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Heuristics for optimizing minimum interference channel allocation problem in cellular networks

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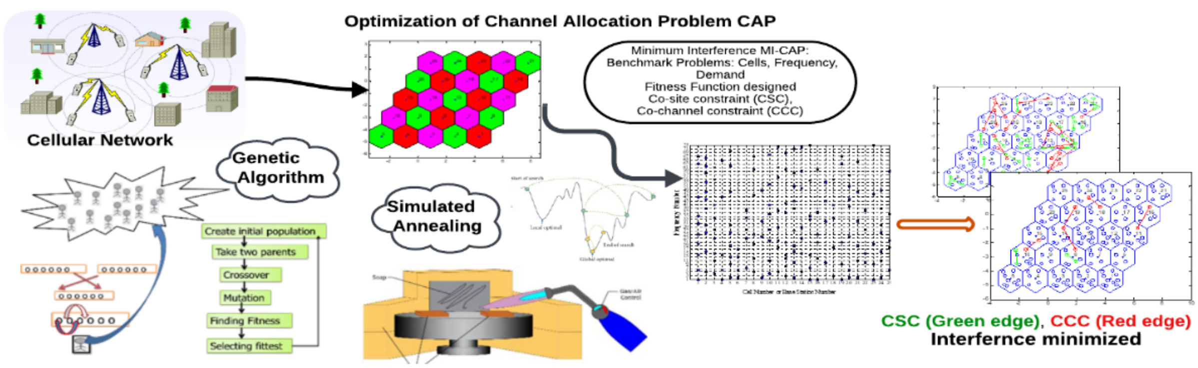
Article

ABSTRACT



The channel allocation problem (CAP) requires cellular communication services to meet electromagnetic constraints, such as having the least bandwidth, satisfy customer demand/capacity, less call-blocking probability, and the least level of interference. With a limited bandwidth and cumulative growth in non-uniform dynamic demand which varies depending on the times of day, the problem of channel allocation becomes more crucial. Artificial intelligence Technique for heuristic optimization can be used to minimize the overall interference level (MICAP) and satisfy the channel demand. The MICAP is solved using the Genetic Algorithm and Simulated Annealing. When designing the cost or fitness function, co-channel, and co-site channel constraints are taken into account. The channel allocation matrix is observed, the cost function value is measured for the number of iterations or generations needed to satisfy the demand with constraints imposed. When the simulated observations are compared to previously reported results, the cost function value is found to be reduced for the benchmarks EX1, HEX1, HEX2, HEX3, HEX4, P1, P2, and P3, each of which indicates a distinct number of cells, frequency, and traffic demand.

Keywords: Channel Allocation Problem, Genetic Algorithm, Simulated Annealing, Heuristics, Optimization technique

INTRODUCTION

The cellular idea replaces a single large cell with a high-power transmitter with numerous small cells that each serve a smaller area of the service area and have low-power transmitters. Every single base station (BS) is assigned a subset of the total number of available channels.[1] To minimize inter-BS interference, adjacent base stations are assigned different channel clusters. The provided channels are distributed and reused, or frequency reused, by carefully separating the base station and its channels, provided that the interference remains below acceptable thresholds. More channels are needed inside a service zone to accommodate dynamically growing user counts. By increasing the number of base stations (BSs), surplus radio capacity can be provided without expanding the radio frequency.[2]

Interference is a major limiting factor in system performance due to the limited frequency spectrum and increasing traffic demand. A call in process in the adjacent cell, another call in progress in the same cell, BS operating in the same frequency groups, and so on might all serve as sources of interference. Calls are prevented or ignored due to interference on control channels, which also causes crosstalk. Reuse distance refers to the reuse of the same set of frequencies in a certain cell that is spaced apart sufficiently apart to prevent interference. This work aims to reduce system interference as much as possible. Adjacent channel refers to transmitters in neighbouring cells utilizing adjacent (closely located) frequencies;

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co-site refers to transmitters located in the same cell utilizing different frequencies; and co-channel refers to the use of the same frequency in separate cells.[3]

The CAP idea is critical, and it's necessary to be familiar with types of CAP, such as MSCAP, MBCAP, and MICAP. Minimising span means organising channels in such a manner that unwanted interference is avoided and the spread between the highest and lowest frequencies is decreased. The purpose of minimizing blocking is to lessen the likelihood of calls being stopped in the network. Frequencies are allotted from a pool of accessible frequencies to reduce the overall quantity of interference. To provide the optimum network performance, these considerations must be taken into account while assigning channels.[4]

MSCAP and MICAP are appropriate in today's reality. The primary goal of MSCAP is to reduce the frequency span required to construct a new network for a network operator, whereas MI-CAP focuses on minimising interference with a set number of channels given to operational networks. Because there are more operational networks than new networks to be implemented, this effort concentrates on MICAP rather than MSCAP.[5]

Channels are assigned to mobile stations (MS) based on their position in the network structure. If the number of channels is N and the number of MS is M, then there are NM potential groupings to distribute channels to the network. For a practical network, NM is a large quantity, therefore physically selecting a suitable combination will be time-consuming and difficult.

The CAP is a time-consuming and algorithmically complicated problem. Heuristic approaches can produce near-optimal results at a reasonable computing cost. There is no predetermined approach to generate efficient solutions with heuristic procedures. The quality of the best solution, the time necessary, the algorithm's time to produce a good result, and so on are performance metrics.

Heuristic techniques are fundamental, and Computational Intelligence is an important subset of them. Metaheuristics are classified into several kinds, including simulated annealing (SA) and tabu search (TS), both of which employ a basic local search method. Ant colony optimisation (ACO), evolutionary computation, and genetic algorithms (GA), on the other hand, include a learning component in their search approach. This paper employs SA and GA to discover an optimal solution to the minimal interference channel allocation issue to reduce interference.

Literature Survey

A literature review is conducted on the various strategies used to solve CAP. The widespread work on heuristic approaches is due to the conflict of the many CAPs. The work on solving CAP using Neural Network (NN), SA, TS, and GA is given.

The Kunz benchmark instances is formulated with NN by Dietmar Kunz,[1] the weight between two discrete neurons represents cochannel, cosite and adjacent interference while allocating two frequencies. The min interference variant is formulated by considering cochannel interference. The generated frequency plan for Kunz 4 instance is the Channel Allocation Matrix (CAM).

A parallel algorithm comprising of artificial NN is employed with modified Hopfield network which includes 'hill-climbing' mechanism in order to escape from local minima.[2] This algorithm is tested on eight benchmark problems comprising,[3] of nm (n cell and m Frequencies) processing elements. The frequencies are ranging between 100 to 533 frequencies.

A simple frequency assignment model considering distance amid frequencies and constraint graph is generated using SA.[4] This model is executed and compared using Local search and SA algorithm. It is implemented is with C++ with the environment of VC++ compiler.

The study by O. Abuajwa et.al.[5] focuses on optimizing downlink non-orthogonal multiple access (NOMA)-based 5G network throughput through a proposed resource allocation method and simulated annealing, achieving a 7% improvement over existing methods. The approach involves, addressing the NP-hard nature of the problem with reliable performance and low time complexity.

A multistage TS algorithm is applied on different initial solutions initiated randomly,[6]. It is worked to solve fixed allocation focusing on to minimize interference. A reactive TS is used to augment the traditional system's strength by adapting the tabu list scope to the property of the optimization issue,[7]. TS is applied considering cosite and adjacent channel constraint to solve CAP. 1-exchange approach is performed where the nodes initiated from diverse frequency plans are exchanged.[8]

The hamming GA is presented by A. Hassanat et.al.[9] in a 2-dimentional cellular mechanism. The search for the global optimum solution of problematic non-linear optimization problems is carried out. A plot of percentage of attaining an optimum solution in varied iterations is showed. The QoS balancing function is proposed that helps to maximise sum-rate while simultaneously achieving cell-based equality via a linked and decoupled power allocation structure.[10] The study on accommodation of dynamic plan at low traffic load and fixed plan at higher traffic is done. A plot of blocking probability v/s traffic load for 49 cell benchmark case is depicted,[11]. GA, PSO and ACO tries to solve hybrid channel allocation problem leading to best solution with fast convergence and reducing call blocking probability.[12]

Channel Assignment Problem

The CAP is the way of allocating channels to cellular cells while fulfilling frequency separation constraints with Minimum Channel Interference, Minimum Blocking Probability and optimum bandwidth. In this work the CAP is solved with MICAP giving second priority to the use of bandwidth and blocking probability.

Problem Description

A set of available channels, $M = \{1,2,3,\dots,m\}$ where m is the available channels in the network by positive integers. The CAP's fundamental model may be expressed as follows:

- N : number of cells
- d_i : number of frequencies assigned to cell i $(1 \le i \le N)$
- C: Compatibility matrix, $C = (c_{ij})$, $N \times N$ the Min channel difference between channels in cells i and j, $1 \le i,j \le N$.
- $Call_{ik}$: Cell i with call k, where $1 \le i \le N, 1 \le k \le d_i$.
- RC_{ik} : A radio channel is assigned to $Call_{ik}$, where $RC_{ik} \in$ a set of radio channel F.

- *Frequency separation constraint:* $|RC_{ik} - RCf_{im}| \geq c_{ij}, for\ all\ i,j,k,m\ (i \neq j, k \neq m), c_{ij}$ is defined in C. If $i = j$, it is co-site constraint (CSC).

Objective Function

In CSC, if frequency q is within $C(i,i)$ from j frequency which is allotted to cell i, then j not be allocated to i. If the allocating of frequency j, ($|j-q| < C(i,j)$ to cell i, violates the CSC, it is nonzero.

$$\sum_{\substack{q=j-(c_{ii}-1)\\ q\neq j\\ 1\leq q\leq M}}^{j+(c_{ii}-1)} F_{iq} \qquad (1)$$

If q frequency is within $C(i,p)$ of frequency j, ($|j-q| < C(i,p)$ is allotted to cell p for $C(i,p) > 0$ and $p \neq i$, and pi, frequency j must not be assigned to cell i, according to the co-channel constraint (CCC). If the cell j to cell i assignment satisfies the CCC, it is nonzero.

$$\sum_{\substack{p=1\\ p\neq i\\ c_{ip}>0}}^{N} \sum_{\substack{j-(c_{ip}-1)\\ 1\leq q\leq M}}^{j+(c_{ip}-1)} F_{pq} \qquad (2)$$

Total cost function,

$$\sum_{i=1}^{n}\sum_{j=1}^{j=M}\left(\sum_{\substack{q=j-(c_{ii}-1)\\ q\neq j\\ 1\leq q\leq M}}^{j+(c_{ii}-1)} F_{iq} + \sum_{\substack{p=1\\ p\neq i\\ c_{ip}>0}}^{N} \sum_{\substack{j-(c_{ip}-1)\\ 1\leq q\leq M}}^{j+(c_{ip}-1)} F_{pq}\right) \qquad (3)$$

The cost functions,[13] is given in equation (1), (2) and (3). The Solution is represented as a binary matrix N (no. of cells) × m (no. of channels).

Table 3.1: Specifications of Simulated problems

Sr. No.	Problem	Number of cells N	Number of frequencies M	Compatibility matrix C	Demand vector D
1	EX1	4	11	*C1*	*D1*
2	HEX1	21	37	*C2*	*D2*
3	HEX2	21	91	*C3*	*D3*
4	HEX3	21	21	*C2*	*D4*
5	HEX4	21	56	*C3*	*D5*
6	P1	25	73	*C4*	*D6*
7	P2	21	533	*C5*	*D7*
8	P3	21	381	*C3*	*D8*

The Benchmark Problems,[14] is considered for solving allocation problem. The compatibility matrix and the demand vectors for the tested instances are as given

Compatibility matrix (C)

C1

5 4 0 0
4 5 0 1
0 0 5 2
0 1 2 5

C2

2 1 1 0 0 1 1 1 1 0 0 0 0 1 1 1 0 0 0 0 0
1 2 1 1 0 0 1 1 1 1 0 0 0 0 1 1 1 0 0 0 0
1 1 2 1 1 0 0 1 1 1 1 0 0 0 0 1 1 1 0 0 0
0 1 1 2 1 0 0 0 1 1 1 1 0 0 0 0 1 1 0 0 0
0 0 1 1 2 0 0 0 0 1 1 1 0 0 0 0 0 1 0 0 0
1 0 0 0 0 2 1 1 0 0 0 0 1 1 1 0 0 0 0 0 0
1 1 0 0 0 1 2 1 1 0 0 0 1 1 1 1 0 0 1 0 0
1 1 1 0 0 1 1 2 1 1 0 0 0 1 1 1 1 0 1 1 0
1 1 1 1 0 0 1 1 2 1 1 0 0 0 1 1 1 1 1 1 1
0 1 1 1 1 0 0 1 1 2 1 1 0 0 0 1 1 1 0 1 1
0 0 1 1 1 0 0 0 1 1 2 1 0 0 0 0 1 1 0 0 1
0 0 0 1 1 0 0 0 0 1 1 2 0 0 0 0 0 1 0 0 0
0 0 0 0 0 1 1 0 0 0 0 0 2 1 1 0 0 0 0 0 0
1 0 0 0 0 1 1 1 0 0 0 0 1 2 1 1 0 0 1 0 0
1 1 0 0 0 1 1 1 1 0 0 0 1 1 2 1 1 0 1 1 0
1 1 1 0 0 0 1 1 1 1 0 0 0 1 1 2 1 1 1 1 1
0 1 1 1 0 0 0 1 1 1 1 0 0 0 1 1 2 1 1 1 1
0 0 1 1 1 0 0 0 1 1 1 1 0 0 0 1 1 2 0 1 1
0 0 0 0 0 0 1 1 1 0 0 0 0 1 1 1 1 0 2 1 1
0 0 0 0 0 0 0 1 1 1 0 0 0 0 1 1 1 1 1 2 1
0 0 0 0 0 0 0 0 1 1 1 0 0 0 0 1 1 1 1 1 2

C3

5 1 1 0 0 1 1 1 1 0 0 0 0 1 1 1 0 0 0 0 0
1 5 1 1 0 0 1 1 1 1 0 0 0 0 1 1 1 0 0 0 0
1 1 5 1 1 0 0 1 1 1 1 0 0 0 0 1 1 1 0 0 0
0 1 1 5 1 0 0 0 1 1 1 1 0 0 0 0 1 1 0 0 0
0 0 1 1 5 0 0 0 0 1 1 1 0 0 0 0 0 1 0 0 0
1 0 0 0 0 5 1 1 0 0 0 0 1 1 1 0 0 0 0 0 0
1 1 0 0 0 1 5 1 1 0 0 0 1 1 1 1 0 0 1 0 0
1 1 1 0 0 1 1 5 1 1 0 0 0 1 1 1 1 0 1 1 0
1 1 1 1 0 0 1 1 5 1 1 0 0 0 1 1 1 1 1 1 1
0 1 1 1 1 0 0 1 1 5 1 1 0 0 0 1 1 1 0 1 1
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0 0 0 1 1 0 0 0 0 1 1 5 0 0 0 0 0 1 0 0 0
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1 1 0 0 0 1 1 1 1 0 0 0 1 1 5 1 1 0 1 1 0
1 1 1 0 0 0 1 1 1 1 0 0 0 1 1 5 1 1 1 1 1
0 1 1 1 0 0 0 1 1 1 1 0 0 0 1 1 5 1 1 1 1
0 0 1 1 1 0 0 0 1 1 1 1 0 0 0 1 1 5 0 1 1
0 0 0 0 0 0 1 1 1 0 0 0 0 1 1 1 1 0 5 1 1
0 0 0 0 0 0 0 1 1 1 0 0 0 0 1 1 1 1 1 5 1
0 0 0 0 0 0 0 0 1 1 1 0 0 0 0 1 1 1 1 1 5

C4

2 1 1 0 1 0 1 1 1 1 0 1 1 1 1 0 0 0 0 0 0 0 0 0 0
1 2 1 0 1 0 1 1 0 1 0 1 1 1 1 0 0 0 0 0 0 0 0 0 0
1 1 2 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0
0 0 1 2 0 0 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 1 1 1
1 1 1 0 2 0 0 0 0 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0
0 0 1 0 0 2 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
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0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 1 1 1 2 1 1
0 0 0 1 0 0 0 1 1 1 1 0 0 0 0 0 0 0 0 0 0 1 1 2 1
0 0 0 1 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 1 1 1 2

C5

7 2 1 0 0 1 2 2 1 0 0 0 0 1 1 1 0 0 0 0 0
2 7 2 1 0 0 1 2 2 1 0 0 0 0 1 1 1 0 0 0 0
1 2 7 2 1 0 0 1 2 2 1 0 0 0 0 1 1 1 0 0 0
0 1 2 7 2 0 0 0 1 2 2 1 0 0 0 0 1 1 0 0 0
0 0 1 2 7 0 0 0 0 1 2 2 0 0 0 0 0 1 0 0 0
1 0 0 0 0 7 2 1 0 0 0 0 2 2 1 0 0 0 0 0 0
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2 2 1 0 0 1 2 7 2 1 0 0 0 1 2 2 1 0 1 1 0
1 2 2 1 0 0 1 2 7 2 1 0 0 0 1 2 2 1 1 1 1
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0 0 1 2 2 0 0 0 1 2 7 2 0 0 0 0 1 2 0 0 1
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1 0 0 0 0 2 2 1 0 0 0 0 2 7 2 1 0 0 1 0 0
1 1 0 0 0 1 2 2 1 0 0 0 1 2 7 2 1 0 2 1 0
1 1 1 0 0 0 1 2 2 1 0 0 0 1 2 7 2 1 2 2 1
0 1 1 1 0 0 0 1 2 2 1 0 0 0 1 2 7 2 1 2 2
0 0 1 1 1 0 0 0 1 2 2 1 0 0 0 1 2 7 0 1 2
0 0 0 0 0 0 1 1 1 0 0 0 0 1 2 2 1 0 7 2 1
0 0 0 0 0 0 0 1 1 1 0 0 0 0 1 2 2 1 2 7 2
0 0 0 0 0 0 0 0 1 1 1 0 0 0 0 1 2 2 1 2 7

Demand vector (D)

D1= {1,1,1,3}

D2= {2,6,2,2,2,4,4,13,19,7,4,4,7,4,9,14,7,2,2,4,2}

D3= {2,6,2,2,2,4,4,13,19,7,4,4,7,4,9,14,7,2,2,4,2}
D4= {1,1,1,2,3,6,7,6,10,10,11,5,7,6,4,4,7,5,5,5,6}
D5= {1,1,1,2,3,6,7,6,10,10,11,5,7,6,4,4,7,5,5,5,6}
D6= {10,11,9,5,9,4,5,7,4,8,8,9,10,7,7,6,4,5,5,7,6,4,5,7,5}
D7= {8,25,8,8,8,15,18,52,77,28,13,15,31,15,36,57,28,8,10,13,8}
D8= {5,5,5,8,12,25,30,25,30,40,40,45,20,30,25,15,15,30,20,20,25}

HEURISTICS

Heuristics or most investigative properties include: planning the search process, and effectively discovering the search space to identify near-optimal solutions, the algorithms are approximated and non-deterministic, and they are not issue-specific. This section introduces the GA and SA.

GA generates a population of likely solutions to the stated problem and evolves it over several generations to discover improved and enhanced solutions. As the generation proceeds, fresh members are born into the population, at the same time others die out of the population. The superior the solution better is the fitness. The selection progression follows the principal 'survival of the fittest. In crossover the two solutions are mixed to create two fresh individuals. The main component of GA is: Chromosomal representation, Initial population, Fitness function (estimate the excellence of candidate chromosomes), Selection, Crossover and mutation,[15,16].

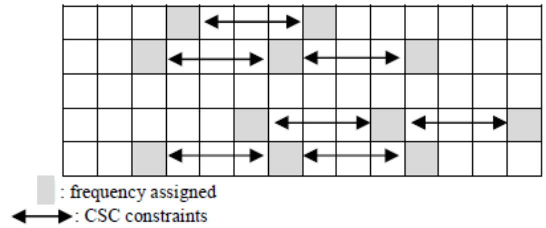
The SA algorithm was inspired by the annealing process used in metal work. It mirrors the process of heating up metal and gradually reducing the temperature to eliminate imperfections. The search area is determined by a probability distribution that correlates to the temperature. The SA considers all points that either minimize or maximize the objective, but with a certain level of probability. It avoids getting stuck in local minima by selecting points that increase the objective and can identify practical solutions globally. As the temperature decreases, the search area narrows down and converges towards a minima.

CHANNEL ALLOCATION WITH GENETIC ALGORITHM

The initial solution is generated to improve the search efficiency. A pair of channels assigned to the similar cell should take the distance definite in the C.

To achieve this following procedure is implemented:

1. For cell *i* with major demand, the channel for k^{th} call is f_{i*k} = (*k*-1) × α+1. Where α = $[\frac{LB}{di}]$ min. freq interval in max. demand cell *i*, where LB - lower bound of entire no. of frequencies and α > c_{ii}. c
2. For cell *i* with following major no. of calls,
   a. Randomly choose frequency between [1, floor $[\frac{LB}{di}]$], where floor (*a*) rounds *a* to the nearest integers less than or equal to *a*. Use this frequency to satisfy the first demand in cell ***i.***
   b. For next demand assign next frequency by the break of α with the earlier allotted frequency.
   c. Repeat step (c) until all demands from cell i have assigned frequencies.
   d. Repeat this procedure for all cells.



In this study, two-parent vectors are formed in the initial population: the base station vector based on demand, and the second is for existing channels.

$$S_D = S_T - S_F \quad (4)$$
$$C_D = C_A - C_F \quad (5)$$

Where S_T is the total no. of base stations (BS) based on demand. S_F: set of BS after channel allocation, S_D: a set of BS that require channel. C_A: set of all available channels; C_F: collection of previously allocated channels; C_D: set of existing channels. In each generation, the fittest chromosome, i.e., channels, is allotted, and $S_F$and C_F are renewed to give a new population.

Two-parents are selected from the population arbitrarily and crossover process is performed. Crossover fraction is set to 0.8 and one-point crossover is used here. The pair of individuals, i.e., children consequential from crossover operation subject to the mutation operator in the concluding step of forming fresh generation. Mutation probability is set to 0.2.

CHANNEL ALLOCATION WITH SIMULATED ANNEALING

There is a noteworthy correlation among the terminology of thermodynamic annealing procedure and the combinatorial optimization. Energy is connected to cost, Change of State is a nearby solution, Temperature is a control parameter, and Frozen state is a heuristic solution.

SA algorithm implemented for channel allocation

```
Construct initial solution s1
s_now = s1
Set initial temperature T = TI (Initial Temperature)
Repeat
For i = 1 to TL do
   produce randomly a neighbouring solution s′ ∈ N (s_now)
   calculate variation of cost ΔC = C(s′) – C (s_now)
     if ΔC ≤ 0 then
           s_now = s′ (admit new state)
           else
           Generate q = random (0,1)
           if q < threshold then
                 s_now = s′
           end if
     end if
end for
Set a new temperature T = f(T)
until the halting criterion
```

Where T_I is the Initial Temperature and T_L is the no. of iterations at a temperature / No. of neighbors created at that temperature to current solution. It is required to have more repetition at lower temperature as at lower temperature the probability of accepting bad solution is decreased. There is increase in *TL* as algorithm goes down with T. In implemented algorithm,

$$TL = floor\left(e^{(-current\ temperature)}\right) + 1 \qquad (6)$$

f(T) is the Cooling function i.e., the amount at which temperature is reduced. In implemented SA algorithm,

$$f(t) = Initial\ Temperature \times 0.95^{I} \qquad (7)$$

where I =iteration number. *s_now* is the Current solution and s' is the neighbouring solution obtained by a move.

SIMULATION RESULT

The heuristics with GA and SA are worked on benchmarks EX1, HEX1, HEX2, HEX3, HEX4, P1, P2 and P3 instances as mentioned in Table 3.1 with compatibility matrix C1 to C5 and Demand vector D1 to D8.

The simulation is performed on MATLAB. The simulation result with GA and SA is presented. The comparison of GA and SA results is compared and presented in Table 5.3b. The simulation result obtained with GA and SA is compared with reports work,[17,18] in Table 5.3a. From the results of simulations, it is observed that results of minimum cost function for benchmark HEX2 and HEX4 are better compared to reported work, [17,18].

BENCHMARK PROBLEM RESULTS WITH GA

Tables 5.1a and 5.1b show the comparison results with GA for benchmarks in terms of minimum value of cost function M_{cf}, average valueof cost function A_{cf}, and generation required.

The Channel assignment for benchmarks with specific demand matrix D and compatibility matrix C along with C(i,i) specific separation between frequencies is presented. The channel assignment plot indicates the allocation of channels to the cells. X-axis: no. of channels, Y- axis: no. of cells, nz (nz = non-zeros) channels for EX1 in Fig 5.1.1, HEX 1 in Fig 5.1.2, HEX 2 in Fig 5.1.3, HEX 3 in Fig 5.1.4, HEX 4 in Fig 5.1.5, P1 in Fig 5.1.6, P2 in Fig 5.1.7 and P3 in Fig 5.1.8. The plot of best and mean fitness value for benchmarks is also presented.

Table 5.1a Comparative results for different benchmarks (GA)

Sr.No.	Problem	M_{cf}	A_{cf}	Minimum generations	Average generations
1	EX1	0	0	1	1
2	HEX1	102	106.4	66	126.6
3.	HEX2	10	12.3	68	70.2
4.	HEX3	170	174.5	47	150
5	HEX4	4	6	95	157

Table 5.1b: Results of simulated problems

Sr No.	Problem	Value of cost function	Generation Required
1	P1	14	86
2	P2	2	414
3	P3	36	707

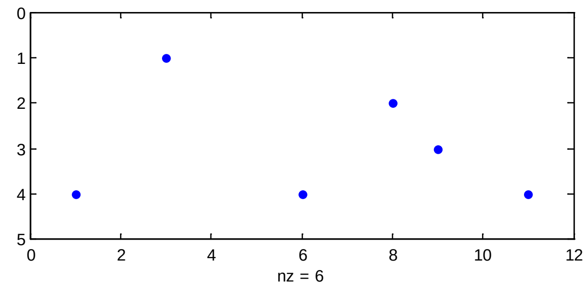


Figure 5.1.1. Channel assignment for EX1, D1, C1, C(i,i)=5

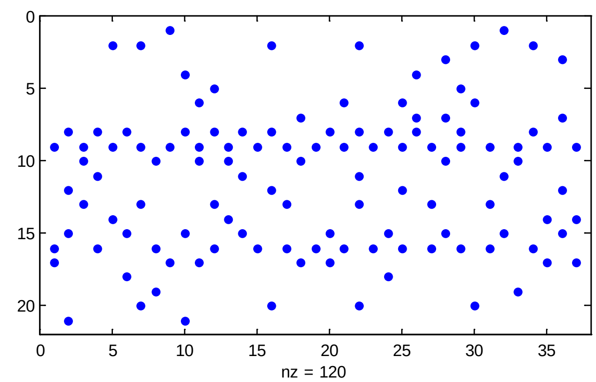


Figure 5.1.2. Channel assignment for Hex1, D2, C2

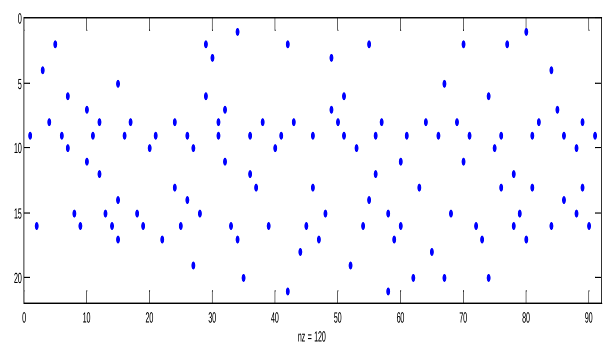


Figure 5.1.3a. Channel assignment for *Hex2, D3, C(i, i)=5*

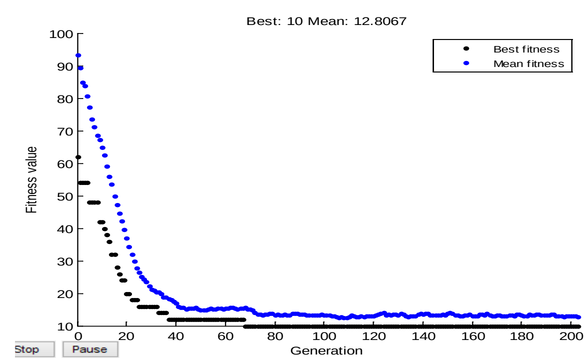


Figure 5.1.3b. Hex 2 Best and Mean value

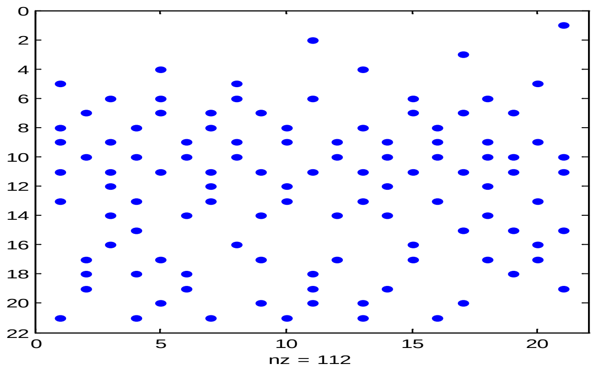


Figure 5.1.4. Channel Assignment for *Hex3, D4, C2, C(i, i)=2*

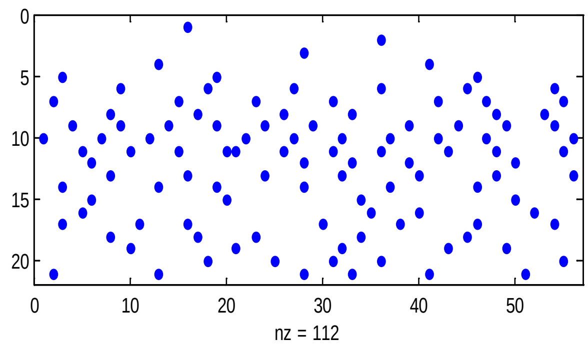


Figure 5.1.5a. Channel assignment for *Hex4, D5, C3, C(i, i)=5*

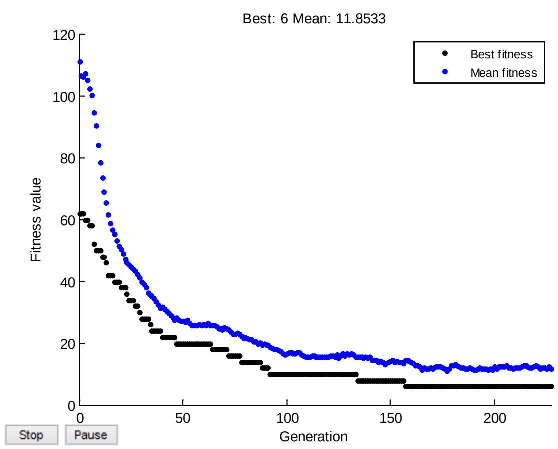


Figure 5.1.5b. Generations versus Fitness Value for *Hex 4*

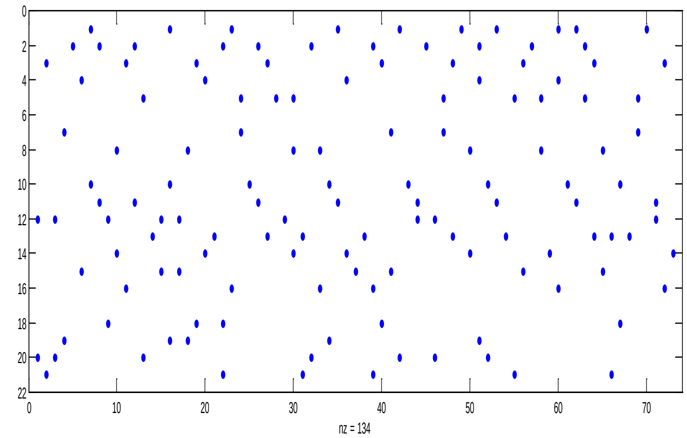


Figure 5.1.6a. Channel Assignment *P1, D6, C4,C(i, i)=2*

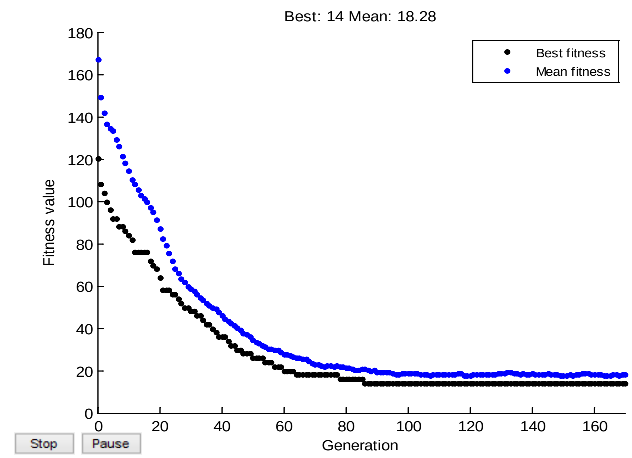


Figure 5.1.6b. Generations versus Fitness Value for *P1*

Graphs shows the best and mean fitness value achieved in each Generation.

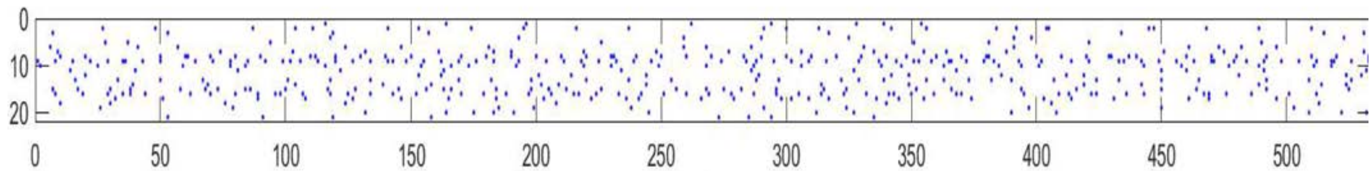


Figure 5.1.7a. Generations versus Fitness Value for *P2*

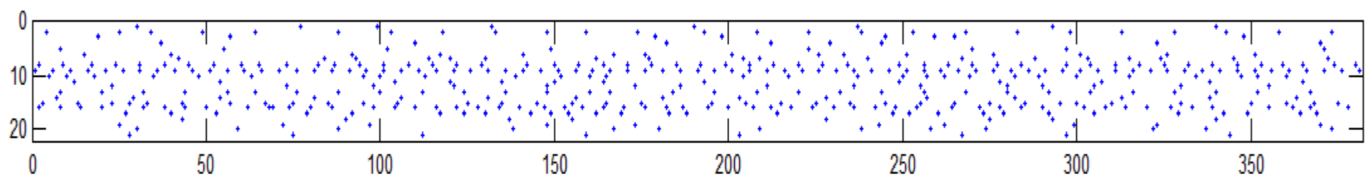


Figure 5.1.8a. Generations versus Fitness Value for *P3*

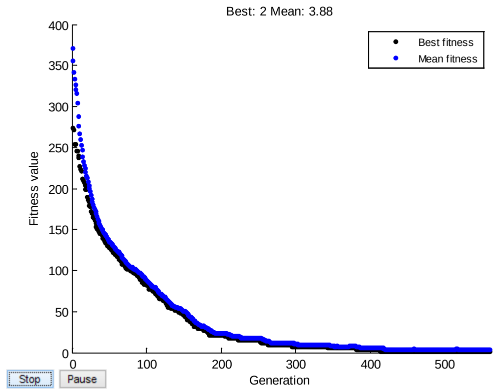


Figure 5.1.7b. Generations versus Fitness Value *for P2*

The plot depicts the best and mean fitness values obtained in each Generation.

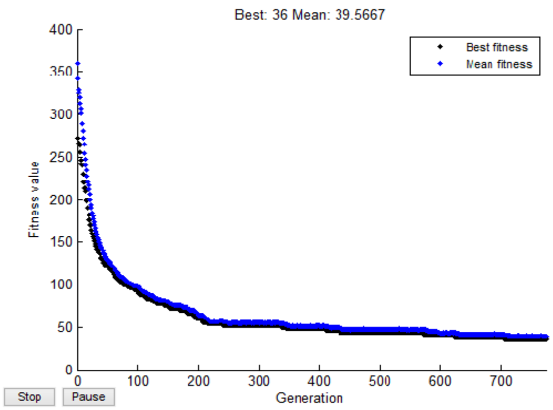


Figure 5.1.8b. Generations versus Fitness Value *for P3*

The graphs display the best and mean fitness values obtained in each Generation.

BENCHMARK PROBLEM RESULTS WITH SA

The comparative results for benchmarks in terms of value of cost function with SA, is presented in Table 5.2.

Table 5.2: Results for simulated problems for SA

Sr No.	*Problem*	*Value of cost function*
1	*HEX1*	*132*
2	*HEX2*	*26*
3	*HEX3*	*226*
4	*HEX4*	*34*
5	*P1*	*24*
6	*P2*	*180*
7	*P3*	*102*

The Channel assignment for benchmarks with specific demand matrix *D* and compatibility matrix *C* along with *C(i,i)* specific separation between frequencies is presented. The channel assignment plot indicates the allocation of channels to the cells. X-axis: no. of channels, Y- axis: no. of cells, *nz* (non-zeros) channels for EX1 in Fig 5.2.1, HEX 1 in Fig 5.2.2, HEX 2 in Fig 5.2.3, HEX 3 in Fig 5.2.4, HEX 4 in Fig 5.2.5, P1 in Fig 5.2.6, P2 in Fig 5.2.7 and P3 in Fig 5.2.8. The plot of *current* function value and *best* function value for benchmarks is also presented.

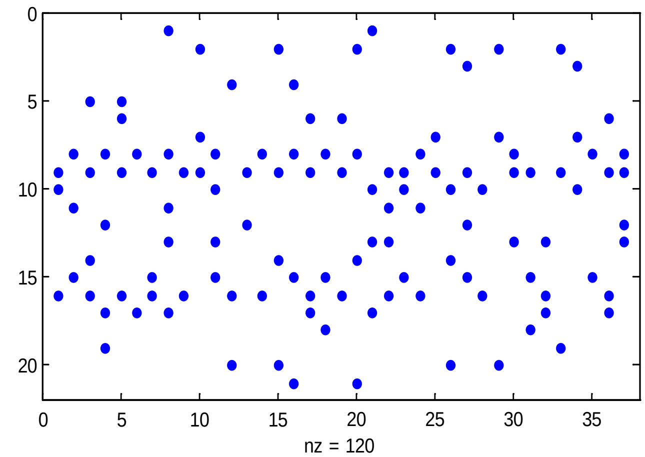


Figure 5.2.1a. Hex 1 Demand D2 Compatibility matrix C2

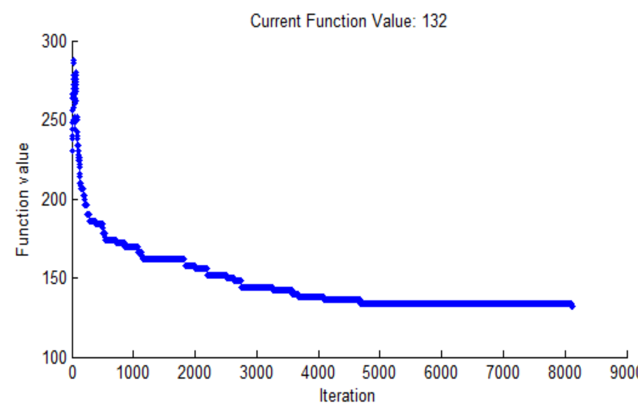


Figure 5.2.1b. Hex 1 Current Function value

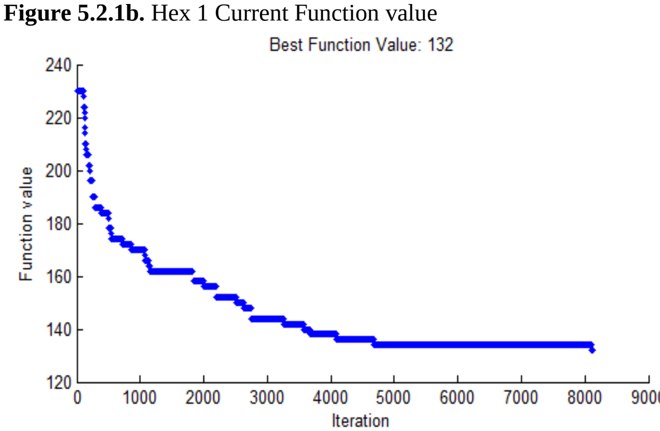


Figure 5.2.1c. Hex 1 Best Function value

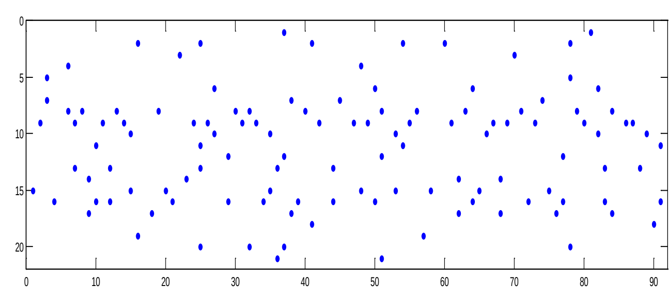


Figure 5.2.2a. Hex 2 Demand D3 Compatibility matrix C3, C(i,i)=5

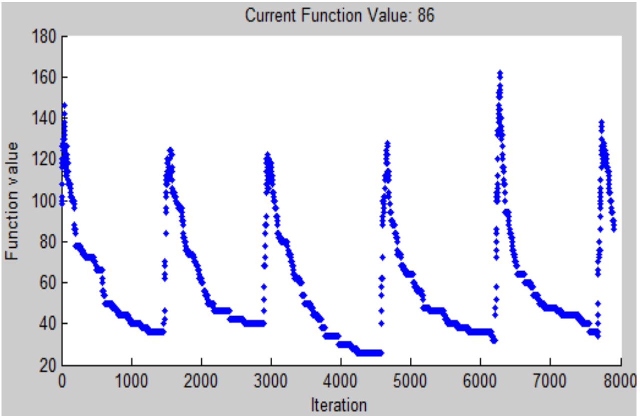


Figure 5.2.2b. Hex 2 Current Function value

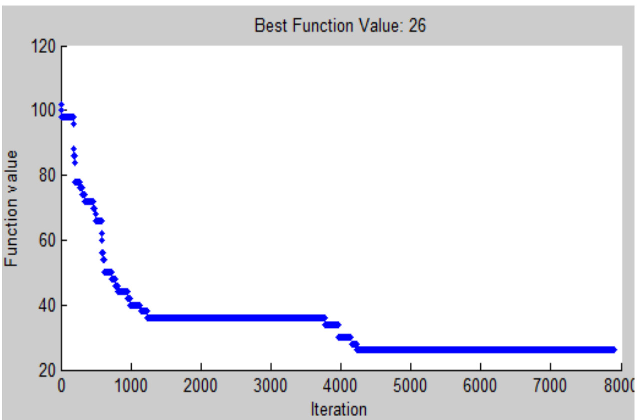


Figure 5.2.2c. Hex 2 Best Function value

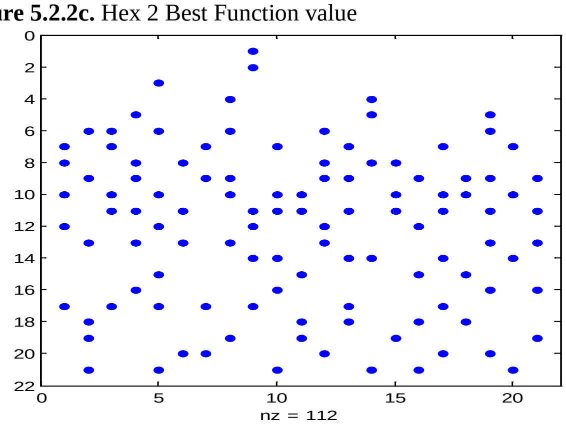


Figure 5.2.3a. Hex 3 Demand D4 Compatibility matrix C2, C(i,i)=2

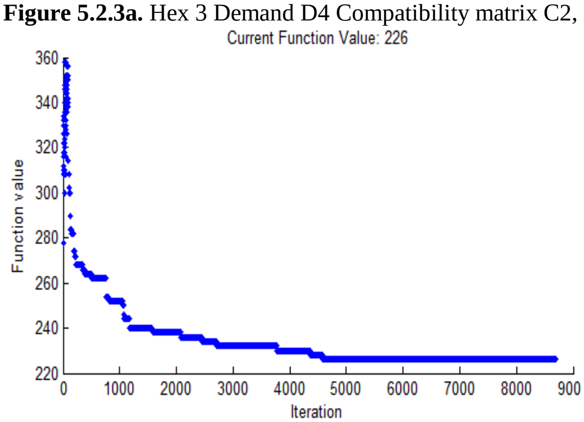


Figure 5.2.3b. Hex 3 Current Function value

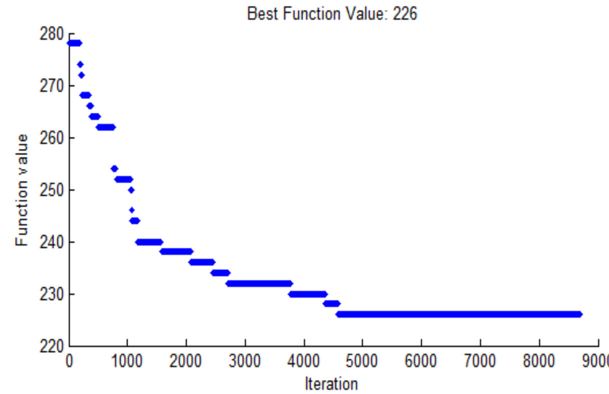


Figure 5.2.3c. Hex 3 Best Function value

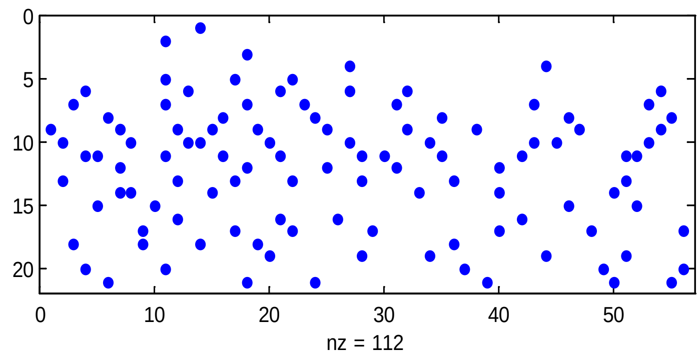


Figure 5.2.4a. Hex 4 Demand D5 Compatibility matrix C3, C(i,i)=5

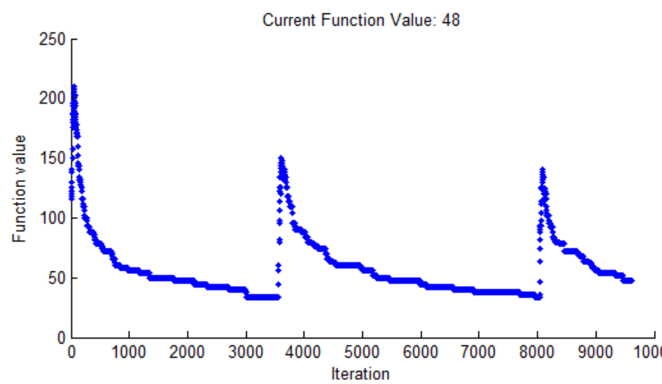


Figure 5.2.4b. Hex 4 Current Function value

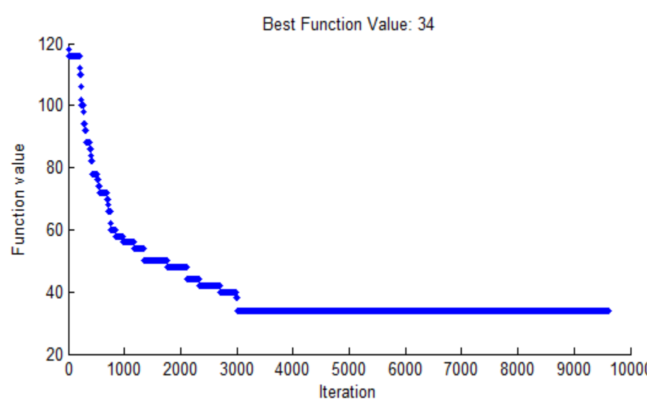


Figure 5.2.4c. Hex 4 Best Function value

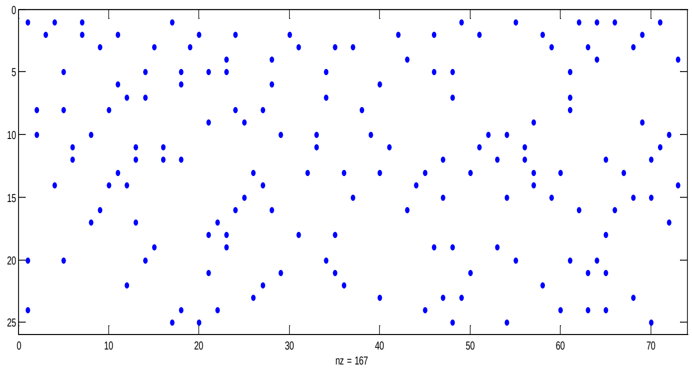


Figure 5.2.5a. P1 Demand D5 Compatibility matrix C4, C(i,i)=2

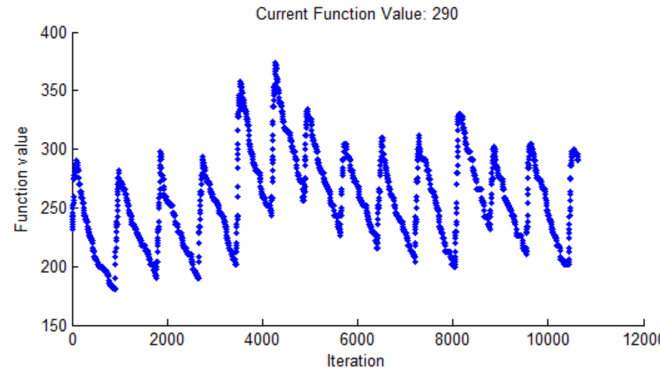


Figure 5.2.6b. P2 Current Function value

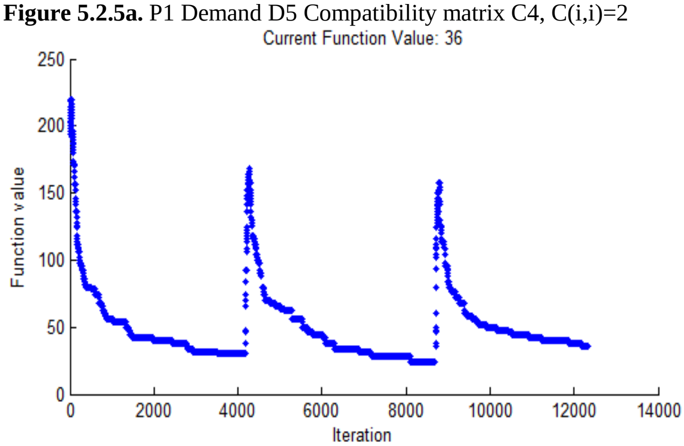


Figure 5.2.5b. P1 Current Function value

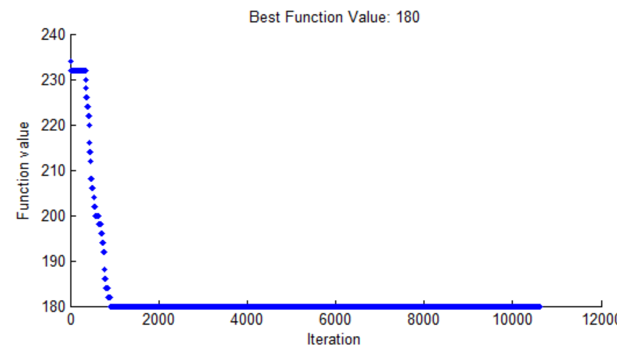


Figure 5.2.6c. P2 Best Function value

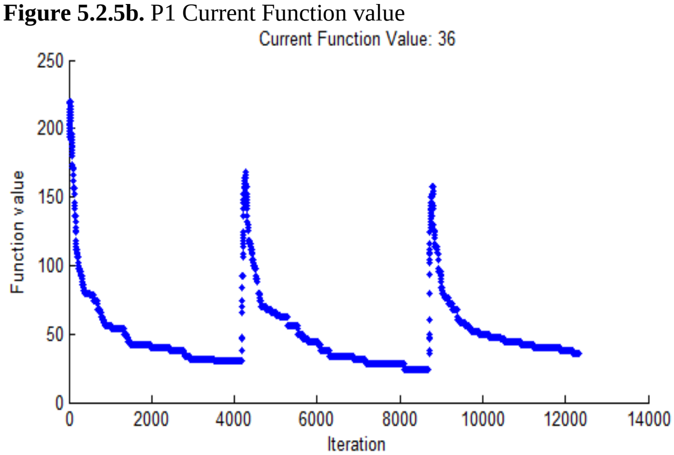


Figure 5.2.5c. P1 Best Function value

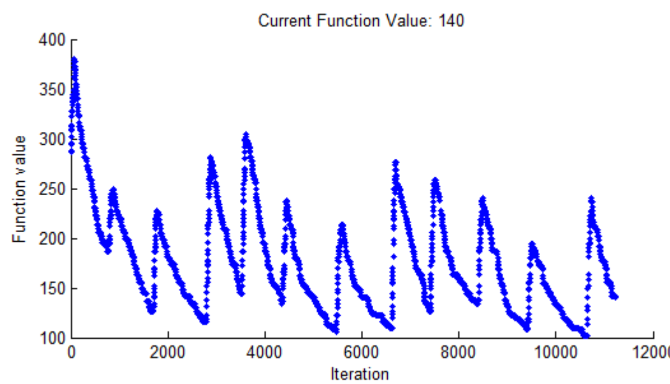


Figure 5.2.7b. P3 Current Function value

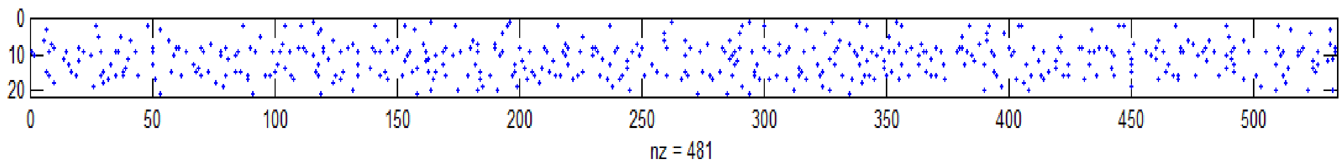


Figure 5.2.6a. P2 Demand D7 Compatibility matrix C5, C(i,i)=7

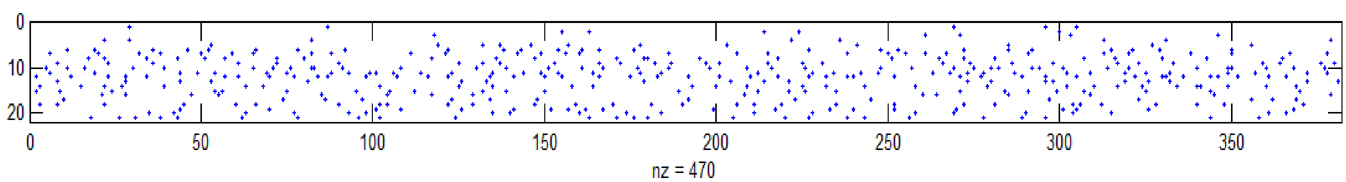


Figure 5.2.7a. P3 Demand D7 Compatibility matrix C3, C(i,i)=5

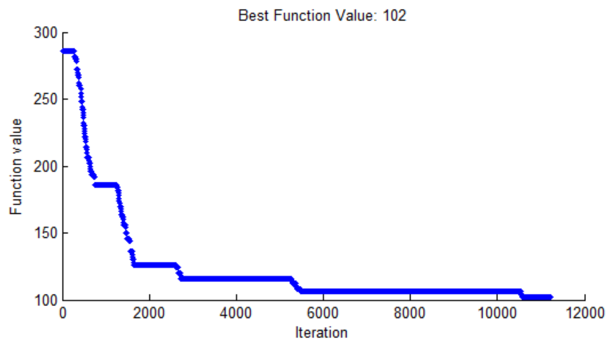


Figure 5.2.7c. P3 Best Function value

Comparison of Benchmark problem results of GA and SA with reported reference

The average cost function A_{cf} and minimum cost function values M_{cf} of GA and SA are compared to reported work, [17,18] .

Table 5.3a Comparison with Reported work

	GA,[17]		SA,[18]		GA		SA
Benchmark	A_{cf}	M_{cf}	A_{cf}	M_{cf}	A_{cf}	M_{cf}	A_{cf}
EX1	-	-	-	2	0	0	-
HEX1	33.9	33	-	54	106.4	102	132
HEX2	14.1	13.5	-	27	12.3	10	26
HEX3	47.5	46.5	-	89	174.5	170	226
HEX4	15.2	14.5	-	31	6	4	34

The average value of cost function and minimum value of cost function of GA and SA is compared with reported work,[17,18].

The results produced for problems HEX2 and HEX4 utilising the GA and SA algorithms are better in terms of minimal cost function value than reported work.[17,18]

Table 5.3b: Comparison of results obtained with GA and SA

Benchmark	A_{cf} *with SA*	A_{cf} *with GA*
HEX1	*132*	*102*
HEX2	*26*	*10*
HEX3	*226*	*170*
HEX4	*34*	*4*
P1	*24*	*14*
P2	*180*	*2*
P3	*102*	*36*

A_{cf} with SA and GA is compared for benchmarks (Table 5.3b), and it is discovered that the results achieved by our GA method for the benchmarks described are better than SA.

Conclusion

The Heuristic optimization techniques SA and GA are used to solve the CAP to minimize the interference level (MICAP) while fulfilling channel demand. The cost or fitness function is created with CCC and CSC in mind. The CAM, value of cost function, and number of iterations or generations required are all measured. The simulated results are based on eight benchmarks, each with a different number of cells, frequency, and traffic demand. Based on the study, the cost function value is substantially lower than in earlier work with GA and SA. To get even better results, it is critical to experiment with other mutation and crossover operators as well as other heuristic strategies. Additionally, while utilizing SA, it is critical to evaluate alternative cooling functions.

Conflict of Interest Statement

The author declared no conflict of interest for the publication of this work.

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