International Journal of Computer Applications (0975 – 8887)
Volume 124 – No.12, August 2015

A Novel Hybrid Multi–objective BB–BC based Channel Allocation Algorithm to Reduce FWM Crosstalk and its Comparative Study

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ABSTRACT
Nature is a good source of inspirations for us. The algorithms developed from the nature are most powerful algorithms for optimizing many complex engineering design problems having multiple objectives (multi–objective). This paper presents an hybrid algorithm based on Multi–objective Big bang–Big Crunch (MOBB–BC) nature–inspired optimization algorithm with Genetic crossover and Differential evolution (DE) mutation operators for solving the minimum length ruler called Optimal Golomb ruler (OGR) as channel–allocation problem to reduce four–wave mixing crosstalk (FWM) effects in optical wavelength division multiplexing (WDM) systems. The comparative study of simulation results obtained by proposed hybrid Multi–objective BB–BC (HMOBB–BC) algorithm demonstrates better and efficient generation of OGRs in a reasonable computational time compared to simple BB–BC algorithm and one of the existing nature–inspired algorithms i.e. Genetic algorithm (GA). Also, the proposed hybrid algorithm outperforms the two existing conventional algorithms i.e. Extended quadratic congruence (EQC) and Search algorithm (SA), in terms of ruler length and total channel bandwidth.

General Terms
Conventional computing, Four–wave mixing, Multi–objective, Nature–inspired, Optimization.

Keywords
Channel spacing, Genetic algorithm, Hybrid Multi–objective Big bang–Big Crunch optimization algorithm, Optimal Golomb ruler.

1. INTRODUCTION
Crosstalk due to four–wave mixing (FWM) is the dominant nonlinear effect in a multi–channel long haul optical communication fiber system which limits the performance of optical wave length division multiplexing (WDM) system. It is therefore important to develop algorithms to allocate the channel frequencies in order to reduce the FWM crosstalk [1]–[6].

There is several unequally spaced channel–allocation algorithms have been proposed [2], [7]–[14] which have the drawback of increased optical channel bandwidth requirement compared to equally spaced channel allocation. This paper proposes a nature–inspired based unequally spaced channel algorithm by using the concept of Optimal Golomb ruler (OGR) sequences [15]–[17].

By using OGRs as channel–allocation, reduction in FWM crosstalk can be achieved in the optical WDM systems without affecting total optical channel bandwidth. Golomb rulers represent a class of *NP*–complete [18] problem. Several different algorithms are proposed to solve Golomb ruler problem such as exact methods [19], [20], constraint programming [21], local searches [22] and exhaustive parallel search [23]. There are various nature–inspired based algorithms such as Genetic algorithm (GA) [24]–[28], Biogeography Based Optimization (BBO) [28]–[30], Big Bang–Big Crunch (BB–BC) algorithm [31], [32], Firefly algorithm (FA) [33], Cuckoo search based algorithm (CSA) [34], and Multi–objective flower pollination algorithm (MOFPA) and its hybridization form [35] to solve the OGRs problem. This paper introduces two concepts i.e. hybridization and multi–objective in simple BB–BC optimization algorithm to solve unequally spaced channel–allocation problem in optical WDM system. The hybridization of BB–BC algorithm is done with Genetic crossover and Differential Evolution mutation operator. The purpose of hybridization is to improve the convergence rate and precision of BB–BC algorithm. Then formed hybrid BB-BC algorithm is extended to multi–objective optimization problems by using a Pareto–based approach [36], [37]. Both these concepts are combined in order to generate OGR sequences for various marks or optical WDM's channels.

This paper has following sections: Section 2 introduces the brief concept of Golomb rulers. Section 3 introduces with hybrid Multi-objective BB–BC nature–inspired optimization algorithm. Section 4 presents the problem formulation. Section 5 presents the simulation results and performance comparison of proposed algorithm and Section 6 presents the conclusion and future scope of the research.

2. GOLOMB RULERS
Golomb ruler refers to a set of positive integers named as *marks* and no distinct pairs of numbers from the set have the same difference [38]–[40]. The difference between the values of any two marks is called the *distance* between those marks. The difference between the largest and smallest number is referred to as the *length* of the ruler. The number of marks on a ruler is referred to as the *size* of the ruler.

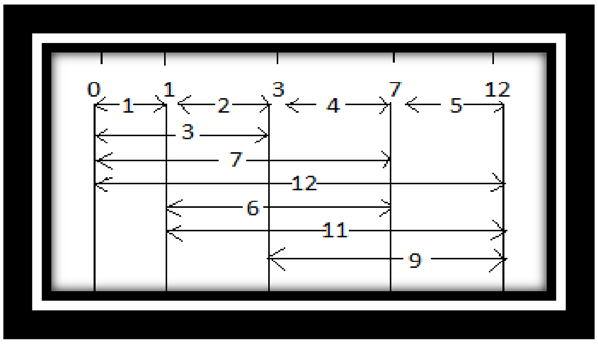


Fig1: A 5–Marks non–OGR having Ruler Length 12with its associated distances

A *perfect Golomb ruler* measures all the non–negative integer distances from 0 to length L of the ruler [40]–[43]. An *optimal Golomb ruler* is the shortest length ruler for a given mark. There can be numerous different OGRs for a specific marks value. Figure 1 show an example of 5–marks non– optimal Golomb ruler having ruler length 12. The distance associated between each pair of marks is also shown in Figure 1. As clear from Figure 1 that the distance numbers 8 and 10 are missing so it is not a perfect Golomb ruler sequence.

3. HYBRID MULTI–OBJECTIVE BIG BANG–BIG CRUNCH ALGORITHM

Big Bang–Big Crunch algorithm, a meta–heuristic population–based optimization algorithm relies on the theories of the evolution of universe; called the Big Bang and Big Crunch theory [44]–[46]. It states us that the Universe‘s expansion is due to the Big Bang and will not continue forever. Instead, at a certain point in time, it will stop expanding and collapse into itself, pulling everything with it until it eventually turns into the biggest black hole ever. Erol and Eksin [47], inspired by these theories, introduced an optimization algorithm named Big Bang–Big Crunch optimization algorithm. This algorithm has two phases: the first phase is Big Bang phase and the second phase is Big Crunch phase where a contraction procedure calculates a center of mass for the population [48], [49]. These two phases represent the best solution exploitation and large search space exploration, respectively. The first phase (energy dissipation) randomly generates an initial population of feasible candidate solutions. Generally, this phase represents the search space exploration process. After the Big Bang phase, a contraction procedure is applied during the Big Crunch. This aims to have quick convergence and reduce computational time, while maintaining the quality of solutions and search diversity. The best candidate solution is represented as the centre of mass that will attract other solutions. In the Big Crunch phase, the contraction operator takes the current positions of each candidate solution in the population and its associated fitness/cost function value and computes a centre of mass according to the equation (1) [47]:

$$x_c = \frac{\sum_{i=1}^{Popsize} \frac{1}{f_i} x_i}{\sum_{i=1}^{Popsize} \frac{1}{f_i}} \tag{1}$$

where, x_c is position of the centre of mass, x_i is position of the candidate, f_i is fitness (cost) function value of the candidate i; and *Popsize* is the population size.

Instead of the centre of mass, best fit individual can also be chosen as the starting point in the Big Bang phase. The new candidates (x_{new}) around the centre of mass are calculated by subtracting or adding a normal random number whose value decreases as the iterations elapse. This can be formalized by the equation (2):

$$x_{new} = x_c + r \times c_1 \times \frac{(x_{\max} - x_{\min})}{1 + t / c_2} \tag{2}$$

where r is a standard normal distribution random number, c_1 is a limiting the size parameter of the search space, parameter c_2 denotes after how much iteration the search space will be restricted to half, $x_{\max}$ and $x_{\min}$ are the upper and lower limits, and t is the iteration index.

Although the algorithm, BB–BC has exceptional property as compared to numerous nature–inspired optimization algorithms while solving lower–dimensional optimization design problems, but may become challenging for higher–dimensional optimization design problems because of the phenomenon of slow convergence and low accuracy rates. This means there are some problems in the global exploitation and exploration of the search space.

Therefore, this paper forward an improved hybrid BB–BC with multiple objectives, namely, HMOBB–BC, that relies on Genetic crossover [50] and fitness values based differential mutation strategy [51], [52] to accelerate the convergence speed of multi–objective BB–BC (MOBB–BC) algorithm. A multi–objective optimization problem with M objectives can be written in general as [37]:

$$\text{Maximize/Minimize } f_1(x), f_2(x), ..., f_M(x)$$

subject to the non-linear equality and inequality constraints.

$$h_j(x) = 0, (j = 1,2,..., J) \text{ and } g_k(x) \ge 0, (k = 1,2,..., K).$$

One of the simplest ways is to use a weighted sum to combine multi–objective into a composite single objective is given by equation (3) [37]:

$$f = \sum_{m=1}^{M} w_m f_m \tag{3}$$

$$\text{with } \sum_{i=1}^{M} w_i = 1, \qquad w_i > 0 \tag{4}$$

where $w_i (i = 1,..., M)$ are randomly generated non–negative weights.

The fundamental idea of this weighted sum approach is that these weighting coefficients act as the preferences for these multi–objectives [37].

In proposed HMOBB–BC, algorithm the mutation rate probability MR_i^t of each solution x_i at running iteration index t is determined based on the fitness value f_i^t of each solution:

$$MR_i^t = \frac{f_i^t}{Max(f^t)} \tag{5}$$

where $Max(f^t)$ is maximum fitness value in the population of solutions at iteration t.

In order to improve the search efficiency and increase the population diversity, based on the mutation rate probability the positions of the candidates x_i (solutions) are updated by using the "$DE/rand/1$" [52] mutation equation (6):

$$x_i^t = x_{r_1}^{t-1} + P_{mutate}(x_{r_2}^{t-1} - x_{r_3}^{t-1}) \tag{6}$$

Begin
  /* Big Bang Phase */
    Define Pareto front points N and objective functions $f_1(x),\ldots,f_M(x)$, $x=(x_1,\ldots,x_d)^T$;
    Generate populations of *NP* candidates randomly;
    Generate M weights $w_m \geq 0$ so that equation (4) is satisfies;
    Form a single objective by using equation (3);
    Based on fitness value, find the global best solution x_*among the population of *NP* candidates;
  /* End of Big Bang Phase */
  For $i = 1 : N$
   Generate M weights randomly which satisfies equation (4);
   While not *TC* /* *TC* is a termination criterion */
    /* Big Crunch Phase */
      Compute the center of mass. Either the best fit individual or the center of mass is chosen as the point of Big Bang phase;
    /* End of Big Crunch Phase */
    /* Big Bang Phase */
      Calculate new candidates around the center of mass by adding or subtracting a normal random number whose value decreases as the iterations elapse by using equation (2);
    /* End of Big Bang Phase */
    /* Crossover */
      Apply crossover operator with probability based on crossover rate P_{cross};
    /* End of crossover */
    /* Mutation*/
      Based upon the mutation rate probability *MR* (equation 5) perform mutation by using equation (6);
    /* End of mutation */
     Re–evaluate fitness values of all the generated candidates;
     Rank the candidates and find the global best Pareto front solution x_* solutions;
   End while
   Record x_* as a non–dominated solution;
  End for *i*
  Postprocess the results and visualization;
End

Fig 2: Pseudo–code for Hybrid Multi-objective Big Bang–Big Crunch Algorithm

Begin
  /* Big Bang Phase */
    Initialize number of channels n, upper bound on the ruler length and Pareto fronts point N;
    Generate a random set of *NP* candidates (integer population) corresponding to Golomb ruler to the specified channels;
      /* Number of integers in candidates is equal to the number of channels */
    Based on fitness value, find the global best solution x_*among the population of *NP* candidates;
  /* End of Big Bang Phase */
  For $i = 1 : N$
    Generate M weights randomly which satisfies equation (4);
    While not *TC* /* *TC* is a termination criterion */
      /* Big Crunch Phase */
        Compute the center of mass; /* The best fit individual is chosen as the center of mass */
      /* End of Big Crunch Phase */
  A: Calculate new candidate around the center of mass by adding or subtracting a normal random number whose value decreases as the iterations elapse by using equation (2); /* Big Bang Phase */
      /* Crossover */
        Apply crossover operator with probability based on crossover rate P_{cross};
      /* End of crossover */
      /* Mutation*/
        Based upon the mutation rate probability *MR* (equation 5)perform mutation by using equation (6);
      /* End of mutation */
      Check Golombness of updated candidates;
      If Golombness is satisfied
        Retain that candidate and then go to **B**;
     Else
        Remove that particular generated candidate and then go to **A**;
     End if
  B: Evaluate fitness values of the generated *NP* candidates and form a single optimize objective $f(x)$;
     If new solutions are better, update them in the population;
     Rank the solutions and find the global best solution x_*;
    End while
    Record x_* as a non–dominated solution;
  End for *i*
  Postprocess the results and visualization;
End

Fig 3: Pseudo–code for HMOBB–BC Algorithm to Generate OGR Sequences

where r_1, r_2 and r_3 are randomly chosen mutually different integers from the interval [0, *NP*-1] and $P_{mutate} > 0$ is the mutation rate. The integers r_1, r_2 and r_3 are different from the running index *i*. P_{mutate} is a real and constant factor which controls the amplification of the differential variation. The differential mutation strategy increases the chances for a good solution, but a high mutation rate (>1) results in too much exploration and is disadvantageous to the improvement of candidate solutions [28]. Based upon the above discussion, the corresponding pseudo code for HMOBB–BC algorithm is shown in Figure 2.

4. PROBLEM FORMULATION

If the spacing between any pair of channels is denoted as *CS* and the total number of channels is *n*, then the objective is to optimize the length of the ruler denoted as *RL*, which is given by the equation (7) [28]:

$$RL = \sum_{i=1}^{n-1} (CS)_i \tag{7}$$

subject to $(CS)_i \neq (CS)_j$.

If each individual element is a Golomb ruler, the sum of all elements of an individual forms the total optical bandwidth of the channels. Thus, if an individual element is denoted as *IE* then the second objective is to minimize the total optical bandwidth *TBW* which is given by the equation (8):

$$TBW = \sum_{i=1}^{n} (IE)_i \tag{8}$$

subject to $(IE)_i \neq (IE)_j$.

where $i, j = 1, 2, ..., n$ with $i \neq j$ are distinct in both equations (7) and (8).

The proposed pseudo–code for HMOBB–BC algorithm to generate OGR sequences as unequally spaced channel–allocation in optical WDM system is shown in Figure 3.

5. SIMULATION RESULTS AND DISCUSSION

To find unequal spaced channel–allocation algorithm in optical WDM systems i.e. OGR sequences, the proposed HMOBB–BC algorithm has been written and verified in Matlab–7 language [53] under Windows 7 operating system. To show the effectiveness of the proposed algorithm, its performance is being compared with known OGRs [15], [20], [38]–[42], [54]–[56], EQC, SA [2], [13], [24], GA [28], and BB–BC [31], [32] algorithms of generating unequal spaced WDM channel–allocation sequences.

5.1 Simulation Parameters for Hybrid Multi-objective Big Bang–Big Crunch

To generate optimal Golomb ruler sequences as optical WDM channel–allocation, after a number of careful experimentation, the optimum values of HMOBB–BC parameters finally been settled in this research is reported in Table 1.

It is noted that the iterations has little effect for low order marks for examples *n* = 3 and 4. But for higher order marks, the iterations has a great effect on the performance of HMOBB–BC algorithm i.e. ruler length and total bandwidth gets optimized after a certain numbers of iterations. As the number of iterations increases, the length of the ruler and hence the total optical bandwidth of the sequence tends to decrease; it means that the rulers reach their optimum values after a certain number of iterations. This is the point where the results are optimum and no further improvement is seen, that is, we are approaching towards the optimal solution. By carefully observation, the paper fixed the iterations of 1000 for HMOBB–BC algorithm. With these parameters values, a number of sets of trials for various order marks are conducted.

Table 1. Simulation parameters for HMOBB-BC Algorithm

Parameter	Value
c_1	0.1
c_2	5
Number of candidates (*Popsize*)	20
Crossover method	Single Point
Crossover probability (P_{cross})	1
Mutation rate (P_{mutate})	0.05
Iterations	1000

5.2 Comparison of HMOBB–BC Algorithm with Previous Existing Algorithms in Terms of Ruler Length, Total Bandwidth and Average CPU Time

The purpose to use HMOBB–BC algorithm in this paper is to optimize the length of the ruler so as to conserve the total bandwidth occupied by the channels in less computational time. Table 2 list the length of ruler (*RL*), total optical bandwidth (*TBW*) and average CPU time occupied by different sequences obtained by proposed algorithm for various channels *n* and its comparison with known OGRs [15], [20], [38]–[42], [54]–[56], EQC, SA [2], [13], [24], GA [28], and BB–BC [31], [32] algorithms.

The application of conventional algorithms i.e. EQC and SA is limited to prime powers [2], so the length of ruler and total bandwidth for EQC and SA are shown by a dash line in Table 2. Comparing the simulation results obtained from HMOBB–BC algorithm with known OGRs, EQC, SA, GA and BB-BC; it is perceived that there is a significant improvement with respect to the length of the ruler, the total bandwidth occupied and average CPU time that is, the results gets better. Figure 4 (a) and 4 (b) illustrates the graphical comparison of HMOBB–BC algorithm to generate OGR sequences for optical WDM system with existing algorithms in terms of the length of the ruler and total optical bandwidth occupied by the various order mark values respectively, whereas Figure 5 illustrates the comparison of proposed HMOBB–BC algorithm with GA and BB–BC algorithm in terms of average CPU time (in Sec.) for various order marks. So, it is concluded from Table 2, Figures 4 and 5 that the performance of proposed HMOBB–BC algorithm is better than the existing algorithms.

6. CONCLUSION

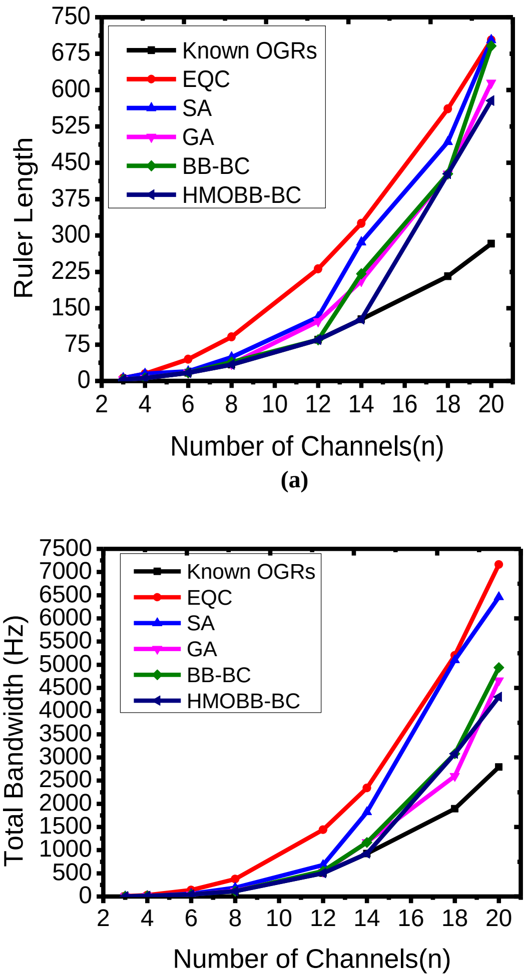
This paper presented the application of nature–inspired multi–objective BB–BC optimization algorithm and its hybridization with Genetic crossover and differential mutation operator to find optimal Golomb ruler sequences needed for optical WDM systems. The optimal Golomb ruler's sequence provides the unequal channel–allocation in optical WDM systems to reduce the FWM crosstalk. It has been observed that proposed HMOBB–BC algorithm produces Golomb ruler sequences very efficiently and effectively. The performance is being compared with the existing conventional and nature–inspired algorithms in terms of the length of ruler, total optical channel bandwidth and average CPU time obtained by the

Table 2: Performance Comparison of proposed HMOBB-BC Algorithm with Known OGR, EQC, SA, GA and BB–BC in terms of Ruler Length, Total Bandwidth, and Average CPU Time

n	Known OGRs [15], [20], [38]–[42], [54]–[56]		ALGORITHMS													
			Conventional Algorithms				Existing Nature–Inspired Algorithms						Proposed Algorithm		
			EQC [2], [13], [24]		SA [2], [13], [24]		GA [28]			BB–BC [31], [32]			HMOBB-BC		
	RL	***TBW (Hz)***	***RL***	***TBW (Hz)***	***RL***	***TBW (Hz)***	***RL***	***TBW (Hz)***	***Average* CPU time (Sec.)**	***RL***	***TBW (Hz)***	***Average CPU time (Sec.)***	***RL***	***TBW (Hz)***	***Average CPU time (Sec.)***
4	6	11	15	28	15	28	6 7	11	0.001	6 7	11	0.000	6 7	11	0.000
5	11	25 28	—	—	—	—	12 13	23 25 29	0.021	11 12	23 25	0.009	11 12 13	23 25	0.001
6	17	44 47 50	45	140	20	60	17 18 21	42 44 45	0.780	17 18	42 44	0.659	17 18	42 44	0.0539
7	25	77 81 87 90 95	—	—	—	—	27 28 29 30 31 32	73 78 79 80 83 86 95	1.120	25 26 28 30	73 74 77 81	1.170	25 28	74 77 81 90	0.0899
8	34	117	91	378	49	189	35 41 42 45 46	121 126 128 129 131 133	1.241	39 41 42	113 118 119	1.210	34 39	113 117	0.1441
9	44	206	—	—	—	—	52 56 59 61 63 65	192 193 196 203 225	1.711	44 45 46 61	179 248 253 262	1.698	44	206	1.1895
10	55	249	—	—	—	—	75 76	283 287 301	5.499e+01	77	258	5.450e+01	55	249	3.151e+01
11	72	386 391	—	—	—	—	94 96	395 456	7.200e+02	72 105	377 490 456	6.990e+02	72	386	4.765e+02
12	85	503	231	1441	132	682	123 128 137	532 581 660	8.602e+02	85 91	550 580 613	7.981e+02	85	503	5.659e+02
13	106	660	—	—	—	—	203 241	1015 1048	1.070e+03	110 113	768 753	1.020e+03	106	660	8.751e+02
14	127	924	325	2340	286	1820	206 228 230	1172 1177 1285	1.028e+03	221	1166	1.021e+03	127	924	1.013e+03
15	151	1047	—	—	—	—	275 298	1634 1653	1.440e+03	267	1322	1.291e+03	151	1047	1.165e+03
16	177	1298	—	—	—	—	316	1985	1.680e+03	316	1985	1.450e+03	177	1298	1.341e+03
17	199	1661	—	—	—	—	355	2205	5.048e+04	369	2201	4.075e+04	199	1661	3.462e+03
18	216	1894	561	5203	493	5100	427 463	2599 3079	6.840e+04	427	3079	5.897e+04	427	3079	4.077e+04
19	246	2225	—	—	—	—	567 597	3432 5067	8.280e+04	584	4101	7.158e+04	467	3337	6.685e+04
20	283	2794	703	7163	703	6460	615 673 680 691	4660 4826 4905 4941	1.12428e+05	691	4941	1.0012e+05	578 615	4306 4660	7.333e+04

different sequences. The preliminary results indicate that proposed HMOBB–BC algorithm appears to be most efficient algorithm to generate OGRs for optical WDM systems and outperforms the existing algorithms.

In order to see the complexity of realizing the unequal channel spacing, the existing researches does not show the implementation of their algorithms in real optical WDM systems. So, in order for the algorithms to be of practical use, it is desired that the performance of the algorithms for higher order OGRs channels may be evaluated and may be used to provide unequal channel spacing in real optical WDM systems.



(a)

(b)

Fig 4: The proposed HMOBB–BC algorithm exhibits the significant reduction in (a) ruler length and (b) total occupied optical bandwidth in comparison to the existing algorithms i.e. Known OGR, EQC, SA, GA and BB-BC

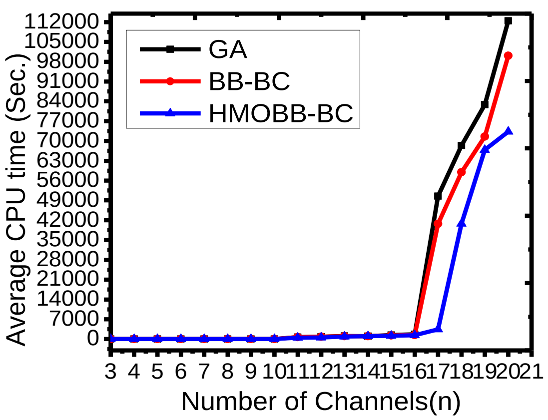


Fig 5: The proposed HMOBB–BC algorithm exhibits the significant reduction in average CPU time in sec. in comparison to the existing algorithms i.e. GA and BB-BC

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