

# APPLICATION OF RESTART COVARIANCE MATRIX ADAPTATION EVOLUTION STRATEGY (RCMA-ES) TO GENERATION EXPANSION PLANNING PROBLEM

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## Abstract

*This paper describes the application of an evolutionary algorithm, Restart Covariance Matrix Adaptation Evolution Strategy (RCMA-ES) to the Generation Expansion Planning (GEP) problem. RCMA-ES is a class of continuous Evolutionary Algorithm (EA) derived from the concept of self-adaptation in evolution strategies, which adapts the covariance matrix of a multivariate normal search distribution. The original GEP problem is modified by incorporating Virtual Mapping Procedure (VMP). The GEP problem of a synthetic test systems for 6-year, 14-year and 24-year planning horizons having five types of candidate units is considered. Two different constraint-handling methods are incorporated and impact of each method has been compared. In addition, comparison and validation has also made with dynamic programming method.*

## Keywords:

*Constraint Handling, Dynamic Programming, Generation Expansion Planning, Restart Covariance Matrix Adaptation Evolution Strategy and Virtual Mapping Procedure*

## 1. INTRODUCTION

The Generation Expansion Planning (GEP) problem seeks to identify which generating units should be commissioned and when they should become available over the long-term planning horizon [1], [2]. This GEP model is applicable for developing countries like India, where planning is coordinated by central or state government owned utilities for capacity addition. The major objectives of GEP are to minimize the total investment and the operating cost of the generating units, and to meet the demand criteria, fuel-mix ratio, and the reliability criteria. GEP is a constrained, nonlinear, discrete optimization problem. The solution for the GEP problem can be obtained, through complete enumeration in the entire planning horizon. Linear programming and Dynamic Programming (DP) were applied to solve the GEP problem [3], [4]. The emerging techniques applied to solve GEP were reviewed in [5]. The improved Genetic Algorithm (GA) was used to solve the GEP problem in [6]. The Evolutionary Programming (EP) technique with Gaussian mutation and quadratic approximation technique was applied to solve the GEP problem [7]. The comprehensive survey of the GEP models can be found in [8]. Nine different meta-heuristic techniques were applied to solve the GEP problem [9]. The Elitist Non-dominated Sorting Genetic Algorithm version II (NSGA-II) is applied to multi-objective GEP problem [10], [11]. The environmental constraints and impact of various incentive mechanisms are considered in [12], [13] and [14].

The Covariance Matrix Adaptation Evolution Strategy (CMA-ES) is a robust stochastic evolutionary algorithm for difficult non-linear non-convex optimization problems [15]. The CMA-ES is typically applied to unconstrained or bounded constraint optimization problems, and it efficiently minimizes unimodal objective functions and is in particular superior for ill-conditioned and non-separable problems [15], [16]. Anne Auger and Nikolaus Hansen showed that increasing the population size improves the performance of the CMA-ES on multi-modal functions [17]. They suggest a CMA-ES restart strategy with successively increasing population size. In this paper, CMA-ES with restart strategy is applied for solving GEP Problem with two different constraint handling schemes namely Penalty factor less constraint handling scheme (PFL) and Self-Adaptive Penalty scheme (SAP). The paper is organized as follows: Section 2 describes the GEP problem formulation. Section 3 describes RCMA-ES implementation to the GEP problem. Section 4 explains two different constraint-handling methods; Section 5 provides test results and section 6 concludes.

## 2. GENERATION EXPANSION PLANNING PROBLEM FORMULATION

The GEP problem is equivalent to finding a set of best decision vectors over a planning horizon that minimizes the investment and operating costs under relevant constraints.

### 2.1 COST OBJECTIVE

The cost objective is represented by the following expression:

$$\min Cost = \sum_{t=1}^T [I(U_t) + M(X_t) + O(X_t) - S(U_t)] \quad (1)$$

where,

$$X_t = X_{t-1} + U_t, \quad t = 1, 2, \dots, T \quad (2)$$

$$I(U_t) = (1+d)^{-2t} \sum_{i=1}^N (CI_i \times U_{t,i}) \quad (3)$$

$$S(U_t) = (1+d)^{-T} \sum_{i=1}^N (CI_i \times \delta_i \times U_{t,i}) \quad (4)$$

$$M(X_t) = \sum_{s=0}^1 \left( (1+d)^{1.5t+s} (\sum (X_t \times FC) + MC) \right) \quad (5)$$

$$O(X_t) = EENS \times OC \times \sum_{s=0}^1 \left( (1+d)^{1.5+t+s} \right) \quad (6)$$

The outage cost calculation of Eq.(6), used in Eq.(1), depends on Expected Energy Not Served (EENS). The equivalent energy function method [2] is used to calculate EENS (and also to calculate loss of load probability, LOLP, used in the constraint objective).

$$t' = 2(t-1) \text{ and } T' = 2 \times T - t' \quad (7)$$

and

Cost total cost, \$

$U_t$  N-dimensional vector of introduced units in  $t$ -th stage (1 stage = 2 years)

$U_{t,i}$  the number of introduced units of  $i$ -th type in  $t$ -th stage

$X_t$  cumulative capacity vector of existing units in  $t$ -th stage, (MW)

$I(U_t)$  is the investment cost of the introduced unit at the  $t$ -th stage, \$

$M(X_t)$  total operation and maintenance cost of existing and the newly introduced units, \$

$s'$  variable used to indicate that the maintenance cost is calculated at the middle of each year

$O(X_t)$  outage cost of the existing and the introduced units, \$

$S(U_t)$  salvage value of the introduced unit at  $t$ -th interval, \$

$d$  discount rate

$CI_i$  capital investment cost of  $i$ -th unit, \$

$\delta_i$  salvage factor of  $i$ -th unit

$T$  length of the planning horizon (in stages)

$N$  total number of different types of units

$FC$  fixed operation and maintenance cost of the units, \$/MW

$MC$  variable operation and maintenance cost of the units, \$

$EENS$  Expected energy not served, MWhrs

$OC$  value of outage cost constant, \$/ MWhrs

## 2.2 CONSTRAINTS

- 1) *Construction limit:* Let  $U_t$  represent the units to be committed in the expansion plan at  $t$ -th stage that must satisfy,

$$0 \leq U_t \leq U_{max,t}$$

where,  $U_{max,t}$  is the maximum construction capacity of the units at  $t$ -th stage.

- 2) *Reserve Margin:* The selected units must satisfy the minimum and maximum reserve margin.

$$(1 + R_{min}) \times D_t \leq \sum_{i=1}^N X_{t,i} \leq (1 + R_{max}) \times D_t \quad (9)$$

where,

$R_{min}$  minimum reserve margin

$R_{max}$  maximum reserve margin

$D_t$  demand at the  $t$ -th stage in megawatts (MW)

$X_{t,i}$  cumulative capacity of  $i$ -th unit at  $t$ -th stage

- 3) *Fuel Mix Ratio:* The GEP has different types of generating units such as coal, liquefied natural gas (LNG), oil, and nuclear. The selected units along with the existing units of each type must satisfy the fuel mix ratio,

$$FM_{min}^j \leq X_{t,j} / \sum_{i=1}^N X_{t,i} \leq FM_{max}^j \quad j = 1, 2, \dots, N \quad (10)$$

where,

$FM_{min}^j$  minimum fuel mix ratio of  $j$ -th type

$FM_{max}^j$  maximum fuel mix ratio of  $j$ -th type

$j$  type of the unit (e.g., oil, LNG, coal, nuclear)

- 4) *Reliability Criterion:* The introduced units along with the existing units must satisfy a reliability criterion on loss of load probability (LOLP),

$$LOLP(X_t) \leq \varepsilon \quad (11)$$

where,  $\varepsilon$  is the reliability criterion, a fraction, for maximum allowable LOLP. Minimum reserve margin constraint avoids the need for a separate demand constraint.

## 3. IMPLEMENTATION TO THE GEP PROBLEM

### 3.1 VIRTUAL MAPPING PROCEDURE (VMP) [9]

Convergence problems were encountered when implementing the standard RCMA-ES algorithm on the GEP problem. Investigation revealed the reason pertained to the sensitivity of capacity to changes in the decision vector. To illustrate, consider the range of the decision vector lies between [0] and  $U_{max,t}$  as given in [6]. The capacity vector is [200 450 500 1000 700]. Let a candidate solution be  $U_1 = [5 \ 0 \ 1 \ 1 \ 0]$ ; then its corresponding capacity will be 2500 MW ( $5 \times 200 + 0 \times 450 + 1 \times 500 + 1 \times 1000 + 0 \times 700$ ). If  $U_1$  changes to [5 0 1 2 0] (via mutation operators), then the capacity is increased from 2500 MW to 3500 MW, a difference of 1000 MW, which is a large deviation.

So VMP is introduced to improve the effectiveness of the RCMA-ES in solving the GEP problem. VMP is concerned with the solution representation; it transforms each combination of candidate units for every year into a dummy decision variable, referred to as the VMP variable. The value of the VMP variable for a specific candidate solution is the rank of that solution when all solutions are sorted in ascending order of capacity. For example, the solution [5 0 1 1 0] with capacity of 2500 has VMP value of 190. A change (by mutation) to VMP value of 198 would correspond to a solution of [2 1 2 0 1] with capacity of 2550, a relatively small change in capacity. Without VMP, to get a solution with capacity of 2550 MW, all 5 variable values must

be changed. This may take a very large number of iterations, and in general, moving from sub-optimal to optimal may take much iteration.

Since five different types of units are assumed to be available for each stage, the size of the decision vector increases by multiples of 5 as the number of stages increases. However, when using VMP, the number of decision variables obtained is a multiple of its number of stages; the size of the decision vector becomes 3 for a 3-stage problem. Thus, a size reduction of 80%, [(15-3)/15, for 3 stages] is realized. Hence, the dimensionality of the problem, in terms of the number of decision variables, is reduced, and computational time and memory requirements reduce accordingly.

### 3.2 RESTART CMA-ES

The RCMA-ES is a class of continuous evolutionary algorithm (EA) that generates new population members by sampling from a probability distribution that is constructed during the optimization process. The probability distribution characterizes the objective function that is being optimized. The RCMA-ES adapts the complete covariance matrix of the normal distribution used in mutation operation. RCMA-ES is computationally complex compared to the other evolutionary algorithms as it involves Eigen decomposition. The CMA-ES algorithm with restart strategy (RCMA-ES) is summarized below [15],

#### Restart CMA-ES Algorithm [15, 16]

**Step 1:** Generate an initial random solution.

**Step 2:** Then new solution vectors  $X_k^{g+1}$ ,  $k = 1, \dots, \lambda$ , of generation  $g+1$  is generated by adding a realization of a  $N(0, (\delta^g)^2 C^g)$  distributed random vector. The random vector is generated by linear transformation of  $z = N(0, I)$  where  $I$  is the identity matrix.

$$X_k^{g+1} = \langle x \rangle_\mu^{g+1} + \delta^g \mathbf{B}^g \mathbf{D}^g z_k \quad (12)$$

where,

$X_k^{g+1} \in \mathfrak{R}^n$  Solution vector of  $k$ -th individual at generation  $g+1$

$\langle x \rangle_\mu^g$  Center of mass of the  $\mu$  (no. of individuals) selected as best individuals of generation (iteration)  $g$

$\mathbf{B}^g$  Matrix formed by the Eigenvectors of the covariance matrix  $\mathbf{C}^g$  of generation  $g$

$\mathbf{D}^g$  Diagonal Eigen value matrix of  $\mathbf{C}^g$  of generation  $g$

**Step 3:** The covariance matrix  $\mathbf{C}$  determines  $\mathbf{B}$  and  $\mathbf{D}$ , and is adapted by means of the summation of weighted center of mass differences. The step size  $\delta$  is adapted separately and generation count  $g$  is incremented by one.

**Step 4:** The RCMA-ES is stopped whenever one stopping criterion [17] as described below is met, and an independent restart is launched with the population size increased by a factor of two.

- Stop if the range of the best objective function values of the last  $10 + \lceil 30n / \lambda \rceil$  generations is zero.
- Stop if the standard deviation of the normal distribution is smaller than  $10^{-12} \delta^{(0)}$  in all coordinates.
- Stop if adding a 0.1-standard deviation vector in a principal axis direction of  $\mathbf{C}^g$  does not change  $\langle x \rangle_\mu^g$ .
- Stop if adding 0.2-standard deviation in each coordinate does change  $\langle x \rangle_\mu^g$ .
- Stop if the condition number of the covariance matrix exceeds  $10^{14}$ .

**Step 5:** Repeat steps 2-4 until a maximum number of function evaluations are carried out.

## 4. CONSTRAINT HANDLING SCHEMES

In most of the Evolutionary optimization techniques, to handle constraints the penalty function approach is used. The difficulty of using this approach is in choosing the correct penalty factor for the particular infeasible solution, because it is unknown. The convergence of the algorithm largely depends on the value of the penalty factor chosen. Hence in this paper, two constraint handling methods such as Penalty factor-less constraint handling scheme and Self Adaptive Penalty scheme are considered.

### 4.1 PENALTY FACTOR-LESS (PFL) CONSTRAINT HANDLING SCHEME

In this scheme, the fitness function is calculated using following formula [19],

$$F(\bar{x}) = \begin{cases} f_{\max} + \sum_{j=1}^m g_j(\bar{x}) & \text{if } g_j(\bar{x}) \geq 0 \forall j \\ f(\bar{x}) & \text{otherwise} \end{cases} \quad (13)$$

where,  $F(\bar{x})$  is fitness function,  $f(\bar{x})$  the objective function,  $g_j(\bar{x})$  the  $j$ -th normalized absolute constraint violations and  $f_{\max}$  is the objective function value of the worst feasible solution in the population. Thus, the fitness of an infeasible solution not only depends on the amount of constraint violation, but also on the current population. However, the fitness of a feasible solution is always fixed and is equal to its objective function value [19].

### 4.2 SELF ADAPTIVE PENALTY (SAP) SCHEME

In this scheme, two different penalties are added to each individual infeasible solution in the current population [20]. The number of feasible solutions in the current population decides the amount of penalties added. If there is more number of feasible solutions, then the infeasible solutions are added with more amount of penalty with more constraint violations and vice-versa. The final fitness value is given by  $F(X) = d(X) + p(X)$ , where  $d(X)$  is the distance value and  $p(X)$  is the penalty value [20]. The distance value is calculated by the formula,

$$d(X) = \begin{cases} v(X) & \text{if } r_f = 0 \\ \sqrt{f(X)^2 + v(X)^2} & \text{otherwise} \end{cases} \quad (14)$$

where,  $r_f$  = (Number of feasible individuals)/(population size),  $v(X)$  is the overall constraint violation for an infeasible solution, that is weighted mean of all the constraints. The penalty value is given by,  $p(X) = (1 - r_f)M(X) + r_fN(X)$  where,

$$M(X) = \begin{cases} 0 & \text{if } r_f = 0 \\ v(X) & \text{otherwise} \end{cases} \quad (15)$$

$$N(X) = \begin{cases} 0 & \text{if } X \text{ is feasible} \\ f(X) & \text{otherwise} \end{cases} \quad (16)$$

## 5. TEST RESULTS

The implementation was done using MATLAB version 7.2, on a desktop PC with Intel Core i5 processor having 3.10 GHz speed and 4 GB RAM. The MATLAB code for RCMA-ES algorithm is taken from N. Hansen website [18] and necessary changes have been made to incorporate constraint handling schemes.

### 5.1 TEST SYSTEM DESCRIPTION

The forecasted peak demand and other data are taken from [6]. The test system with 15 existing power plants and 5 types of candidate options is considered for a 6-years, 14-years and 24-years planning horizon. The planning horizon comprises of stages with 2-year intervals. The forecasted peak demand is given in Table.A1 of the Appendix. Economic and technical data of existing plants are provided in Table.A2 of the Appendix, and data of candidate plants are given in Table.A3 of the Appendix.

### 5.2 PARAMETERS FOR GEP

The lower and upper bounds for reserve margin are set at 20% and 40% respectively. The salvage factor ( $\delta$ ) for oil, LNG,

coal, PWR, and PHWR are taken as 0.1, 0.1, 0.15, 0.2 and 0.2, respectively. Cost of EENS is set at 0.05 \$/kWh. The discount rate is 8.5%. It is assumed that the date of availability of new generation is two years beyond the current date. The year  $k$  investment cost is assumed to incur in the beginning of year  $k$ ; the year  $k$  maintenance cost is assumed to incur in the middle of year  $k$  and is calculated by using the equivalent energy function method [2]. The year  $k$  salvage cost is estimated at the end of the planning horizon.

### 5.3 PARAMETERS FOR THE RCMA-ES ALGORITHM

In RCMA-ES, the strategy parameters get adapted during evolution and the need for tuning of parameter does not arise. The value of  $\sigma$  was chosen as 0.25 times range of the variables.

### 5.4 RESULTS AND DISCUSSIONS

The impact of the two constraint handling schemes on the performance of the RCMA-ES in finding out minimum cost is tabulated in the Table.1. Here RCMA-ES is considered with VMP technique. For comparing the performance of RCMA-ES on two different constraints handling schemes, for all the 6-year, 14-year and 24-year planning horizon, the initial population size is taken as 200. A maximum function evaluation of 15,000 is used as a stopping criterion. The overall normalized constraint violation is represented as a constraint error in the Table.1. The best result out of the 10 simulations are taken and tabulated.

From the Table.1, it is clear that the penalty factor less constraint handling scheme has been performing well, since constraint errors for all three planning horizons are low in this method as compared to other schemes. Even though the SAP scheme produces minimum cost value, it fails to provide the lesser constraint error. That means it struggles to produce more number of feasible solutions than the PFL scheme.

Table.1. Impact of Constraint Handling Schemes

Constraint Handling Method	Planning Horizon					
	6-year		14-year		24-year	
	Cost $10^{10}$ \$	Constraint Error	Cost $10^{10}$ \$	Constraint Error	Cost $10^{10}$ \$	Constraint Error
PFL	1.2071	0	2.2327	0.0037	3.0982	0.0442
SAP	1.0889	4.6219	2.1186	3.0569	2.8836	2.8009

Table.2. Minimum Cost for 6-year planning horizon

Technique	Cost $\times 10^{10}$ \$		Error (%)	SR (%)	Mean execution time (seconds)
	Best	Worst			
RCMA-ES (Without VMP)	1.2009	1.2050	0-0.34	10	101
RCMA-ES (with VMP)	1.2009	-	0	100	82
Dynamic Programming	1.2009	-	-	-	288

Table.3. Minimum cost for 14-year planning horizon

Technique	Cost $\times 10^{10}$ \$		Error (%)	SR (%)	Mean execution time (seconds)
	Best	Worst			
RCMA-ES (Without VMP)	2.1911	2.2011	0.52-0.98	-	834
RCMA-ES (with VMP)	2.1842	2.1945	0.2-0.6	-	352
Dynamic Programming	2.1797	-	-	-	2637

Table.4. Minimum cost for 24-year Planning horizon

Technique	Cost $\times 10^{10}$ \$		Error (%)	SR (%)	Mean execution time (seconds)
	Best	Worst			
RCMA-ES (Without VMP)	2.9401	2.9627	0.66-1.44	-	3886
RCMA-ES (with VMP)	2.9376	2.944	0.58-0.8	-	2819
Dynamic Programming	Unknown*	-	-	-	-

\*2.9206 have been considered as the best and errors are calculated [9].

The minimum cost for the 6-year planning horizon with PFL scheme has been tabulated in Table.2. Since PFL scheme provides better results, it has been used in all the planning horizons. For the purpose of comparison 50 independent test runs are made. The initial population size and maximum function evaluations are taken as 500 and 15000 respectively.

The success rate is the ratio of the number of times the optimal solution found to the number of test runs. The error is estimated as the difference between the optimal value (found using Dynamic Programming) and the obtained value (found using RCMA-ES).

In [9], it is reported that, except Differential Evolution (DE) technique, all the other techniques, Genetic Algorithm, Evolutionary Programming, Evolutionary Strategy, Ant Colony Optimization, Particle Swarm Optimization, Tabu Search, Simulated Annealing, and Hybrid Approach have success rate less than 100%. The Hybrid approach has the maximum success rate of 90% [9]. All such techniques, suffered from the problem of parameter tuning and the results depended on parameter.

Without VMP, the optimal or near optimal solution is obtained. The success rate is 10% which is very low. Maximum error is 0.34%. In contrast, if VMP variable is used, the success rate is 100%. The results for the 14-year planning horizon

without VMP and with VMP are given in the Table.3. The initial population size and maximum function evaluations are taken as 700 and 80000 respectively which gave the constraint error zero.

The results for the 24-year planning horizon with initial population size of 1000 and maximum function evaluations of 100000 are tabulated in the Table.4. With VMP for the 14 and 24-year planning horizon, the near optimal solution is obtained. Maximum error is 0.6% for 14-year and 0.8% for 24-year planning horizon. For 24-year problem, Dynamic Programming takes longer time due to the "Curse of Dimensionality", so the best value quoted in [9] is taken for calculating the error.

## 6. CONCLUSION

The RCMA-ES technique is applied to solve the least-cost GEP problem. Compared to other algorithms, the RCMA-ES has less user defined parameters. The representation of the solution has a major role in success rate. The optimal solution is obtained by incorporating Virtual Mapping Procedure. Two constraint handling methods are applied to the problem and it is found that Penalty factor less constraint handling scheme is performing well for the GEP problem.

## APPENDIX

Table.A1. Forecasted Peak Demand [6]

Stage (Year)	0 (2012)	1 (2014)	2 (2016)	3 (2018)	4 (2020)	5 (2022)	6 (2024)
Peak (MW)	5000	7000	9000	10000	12000	13000	14000
Stage (Year)	-	7 (2026)	8 (2028)	9 (2030)	10 (2032)	11 (2034)	12 (2036)
Peak (MW)	-	15000	17000	18000	20000	22000	24000

Table.A2. Technical and Economic Data of Existing Plants [6]

Name (Fuel Type)	No. of Units	Unit Capacity (MW)	FOR (%)	Operating Cost (\$/KWh)	Fixed O & M Cost (\$/Kw-Mon)
Oil#1(Heavy Oil)	1	200	7.0	0.024	2.25
Oil#2(Heavy Oil)	1	200	6.8	0.027	2.25
Oil#3(Heavy Oil)	1	150	6.0	0.030	2.13
LNG G/T#1(LNG)	3	50	3.0	0.043	4.52
LNG C/C#1(LNG)	1	400	10.0	0.038	1.63
LNG C/C#2(LNG)	1	400	10.0	0.040	1.63
LNG C/C#3(LNG)	1	450	11.0	0.035	2.00
Coal#1(Anthracite)	2	250	15.0	0.023	6.65
Coal#2(Bituminous)	1	500	9.0	0.019	2.81
Coal#3(Bituminous)	1	500	8.5	0.015	2.81
Nuclear#1(PWR)	1	1,000	9.0	0.005	4.94
Nuclear#2(PWR)	1	1,000	8.8	0.005	4.63

Table.A3. Technical and Economic Data of Candidate Plants [6]

Candidate Type	Construction Upper limit	Capacity (MW)	FOR (%)	Operating Cost (\$/KWh)	Fixed O & M Cost (\$)	Capital Cost (\$/Kw)	Life Time (Yrs)
Oil	5	200	7.0	0.021	2.20	812.5	25
LNG C/C	4	450	10.0	0.035	0.90	500.0	20
Coal(Bitum.)	3	500	9.5	0.014	2.75	1062.5	25
Nuc.(PWR)	3	1,000	9.0	0.004	4.60	1625.0	25
Nuc.(PHWR)	3	700	7.0	0.003	5.50	1750.0	25

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