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# Artificial Co-operative Search Algorithm based Solution Technique for Economic Load Dispatch Problems

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## ABSTRACT

Economic load dispatch is one of the most important problems in power system operation. Therefore the aim of this paper is to establish a method to reduce electricity generation costs with a new approach. In this paper, Particle Swarm Optimization (PSO), Artificial Bee Colony Algorithm (ABC) and Artificial Cooperative Search algorithm (ACS) solutions to Economic Dispatch (ED) have been found. A sample consisting of six and ten thermal generators are presented. Transmission losses are included. Results taken with both methods have been compared to each other.

**Keywords:** Particle Swarm Optimization, Artificial Bee Colony Algorithm, Artificial Cooperative Search Algorithm, Economic Dispatch

## I. INTRODUCTION

Economic Dispatch (ED) is defined in [1] as the process of allocating generation levels to the generating units so that the system load is supplied entirely and most economically. Many economic dispatch approaches have been proposed in the literature to formulate and solve this problem. It is provided in [1] a review of the advances in such field that the economic dispatch definition as above is quite large so that many specific optimization models applied to power system, such as optimal power flow, unit commitment, generation scheduling, etc., may be faced as economic dispatch models. It must be clear however that these models vary in complexity and they also have different scope of application.

The basic objective of economic load dispatch of electric power generation is to schedule the committed generating unit outputs so as to meet the load demand at minimum operating cost while satisfying all unit and system equality and inequality constraints. Different models and techniques have been reported in the literature [1-5].

In order to solve the ED problem, various conventional methods such as lambda-iteration methods, gradient method, and dynamic programming etc., have been employed [6, 7]. Many nature inspired algorithms were developed, such as Simulated Annealing (SA) [8], Genetic Algorithm (GA) [9, 10], Evolutionary algorithm [11, 12], Tabu Search (TS) algorithm [13,14], Ant Colony Optimization (ACO), PSO etc., honey Bee Colony Optimization (BCO) was proposed by Karaboga [15, 16] in 2005, which are probabilistic heuristic algorithms, have been successfully used to solve the ED problem. These algorithms can provide far better solution in comparison to classical algorithms.

## II. ECONOMIC POWER DISPATCH

The ED is a nonlinear optimization problem. The objective of ED problem is to discover the optimal combination of power generation that minimizes the total generation cost, while satisfying the system load demand, spinning reserve capacity and practical operation constraints of generators including the ramp rate limit and the prohibited operating zone [14, 15].

The objective function of ED problem can be modified as,

$$\min F_t = \sum_{i=1}^{m} F_i(P_i) \sum_{i=1}^{m} (a_i + b_i P_i + c_i P_i^2) \qquad (1)$$

Where $F_t$ is the total generation cost; $F_i$ is the generation cost function of $i^{th}$ generator is usually expressed as a quadratic polynomial; $a_i$, $b_i$, and ci are the cost coefficients of the $i^{th}$ generator; $P_i$ is the power output of the $i^{th}$ generator and m is the number of generators committed to the operating system.

Power balance constrains

$$\sum_{i=1}^{m} P_i = P_D + P_L \qquad (2)$$

Where $P_D$ is the load demand and $P_L$ is the total transmission network losses, which is a function of unit power outputs that can be represented using B coefficients:

$$P_L = \sum_{i=1}^{m}\sum_{j=1}^{m} P_i B_{ij} P_j + \sum_{i=1}^{m} B_{0i} P_i + B_{00} \qquad (3)$$

Generators limit values have been given as,

$$P_G^{min} \le P_{Gi} \le P_{Gi}^{max} \qquad i = 1,........N \qquad (4)$$

## III. OPTIMIZATION OF ED PROBLEM

### A. PSO Algorithm

Particle swarm optimization algorithm was introduced by Kennedy and Eberhart in 1995, as inspired from fish schooling and birds flocking, is a powerful yet simple optimization algorithm that can perform extensive exploration of the problem space. Besides, it does not rely on derivative information to guide the search toward the problem solution. Particle swarm optimization and some of its variants have been proposed and successfully applied to economic dispatch problems with piecewise quadratic cost functions [12, 17-19].

The PSO algorithm is based on the behavior of individuals of a swarm developed by Kennedy and Eberhart. Its roots are in zoologist-modeling of the movement of individuals (i.e., fish, birds, and insects) within a group. It has been noticed that members of the group seem to share information among them to lead to increased efficiency of the group. The particle swarm optimization algorithm searches in parallel using group of individuals similar to other AI-based heuristic optimization techniques. Each individual corresponds to a candidate solution to the problem. Individuals in a swarm approach to the optimum through its present velocity, previous experience and the experience of its neighbours. In a physical n-dimensional search space, the position and velocity of individual i are represented as the velocity vectors. Using these information individual i and its updated velocity can be modified under the following equations in the particle swarm optimization algorithm. The flowchart of the particle swarm optimization is shown in Figure 1.

$$x_i^{k+1} = x_i^{(k)} + v_i^{(k+1)} \qquad (5)$$

$$v_1^{k+1} = v_i^k + \alpha_i\left(x_i^{lbest} - x_i^{(k)}\right) + \beta_i\left(x_i^{gbest} - x_i^{(k)}\right) \qquad (6)$$

Where,

$x_i^{(k)}$ is the individual i at iteration k

$v_i^{(k)}$ is the updated velocity of individual i at iteration k

$\alpha_i ; \beta_i$ are uniformly random numbers between [0,1]

$x_i^{lbest}$ is the individual best of individual i

$x^{gbest}$ is the global best of the swarm

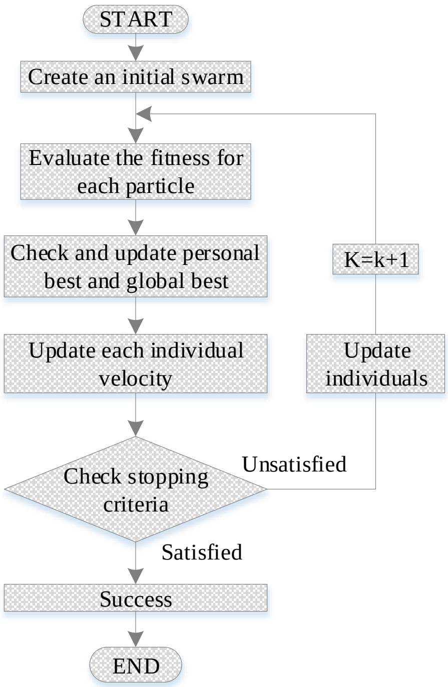


Figure 1: Flowchart of the PSO algorithm

B. **ABC Algorithm**

Artificial Bee Colony (ABC) optimization algorithm was proposed by Karaboga [15] for optimizing numerical problems in 2005. This algorithm mimics the food foraging behaviour of swarms of honey bees. Honeybees use several mechanisms like waggle dance to optimally locate food sources and to look for new ones. This makes them a good candidate for developing new intelligent search algorithms. It is a very simple, robust and population based stochastic optimization algorithm. In ABC algorithm, the colony of artificial bees contains two groups of bees as scout and employed bees. The scout bees have the responsibility to seek for a new food source. The responsibility of employed bees is to look for a food source within the neighbourhood of the food source in their memories and share their information with other bees within the hive.

The algorithm requires a number of parameters to be set, namely: NC is number of iteration, $n_s$ is number of scout bees, m is number of sites selected out of $n_s$ visited sites, e is number of best sites out of m selected sites, nep is number of bees recruited for best e sites, nsp is number of bees recruited for the other (m-e) selected sites, ngh is initial size of patches which include site and its neighbourhood and stopping criterion. In this paper, the structure of a solution for ED problem is composed of a set of generation outputs. Consequently, the initial solutions of ns scout bees can be represented as the vector of

$$X_i^k = (P_{i1}^k,........, P_{in}^k), \qquad i = 1,......n_S \qquad (7)$$

where $n_s$ is the number of scout bees and n is the number of generators. Note that it is very important to create a set of solution satisfying the equality constraint and inequality constraints.

The process of the ABC algorithm can be summarized as follows:

Step1: Generate randomly the initial populations of n scout bees. These initial populations must be feasible candidate solutions that satisfy the constraints. Set NC=0.

Step2: Evaluate the fitness value of the initial populations.

Step3: Select m best solutions for neighbourhood search.

Step4: Separated the m best solutions to two groups, the first group has e best solutions and other group has m-e best solutions.

Step5: Determine the size of neighbourhood search of each best solutions (ngh).

Step 6: Generate solutions around the selected solutions within neighbourhood size.

Step7: Select the fittest solution from each patch.

Step8: Check the stopping criterion. If satisfied, terminate the search, else NC=NC+1.

Step 9: Assign the n-m population to generate new solutions. Go to Step 2.

C. **ABC Algorithm**

Artificial Cooperative Search algorithm (ACS) [20] is a swarm intelligence algorithm developed for solving real valued numerical optimization problems. A mutualism based biological interaction exists between different living species in nature. The living species involved in a mutualism based biological interaction try to derive mutual benefits from the mentioned interaction. Cooperation is the interaction of homogenous living species that adopt mutualism. Mutualism and cooperation based biological interaction of two eusocial superorganisms living in the same environment inspired the ACS algorithm. The habitat concept in ACS algorithm matches the search space concept that belongs to the related problem.

In ACS algorithm, a superorganism consisting of random solutions of the related problem corresponds to an artificial superorganism migrating to more productive feeding areas. ACS algorithm contains two superorganisms; α and β that have artificial sub-superorganisms equal to the dimension of the population (N). The dimension of the problem (D) is equal to the number of individuals within the related sub-superorganisms. In ACS algorithm, α and β superorganisms are used for the detection of artificial Predator and Prey sub-superorganisms. The Predator sub-superorganisms in ACS algorithm can pursue the Prey sub-superorganisms for a period of time, while they migrate towards global minimum of the problem. When the iterative calculation process of ACS algorithm that is named as co evolution process is considered, it can be seen that the two superorganisms looking for the global minimum of the related problem, establish cooperation based biological interaction between each other. In ACS algorithm the initial values of the individuals of ith sub-superorganism of α (i.e., α_(i, j)) and β (i.e., β_(i,j)) are defined by using (8) and (9) as;

$$\alpha_{i,j,g=0} = \text{rand}.(\text{up}_j - \text{low}_j) + \text{low}_j \qquad (8)$$

$$\beta_{i,j,g=0} = \text{rand}.(\text{up}_j - \text{low}_j) + \text{low}_j \qquad (9)$$

where i = 1, 2, 3, ... , N, j = 1, 2, 3, ... , D and g = 0, 1, 2, 3, ... , max cycle. The ‘g’ value here denotes the generation number expressing the co evolution level containing the related superorganisms. The rand shows a random number chosen from the uniform distribution with U~[0 1]. The $\text{up}_j$ and $\text{low}_j$ are the upper and lower limits of search space for $j^{th}$ dimension of the related problem. The productivity values (i.e., fitness values) obtained by the related sub-superorganisms are computed by using,

$$y_{i;\alpha} = f(\alpha_i) \qquad (10)$$

$$y_{i;\beta} = f(\beta_i) \qquad (11)$$

The biological interaction location, X, between Predator and Prey sub-superorganisms is modelled using the equation given below;

$$X = \text{Predator} + R(\text{Prey} - \text{Predator}) \qquad (12)$$

where, R is the Scale factor that controls the speed of biological interaction. The probabilistic nature of ACS algorithm causes the super-organism that is determined as the predator to be changed in each generation. Therefore, ACS algorithm provides a cooperative/co-evolution process for both of the superorganisms. The pseudo code of ACS algorithm is provided in [20]. The proposed algorithm can be implemented with convergence, iteration or tolerance as the stopping criteria. In this proposed study, iteration count has been taken as the stopping criteria.

Table 1: Comparison of the results for test system 1 (six generator system)

| POWER DEMAND | PSO | ABC | ACSA | PSO | ABC | ACSA | PSO | ABC | ACSA |
|---|---|---|---|---|---|---|---|---|---|
| | 500 MW | | | 800 MW | | | 1000 MW | | |
| PG1 | 35.20 | 10.00 | 36.39 | 34.77 | 20.10 | 33.03 | 54.91 | 47.43 | 41.82 |
| PG2 | 13.88 | 10.00 | 10.00 | 20.97 | 34.71 | 15.46 | 27.26 | 36.46 | 28.68 |
| PG3 | 71.74 | 89.38 | 84.80 | 129.16 | 140.71 | 141.04 | 216.68 | 219.70 | 192.18 |
| PG4 | 101.98 | 93.56 | 84.77 | 157.09 | 128.77 | 138.19 | 148.73 | 170.30 | 171.87 |
| PG5 | 141.89 | 130.00 | 168.45 | 213.27 | 238.62 | 257.64 | 323.08 | 250.80 | 304.54 |
| PG6 | 146.09 | 176.90 | 125.01 | 271.96 | 262.23 | 239.87 | 270.21 | 313.48 | 300.12 |
| $P_{Total}$ | 510.78 | 509.83 | 509.42 | 827.21 | 825.13 | 825.25 | 1040.87 | 1038.18 | 1039.22 |
| $P_{Loss}$ | 9.46 | 9.83 | 9.41 | 25.37 | 25.10 | 25.24 | 38.79 | 38.17 | 39.22 |
| $P_{Excess}$ | 1.31 | 0.00 | 0.00 | 1.84 | 0.03 | 0.00 | 2.08 | 0.01 | 0.00 |
| Fuel Cost ($/h) | 27596 | 27532 | 27507 | 42081 | 41987 | 41899 | 52576 | 52497 | 52365 |

## IV. RESULTS AND DISCUSSION

To assess the efficiency of ACS, it has been applied to the ELD problem by considering two different test systems. These test systems are widely used as benchmarks in the power system field for solving the ELD problem and have been used by many other research groups around the world for similar purposes. The results obtained from the ACSA are compared with other population-based optimization techniques, such as PSO and ABC. Maximum iteration numbers are 400 for all test systems, whose results are presented as;

**Test System I:** This system consists of six generating units having quadratic cost function. The input data for the 6-generator system are taken from [21], and the total demand is set as 500 MW, 800 MW and 1000 MW. In this test system, loss coefficients are not taken into account. Unit data can been found in Appendix. The proposed approach is compared with other population-based heuristic methods such as PSO and ABC and the obtained results, with the proposed approach, are given in Table 1 and Figure 2 respectively. In the proposed approach, fuel cost is 52365 $/h, which is less than the other method for the power demand of 1000 MW. From Figure 2, it is clear that the proposed ACSA gives the best results for the ED problem.

**Test System II:** This system consists of ten generating units, having the effects of valve-point loading quadratic cost function. The input data for the 10-generator test system are taken from [22], and has a total load of 2000 MW. Also, the network losses are calculated by a B-matrix loss formula.

Table 1: Comparison of the results for test system 2 (Ten generator system)

| POWER DEMAND | PSO | ABC | ACSA | PSO | ABC | ACSA | PSO | ABC | ACSA |
|---|---|---|---|---|---|---|---|---|---|
| | 1500 MW | | | 1800 MW | | | 2000 MW | | |
| **PG1** | 53.30 | 50.08 | 10.00 | 45.47 | 13.60 | 55.00 | 35.35 | 10.45 | 53.78 |
| **PG2** | 67.38 | 29.69 | 60.01 | 67.82 | 59.44 | 80.00 | 47.13 | 55.49 | 77.11 |
| **PG3** | 57.30 | 70.03 | 69.00 | 91.02 | 98.54 | 79.83 | 96.50 | 73.96 | 108.00 |
| **PG4** | 25.44 | 20.00 | 62.36 | 75.58 | 86.57 | 74.21 | 118.56 | 118.84 | 93.32 |
| **PG5** | 57.55 | 50.00 | 50.00 | 78.71 | 91.87 | 59.68 | 131.72 | 118.74 | 143.24 |
| **PG6** | 83.25 | 87.65 | 70.00 | 116.10 | 90.38 | 70.00 | 197.55 | 223.69 | 158.54 |
| **PG7** | 146.23 | 263.77 | 214.67 | 139.38 | 279.44 | 258.87 | 278.89 | 248.66 | 275.85 |
| **PG8** | 191.51 | 266.26 | 244.57 | 332.96 | 305.26 | 292.60 | 333.69 | 312.93 | 302.38 |
| **PG9** | 436.46 | 330.57 | 377.88 | 460.42 | 435.93 | 438.55 | 418.84 | 456.46 | 455.37 |
| **PG10** | 433.81 | 381.12 | 390.72 | 463.83 | 412.87 | 462.93 | 450.29 | 464.87 | 418.27 |
| **$P_{Total}$** | 1552.24 | 1549.16 | 1549.22 | 1871.29 | 1873.90 | 1871.67 | 2108.51 | 2084.10 | 2107.70 |
| **$P_{Loss}$** | 51.45 | 49.15 | 49.21 | 71.19 | 69.81 | 71.65 | 85.03 | 84.03 | 85.84 |
| **$P_{Excess}$** | 0.79 | 0.01 | 0.00 | 0.10 | 4.09 | 0.02 | 23.48 | 0.07 | 0.00 |
| **Fuel Cost ($/h)** | 81921 | 81894 | 81423 | 99907 | 99790 | 98824 | 115970 | 115240 | 113550 |

Unit data and loss coefficients can be found in Appendix. The results obtained for this case are given in Table 5. In Table 5, simulation results of the proposed approach are shown for a power demand of 1500 MW, 1800 MW and 2000 MW in order to compare them with other stochastic search algorithms presented.

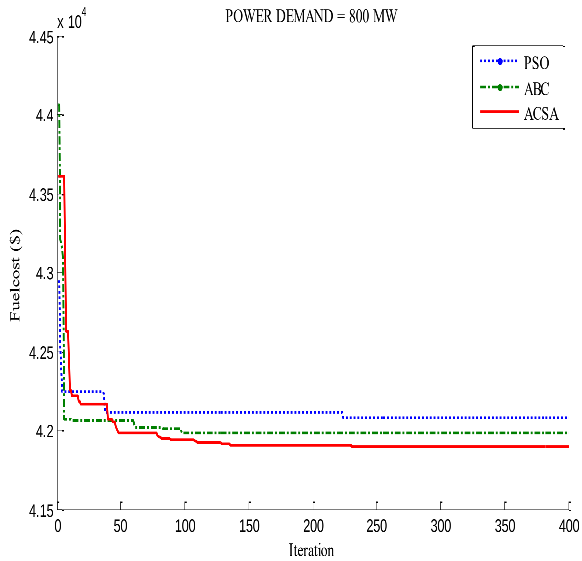


Figure 2: Comparison of the results for PD=800 MW

The results obtained from the proposed approach are better than other optimization algorithms. In the proposed approach, fuel cost is 113550 $/h, which is less than other method for the power demand of 2000 MW.

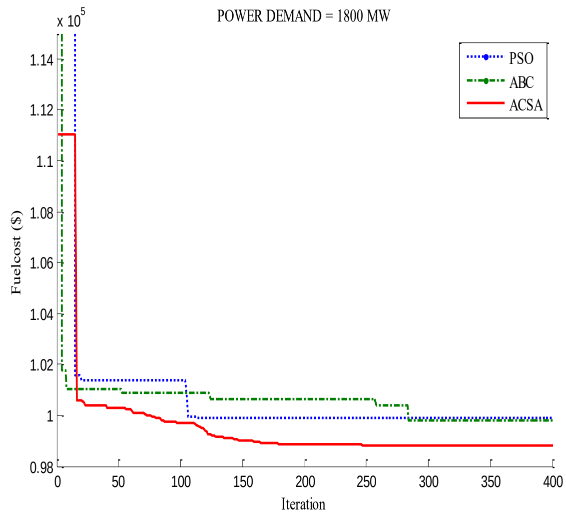


Figure 3: Comparison of the results for PD=1800 MW

## V. CONCLUSION

Economic power dispatch always attracts much attention worldwide, because it involves minimization of both the operating cost and the fuels used. Hence, the Artificial Cooperative Search algorithm has been proposed for solving economic dispatch problems with cost minimization as the objective function. Based on the results, it shows that the developed ACS is capable of determining the optimal combination of generators' output, so as to minimize the total fuel cost, while satisfying the constraints. The results are compared with PSO and ABC algorithms.

## VI. APPENDIX

Six-unit generator system

Table.3. Six-unit generator characteristics

| Unit | $P_{min}$ (MW) | $P_{max}$ (MW) | a (\$/h) | b (\$/MWh) | c (\$/(MW)$^2$h |
|---|---|---|---|---|---|
| 1 | 10 | 125 | 756.800 | 38.540 | 0.1525 |
| 2 | 10 | 150 | 451.325 | 46.160 | 0.1060 |
| 3 | 35 | 225 | 1050.000 | 40.400 | 0.0280 |
| 4 | 35 | 210 | 1243.530 | 38.310 | 0.0355 |
| 5 | 130 | 325 | 1658.570 | 36.328 | 0.0211 |
| 6 | 125 | 315 | 1356.660 | 38.270 | 0.0180 |

$$B = \begin{bmatrix} 0.00014 & 0.000017 & 0.000015 & 0.000019 & 0.000026 & 0.000022 \\ 0.000017 & 0.00006 & 0.000013 & 0.000016 & 0.000015 & 0.00002 \\ 0.000015 & 0.000013 & 0.000065 & 0.000017 & 0.000024 & 0.000019 \\ 0.000019 & 0.000016 & 0.000017 & 0.000071 & 0.00003 & 0.000025 \\ 0.000026 & 0.000015 & 0.000024 & 0.00003 & 0.000069 & 0.000032 \\ 0.000022 & 0.00002 & 0.000019 & 0.000025 & 0.000032 & 0.000085 \end{bmatrix}$$

Ten-unit generator system

Table.4. Ten-unit generator characteristics

| Unit | $P_{min}$ (MW) | $P_{max}$ (MW) | a (\$/h) | b (\$/MWh) | c (\$/(MW)$^2$h | d (\$/h) | e (rad/MW) |
|---|---|---|---|---|---|---|---|
| 1 | 10 | 55 | 1000.403 | 40.5407 | 0.12951 | 33 | 0.0174 |
| 2 | 20 | 80 | 950.6060 | 39.5804 | 0.10908 | 25 | 0.0178 |
| 3 | 47 | 120 | 900.7050 | 36.5104 | 0.12511 | 32 | 0.0162 |
| 4 | 20 | 130 | 800.7050 | 39.5104 | 0.12111 | 30 | 0.0168 |
| 5 | 50 | 160 | 756.7990 | 38.5390 | 0.15247 | 30 | 0.0148 |
| 6 | 70 | 240 | 451.3250 | 46.1592 | 0.10587 | 20 | 0.0163 |
| 7 | 60 | 300 | 1243.531 | 38.3055 | 0.03546 | 20 | 0.0152 |
| 8 | 70 | 340 | 1049.998 | 40.3965 | 0.02803 | 30 | 0.0128 |
| 9 | 135 | 470 | 1658.569 | 36.3278 | 0.02111 | 60 | 0.0136 |
| 10 | 150 | 470 | 1356.659 | 38.2704 | 0.01799 | 40 | 0.0141 |

$$B = \begin{bmatrix} 0.000049 & 0.000014 & 0.000015 & 0.000015 & 0.000016 & 0.000017 & 0.000017 & 0.000018 & 0.000019 & 0.000020 \\ 0.000014 & 0.000045 & 0.000016 & 0.000016 & 0.000017 & 0.000015 & 0.000015 & 0.000016 & 0.000018 & 0.000018 \\ 0.000015 & 0.000016 & 0.000039 & 0.000010 & 0.000012 & 0.000012 & 0.000014 & 0.000014 & 0.000016 & 0.000016 \\ 0.000015 & 0.000016 & 0.000010 & 0.000040 & 0.000010 & 0.000010 & 0.000011 & 0.000012 & 0.000014 & 0.000015 \\ 0.000016 & 0.000017 & 0.000012 & 0.000014 & 0.000035 & 0.000011 & 0.000013 & 0.000013 & 0.000015 & 0.000016 \\ 0.000017 & 0.000015 & 0.000012 & 0.000010 & 0.000011 & 0.0000136 & 0.000012 & 0.000012 & 0.000014 & 0.000015 \\ 0.000017 & 0.000015 & 0.000014 & 0.000011 & 0.000013 & 0.000012 & 0.000038 & 0.000016 & 0.000016 & 0.000018 \\ 0.000018 & 0.000016 & 0.000014 & 0.000012 & 0.000013 & 0.000012 & 0.000016 & 0.000040 & 0.000015 & 0.000016 \\ 0.000019 & 0.000018 & 0.000016 & 0.000014 & 0.000015 & 0.000014 & 0.000016 & 0.000015 & 0.000042 & 0.000019 \\ 0.000020 & 0.000018 & 0.000016 & 0.000015 & 0.000016 & 0.000015 & 0.000018 & 0.000016 & 0.000019 & 0.000044 \end{bmatrix}$$

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