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AN EVOLUTIONARY ALGORITHM FOR CHANNEL ASSIGNMENT PROBLEM IN WIRELESS MOBILE NETWORKS

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Abstract
The channel assignment problem in wireless mobile network is the assignment of appropriate frequency spectrum to incoming calls while maintaining a satisfactory level of electromagnetic compatibility (EMC) constraints. An effective channel assignment strategy is important due to the limited capacity of frequency spectrum in wireless mobile network. Most of the existing channel assignment strategies are based on deterministic methods. In this paper, an adaptive genetic algorithm (GA) based channel assignment strategy is introduced for resource management and to reduce the effect of EMC interferences. The most significant advantage of the proposed optimization method is its capability to handle both the reassignment of channels for existing calls as well as the allocation of channel to a new incoming call in an adaptive process to maximize the utility of the limited resources. It is capable to adapt the population size to the number of eligible channels for a particular cell upon new call arrivals to achieve reasonable convergence speed. The MATLAB simulation on a 49-cells network model for both uniform and nonuniform call traffic distributions showed that the proposed channel optimization method can always achieve a lower average new incoming call blocking probability compared to the deterministic based channel assignment strategy.

Keywords:
Evolutionary Optimization, Genetic Algorithm, Hybrid Channel Assignment, Wireless Mobile Network

1. INTRODUCTION

The widespread of cellular concept among the mobile wireless network is due to the extraordinary development of cellular radio broadcasting. According to the cellular principles in the wireless mobile network, the covered geographical areas are divided into a set of service areas called cells [1]. The channel assignment mechanism comprises of efficient frequency spectrum channel allocation among the cells in cellular network while satisfying the EMC constraints and call traffic demands. In addition, this mechanism plays a major role in minimizing the call blocking or call dropping probabilities, at the same time maximizing the quality of the services.

In general, the channel assignment techniques can be classified into two main classes: fixed channel assignment (FCA) scheme and dynamic channel assignment (DCA) scheme. The set of channels in FCA are equally assigned permanently to each cell in advance. On the other hand, in DCA, the set of available channels are assigned dynamically to each cell upon call request, instead of utilizing permanent allocation of channels as in FCA scheme. The FCA scheme is simpler but does not adapt to the dynamic traffic demands. DCA approach overcomes this deficiency since it surpass FCA in terms of the capability in dealing with changing traffic conditions, however it has the drawback of requiring more complex control process and consuming more computational time under heavy traffic load [1].

Most of the channel allocation methods are based on the deterministic methods. A set of known input parameters and rules is required for the deterministic methods to predict the channel allocation solutions. However, the deterministic methods are inefficient in solving complicated channel assignment problem due to the complexity and computational time consuming [2].

The channel capacity in cellular network can be maximized by frequency reuse and cell splitting techniques. According to the frequency reuse concept, the same frequency channel is used simultaneously with other cells subject to the base transceiver station (BTS) distance. However this technique might lead to EMC interferences such as co-channel constraint (CCC), adjacent channel constraint (ACC), and co-site channel constraint (CSC). Hence it is very crucial to determine a frequency reuse pattern which can minimize the interferences. There are numbers of approaches have been suggested to overcome these problems based on fixed reuse distance concept such as neural networks (NNs), simulated annealing (SA), Tabu search (TS) and genetic algorithm (GA).

Channel optimization approaches based on NNs in [3] and SA in [4] have been investigated coincide with the evolutionary approaches. SA is a meta-heuristic method derived from statistical mechanics which perform using the neighborhood principle and measures potential based on cost function. SA achieves the global optimum asymptotically and thus capable to solve the local optimum trap which would happen in NNs, however it has the drawback of slow convergence speed.

TS is also a meta-heuristic method based on neighborhood principle. It has been identified to achieve better performance than SA in terms of its ability of finding the minimum number of frequencies for channel allocation by consuming shorter computational time [5].

The evolutionary approaches such as GA outperform other approaches since they show implicit parallelism corresponding to the capability to explore over search spaces effectively. They can be used to solve most of the optimization tasks, include optimal-local, multi-constrained and NP-complete problems [6].

GA is one form of evolutionary algorithm (EA) which originates from the principal of natural selection and survival of the fittest, and constitutes an alternative method for finding solutions to highly-nonlinear problems, by exploring multimodal solution space [7]. GA is defined as highly parallel mathematics algorithm which a set of individuals called population, each with an associated fitness value, can be transformed into a new generation using operations based on the evolution theories [8].

The channel assignment problem has been solved by several GA-based optimization approaches. An asexual crossover and a special mutation are suggested to solve the problem. However this technique has the difficulty to converge as the structure of current solution is easily destroyed by such crossover [9]. On the other hand, the channel assignment solution is defined as a string of channel numbers [10]. This representation ensures that each cell has a specified number of channels rather than using binary string.

In this paper, a DCA optimization algorithm based on GA is presented to solve the channel assignment problem. Channel optimization based on GA is suitable because it is robust in optimizing a complex problem and its inherent features enable the algorithm to search for a global minimum without being trapped into a local minimum. In this algorithm, reasonable convergence speed can be achieved by adapting the population size according to the number of eligible channels for a particular cell upon new call request, instead of maintaining a fixed population size throughout the simulation.

2. OVERVIEW OF CHANNEL ASSIGNMENT PROBLEM

2.1 CHANNEL ASSIGNMENT CONSTRAINT

Radio transmission with frequency reuse concept in a frequency spectrum channel would cause interferences with other channels, which may degrade the quality of the service. Three types of electromagnetic compatibility (EMC) interference are:

1) CCC: A form of interference arises due to the allocation of the same channel to certain pair of the cells within the BTS distance or reuse distance simultaneously.
2) ACC: A form of interference happens due to the allocation of the adjacent or neighborhood channels to certain pairs of cells simultaneously.
3) CSC: A form of interference occurs in between channels in the same cell which are not separated by some minimum spectral distance.

These EMC constraints are known as hard constraints. The channel assignment problem is shown to be NP-hard since it consists of the assignment of the required number of channels to each cell in such a way that the interferences are avoided and the frequency spectrum is used efficiently.

Besides the hard constraints, soft constraints include the resonance condition, packing condition, and the limitation of reassignment are proposed to help in further lowering the call blocking probabilities. The resonance condition maximizes the use of channels within the same reuse scheme by allowing the same channels to be assigned to cells that belong to the same reuse scheme. This would reduce the call dropping or call blocking probabilities in a great extent.

On the other hand, the packing condition is an approach to permit the repeated selection of the channels in use in other cells as long as the CCC interference is maintained. This condition uses minimum number of channels each time a new call arrives.

In DCA, the reassignment process upon a new call arrival is complex in both time and computation effort although it can reduce the call blocking probabilities. Therefore the limitation of reassignment limits this process to the cells which involved in new call arrival. It will attempt to assign the channels which are assigned before. This could reduce the situation of excessive reassignment in a cell.

The reuse of channels is a main cause to CCC interference. Therefore the channels to be assigned in different cells need to be separated by a reuse distance sufficient enough to reduce the CCC interference to a tolerable level.

2.2 FREQUENCY REUSE SCHEME

The reuse distance indicates the minimum distance required between the centers of two cells using the same channel to maintain a desirable level of signal quality. The distance between the centers of two adjacent cells is considered as a unit distance. The cells with center-to-center distance equals to or multiples of the value of reuse distance belong to the same reuse scheme. Cells within the same reuse scheme may use the same channels.

The total number of channel sets that can be formed from the whole frequency spectrum can be determined by the number of cells per reuse scheme. The longer the reuse distance, the smaller is the CCC interference level. However, this reduces the reuse efficiency. Thus both the CCC interference level and the reuse efficiency have to be taken into consideration in the design of reuse pattern.

The co-channel cells are located with a reuse distance of 3 units which divided the network topology model of 49-cells into seven different reuse schemes. Table.1 shows the co-channel cell matrix for reuse scheme. The co-channel cell matrix consists of a 7×7 matrix with y coordinate represents the row of the cells and x coordinate represents the columns of the cells. Manhattan distance is used to determine whether each cell in the same reuse scheme can be associated with horizontal path length 2 and vertical path length 1. This indicates that x coordinate has to moves two units distance and y coordinate needs to moves one unit distance to achieve the required three unit of reuse distance. It can be seen from Table.1 that the two cells belong to the same reuse scheme contains the same number at the i^{th} row and j^{th} column of the co-channel matrix.

2.3 CELLULAR TRAFFIC MODEL ASSUMPTION

Simulation of the proposed cellular traffic model is implemented based on blocked-calls-cleared principle. The call is blocked and dropped without queuing of the blocked calls when the entire set of channels in the cellular network is occupied and the cell which involved new call request and its neighborhood is within the reuse distance. There are 70 channels available in the model to allocate the incoming calls.

There are 49 hexagonal cells in the cellular topological model forming a parallelogram structure with equal number of cells along both axes. The traffic simulation with uniform or nonuniform distribution can be selected. Uniform cellular traffic distribution provides each cell with the same traffic load or demand and nonuniform cellular traffic distribution gives different traffic load in each cell.

Table.1. Co-channel Cell Matrix

***y*-coordinate**	***x*-coordinate**						
	1	**2**	**3**	**4**	**5**	**6**	**7**
1	1	5	6	3	2	4	7
2	4	7	1	5	6	3	2
3	3	2	4	7	1	5	6
4	5	6	3	2	4	7	1
5	7	1	5	6	3	4	4
6	2	4	7	1	5	6	3
7	6	3	2	4	7	1	5

Table.2. Nonuniform Traffic Distribution (Simulation Calls/Minute)

***y*-coordinate**	***x*-coordinate**						
	1	**2**	**3**	**4**	**5**	**6**	**7**
1	60	20	15	30	15	60	30
2	60	30	15	30	20	20	60
3	15	30	20	60	60	30	20
4	60	15	20	30	20	30	60
5	20	60	15	60	20	30	20
6	30	20	20	60	30	30	60
7	60	60	15	60	15	20	30

Table.2 shows the implemented nonuniform traffic patterns in the model where the pattern is used as the initial call rate for simulation. The average call holding time is 180 seconds and average call arrival rate per minute for the corresponding cell is represented by each of the value in Table.2.

2.4 CHANNEL ASSIGNMENT PROBLEM REPRESENTATION

The channel assignment problem comprises of the allocation of an available channel to a new incoming call with possible reassignment of channel to the ongoing calls in the cell. Assume that a new call arrives in cell m with $t-1$ existing calls before the arrival of the new call, then a potential solution vector, V_m represents the assignment of channels to ongoing calls and the new call at cell m. This solution vector of length t is expressed as a chromosome in the GA representation, where each gene is a channel number being assigned to a call in cell m. This representation has the advantage of shorter length of the solution vector and thus consumes shorter computational time to manipulate the vector.

3. GENETIC ALGORITHM REPRESENTATION

Generally, GA provides an efficient approach in searching for an optimum solution in the optimization problem. It is different from deterministic methods since GA employs randomization. The generic GA framework is illustrated in Fig.1. It is modified to fit for use with the DCA scheme.

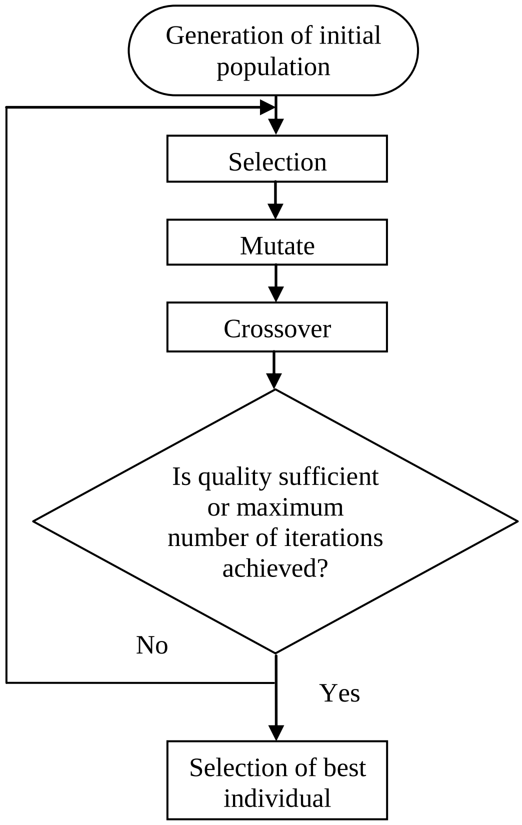

Fig.1. Genetic Algorithm Framework

3.1 INITIAL POPULATION

To generate the initial population for possible channel allocation solutions, V_k is used as the initial stage of the GA algorithm. A set of eligible channels $E(k)$ is determined in order to assign a possible channel upon a new call requests in cell k. In this case $E(k) = S - (O(k) \cup P(k))$, where S is the entire set of available channels, $O(k)$ is the set of channels allocated to the existing calls in cell k, and $P(k)$ is the set of channels used in the neighboring cells which less than the reuse distance with cell k. The channels allocation matrix A will include all the information related to the channel usage. The initial population consists of the solution vectors with length equals to the magnitude of vector $E(k)$. Each solution from the vector contains a unique integer. The remaining $(t-1)$ integers in all the solution vectors are determined as the channels allocated to the ongoing calls in cell k.

3.2 FITNESS FUNCTION

To decide the fitness value of each individual among the population, a quality measure is necessary after the generation of the population which is called fitness function.

Other than the hard constraint, the soft constraints such as packing condition, the resonance condition and the limitation of reassignment will reduce the call dropping probabilities. These soft constraints are modeled as the fitness function as shown in Eq.(1).

In the first term of Eq.(1), fitness value increases if the j^{th} element of vector V_k is used in cell i where cells i and k does not belong to the same reuse scheme and this term represents the resonance condition. The fitness value of the second term decreases if the j^{th} element of vector V_k is used in cell i, and cells i and k are free from CCC interference, which the term represents the packing condition. The fitness value decreases with the distance between cells i and k.

The fitness value of the last term decreases when the new allocation for the ongoing calls in cell k is the same as the previous allocation, which the term represents the limiting reassignment condition. Smallest value of F indicates that it is the fittest individual to find the solution for optimal channel allocation.

$$F = \sum_{j=1}^{t_k} \sum_{i=1 i \neq k}^{C} A_{i,V_{k,j}} . reuse(i,k) - \sum_{j=1}^{t_k} \sum_{i=1 i \neq k}^{C} A_{i,V_{k,j}} . \frac{1}{dis(i,k)} - \sum_{j=1}^{t_k} A_{k,V_{k,j}} \quad (1)$$

where,

k	–	defines the cell coordinates when a call arrives
t_k	–	defines the total number of channels allocated to cell k
C	–	defines the total number of cells in the network model
V_k	–	defines the solution vector for cell k with dimension t_k
$V_{k,j}$	–	defines the j^{th} element of vector V_k
$A_{i,V_{k,j}}$	–	defines the element at i^{th} row and $V_{k,j}{}^{th}$ column of the channels allocation matrix A
$dis(i, k)$	–	defines the distance between cells i and k
$reuse(i, k)$	–	defines a function that returns a value of 0 if the cells i and k belong to the same reuse scheme, otherwise return as 1.

3.3 MUTATION

To indicate the probability of mutation, a mutation rate is selected to mutate chromosome in a gene. High mutation rate will result in random global search for optimal solution whereas low mutation rate will prevent any gene in the chromosome to remain fixed on a single value of population. Therefore to maintain balance in such extreme situations, a moderated value is needed to be selected.

The parent chromosome undergoes iteration and will determine whether the mutation of the gene according to the mutation rate. If the mutation rate is hit, the gene which is represented by the channel number will swap its value with the corresponding vector of eligible channels. This process does not affect the length of the parent chromosome and does not duplicate channel number which ensures the production of feasible child chromosome.

3.4 CROSSOVER

To produce a better child chromosome, a crossover rate is selected to indicate the probability for parents' vectors to crossover. The child chromosome will take the best characteristics from each of the parents and the proposed crossover strategy is one-point crossover which requires less computational cost. Then the channel numbers which are beyond the crossover point that is selected for both parents' vectors are swapped and give birth to the child chromosome.

4. SIMULATION RESULTS AND DISCUSSIONS

In the simulation, the performance of the GA based algorithm for the channel assignment problem is evaluated in terms of the new incoming call blocking probability. The call blocking probability is calculated by the ratio of the total number of new call blocked and the total number of call arrived in the cellular network system. An instance of a valid assignment of channels which fulfills the channel assignment constraints for the cellular network of 49-cell is illustrated in Fig.2. This simulation result is optimized by GA and performs under nonuniform call traffic pattern as shown in Table.2.

The performance of the proposed algorithm is compared with FCA scheme and DCA scheme of deterministic method which always produces the same channel allocation solutions at each simulation. The DCA scheme with deterministic method without the optimization by the GA approach is based on channel-ordering property, where the first channel in the set of eligible channels is given the highest priority to be assigned to new call request. The call blocking probability performance under nonuniform call traffic distribution as the initial traffic rates in Table.2 is demonstrated in Fig.3. On the other hand, the call blocking probability performance under uniform traffic distribution with average 15 calls per minute as the initial traffic rate is demonstrated in Fig.4. The percentage increase of traffic load implies that the traffic rates for each of the cell are increased by a percentage with respect to the initial traffic rates. From these results, DCA scheme based on GA produces the lowest call blocking probability compared to the DCA scheme of deterministic method and the FCA scheme, under both uniform and nonuniform call traffic distribution. The decrease in the call blocking probability supports the reliability of the proposed channel allocation scheme.

Specifically, there are several parameters which are crucial in determining the convergence behavior of the GA, such as population size, mutation rate and crossover rate. In this proposed algorithm, the population size is not fixed and is adapted according to the number of eligible channels for a particular cell.

The effect of the crossover rate on the convergence speed is demonstrated in Fig.5, with the mutation rate fixed at 0.2. The crossover rate of 0.6-0.8 is suggested in GA to maintain a randomized gene exchange between individuals yet maintain a reasonable continuity from the previous populations to the current populations, with comparatively fast convergence speed.

On the other hand, the crossover rate is fixed at 0.8 and the effect of the mutation rate on the convergence speed is investigated in Fig.6. The mutation rate of 0.2-0.4 is sufficient to avoid local minima when the population of chromosomes evolves from generation to generation, yet maintain a comparatively fast convergence speed compared to the simulation results of higher mutation probability.

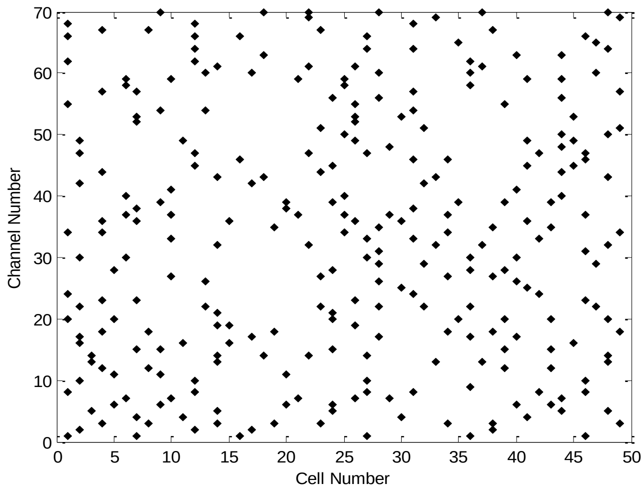

Fig.2. A Channel Assignment Results for the Network under Nonuniform Traffic Distribution at 20 Iterations

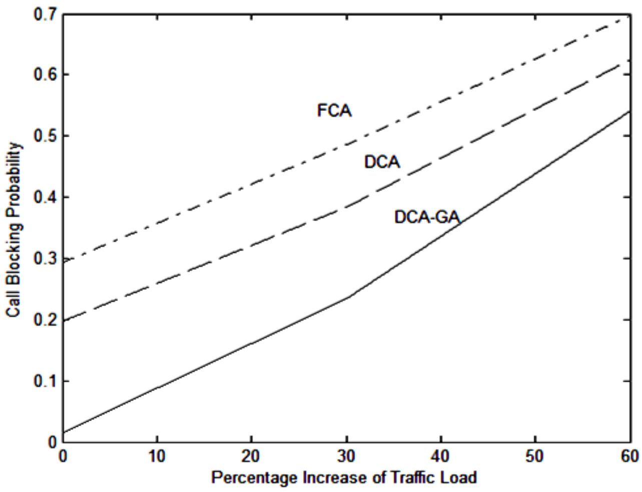

Fig.3. Call Blocking Probability Performance of DCA-GA for the Cellular Network with Nonuniform Traffic Distribution and Comparison with the Other Channel Allocation Schemes

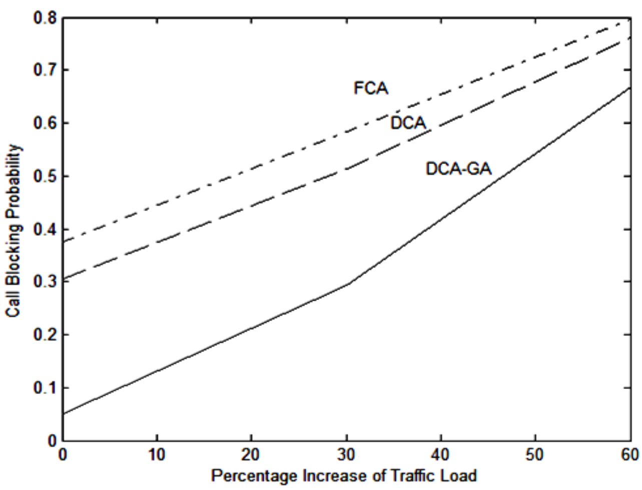

Fig.4. Call Blocking Probability Performance of DCA-GA for the Cellular Network with Nonuniform Traffic Distribution and Comparison with the Other Channel Allocation Schemes

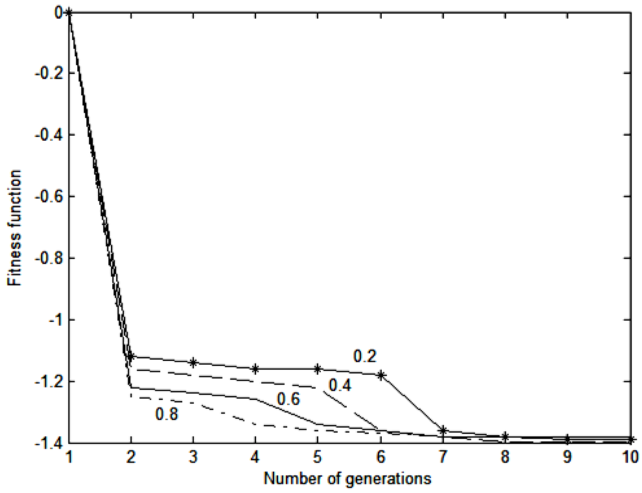

Fig.5. The Effect of Crossover Rate on GA Convergence Speed

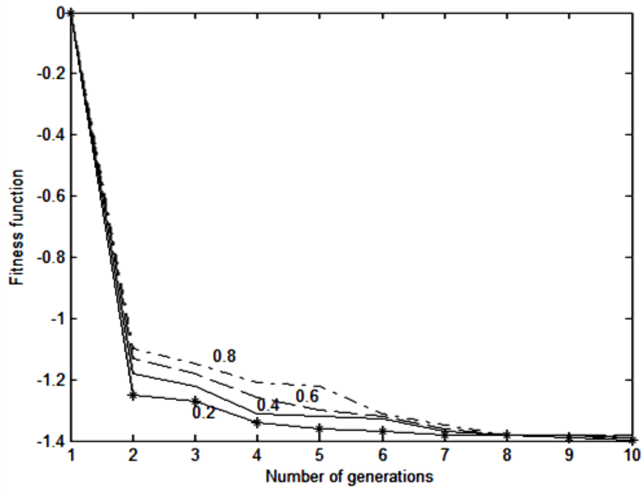

Fig.6. The Effect of Mutation Rate on GA Convergence Speed

It can be observed that the proposed algorithm is not over sensitive to parameters tuning for moderately selected values for crossover rate and mutation rate. The number of generations can be maintained at a desirable level with these moderately selected values. This shows a significant advantage compared to some existing parameter-sensitive algorithm, such as simulated annealing.

5. CONCLUSION

An optimization algorithm based on GA is proposed to solve the channel assignment problem in the cellular mobile network to achieve lower call dropping or call blocking probability. It is capable to mimic the evolutionary process in nature in order to optimize the channel assignment problem. Its characteristics to evolve through generations and to select the fittest optimum chromosomes enable it to be self-optimized from generation to generation.

The performance of the proposed algorithm has been investigated in terms of the call blocking probability which represents the quality of solutions. Besides that, the effect of the crossover rate and mutation rate parameters to the GA convergence speed to find the solution is investigated. As a conclusion, the proposed GA-based algorithm is capable to perform the channel optimization smoothly with minimum level of calls blocked.

Currently, the simulation is implemented based on sequential fashion, which is not significant in reducing the computational time. In the future research work, it is believed that by implementing the algorithm in parallel fashion, the optimization process will consume shorter computational time. It aims to realize the real time simulation purposes.

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