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Shunt Compensation and Optimization of Nigerian 330Kv 34 Bus Power System using Metaphorless Rao-Type Algorithms

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Abstract
Power system networks suffer from power losses and bus voltage violations due to heavy loading at the various buses. As a consequence, there is a need for some sort of compensation at the heavily loaded bus points. In this paper, a novel type of optimizer with fast convergence and simplicity called Rao-1, which is based on metaphorless programming, is presented for the task of optimization with shunt compensation on Nigerian 330-kV power network. The application of this algorithm for optimal shunt compensation of the Nigerian 330kV, 34-bus power transmission network is presented. The results obtained by Rao-1 technique are compared with particle swarm optimization (PSO). The findings show that using shunt compensation generally improves the precision of objective function values even though at some trials there might be deviations. Comparative results also show the competitiveness and efficacy of proposed Rao-1 type algorithm in terms of fitness scores and computational run time.

Keywords: Optimization, metaphorless programming, shunt compensation, power transmission network, voltage violation.

1.0 INTRODUCTION

The power transmission network represents a very vital part of modern society by providing electricity which is useful for a variety of applications in residential communities, educational servicing, and many areas in commerce and industry. To meet with the demand for energy, power transmission networks have to supply power at a certain voltage and at reduced power losses. However, this is not always possible as the ever-increasing power demand by the teeming populace results in stretching the network beyond limits leading to bus voltage violations such as reduced voltages and power losses. In order to reduce this effect, shunt compensation is typically added to the weak buses. However, the optimal allocation of shunt compensation devices presents another challenging problem. Thus, there is a need for optimization strategies to alleviate these problems. In this regard, [1] applied both conventional and non-conventional technique.

Recently, interest in metaphor-based solutions has increased exponentially because of their inherent successes over conventional non-linear, and gradient techniques, and also because of their avoidance of local optimality, poor convergence and simplicity. This is true for metaphor-based programming using such techniques as particle swarm optimization (PSO), Artificial Bee Colony (ABC), Ant colony optimization (ACO), Biogeography Based Optimizer (BBO), and Generic Algorithm (GA) etc [1]. Several types of metaphors exist for the optimization of power system based on reactive power. In [1], BBO, a species-based optimizer is used for optimizing (minimizing) voltage deviations and transmission losses.
The BBO is applied to IEEE 30-bus and IEEE 118-bus power transmission network. The simulation result is compared with other popular metaphor such as PSO and it was shown that BBO l outperforms them within a promising computational time span. The use of dynamic programming (DP) and GA for reactive power compensation and optimization of the Saudi Electricity 380 kV power transmission network is reported in [2]. In their model, monetary costs are included in the optimization process. On the other hand, [3] reported the performance of an Adaptive Whale Optimization

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Algorithm (AWOA) in minimizing the problems associated with power system quality. The technique in [3] was applied to IEEE30-bus and IEEE 57-bus power transmission networks. Simulation results showed improvements over popular techniques like Artificial Bee Colony, GA, Firefly and PSO.

Other important related researches based on power transmission network shunt or reactive compensation can be found in: [4] using standard Newton-Raphson, [5] using the Fuzzy Logic (FL) technique, [6] using non-linear programming (NLP) and hybrid techniques exploiting chemical reaction theory and Cuckoo Search (CS) metaphor [7]. Also, extensive reviews bordering on FACTS devices including shunt compensation effects in power transmission network optimization are provided in [8] and in [9]. Despite the successes recorded in using the metaphor techniques, the problem of the existence of a simple but metaphorless programming solution to power system related problems is still being investigated. Accordingly, in this paper, in contrast to existing results, a metaphorless programming solution called Rao-1 algorithm for shunt compensation and optimization of Nigerian 330kV 34-bus power system network is investigated. The main objective of using this technique is to optimally allocate the compensation level for minimizing the bus voltage violations and power system loss. This is closely related to the Optimal Reactive Power Flow (ORPF) formulation and will be studied in this paper.

2.0 MATERIALS AND METHOD

The development of an optimization solution model for a power system requires that the objective (fitness or cost) function be specified and that optimization decision variables including boundary conditions and constraints be clearly defined. In the case where overloading occurs frequently resulting in voltage drop, there is a need for shunt compensators.

Hence, the optimization of such a system will include the load flow considering voltage deviations, and power losses specifically constrained in an adaptive manner by shunt compensating devices. In this study, the system model depicted in Fig.1 is employed.

In practice, the decision variables (DV) are built into a set of equality (power balance) and inequality (power in-balance) expressions; the constraints are also defined programmatically in a concatenated list of DV maxima and minima states and where appropriate conditional expressions such as <, >, <= or >= are used for further enforcement. The symbols P, Q, V, d and Qc are representative of power system optimizer variables used in network solution. Once these constraints are defined, the fitness function is defined.

In this study the fitness function consists of three objectives:

i. The computed and injected real power deviations
ii. The computed and injected reactive power deviations
iii. The bus voltage violations (deviations)

In the considered algorithms, these objectives must be minimized after a net summation operation.

The equality constraints used are described as in [10-11] by the following relations eqn (1)-eqn (4):

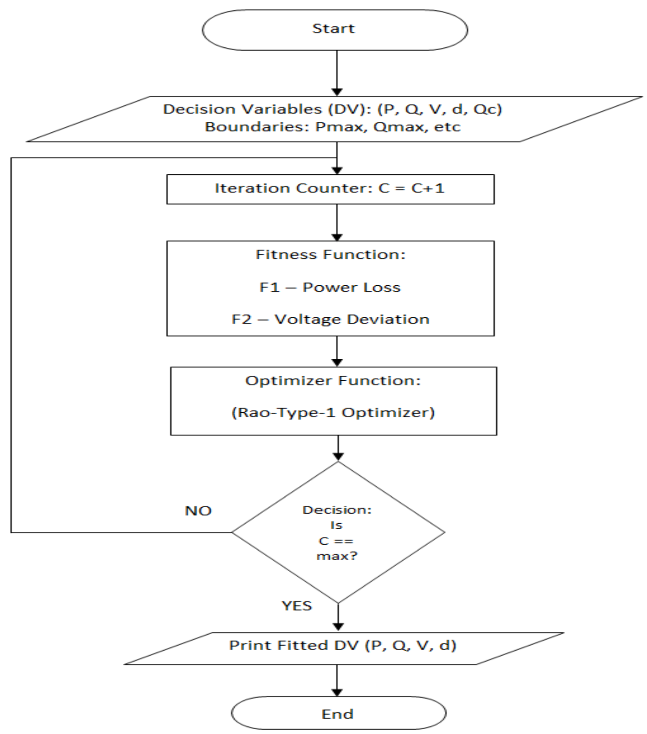

Fig. 1: Flow chart of Systems Methodology proposed in this paper

$$P_G - P_D - P_L = 0 \quad (1)$$

$$Q_G - Q_D - Q_L = 0 \quad (2)$$

$$P_{Lj} = |V_i||V_j||Y_{ij}|\left|\sum_{n-1}^{N}\cos(\alpha_{ij} - \delta_i - \delta_j)\right) \quad (3)$$

$$Q_{Lj} = |V_i||V_j||Y_{ij}|\left|\sum_{n-1}^{N}\sin(\alpha_{ij} - \delta_i - \delta_j)\right), \quad (4)$$

where

P_G = Generator Real Power

Q_G = Generator Reactive Power

P_D = Load Demand Real Power
Q_D = Load Demand Reactive Power
P_L = Real Power Losses
Q_L = Reactive Power Losses.

Equations (3) and (4), respectively, represent the values of P_L and Q_L of i-th bus. Thus, the ultimate goal of the optimization system model is to minimize equation (1) subject to the following constraints:

$$P_G^{\min} \le P_G \le P_G^{\max} \tag{5}$$

$$Q_G^{\min} \le Q_G \le Q_G^{\max} \tag{6}$$

$$P_D^{\min} \le P_D \le P_D^{\max} \tag{7}$$

$$V_{bus}^{\min} \le V_{bus} \le V_{bus}^{\max} \tag{8}$$

$$d_{bus}^{\min} \le d_{bus} \le d_{bus}^{\max} \tag{9}$$

$$P_{li}^{\max} \ge P_{li} \tag{10}$$

$$Q_c^{\min} \le Q_c \le Q_c^{\max}. \tag{11}$$

Where the expressions in equations (5)–(9), represent the lower (min) and upper (max) limits of their respective variables, and the expression in equation (10) represents the maximum possible active power flow [10]. Shunt compensation (Q_c) is achieved using a specific range of MVAR injections as described in [1], and it is modeled using continuous differentiable approach. In this study, a range of 0 to 50MVARS is inserted programmatically in the optimizer power flow programme at the bus injection node to enforce compensation. In particular, it must be emphasized here that the optimizer (be it the Rao-1 or PSO technique) automatically assigns optimal MVARs to the buses as is needed. Thus, no human intervention is required during compensation.

The expressions define a first and primary objective during shunt compensation and load flow optimizations of power transmission network, and are handled by the fitness function block in Fig.2. In addition to minimizing power losses, there is also the need of minimizing bus voltage violations [11-13]. Thus, another important objective is the total voltage deviation or violation (TVV) accumulated over several simulation time iterations. In this paper, the TVV is computed using the reference model expression described in equation (12) as:

$$TVV = V_j^t - V_{ref}, \tag{12}$$

where

V_j^t = the calculated voltage at bus j for simulation time step, t

V_{ref} = pre-specified reference voltage.

In this paper, a V_{ref} = 1.0pu is used as control voltage during shunt compensation. In order to achieve the aforementioned objectives, an optimizer function is used. The generalized steps in performing an optimization procedure with shunt compensation are as follows:

1) Define the Decision Value (DV) boundaries, the required shunt compensation values and constraints as highlighted in the aforementioned paragraphs.
2) Construct the fitness (cost) function model.
3) Using a suitable optimizer, iterate the fitness function(s) on the values of the DV boundaries over a given number of simulation time steps.
4) Once the desired number of iteration time steps are over, one can now extract the best DV set from the finite number of computed sub-optimal DV states.

Therefore, the process of optimization involves a process of definition, construction, iteration and extraction of DV states, cost model(s), optimizer states, and best DV states, respectively. In the sub-section that follows, the Rao-1 type optimizer employed in this study is described.

2.1 Rao-1 Algorithm

The Rao algorithms are recent metaphorless optimization algorithms developed to overcome the complexities associated with the metaphor based approaches such as the PSO's, the ABC,'s, GA's etc. They are basically three types [14]; Rao-1, Rao-2 and Rao-3 type algorithms. The differences in these algorithms are based on their manner of update. In this sub-section, the Rao-1 type algorithm is described as it is more stable than the other two.

Rao-1 algorithm – Fundamentally, Rao-Type algorithms describe a Best-Worst case scenario for modeling its optimization (fitness) update or improvement process over a population of candidate possible sub-optimal solutions. The Rao-1 algorithm performs its improvement strategy using the model described below [14]:

$$X_{j,k,i}^{new} = X_{j,k,i}^{old} + r_{1,j,i}\left(X_{j,best,i} - X_{j,worst,i}\right). \tag{13}$$

Where

$X_{j,k,i}^{old}$ = the initial or past candidate value of *j-th* variable for *k-th* candidate at *i-th* iteration

$r_{1,j,i}$ = a random perturbation factor of *j-th* variable at *i-th* iteration

$X_{j,best,i}$ = the best (minimum) candidate value of *j-th* variable at *i-th* iteration

$X_{j,worst,i}$ = the worst (maximum) candidate value of *j-th* variable at *i-th* iteration.

This simple but sophisticated model can be used to describe the solution of very complex optimization functions. More importantly, it requires only two specific tuning parameters: the size of its candidate population, and the number of required generations (iterations) to evolve its solution process. Thus, the application of Rao-1 algorithm is programmatically very feasible and efficient not only in software PC's but in embedded (device constrain) hardware as well. In the proposed metaphorless programming solution, the Rao-1 optimizer is used to fit power system data to the combined objective of power loss minimization (refer to equations 1 and 2) and TVV minimization (refer to equation 12).

3.0 RESULTS AND DISCUSSIONS

The results using the Nigerian 330-kV 34-bus power transmission network are reported in this study using simulations (see Fig.2). The line and bus data for simulation experiments can be found in [15]. The simulations and metaphorless programming were conducted using the MATLAB environment. The decision variables (DV): bus voltage and angle constraints, real and reactive power constraints, the real and reactive power demands, and the shunt compensation requirements are provided in Table 1- full details of the data used can be found in [15]. For all optimization simulations, the population size and maximum generation of the Rao-1 and PSO optimizers are set to a default of 50 candidates and 100 iterations, respectively.

Table 1: DV Boundary Constraints

DV	Lower Bound (p.u)	Upper Bound (p.u)
Bus Voltage	0.95	1.05
Bus Angle	-5.00	+5.00
Real Power Demand	0.00	+5.00
Reactive Power Demand	0.00	+0.90
Generation Real Power	0.00	+5.00
Generation Reactive Power	0.00	+1.50
Shunt	0.00	+0.50

Base Case – No Shunt Compensation: The simulation results showing fitness response of the proposed technique without the inclusion of shunt injections is shown in Fig.3 (see first trial run Rao-1 optimizer). Table 2 also show the fitness scores after 5 trial simulation run for both optimizers.

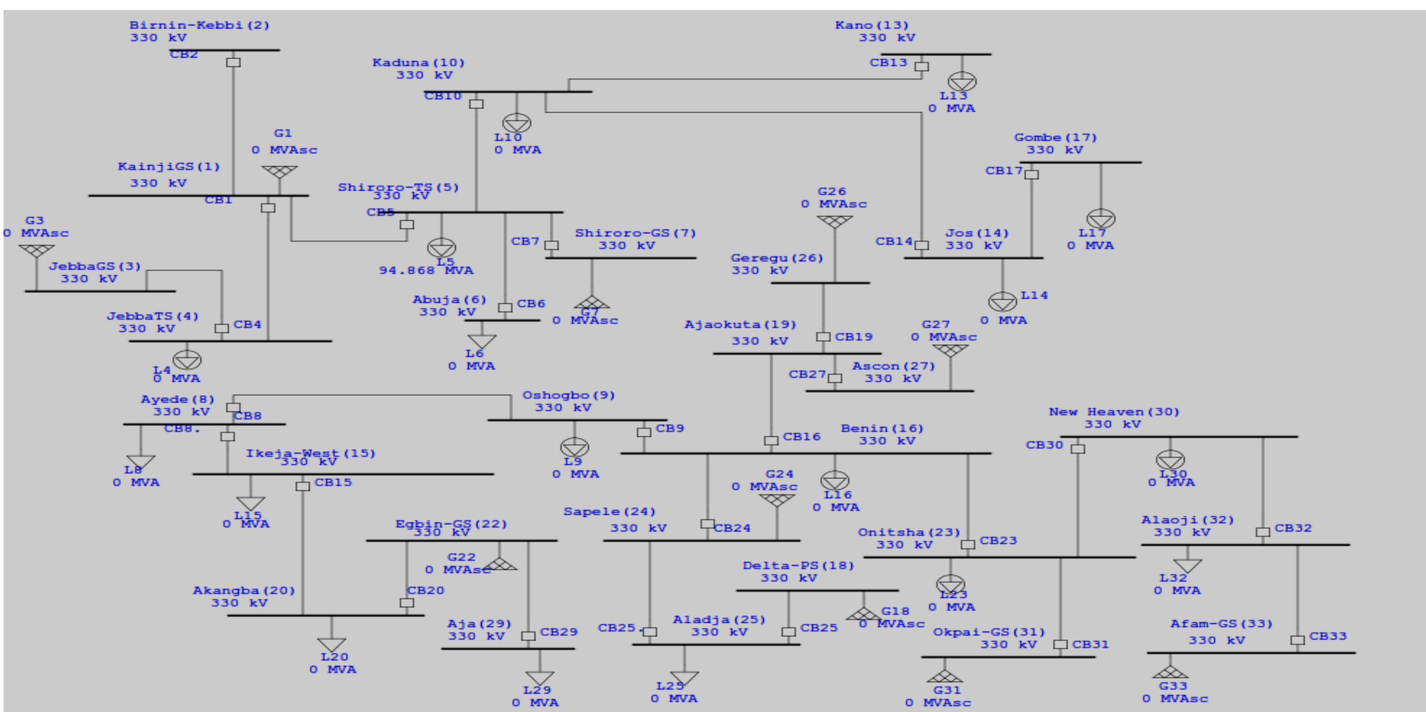

Fig.2: Nigerian 330kV 34-bus Power System Network

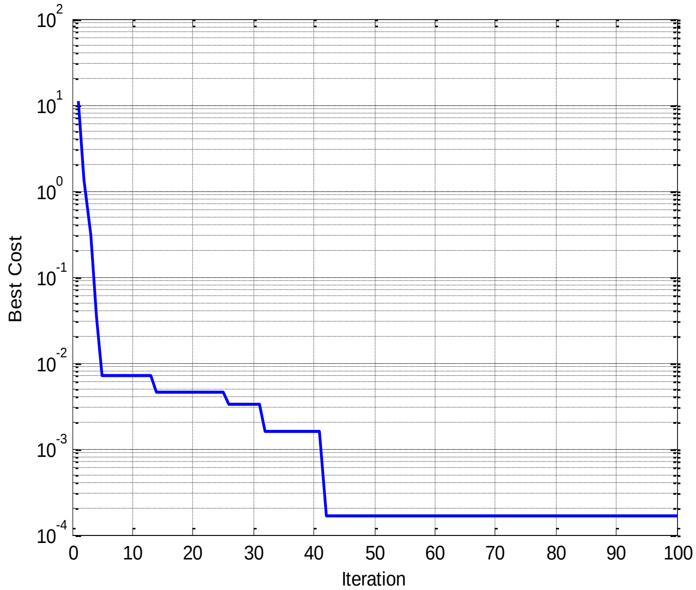

Fig 3: Fitness response (uncompensated case)

Fig. 3. shows a graded drop in the objective function value indicating that there will be improvement as the iteration (generation) step is incremented.

From the results in Table 2, it can be observed that for the uncompensated case, the Rao-1 type optimizer outperformed the PSO only for trial runs 3 and 4. On the average, the PSO technique gave better fitness scores.

Table 2: Comparative Fitness scores for 5 trial runs (uncompensated case)

Trial No.	Fitness Score$_{RAO}$ (10^{-4})	Fitness Score$_{PSO}$ (10^{-4})
1	1.6	0.4
2	6.2	0.4
3	0.2	0.3
4	0.9	1.0
5	2.7	0.5
Mean:	0.00230	**0.00052**

From the results in Table 3, it is clearly observed that for the uncompensated case, the Rao-1 type optimizer outperformed the PSO in computational run-times for all trial runs.

The solved bus voltages of the uncompensated network for
trial run with best fitness score are provided in Appendix.

Modified Case – With Shunt Compensation: The fitness response for the case when a shunt injection (MVARS) is included in the system is shown in Fig.4 (shown for Rao-1 optimizer). Table 4 also show the fitness scores after 5 trial simulation run.

Table 3: Comparative Run-time scores for 5 trial runs (uncompensated case)

Trial No	Run-time$_{RAO}$ (s)	Run-time$_{PSO}$ (s)
1	1.16	9.16
2	1.42	10.00
3	1.39	7.52
4	1.14	7.57
5	1.11	7.70
Mean	**1.24**	8.39

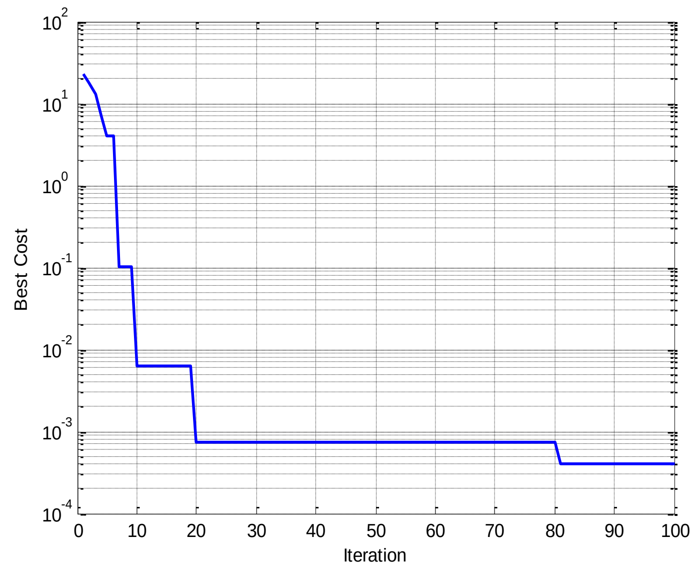

Fig.4: Fitness response (compensated case)

Table 4: Comparative Fitness scores for 5 trial runs (compensated case)

Trial No.	Fitness Score$_{RAO}$ (10^{-4})	Fitness Score$_{PSO}$ (10^{-4})
1	4.0	1.2
2	2.4	7.9
3	8.6	0.9
4	1.6	0.4
5	2.2	0.4
Mean	0.0038	**0.0022**

Fig. 4. also shows a graded drop in the objective function value indicating that there will be improvement as the iteration step is incremented. Using shunt compensation generally improves the precision of objective function values even though at certain trials there might be deviations.

Table 5: Comparative Run-time scores for 5 trial runs (compensated case)

Trial No	Run-time$_{RAO}$ (s)	Run-time$_{PSO}$ (s)
1	1.79	8.61
2	2.41	8.33
3	2.29	8.26
4	2.14	9.07
5	2.35	9.93
Mean	**2.20**	8.84

From the results in Table 5, it is clearly observed that for the compensated case, the Rao-1 type optimizer outperformed the PSO in computational run-times for all trial runs.

The solved bus voltages of the compensated network for trial run with best fitness scores for both optimizers are provided in Appendix. The corresponding error metrics – mean squared error (mse), root mean squared error (rmse) and sum-of-squared error of the compared techniques for the compensated case are also shown in Table 6.

Table 6: Error performance of optimizers (compensated case)

Error-metric	Value
mse	0.0003
rmse	0.0163
sse	0.0090

The results shown in Table 6 shows reasonable deviation from reference voltage (1.p.u) indicating that both algorithms can be safely said to give identical results. In particular, the sum-deviation from reference voltage showed the Rao-1 type optimizer to be generally better than PSO for the considered power system optimization task (see Table 7).

Table 7: Sum-deviation of optimizers from reference voltage (compensated case)

Optimizer	Sum-deviation Value (p.u)
Rao-1	0.49
PSO	0.53

4.0 CONCLUSIONS AND FUTURE WORK

This paper employed a new kind of optimizer that exhibits metaphorless property – the Rao-1 algorithm. This optimizer does not require extensive parameterization and also uses a straightforward updating (improvement) strategy to evolve better candidate solutions. The proposed Rao-1 optimizer has been applied to the task of multi-objective optimization of the Nigerian 330 kV 34-bus power transmission network where the power losses and voltage violations within the system are minimized. The objectives included the sum deviations in real and reactive powers (computed and solved) and voltage deviations for which the primary task was to minimize these variations in the presence of shunt compensation. The proposed Rao-1 type algorithm is compared with the PSO, which is very popular type of optimization algorithm used in power systems. The Rao-1 technique showed very promising results in terms of fitness scores and exhibited faster computational run-times than PSO type algorithm. Thus, Rao-1 algorithms are suggested to be more feasible power system optimizer solutions for shunt compensation in real power system. In future, research should be carried out on real power system network including online learning of Rao-1 optimizers in both transmission and distribution networks in any existing power network. Also, studies on how to improve the Rao-1 type algorithm fitness score and exploration of other Rao-type algorithms on this matter is envisaged.

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Appendix:

uc – uncompensated voltages in p.u.

co – compensated voltages in p.u.

Table A.1: Solved Bus Voltages

Rao-1 (uc)	Rao-1 (co)	PSO (uc)	PSO (co)
1	1	1.00	1.00
0.95	0.98	0.97	0.98
1	1	1.00	1.00
0.97	0.97	0.97	0.97
1.01	0.98	0.96	0.97
0.96	0.99	0.96	0.98
1	1	1.00	1.00
1.01	1	0.97	0.98
1.01	0.95	0.97	0.98
1	1.01	0.97	0.97
1	1	1.00	1.00
1.01	0.98	0.97	0.97
0.96	0.96	0.96	0.98
0.96	0.96	0.97	0.97
0.98	1.01	0.98	0.98
0.98	1.01	0.97	0.98
0.99	0.96	0.97	0.97
1	1	1.00	1.00
0.96	0.98	0.97	0.98
0.95	0.96	0.97	0.97
0.95	0.95	0.97	0.98

Rao-1 (uc)	Rao-1 (co)	PSO (uc)	PSO (co)
1	1	1.00	1.00
1.01	0.97	0.97	0.97
1	1	1.00	1.00
0.99	0.95	0.97	0.97
1	1	1.00	1.00
1	1	1.00	1.00
1	1	1.00	1.00
0.95	0.95	0.97	0.97
1.01	1.01	0.97	0.97
1	1	1.00	1.00
0.95	0.98	0.96	0.98
1	1	1.00	1.00
1	1	1.00	1.00