaining solving the optimal reactive power dispatch problem. The objective function has been utilized to decrease power loss in the power system branches and improve voltage profile. The efficiency and high quality of CPSO algorithm have been proved by examining on IEEE Node-118 system. CPSO provided the best technique to search for an optimal solution that decreased the calculation time and has high speed convergence in both power loss minimization and voltage profile improvement compared with the results obtained from using simple PSO and other results reported in the literature like comprehensive learning particle swarm optimization algorithm. Where, a percentage reduction in power loss be (15.1%) for CPSO, (10.1%) for PSO, and (1.3%) for CLPSO.

6. SUGGESTIONS FOR FUTURE WORK

In the future, the research can be developed by optimizing total voltage deviation (TVD) and voltage stability index (VSI) separately as a single objective function or as multi-objective functions in order to achieve more improvement in the RPC problem.

APPENDIX

Table 3. Simulation result of IEEE- 118 node systems

Control Variables	Base Case	CPSO	PSO	CLPSO [32]
V_G 1	0.955	1.028	1.019	1.033
V_G 4	0.998	1.048	1.038	1.055
V_G 6	0.990	1.036	1.044	0.975
V_G 8	1.015	1.047	1.039	0.966
V_G 10	1.050	1.099	1.040	0.981
V_G 12	0.990	1.033	1.029	1.009
V_G 15	0.970	1.026	1.020	0.978
V_G 18	0.973	1.034	1.016	1.079
V_G 19	0.962	1.028	1.015	1.080
V_G 24	0.992	1.047	1.033	1.028
V_G 25	1.050	1.075	1.059	1.030
V_G 26	1.015	1.091	1.049	0.987
V_G 27	0.968	1.027	1.021	1.015
V_G31	0.967	1.012	1.012	0.961
V_G 32	0.963	1.021	1.018	0.985
V_G 34	0.984	1.047	1.023	1.015
V_G 36	0.980	1.046	1.014	1.084
V_G 40	0.970	1.024	1.015	0.983
V_G 42	0.985	1.029	1.015	1.051
V_G 46	1.005	1.054	1.017	0.975
V_G 49	1.025	1.069	1.030	0.983
V_G 54	0.955	1.033	1.020	0.963
V_G 55	0.952	1.030	1.017	0.971
V_G56	0.954	1.032	1.018	1.025
V_G 59	0.985	1.062	1.042	1.000
V_G 61	0.995	1.077	1.029	1.077
V_G 62	0.998	1.072	1.029	1.048
V_G 65	1.005	1.096	1.042	0.968
V_G 66	1.050	1.051	1.054	0.964
V_G 69	1.035	1.078	1.058	0.957
V_G 70	0.984	1.043	1.031	0.976
V_G 72	0.980	1.040	1.039	1.024
V_G 73	0.991	1.039	1.015	0.965
V_G 74	0.958	1.028	1.029	1.073
V_G 76	0.943	1.026	1.021	1.030
V_G 77	1.006	1.053	1.026	1.027
V_G 80	1.040	1.067	1.038	0.985
V_G 85	0.985	1.062	1.024	0.983
V_G 87	1.015	1.025	1.022	1.088
V_G 89	1.000	1.083	1.061	0.989
V_G 107	0.952	1.024	1.008	0.976
V_G 110	0.973	1.041	1.028	1.041
V_G 111	0.980	1.049	1.039	0.979
V_G 112	0.975	1.023	1.019	0.976
V_G 113	0.993	1.039	1.027	0.972
V_G 116	1.005	1.080	1.031	1.033
Q_C 48	0.150	0.047	0.056	0.028
Q_C 74	0.120	0.112	0.120	0.005
Q_C 79	0.200	0.150	0.140	0. 148
Q_C 82	0.200	0.190	0.180	0.194
Q_C 83	0.100	0.163	0.166	0.069
Q_C 105	0.200	0.026	0.190	0.090
Q_C 107	0.060	0.077	0.129	0.049
Q_C 110	0.060	0.137	0.014	0.022
P_G (MW)	4374.8	4354.7	4361.4	NR*
Q_G (Mvar)	795.68	535.56	653.58	NR*
Reduction in P_{Loss} (%)	0	15.1	10.1	1.3
(Mw) Total P_L	132.8	112.65	119.34	130.96

NR*: means that the value was not reported.

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