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A Cognitive Channel Allocation Model in Cellular Network using Genetic Algorithm

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Abstract In cellular network, channels are scarce radio resources. These resources are to be utilized judiciously. Though efforts have been made in the past for maximum channel utilization, studies show that effective channel utilization is often not done because of various constraints. The cognitive radio concept suggests that opportunistic channel utilization is possible if the mobile services are classified into two classes. The usage of the channels are based on the cognition that the radio derives. This work proposes a new model that applies a meta-heuristic Genetic Algorithm and the concept of cognitive radio for better channel utilization. The concept of single channel and multi-channel lending is also introduced towards this. Priority is given to the handoff services in comparison to the new services. The performance study, of the model, suggest the effective channel utilization in terms of blocked and dropped services.

Keywords Cognitive radio · Cognitive channel allocation · Genetic algorithm · Single channel · Multi-channel · Co-channel interference

1 Introduction

A mobile communication network is divided into several cells with their respective base stations to facilitate the communication. Such communication network is referred as Cellular network. The frequency bandwidth is the main resources available with this

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network which is to be allocated properly for its better utilization as the users are more and bandwidth is scarce. Thus, resource allocation for efficient utilization in a cellular system is a challenging and non-trivial task. Though several techniques have been designed for the efficient utilization of the cellular resources, still new perspectives are emerging to further enhance the cellular resource utilization as is felt that the utilization is not up-to the mark.

A Federal Communication Commission (FCC) report highlights that more than 70% of the allocated spectrum in USA is not utilized [1]. As a result, Cognitive Radio (CR) came into picture that enables the opportunistic sharing of the licensed frequency bands [2]. Based on the spectrum licensing, two types of users are considered; primary and secondary. Primary Users (PU) use the licensed spectrum and Secondary Users (SU) are the users of un-licensed spectrum. Being the licensed users, PUs have higher priority to use the frequency bands but as noticed these users often do not utilize the allotted spectrum fully. CR senses this and enables the SUs to utilize the spectrum allotted to the PUs in an opportunistic manner. Though, on PUs arrival SUs have to delink the allocated frequency band if no free channels are available to serve the PU. Cognitive radio, imbibed with the ability to sense the channel usage, uses the spectrum for opportunistically. CR has the ability to learn and to adapt to the outside environment based on their interaction with the environment [3]. The CR technology is proposed as an extension of Software Defined Radio (SDR) [4, 5]. Cognitive radio [6] facilitates the spectrum users with the most suitable radio bands through some functionality such as spectrum sensing, spectrum management, spectrum mobility, spectrum sharing etc.

Cellular resources are basically the frequency channels. Normally two techniques are used for distribution of channels in the cellular system; Centralized technique and Distributed technique. In centralized technique, all the channels are allocated to MSC (Mobile switching center). It provides the channels to base-station dynamically as per their demand. In distributed technique, channels are allocated to each cell in the beginning itself and they satisfy the channel requirements of the mobile hosts.

As mentioned, the resource allocation in cellular network is a computationally complex problem [7] various method utilizing machine intelligence techniques have been proposed for this. Genetic algorithm is one such technique which helps to solve such problem [8].

This work allows the sharing of channels in a cellular system which are detected unoccupied by the primary users among the secondary users. To utilize the CR, the model considers two types of users; primary users and secondary users as per their channel utilization. Also, for a new initiated call a new service and for ongoing communication a handoff service are considered. A GA based model is being proposed in this work that gives priority to the handoff call. Initial channel distribution among the cells is done in a manner that avoids the co channel-interference. The proposed model is simulated for its performance study on both; the blocking of new services and the dropping of the ongoing services. Experimental result indicates that the model performs effectively. Also, the incorporation of the concept of CR helps to utilize the channel in a better manner.

The outline of the paper is as follows. After the introduction in Sect. 1, some related work on channel allocation has been discussed in Sect. 2. The channel allocation problem and the importance of cognitive radio for utilization of free channels are presented in Sect. 3. The proposed model for the channel allocation problem along with single channel lending and multi-channel lending is deliberated in Sect. 4. Performance evaluation of the proposed model with single channel borrowing as well as multi-channel borrowing on varying number of channels and varying number of requests are studied in Sect. 5. Section 6 concludes the paper.

2 Related Work

As the demand of radio spectrum is increasing, there is a need to utilize the radio spectrum effectively. Few related models are discussed, in this section, proposed for channel utilization a cellular network with the objective to minimize the blocked and dropped services.

A GA-based effective fault-tolerant model for channel allocation is developed by Lutfi et al. [8]. In the model, new calls and handoff calls are facilitated to get served effectively. In case, when the number of channels is less than the number of request in the cell, requests are served by borrowing the channels from the neighbor cells. Few channels, in each cell, are reserved proportionally for the handoff call. By doing this, handoff failure is minimized [9].

Improved Genetic Algorithm for Channel Allocation with Channel Borrowing in Mobile Computing is devised by S. Patra et al. In this model, they have proposed improved GA by including the pluck operation to solve the cellular resource allocation problem. Pluck operation helps in the optimal allocation of resources resulting in the minimization of the call blocking and call dropping in the cellular system [10]. The above two models [8, 10] have not categorized the services into primary and secondary services and thus do not make opportunistic utilization of the resources. With the introduction of secondary services, scarce resources such as channels can be utilized more effectively.

For spectrum utilization, cognitive radio plays an important role. The model, channel allocation and reallocation for cognitive radio networks given by Jiang et al. [1], helps to enhance the utilization of radio spectrum. Throughput of secondary users are also significantly improved. This model applied the multi-dimensional Markov analytical chain to analyze the performance. Usually multidimensional Markov chain works well when the number of parameters are less.

A heuristic channel allocation model given by Vidyarthi et al. [11], uses the concept of cognitive radio to enhance the channel utilization. In this model, services are categorized into two categories primary services and secondary services. Secondary services are used by the secondary users (cognitive users). The study shows that secondary services are being served efficiently. But in this model, single channel lending is used which may limit better resource utilization.

Few better techniques for effective utilization of radio spectrum is proposed by Chen et al. [9]. It derives the condition to enable the CR users to avoid the interference to the primary users which helps the secondary users to utilize the spectrum efficiently without interrupting the primary users.

This work applies the concept of genetic algorithm as well as cognitive radio for better channel utilization.

3 The Problem

A cellular network consists of cells which are hexagonal in shape. Each cells are having six neighbors, so it has the leverage to borrow and lend the channels from its neighbors for effective channel utilization. Though there are several mechanisms for effective channel utilization, few basic approaches are distributed channel approach and centralized channel approach.

In the distributed approach, channels are distributed to each cell as per the demand in the cell which will be fixed forever. Because of fixed distribution, it is also known as fixed channel allocation (FCA) mechanism. Centralized approach is controlled by the Mobile Switching Center (MSC). MSC has the system-wide channel usage information and is responsible for channel allocation to cells in such a way that no co-channel interference takes place. This system in not scalable because the whole system depends on MSC. Also, if MSC fails whole system comes to standstill [12]. This is also called a Dynamic Channel Allocation (DCA) as the channels are allocated as per the request/demand arising due to mobile users in the cell. Sometimes a hybrid channel allocation (HCA), that applies the techniques of both FCA and DCA, is used for the channel allocation. Using these techniques, the channels are allocated in a cellular network. FCA has low channel utilization whereas DCA and HCA suffer from a problem known as co-channel interference.

Azarfar et al. suggests that the concept of CR can be used to make the effective and reliable channel allocation [4]. The motivation of using the cognitive radio to enhance the utilization of the radio spectrum is derived from their work. GA has been found to work effectively for this.

To use the CR, the services are classified in two categories in the cellular system: Primary Service and Secondary Service. Primary services are warranted to be completed without an interruption and thus are given priority. It has been observed that most of the time channels allocated to primary services are under-unutilized. This gives an opportunity for the secondary users, utilizing secondary services, to utilize these channels which are allocated for primary services opportunistically. Secondary users, also known as cognitive users, use the cognitive radio technique to locate the un-occupied channels. These users are basically opportunistic users and utilize the primary channels when it is free. The channels designated to primary services are vacated whenever primary users seek the services. Secondary services can be interrupted on the arrival of the request for primary service by primary users which are the licensed users.

4 The Proposed Model

The proposed model applies GA for channel allocation with the concept of cognitive radio. The existing GA based model for channel allocation do not differentiate the services into primary and secondary services. Thus, in the proposed model services are categorized into four categories: Primary New Call, Primary Handoff Call and Secondary New Services, Secondary Handoff services. Primary services are having higher priority to get served than secondary services.

The cellular network, considered in the model, is of 42 cells as shown in Fig. 1. The whole network is considered to be circularly located. With the help of Fig. 1, it is easy to find out the neighbors of each cell. For example, neighbors of cell 1 are 2, 8, 14, 7, 36, and 37.

The model considers a 7-Cell Cluster, in which each cell has different set of channels. In Fig. 2, each cells are having different set of channels so they can lend and borrow the channel to and from any of its neighbors.

Fig. 1 Cellular network

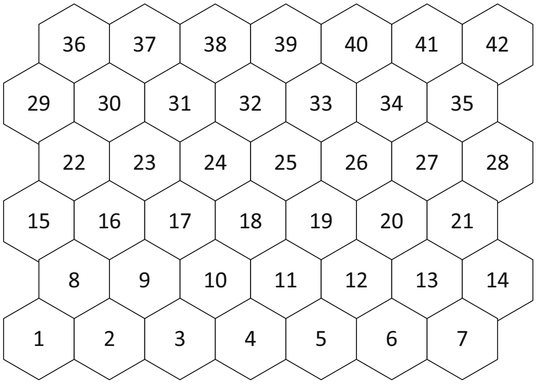
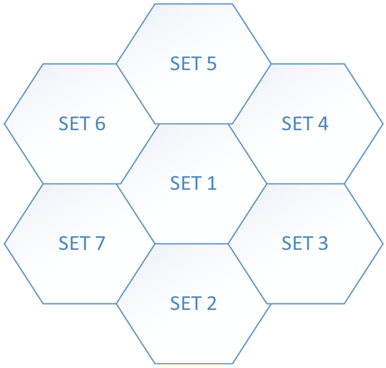


Fig. 2 Seven-cell cluster



Assumptions Some assumptions used in the model are as follows.

- Each cell in the network is hexagonal in shape.
- Initially channels are distributed uniformly in each cell.
- Mobile hosts (Primary and Secondary hosts) are distributed randomly across the network and assumed that movement of hosts is stochastic in nature.
- Cells are enumerated in increasing order as shown in Fig. 1.
- Handoff services are given more priority than the new services and if primary and secondary both kind of user are requesting for the channel then it will be allocated to the primary user.

4.1 Aim of the Model

The model exploits the potential of the GA for the effective utilization of radio spectrum in the form of channel by introducing the concept of secondary users. Secondary users are opportunistic user and they will use the channel when no primary user is requesting for it.

Sometimes it is possible that some cells are exhausted i.e. running short of channels. These cells are known as hotcell.

The model aims to minimize the blocked and dropped requests of Secondary New Requests and Secondary Handoff Requests after facilitating the primary services.

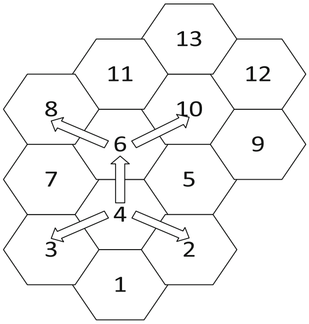


Fig. 3 Multi-lending

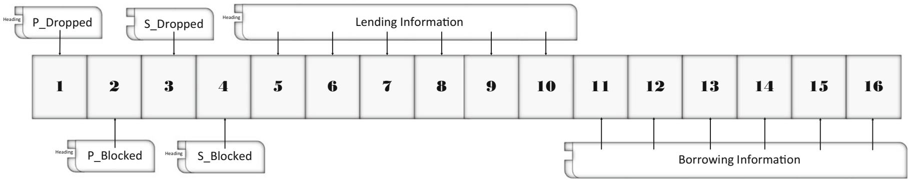


Fig. 4 Chromosome structure

4.2 Multi-lending

This concept tells that one channel may be lent to more than one neighbors with utmost care of channel interference. The concept is shown in Fig. 3 which shows that cell number 6 has only one free channel and cell 4 is requesting the channel. At the same time this channel can be provided to cell 8 and cell 10. So cell 6 is having only one free channel but it can lend it to cell 4, 8, and 10 simultaneously. This is known as multiple lending. In case of single landing one channel can be lent to only one neighbor at a time.

4.3 Encoding used in the Model

The proposed model uses GA that comprised of Chromosome design, Initial population, Genetic operators, reproduction and selection. The Chromosome structure for the problem is given in Fig. 4 that depicts the concept of concurrent lending/borrowing of a channel.

Each cell is represented with the help of a chromosome in the model which is an array of length 16 as shown in Fig. 4.

The first index of the chromosome array is *P_Dropped* which indicates the number of primary dropped requests.

The Second index of the chromosome array is *P_Blocked* which indicates the number of primary blocked requests.

Similarly, third and fourth index of the chromosome array is represented by *S_Dropped* and *S_Blocked* which indicate the number of dropped and blocked secondary requests.

The next six locations contains the lending information to its neighbors. Lending can be concurrent also.

The last six locations contains the information about the borrowing of channels from its neighbors.

The chromosome of a cell along-with the chromosome of its six neighbor cells form the matrix of 42 $\times$ 16 called a super-chromosome.

4.4 GA Operator: Crossover

The model uses one point crossover, the operation for which is elaborated by an example on the following two chromosomes. The example chromosomes are the reduced one and are not 42 × 16 super-chromosome.

1st Super-chromosome

cut point

0	0	0	0	0	0	0	0	0	0	0	0	6	0	2	0
0	0	0	0	0	0	0	0	0	0	0	0	3	0	9	0
2	2	3	1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	9	1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	8	2	0	0	0	0	0	0	0	5	0	2	0	2

2nd Super-chromosome

cut point

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	3	8	1	0	0	0	0	0	0	0	0	3	0	9	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	6	7	0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0
0	0	3	4	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	4	0	0	0	0	0	0	0	5	0	2	0	2

The offspring generated from the two parental matrices after the crossover operation are as follows.

1st offspring

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	3	0	9	0
2	2	3	1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	9	1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	8	2	0	0	0	0	0	0	0	5	0	2	0	2

2nd offspring

0	0	0	0	0	0	0	0	0	0	0	0	6	0	2	0
0	3	8	1	0	0	0	0	0	0	0	0	3	0	9	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	6	7	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0
0	0	3	4	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	4	0	0	0	0	0	0	0	5	0	2	0	2

4.5 GA Operator: Repair

It is possible that after the crossover operation, some of the offspring becomes invalid. It is necessary to repair such strings before we move for further processing. During crossover, sometimes it may happen that the hosts have moved in some other cell. So we need to update the information in the chromosome accordingly. This function is used to evaluate the string and update it if it is irrelevant.

If the number of requests are greater than the number of free channels, update the lending fields with zero for all neighbors in the chromosome. Similarly, if the number of requests are lesser than the number of free channels then update the fields *P_Dropped*, *P_Blocked*, *S_Dropped* and *S_Blocked* with zero. Borrowing fields for the chromosome is updated with zero.

4.6 Fitness Function

Fitness function is devised in such a way so that *secondary_blocked* and *secondary_dropped* requests can be minimized. In the model, primary services are having higher priority than secondary services. Secondary services are using the services in an opportunistic manner. Thus, blocking and dropping will already be minimum for primary requests. The fitness, in the work, focuses on the secondary services as is derived as given in Eq. 1. In the equation W_1 and W_2 helps to control the convergence of the fitness function.

$$Fitness = W_1 \times secondary\_blocked + W_2 \times secondary\_dropped \tag{1}$$

4.7 The Algorithm

The GA based algorithm for the channel allocation model is as follows.

Input

{

Total number of channels in the network

Primary New Request

Primary Handoff Requests

Secondary New Requests

Secondary Handoff Requests

}

Initialize *the super-chromosome using the number of requests made in the cell*

Calculate *primary blocked, primary dropped, secondary blocked and secondary dropped requests*

Repeat *(Until given condition satisfies)*

{

Perform *multiple lending and borrowing operations*

Perform *Crossover on super-chromosome*

Repair *super-chromosome with the current information in the network*

Calculate *fitness of super-chromosome*

Select *the best super-chromosome as the current super-chromosome*

Calculate *Primary _blocked, Primary_dropped, Secondary_blocked and Secondary_dropped requests*

Generation_index = generation_index + 1

}

Output

{ Average_fitness,

Average_Primaryblocked,

Average_Primarydropped,

Average_Secondaryblocked,

Average_Secondarydropped

}

5 Performance Analysis

The model is simulated by writing the program in MATLAB. This section shows the performance evaluation of the proposed model. For experimental purposes, the cellular network is assumed to consist of 42-cells. Crossover probability is 1 and mutation probability is 0 for keeping the cell information relevant as much as possible [8, 10]. The number of generations are 150 for all experiments.

The experiments are conducted by changing the number of effective channels while other parameters are kept same.

5.1 Single Channel Lending

First the experiments are conducted using single channel lending technique. In this, one channel can be lent to maximum one cell.

5.1.1 Varying Number of Channels

The experiments are conducted to observe the Average Fitness on increased number of requests in the network. Total request in the network are 600; in which primary new request are 150, primary handoff request 150, secondary new services 150 and secondary handoff services 150. Total number of GA population is 10.

Experiment 1 For the experiment, number of effective channels in the network are 56. The result is shown by graph in Fig. 5. Best average fitness is 177.1600.

Experiment 2 This experiment observes the Average Fitness by increasing the number of effective channels in the network to 70. Other parameters are same as in Experiment 1.

From Fig. 6, it is observed that after increasing the number of channels for same number of requests, average fitness is decreased significantly. Best average fitness value is 120.56 now.

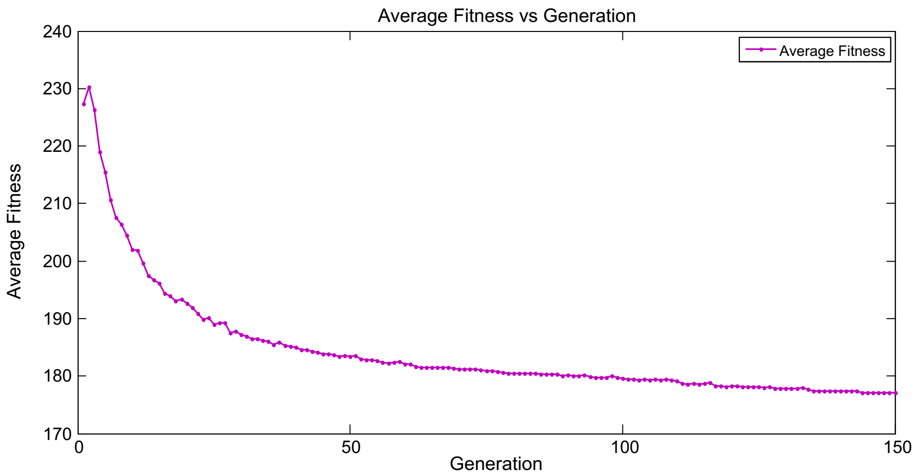


Fig. 5 Average fitness using 56 channels in network

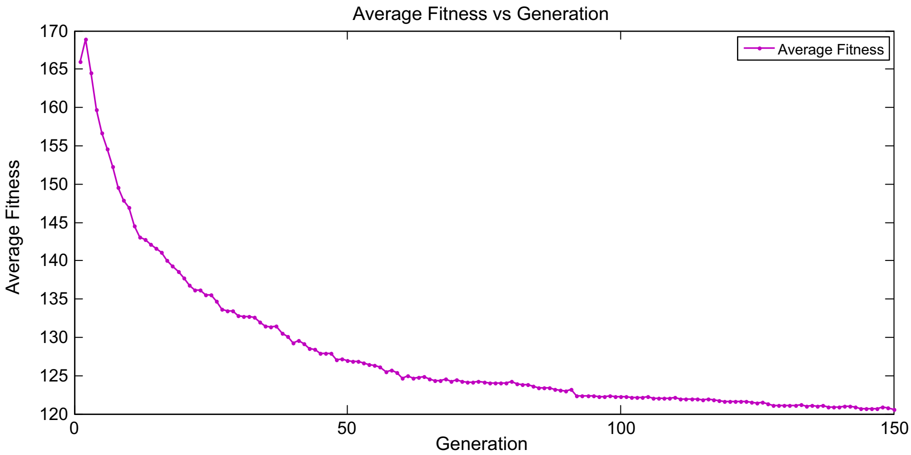


Fig. 6 Average fitness using 70 channels in network

Experiment 3 In this experiment, number of effective channels are further increased to 84. Other parameters remain same as in Experiment 1.

From Fig. 7, average fitness value is almost reduced to half of the value found in Experiment 2. The best average fitness value is 61.14.

Experiment 4 The experiment observes the Average Fitness, by increasing the number of effective channels to 105. Other parameters remain same as in Experiment 1.

From Fig. 8, it is observed that when we keep on increasing the number of channels, the average fitness value almost becomes zero on certain number of channels for a given fixed number of requests. The best average fitness value, as observed in Experiment 4, is 0.

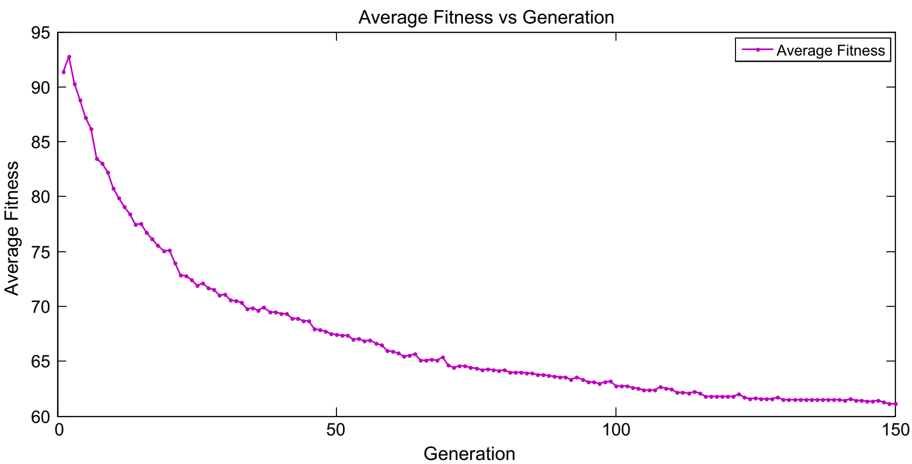


Fig. 7 Average fitness using 84 channels in network

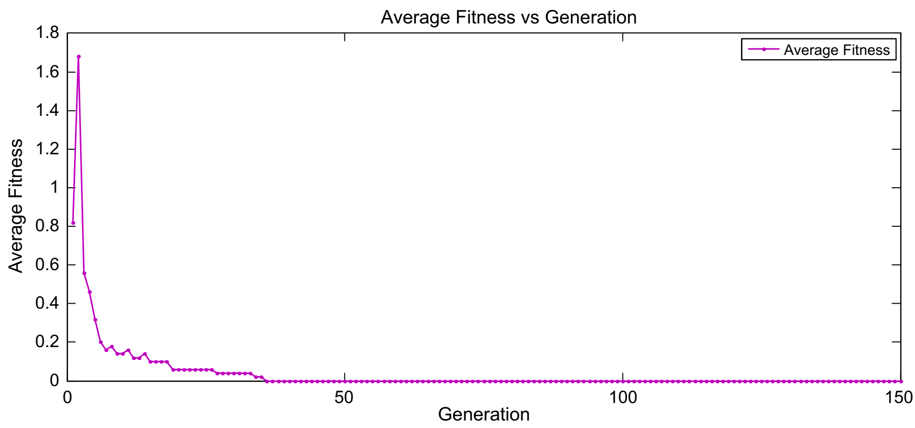


Fig. 8 Average fitness using 105 channels in network

5.1.2 Varying Number of Requests

The experiment are conducted to observe the average fitness on decreasing number of requests in the network using single channel lending. Number of channels in the network are 70 and total 20 GA populations are used for 150 generations.

Experiment 1 For the experiment, total number of requests in the network are 800. In which, each of primary new, primary handoff, secondary new and secondary handoff requests are 200. The result is shown by graph in Fig. 9. Best average fitness is 252.35.

Experiment 2 This experiment is conducted by reducing the number of requests to 700 in the network, where each requests are 175. Number of channels in the network remain same as in the Experiment 1.

Figure 10, shows that after reducing the number of requests in the network, model is able to minimize the average fitness value. The best fitness value is for the experiment is 185.70.

Experiment 3 This experiment is tested by further reducing the number of requests to 600, keeping other parameters same. It is found that average fitness value is getting reduced with better convergence rate. The best fitness value is 117.74.

Experiment 4 Further, the number of requests are reduced to 500, in which each type of requests are 125. With 70 channels in the network, average fitness value is reduced significantly. Graph in Fig. 12 shows that best fitness value is 48.00 which is lower compared to the above experiments.

Experiment 5 Finally, the number of requests are reduced to 400 in which primary and secondary requests of each type are 100. Observation of Fig. 13 shows that it converges around 20th generation and the average becomes 0 i.e. with 70 channels the network is able to satisfy 400 requests without any blockings.

Observations from Figs. 9, 10, 11, 12, and 13 shows that when the number of requests are successively reduced from 800, 700, 600, 500 and 400, average fitness value is also reduced. Also, when the requests are lesser, convergence is better.

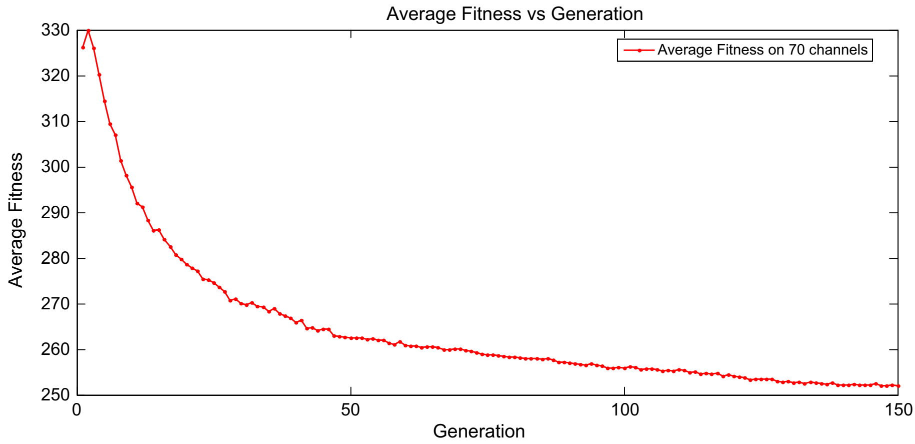


Fig. 9 Average fitness over 800 requests in the network

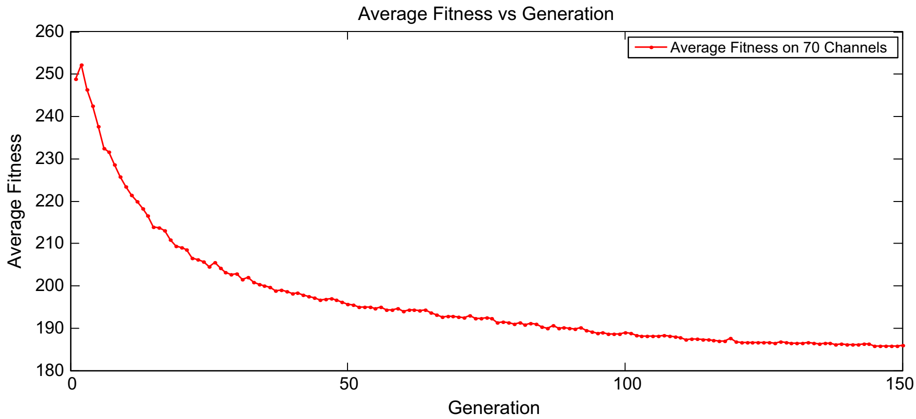


Fig. 10 Average fitness over 700 requests in the network

5.2 Multi-Channel Lending

Another set of experiment focusses on multi-channel lending with varying number of channels and requests.

5.2.1 Varying Number of Channels on 480 Requests

Experiment 1 The experiment observes the average fitness. For this, number of effective channels in the network are 56. Total request in the network are 480, of which 120 primary new request, 120 primary handoff request, 120 secondary new request and 120 secondary handoff request. Total number of GA population is 10 and the total number generation up to which experiment runs is 150. The result is show in Fig. 14.

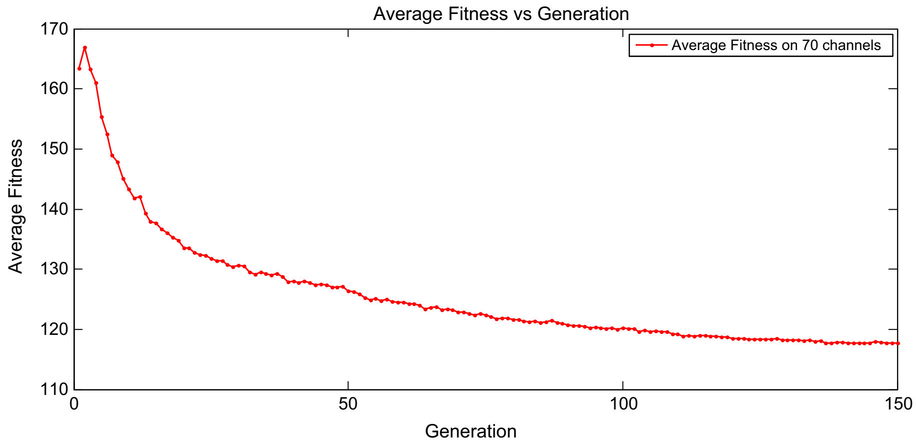


Fig. 11 Average fitness over 600 requests in the network

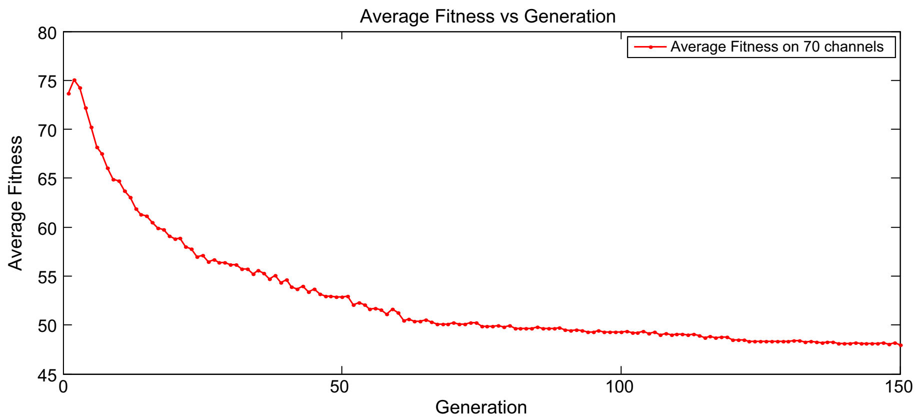


Fig. 12 Average fitness over 500 requests in the network

From Fig. 14, it is observed that fitness value converges with the increase in generations and the best average fitness value obtained is 71.22. So, it is possible to minimize the secondary blocked and secondary dropped requests.

Experiment 2 This experiment also observes the average fitness by increasing the effective channels to 70. The other parameters are same as in Experiment 1. The observation is shown in Fig. 15.

As per the observation of the Fig. 15, it is found that after increasing the number of effective channels average fitness value decreases to 16.20 which is better than what we observed in Experiment 1.

Experiment 3 In experiment 3, number of effective channels in the network are further increased to 84, while keeping other parameters as in Experiment 1. The result is depicted in Fig. 16 where the best average fitness reaches to 0.

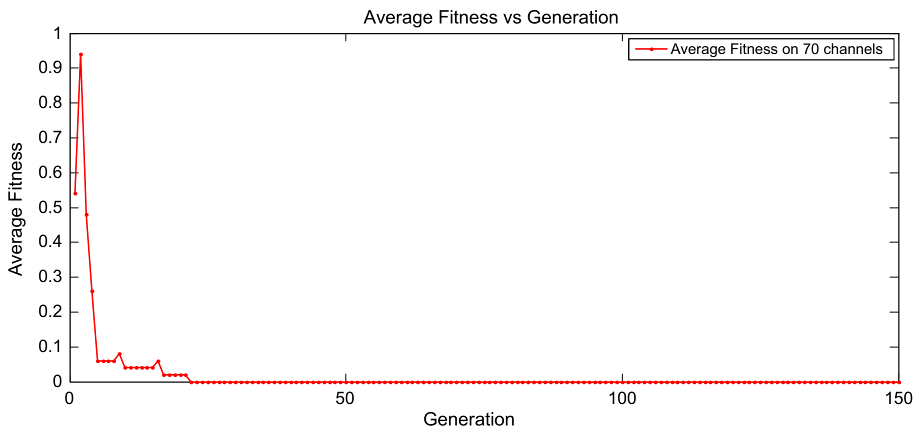


Fig. 13 Average fitness over 400 requests in the network

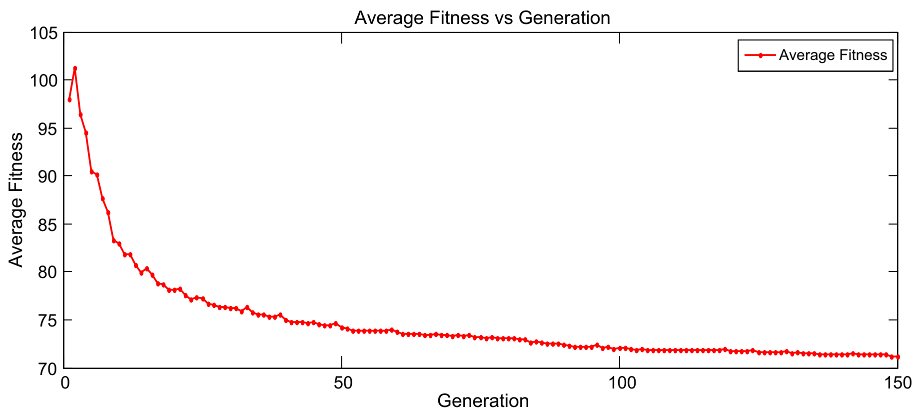


Fig. 14 Average fitness per Generation using 56 effective channels

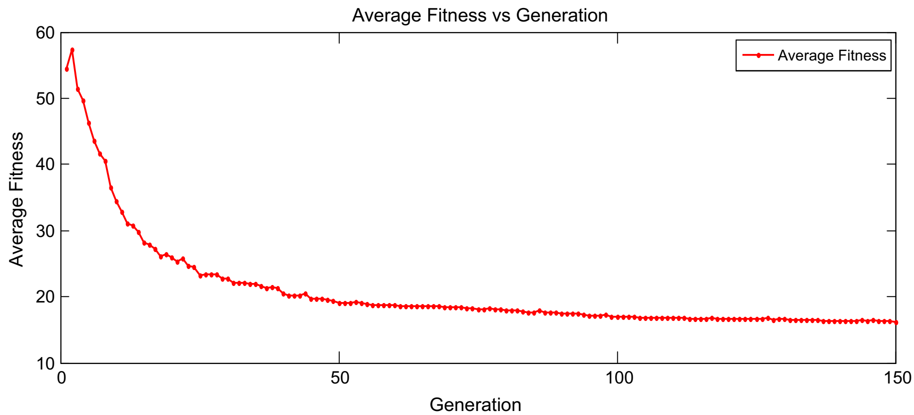


Fig. 15 Average fitness per Generation using 70 effective channels

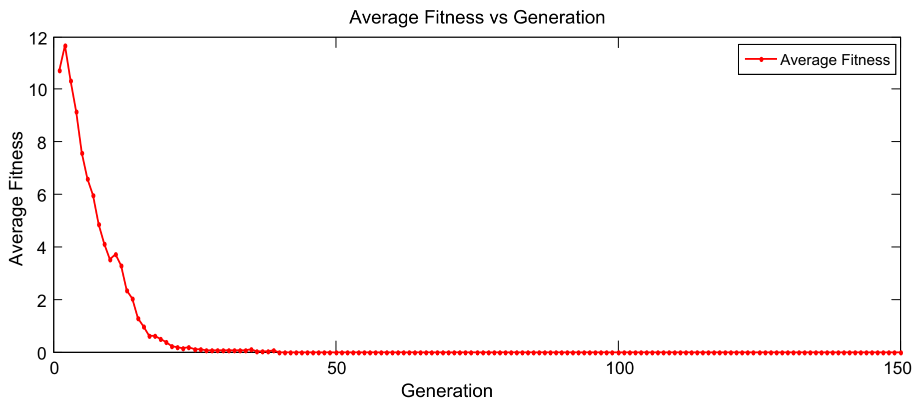


Fig. 16 Average fitness per Generation using 84 effective channels

Figure 16 shows that when we increase the number of effective channels to 84 for 480 requests, it satisfies all the requests and result also converges by 30 iterations.

The observations from Experiment 1, 2 and 3 are that when we increase the number of effective channels in the network, the average fitness values decreases from 71.22 to 16.20 and finally to 0. Convergence rate is also better successively.

5.2.2 Varying Number of Channels on 600 requests

Same set of experiments are conducted on increased number of requests in the network by varying the effective number of channels.

Experiment 1 This experiment observes the average fitness on increased number of requests in the network. For the experiment, number of effective channels in the network are 56. Total request in the network are 600. In which, primary new request are 150, primary handoff request 150, secondary new services 150 and secondary handoff services 150. Total number of GA population is 10 and experiment runs up to 150 generations.

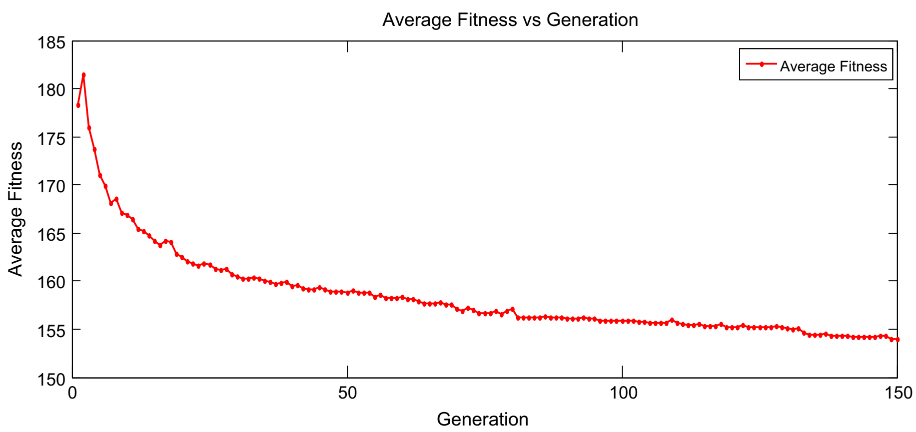


Fig. 17 Average fitness per Generation using 56 effective channels

Observations of Fig. 17 shows that convergence rate is significantly considerable even after increasing the total number request from 480 to 600. Best fitness value obtained is 154.3000.

Experiment 2 This experiment observes the average fitness by increasing the number of effective channels in the network. Number of effective channels are 70 and other parameters remain same as in Experiment 1.

Observations of Fig. 18 shows that after increasing number of effective channels for 56–70, average fitness value is 88.7800. It indicates that secondary blocked and secondary dropped are getting minimized by increasing the number of channels.

Experiment 3 In this experiment, number of effective channels are increased to 84. Other parameters remain same as in experiment 1.

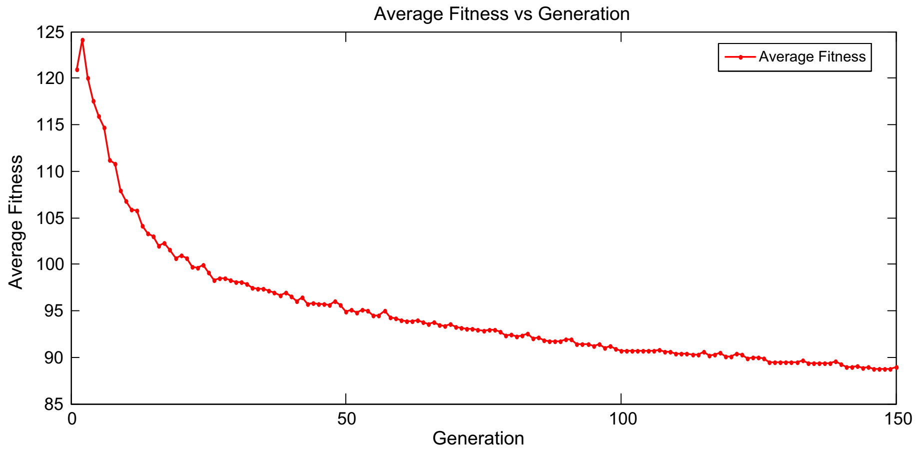


Fig. 18 Average fitness per generation using 70 effective channels

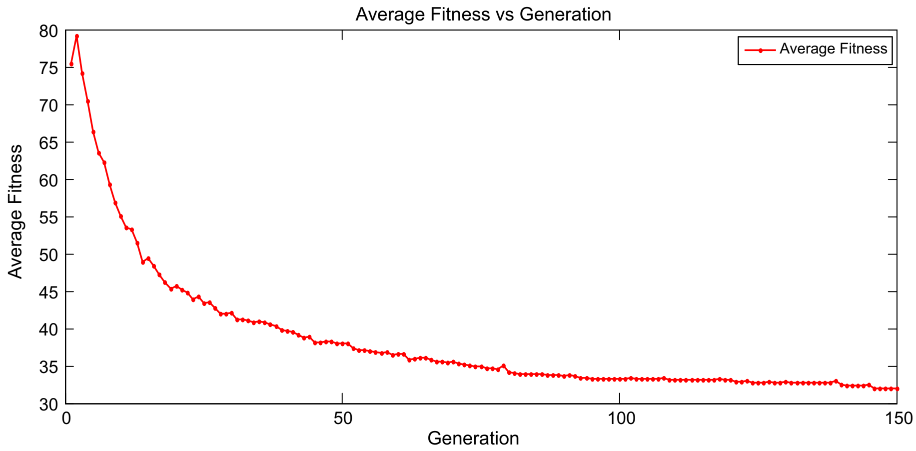


Fig. 19 Average fitness per generation using 84 effective channels

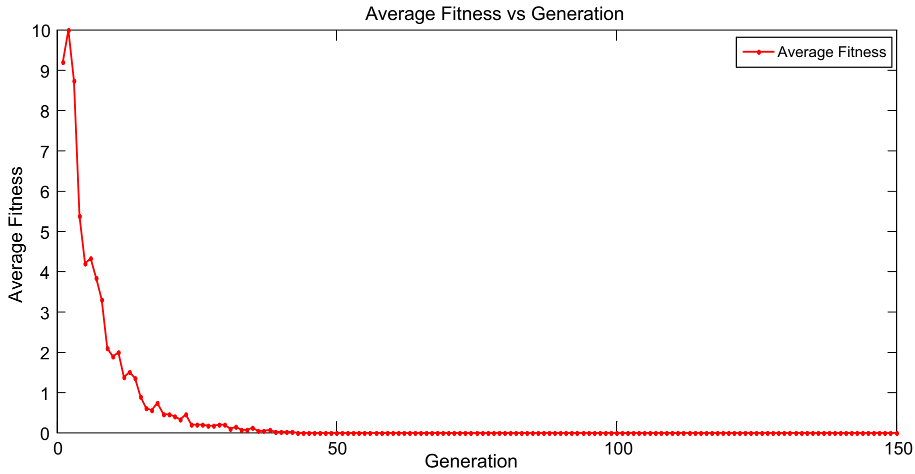


Fig. 20 Average fitness per generation using 105 effective channels

Figure 19 shows that with 84 effective channels in the network, the average fitness value is 32.020.

Experiment 4 In this experiment the average fitness is observed for 105 number of effective channels. Other parameters remain same as in Experiment 1.

Figure 20 shows that when the number of effective channels in the network are 105, the blocked and dropped requests are almost zero. Result also converges by 35 iterations.

Experiment 1, 2, 3 and 4 shows that when we increase the number of request in the network still convergence rate is still significantly good. Average best fitness value decreases when we increase the number of effective channels in the network.

Figure 21 shows the comparison of best average fitness when we vary the number of channels in the network keeping other parameters same. Result shows that when the number of channels are increased, average fitness is getting decreased.

5.2.3 Varying Number of Requests

The experiments are conducted by varying the number of requests from 800 to 400 in steps of 100 on 70 number of channels in the network with multi-channel lending technique. The size of population generated is 20.

Experiment 1 This experiment is tested on 800 requests, in which primary new, primary handoff, secondary new and secondary handoff requests 200 each. From Fig. 22, it is observed that it is converging towards the optimal value and the best fitness value is 227.2400.

Experiment 2 In this experiment, number of requests are 700. Where primary new, primary handoff, secondary new and secondary handoff are 175 each. Rest of the parameters are kept same. Figure 23 shows that it is converging towards the optimal value and the best fitness value is 156.46.

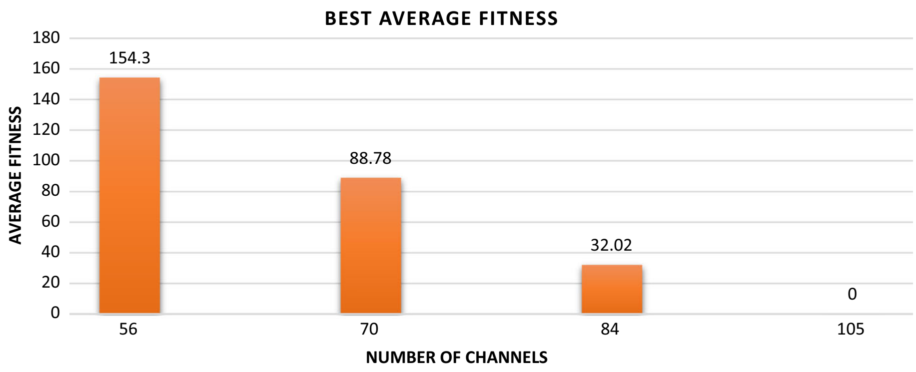


Fig. 21 Comparative best average fitness

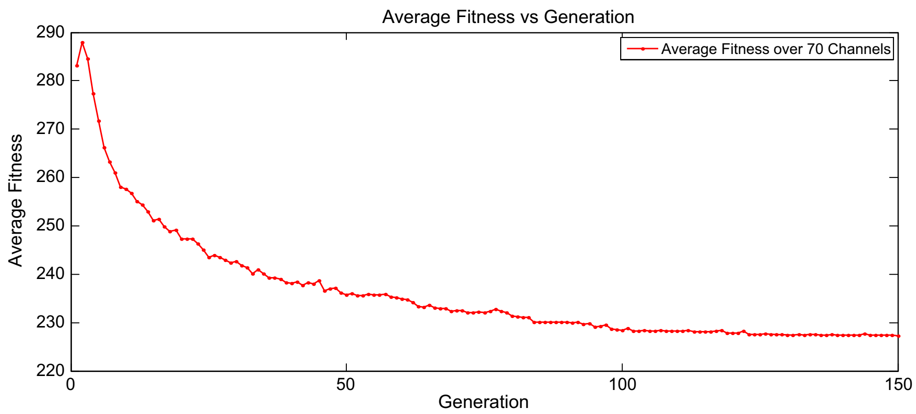


Fig. 22 Average fitness over 800 requests in the network

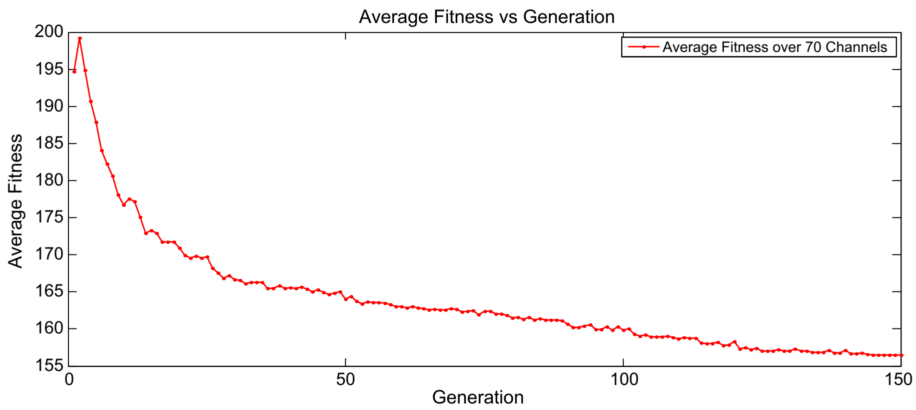


Fig. 23 Average fitness over 700 requests in the network

Experiment 3 In the experiment, total number of requests are reduced to 600, where the requests in each class are 150. Figure 24 shows that it converges by 120 generations and the best fitness value is 87.28.

Experiment 4 This experiment is conducted on 500 requests in the network, where primary new, primary handoff, secondary new and secondary handoff are 125 each. It converges by 50 iterations and the best fitness value is 24.78.

Experiment 5 Finally number of requests are reduced to 400 and each primary new, primary handoff, secondary new and secondary handoff requests 100. Figure 26 shows that it is converged just around after 20 generations and the best fitness value is 0.

Observations from Figs. 22, 23, 24, 25 and 26 is that on decreasing the number of requests average fitness value improves significantly. Figure 26 shows that when the number of requests in the network are 400 then best fitness value approximates to zero.

5.3 Comparison of Single Channel and Multi-Channel Lending

A comparative study is done to observe the fitness with single channel lending and multi-channel lending. The average fitness is observed by varying number of channels and number of requests in separate experiments. The results are as follows.

5.3.1 Comparison of Average Fitness on Varying Number of Channels

Experiment 1 Comparison of Average Fitness over Varying Number of Channels This experiment shows the average fitness comparison for the single channel lending and multi-channel lending on varying number of channels. The number of channels in the network are kept as 56, 70, 84 and 105. The total number of request are taken to be 600, in which primary new requests are 150, primary handoff requests are 150, secondary new requests are 150 and secondary handoff requests 150. The total population size is 10 for 150 generations.

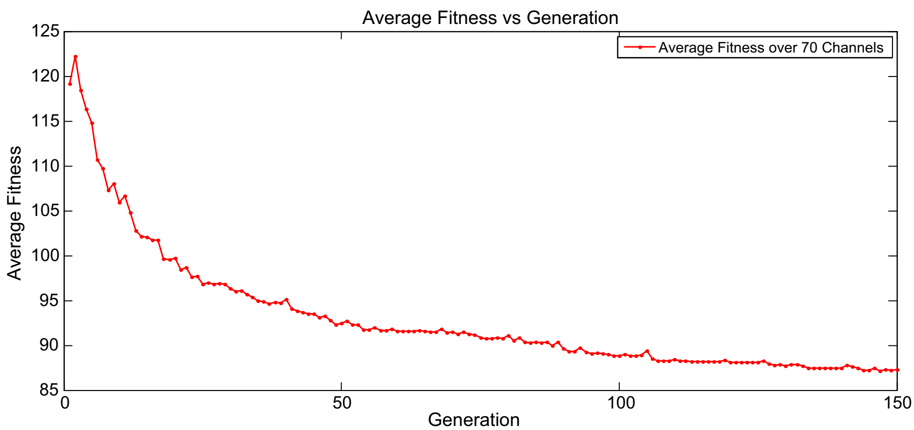


Fig. 24 Average fitness over 600 requests in the network

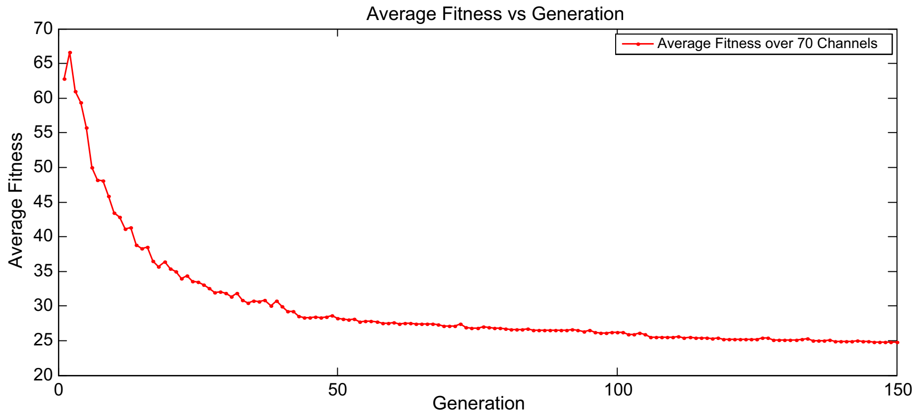


Fig. 25 Average fitness over 500 requests in the network

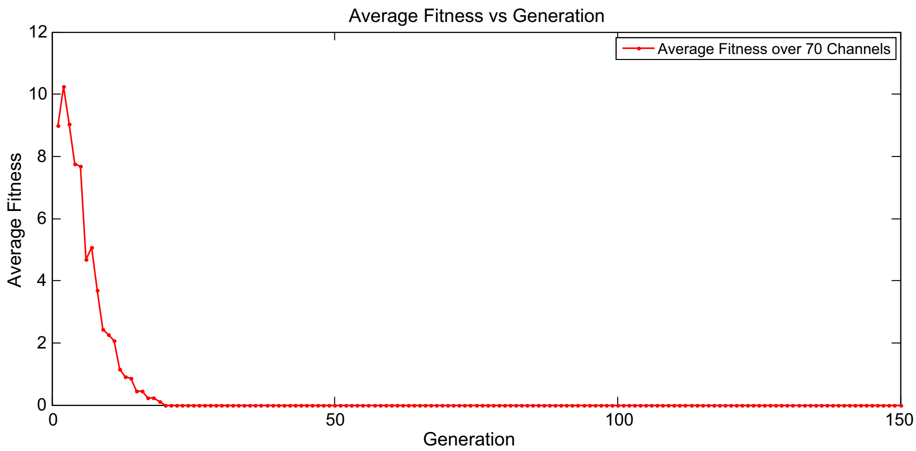


Fig. 26 Average fitness over 400 requests in the network

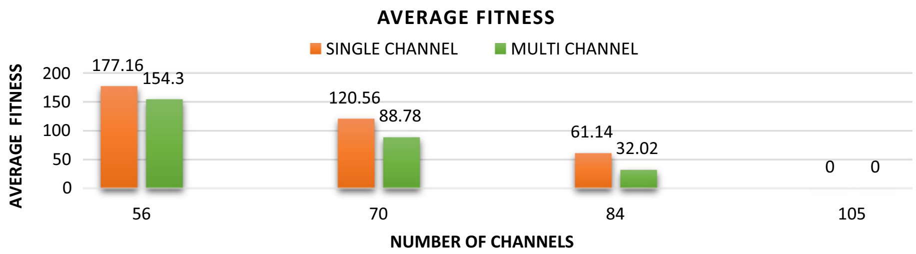


Fig. 27 Average fitness comparison for single and multi-channel lending on varying channels

Figure 27 shows multi-channel lending is better in comparison to single channel lending for the optimal fitness though for 105 number of channels the average fitness becomes 0 for both; single channel as well as multi-channel lending.

Experiment 2 Comparison of Average Fitness over Varying Number of Requests Another experiment shows the comparison of average fitness for single channel lending and multi-channel lending by varying number of requests on fixed number of channels. Number of requests are 800, 700, 600, 500 and 400 and number of channels are 70. In the experiment 20 populations are iterated till 150 generations. Figure 28 shows that the average fitness is better in multi-channel lending over single channel lending. Also observed that when the number of requests are less, average fitness value for multi-channel lending is almost half of single channel lending (average fitness value at 500 requests). For 400 requests, with 70 channels, average fitness reaches to 0 for both; single channel as well as multi-channel lending.

5.3.2 Comparison of Primary and Secondary Requests

This experiment is done to compare single channel and multi-channel lending on the four class of services. Number of channels in the network are 70 and the total requests are 600. Primary new requests are 150, primary handoff requests are 150, secondary new requests are 150 and secondary new requests are 150. Total number of GA population generated is 10 and the total number of generation up to which program runs is 150.

Observation from Fig. 29 is that primary and secondary both services are better served when multi-channel lending is employed. It is also observed that after facilitating the primary services, the model is able to serve the secondary services effectively.

5.4 Comparative Study

To show the importance of the model in channel allocation, we have compared the proposed model with Lutfi et al. FTCA model [8]. In FTCA model, there are two classes of services; primary new and primary handoff whereas our model is having four classes of services; primary new, primary handoff, secondary new and secondary handoff.

The simulation parameter for the comparison is as follows; total number of request in the network is 400, in which primary new request 100, primary handoff request 100, secondary new request 100 and secondary handoff request are 100. Channels are varying from 49 to 56 and 63 in the network. Result is observed at the end of 20 generations to have conformity with FTCA model. The proposed model is depicted as CCAGA with SB as Secondary Blocked and PB as Primary Blocked, SD as Secondary Dropped, PD as Primary Dropped.

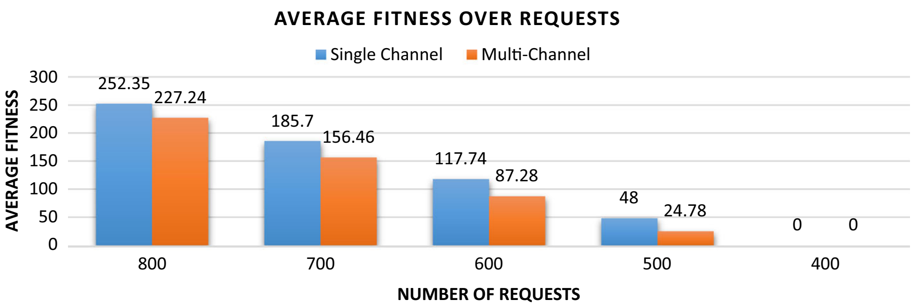


Fig. 28 Average fitness comparison for single and multi-channel lending over varying requests

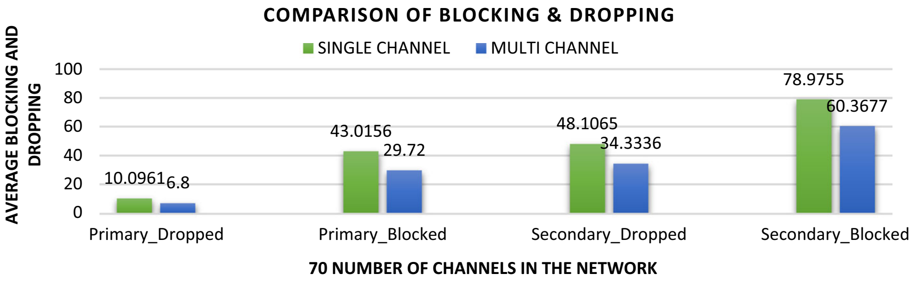


Fig. 29 Comparison of primary & secondary requests on single and multi-channel lending

5.4.1 Comparison for Average Blocking

The experiments are conducted for average blocking.

Experiment 1 These experiments are conducted using hot cell in the network.

Form Fig. 30, it is observed that when the number of channels in the network are 49, FTCA model is slightly better but the proposed CCAGA model is serving approximately same number of primary request. At the same time CCAGA is facilitating secondary users also significantly. After increasing the number of channel, it is observed that primary blockage requests is reduced significantly and also secondary services are getting served better. Finally, after further increasing the number of channels to 63 it is observed that both primary and secondary blockage is less than FTCA algorithm.

Experiment 2 These experiments are conducted excluding hot cell in the network.

From Fig. 31, it is observed that the CCAGA model is performing better after excluding hot cell in the network. For example when the number of channels in the network are 56, average blockage for primary requests is almost half than that of Fig. 30. When the number of channels are 63, primary and secondary services are getting served better than the FTCA model.

Thus, the proposed model performs better than FTCA model in all the cases for primary services. It performs better for secondary services also when number of channels are more.

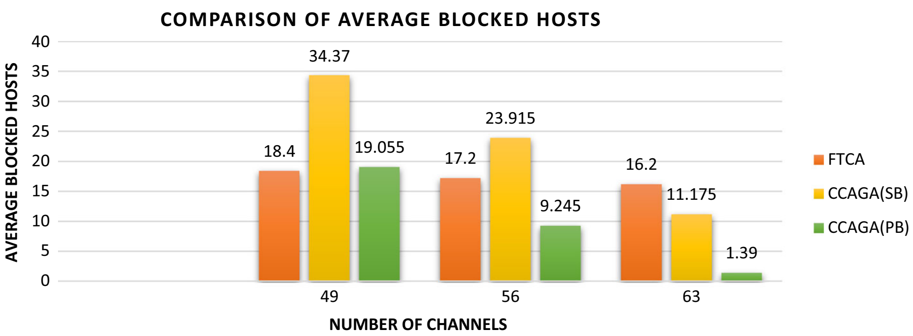


Fig. 30 Comparison of average blocked hosts with hot cells in the network

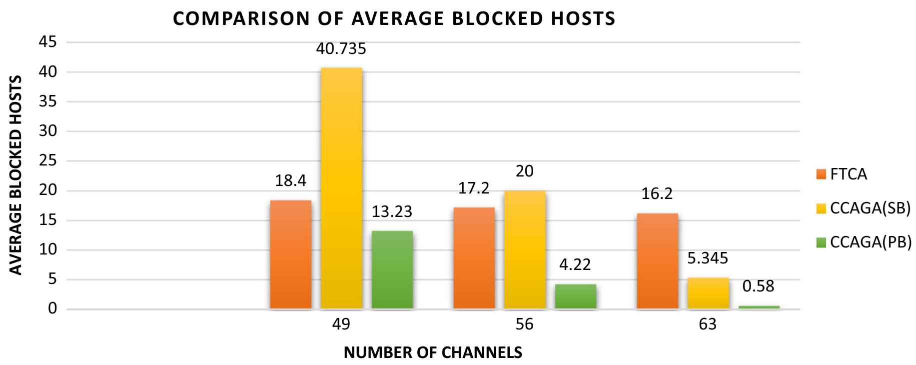


Fig. 31 Comparison of average blocked without hot cells in the network

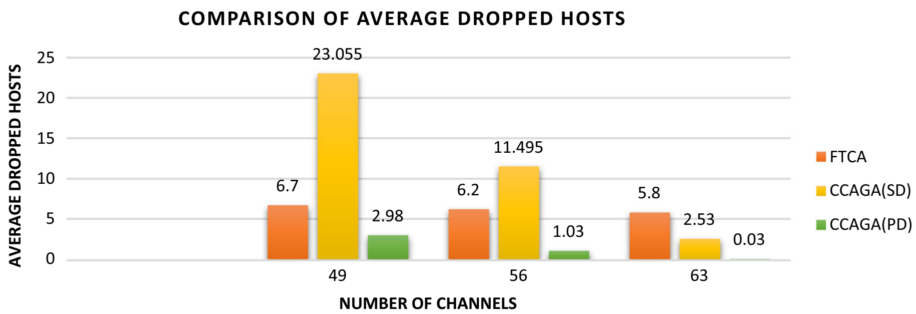


Fig. 32 Comparison of average blocked hosts without hot cells in the network

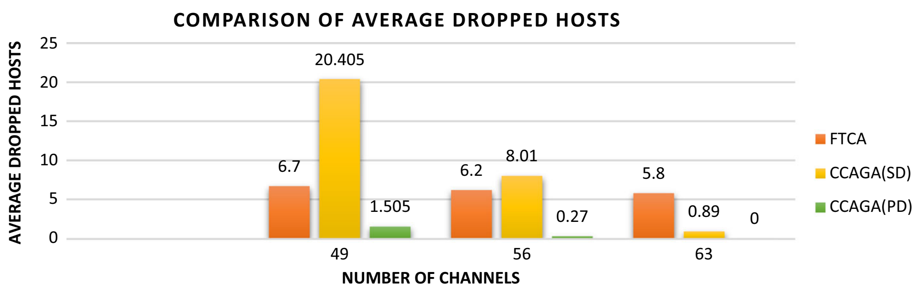


Fig. 33 Comparison of average dropped hosts without hot cells in the network

5.4.2 Comparison for Average Dropping

This experiment are also conducted for comparing the dropped request in the network.

Experiment 1 These experiments are conducted using hot cell in the network.

From Fig. 32, it is observed that primary handoff requests are getting served significantly better than FTCA model. When we increase the number of channel (e.g. 63) then both primary handoff and secondary handoff requests are getting served better than FTCA model.

Experiment 2 These experiments are conducted excluding hot cell in the network.

From Fig. 33, it is observed that when we remove the hot cell then requests are getting served in much better way. At 63 channels primary dropped requests becomes 0 while secondary dropped requests also minimizes to 0.89. It was 2.53 when hot cell was considered (Fig. 32).

The comparative study concludes that while FTCA model is serving total 100 requests, the proposed model is serving 100 secondary request after facilitating 100 primary new request. Thus, the proposed model is serving the secondary requests very significantly. After reaching to a certain number of channels, both primary and secondary requests are being served significantly.

6 Conclusion

This paper applies the concept of Genetic Algorithm and Cognitive Radio for channel allocation problem in a cellular network. In the model, services are categorized into four categories: primary new services, primary handoff services, secondary new services and secondary handoff services. Primary services is to be used by primary users and secondary services by the secondary users. The model introduces the concept of single channel and multi-channel lending which facilitate the primary and secondary user for better services.

Number of experiments have been conducted, by varying different parameters, to study the performance of the proposed model. It is concluded from the result that using the concept of cognitive radio and genetic algorithm, resource utilization is better in the Cellular network. Multi-lending of the resources further improves the resource utilization. The model serves better not only to the primary users availing the primary services but secondary users are also being served much more effectively. A comparative analysis concludes so.

References

1. Jiang, T., Wang, H., & Leng, S. (2013). Channel allocation and reallocation for cognitive radio networks. *Wireless Communications and Mobile Computing, 13*(12), 1073–1081.
2. Mitola, J., & Maguire, G. Q., Jr. (1999). Cognitive radio: Making software radios more personal. *IEEE Personal Communications, 6*(4), 13–18.
3. Zhao, Z., et al. (2009). Cognitive radio spectrum allocation using evolutionary algorithms. *IEEE Transactions on Wireless Communications, 8*(9), 4421–4425.
4. Azarfar, A., Frigon, J.-F., & Sanso, B. (2012). Improving the reliability of wireless networks using cognitive radios. *IEEE Communications Surveys & Tutorials, 14*(2), 338–354.
5. Marojevic, V. (2009). Computing resource management in software-defined and cognitive radios. Ph. D. Dissertation, Universitat Politècica de Catalunya (UPC), Barcelona. http://flexnets.upc.edu/trac/wiki/Publications.
6. Marojevic, V., Gomez, I., & Gelonch, A. (2012). Cognitive resource management: For all wireless access layers. *IEEE Vehicular Technology Magazine, 7*(2), 100–106.
7. Qadir, J. (2013) Artificial intelligence based cognitive routing for cognitive radio networks. arXiv preprint arXiv:1309.0085.
8. Khanbary, L. M. O., & Vidyarthi, D. P. (2008). A GA-based effective fault-tolerant model for channel allocation in mobile computing. *IEEE Transactions on Vehicular Technology, 57*(3), 1823–1833.
9. Chen, K.-C., & Prasad, R. (2009). *Cognitive radio networks*. New York: Wiley.
10. Patra, S. S. M., et al. (2006). Improved genetic algorithm for channel allocation with channel borrowing in mobile computing. *IEEE Transactions on Mobile Computing, 5*(7), 884–892.

11. D. P. Vidyarthi, and S. K. Singh, “A Heuristic Channel Allocation Model Using Cognitive Radio,” *Wireless Personal Communications*, pp. 1-17.
12. Yang, J., et al. (2005). A fault-tolerant distributed channel allocation scheme for cellular networks. *IEEE Transactions on Computers, 54*(5), 616–629.

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