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An Efficient Channel Allocation in Mobile Computing

A.S.C.Padma, M.Chinnaarao
Computer Science and Engineering Department, Kakinada Institute of Engineering and Technology
Korangi, Andhrapradesh, India

***Abstract*—Mobile computing involves bulk data transmission over the transmission media. To achieve highly reliable data transmission, wireless mobile networks require efficient reliable link connectivity, regardless of terminal mobility and, thus, a reliable traffic performance. Mobile networks consist of mobile hosts, base stations, links, etc. that are often vulnerable to failure. It is desirable to design a reliable network, in terms of services of both the base stations and the communication channels of the network, for the reliable transmission of the data. An attempt is made to employ those channels that offer a reliable communication at any given time. The objective of this study is to design an appropriate reliability-based model for channel allocation that retains the overall system reliability with acceptable system performance. The system may achieve acceptable performance not only during normal operations but also under various component failures. A genetic algorithm, which is a search procedure based on evolutionary computation, is suited to solve a class of complex optimization problems. The potential of the genetic algorithm is used, in this paper, to improve the reliability of the mobile communication system. The proposed model designs a reliable mobile communication system, irrespective of the mobile hosts that change their position due to mobility. A simulation experiment to evaluate the performance of the proposed algorithm is conducted, and results reveal the effectiveness of this model.**

***Keywords*—channel allocation, channel reuse, failure, genetic algorithm (GA), handoff, reliability.**

I. INTRODUCTION

A CELLULAR system divides a geographical communication area into smaller regions called cells, which are usually hexagonal for analytical and experimental purposes. A typical mobile network environment consists of cells, each of which is serviced by a base station (BS) located at the center of the cell. The BS provides a connection end point for the roaming mobile hosts (MHs). The BS is interconnected by wired or wireless media [1]–[3]. The channel-allocation problem deals with the allocation of frequency channels of the given network to the MHs. Two important concepts in channel allocation are cellular reuse of channels and handoff [1], [2]. The fundamental and elegant concept of cells relies on the channel or frequency reuse, i.e., the usage of the same channel by different MHs separated by a minimum distance [4], without interfering with each other (co channel interference). Handoff occurs when a user moves from the coverage area of one BS to the adjacent one while it is still involved in communication. A new channel will be assigned to the MHs to continue the ongoing communication. The new channel may be within the same cell (intracell handoff) or in a different cell (intercell handoff). These issues are important in microcellular systems where the cell radius is small [1], [5].A channel-allocation algorithm consists of two phases. *1) channel acquisition* and 2) *channel selection*. The task of the channel acquisition phase is to collect the information of free available channels from the interference cells and ensure that the two cells within the minimum reuse distance do not share the same channel. The channel-selection phase deals with the selection of a channel from the available free channels to get better channel utilization in terms of channel reuse [6]. Wireless channels are scant resources, and there is a need to properly manage these resources.

II.RELATED WORK

Fixed channel allocation (FCA) and dynamic channel allocation (DCA) are well-known channel-allocation schemes. In FCA, the assignment of frequencies to cell is static and does not vary. This approach is easier to implement but is inefficient, because the traffic load varies from time to time. DCA dynamically allocates the channels. One better method, in the case of heavy load on one cell and light load on the neighboring cell, is to borrow channels from the neighbor cells. Cells with heavy traffic are dynamically assigned more channels. This scheme, which is a variant of DCA, is known as borrowing channel allocation (BCA) and is quite common in global systems for mobile communications [3], [4], [7]. However, it requires careful traffic analysis. There are few other ways of dealing with the excess load in mobile networks in addition to channel borrowing, such as channel sharing and cell splitting [8]. The growing importance of mobile networks has stimulated active research into how data can reliably be transmitted over the mobile communication network. This approach suggests allocating channels to the MHs in the presence of various failures in the form of uncertainties. The failure includes signal fading, channel interference, weak transmission power, path loss, etc. This paper suggests a novel idea of channel allocation based on the reliability aspect of the system. Reliability is the ability of a system to successfully perform its functions in routine and in hostile or unexpected circumstances. Reliability is the probability that the network, with various components, performs its intended function for a given time period when operated under normal environmental conditions. The unreliability of a connection is the probability that the experienced outage probability for the connection is larger than a predefined maximum tolerable value. The connection reliability is related to the traffic parameters [9]. The design of reliable resource-management algorithms for cellular networks is an important issue. The MH changes its access point time to time. This instance poses several challenges in terms of ensuring system reliability. The increasing reliance on wireless networks for information exchange makes it critical to maintain reliable communications. Even a short downtime may cause substantial data loss; thus, these networks require high level of reliability. Reliability is a crucial parameter, because any failure will not only has direct cost on maintenance but may also result in dropped calls and terminated connection. This condition may be more catastrophic in mobile computing, because it may result in Byzantine failure. Failures that inhibit communications or result in the loss of critical data are of immense importance. In a wireless cellular network environment, BSs are prone to failure. A BS may either crash or fail to send or receive data. Due to the failure of a BS, all the call connections in the failed cell area get terminated, and all the call services are interrupted until the failed BS is restored. BS failure significantly degrades the performance and bandwidth utilization of the cellular networks. In particular, services for high-priority ongoing calls could be interrupted, which is usually not acceptable. Wireless channels are also inherently unreliable and prone to location-dependent, time-varying, and bursty errors due to noise, multipath fading, shadowing, and interference. Their unreliability is much higher than that of wired links. In recent years, the applications of a genetic algorithm (GA), which is a useful search procedure for optimization problems, have attracted the attention of researchers of various disciplines as a problem-solving tool. The GA is a search procedure based on the natural evolution. The GA has successfully been applied for various optimization problems for which no straightforward solution exists.

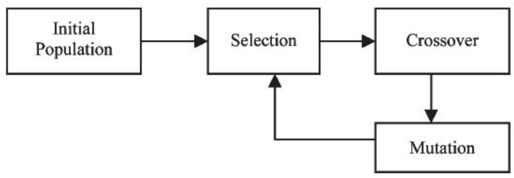

Fig. 1. Operations in the GA.

Channel allocation based on reliability is an important activity towards this end. This paper discusses the effects of the component failure in mobile cellular networks, with emphasis on improving the reliability that is affected by the users' mobility and the wireless environment. A GA-based reliability model for channel allocation is being proposed here to facilitate wireless mobile network design that meets users' demand in terms of reliable services.

III. GENETIC ALGORITHM

GA works from a database of points simultaneously (a population of strings), climbing many peaks in parallel. The Genetic Algorithm (GA), useful for optimization problems, is based on the Darwin's theory of "survival of the fittest." Individuals, from the population of potential solutions, reproduce and solutions are refined successively over the number of generations.

A genetic algorithm emulates biological evolutionary theories to solve optimization problems. GA is comprised of a set of individual elements (the population) and a set of biologically inspired operators defined over the population. According to the evolutionary theory, only the elements most suited for the purpose in a population are likely to survive and generate offspring, thus transmitting their biological heredity to new generations. The chromosomes in a GA population typically take the form of bit strings. But the chromosome can take some other form of string as well, such as letters, digits and integers. Each chromosome can be thought of as a point in the search space of candidate solutions. The GA processes populations of chromosome, successively replacing one such population with another. The GA requires a fitness function that assigns a score (fitness) to each chromosome in the current population. The fitness of a chromosome depends on how well that chromosome solves the problem at hand.

The fitness function in a genetic algorithm is the objective function that is to be optimized. It is used to evaluate the search nodes, thus it controls the GA. As the GA is based on the notion of the survival of the fittest, the better the fitness value, the greater is the chance to survive. Thus, the simplest form of GA involves three types of operators: selection, crossover, and mutation.

The simple structure of the GA is:

```
GA ( )
{
 Initialize population;
Evaluate population;
While termination criterion not reached
{
 Select solutions for next population;
Perform crossover & mutation;
Evaluate population;
}
}
```

A simple GA consists of an initial population followed by selection, crossover, and mutation operations as shown in Fig. 1.

1) Initial Population: Initial population is the set of potential solutions to the problem. To start with, the number of solutions is generated by using any method (e.g., greedy). Borrowing the terminology from genetic engineering, the population is also called a chromosome or a string. On the initial population, various genetic operators are applied in GA.

2) Selection: The selection operation selects good results among the chromosomes by using some objective function (*fitness function*). The fitness function is used to rank the quality of the chromosomes. A fitness value is assigned to the chromosome, and the chromosome is evaluated with this value for its survival. The fitness of the chromosome depends on how well that chromosome solves the problem at hand. A chromosome (string) with a higher value has a higher probability of contributing to one or more offspring in the next generation [3].

3) Crossover: The idea of crossover is to swap part of the information between a pair of chromosomes to obtain the new chromosome. Simple crossover may proceed in two steps. First, members of the newly reproduced strings in the mating pool are mated at random. Second, each pair of strings undergoes crossing over as follows. An integer position k along the string is uniformly selected at random between 1 and the string length less than one $[1, l - 1]$. Two new strings are created by inclusively swapping all characters between positions $k + 1$ and l [3].

4) Mutation: In mutation, a chromosome is slightly randomly altered to get a new chromosome. The mutation operator is used to introduce a new genetic material (e.g., 0 or 1). As a result of its generality, it is an insurance policy against the premature loss of important notions. The probability of applying mutation is often very low. Mutation rates are normally small in natural populations [3].

A) Resource planning model:

The set of all cells is partitioned into k disjointed subsets, S0; S1; . . . ; Sk_1, in such a way that the geographical distance between any two cells in the same subset is at least Dmin. If the distance between any two cells in the same subset is exactly Dmin, then the partition is called an optimal partition. The set of all channels available in the system is divided into k disjointed subsets correspondingly: PC0; PC1; . . . ; PCk_1. Channels in PCi are preallocated to cells in Si and are called primary channels of cells in Si and secondary channels of cells in Sj. When assigning a channel to support a call, a cell, Ci, always selects a primary channel first if this is possible. A secondary channel is selected by Ci only when no primary channel is available for Ci. If Ci selects a primary channel, it can use this channel without consulting with any neighbor. Otherwise, Ci needs to consult with the neighbors to which the selected secondary channel has been preallocated (i.e., the selected secondary channel is a primary channel of these neighbors). After a call using a secondary channel terminates, the secondary channel must be returned to the cell to which it has been preallocated. i.e., *primary* channels are initially preallocated to each cell. Furthermore, the *secondary* (borrowed) channels must be returned to the cell from which it has been borrowed as soon as the communication is over. Each cell has a set of reserved channels (in proportion to primary channels), which will immediately be given to a crossing over MH (to handle handoff). However, at the same time, the cell searches for a new channel. As soon as it gets the new channel, it is allocated to the crossed over MH so that the reserved channel pool is intact. For experimental purposes, the MHs are randomly distributed among the cells in proportion to the number of channels per cell. It is assumed that the MH movement across the cells is stochastic.

III. PROPOSED MODEL

1) Encoding Used: Each cell is represented by a chromosome. A chromosome is an array of length 15. The first location of the chromosome array represents the number of blocked hosts. The second location of the chromosome array is for the number of free primary channels. The third location of the chromosome array represents the number of free reserved channels for the handoff calls. The next six locations contain the information about the channel lending to six neighbor cells.

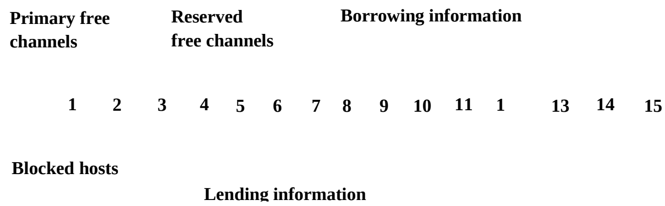

Fig 2.Chromosome structure

The last six locations contain the information about the channel borrowing from six neighbor cells. The chromosome of a cell and the chromosomes of its six neighboring cells form a matrix of 7 $*$ 15, which is called a superchromosome. Chromosomes are combined into a superchromosome, and all the superchromosomes together give the information of the whole network. All GA operations are performed on the superchromosome.

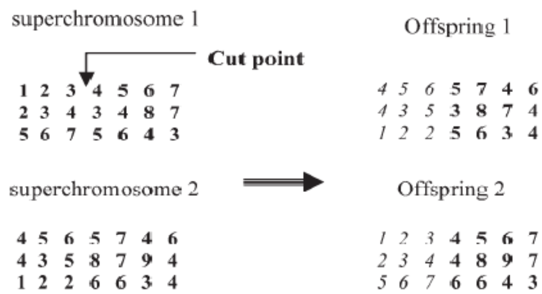

Fig 3.Crossover operation

2) Crossover: The crossover operation occurs between two superchromosomes (two matrices) to generate two offspring from them i.e., two new matrices [7]. After this step, we get two new different chromosomes. In Fig.3, two example superchromosomes are taken, and the crossover operation is illustrated. Crossover site is the cut point in the figure. The example superchromosomes are the reduced ones and are not the same as those used in the model.

In the mobile network, the system is potentially confronted with a wide range of path characteristics to each receiver. Different users perceive different channel quality based on their location. The concern here with the link failure rate is in terms of the failure of the BS and channel assigned to the MH for communication. The work proposed here considers the channel allocation based on the failure rate of the BS and the channel. With the failure of the BS, we mean the total interference level of signals received from the terminal equipment at the BS, the strength of the transmission power, the signal-to-noise ratio between the terminal equipment and the BS, etc. The failure of the channel is determined by the traversal time of a physical path, which is its mean message response time (MMRT). The channel, in fact, is an end-to-end logical entity. The

exact physical path for the channel is a random event, because traversals of the intermediate links on the path are instantaneous decisions determined by the data traffic and the node availability, which are random factors. As with most of the channel-allocation models, cells are assumed to be hexagonal for simplification and analytical reasons. Each cell has one BS that is responsible for allocating the channels for the hosts inside the cell and the crossing-over hosts to this cell. For experimental purposes, MHs are randomly distributed among the cells, depending on the capacity of the cell. It is assumed that the MHs' movement across the cells is stochastic. The channels are assigned to the cells according to the initial requirement of the network traffic. The probability of applying mutation is often very low. The main weakness of mutation in the channel-allocation problem is the taking–borrowing decisions ahead of time that may result in nonoptimality for two reasons: 1) their effectiveness is not measured in the fitness function,
2) These decisions degrade the future quality of service. Each cell has a set of reserved channels that will immediately be given to a crossing-over MH [3]. The performance of the algorithm is evaluated by measuring the maximum reliability value of the simulated model for the allocation. The proposed algorithm exploits the potential of the GA to improve the reliability of the communication network system by assigning the channels to the MHs based on the reliability computation. The computation of the reliability parameter depends on two factors: 1) the reliability of the BS and 2) the reliability of the channels. The assignment of the channels to the MHs based on the reliability parameter enhances the overall reliability of the mobile network system.

A. Explanation of the Model

The reliability of the communication session depends on the services of the BSs and the links (channels) over a time T, in which the communication is made between the MHs and the corresponding node. The availability of these services depends on the failure rates of the devices (BS) and the links (channels). As previously mentioned, the failure of the BS is determined by various factors such as the total interference level of signals received from the terminal equipment at the BS, the strength of the transmission power, and the signal-to-noise ratio between the terminal equipment and the BS. The failure of the channel is determined by the traversal time of a physical path, which is its MMRT. We, in this model, have chosen the reliability parameter to be represented by exponential distribution, because the reliability of both the BS and the channel is invariable over the time. This condition means that this entity (BS and channel), which has been in use for some time (any number of hours), is as good as a new entity with regard to the amount of time remaining until the entities fail. The reliability of the BS over time t is $e{-}\lambda t$, where λ is the failure rate of the BS, and t is the time of a session i.e., in which the BS is involved in communication between the terminal devices.

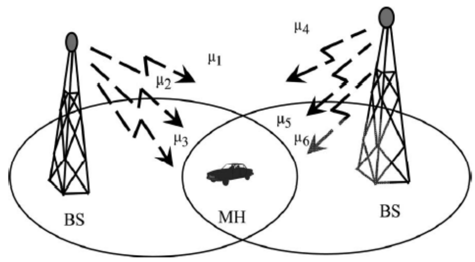

Fig. 4. Network-assigning channels with different failure rates.

If the number of BSs used in the network system for one whole session is m, then the reliability of all the BSs RB in the network for the session is

$$R_B = EXP\left[-\sum_{k=1}^{m}\lambda_k t_k\right]. \qquad (1)$$

This equation is due to the fact that the different BS with different failure rates (λ) are involved over the different time period in one session. Similarly, if the number of total channels used in one session is n, then the reliability RC of all these channels for that session is

$$R_C = EXP\left[-\sum_{i=1}^{n}\mu_i t_i\right] \qquad (2)$$

where μ is the failure rate of the channel (see Fig. 4). Note that the total time taken in a session is T and is evaluated as

$$T = \sum_{i=1}^{n} t_i + \sum_{k=1}^{m} t_k. \qquad (3)$$

The GA is used as a tool for optimizing (maximizing) the reliability, for both the BSs and the channels, in the proposed model. The population with better reliability value, in each generation, will participate for reproduction in one or more of the next generations. The model is designed such that, when an MH requests for a channel (for a new or interhandoff call), it is assigned the channels with better reliability estimate. The simulation study is conducted using the channel-allocation strategy developed in the FTCA model [3] but with different objectives. The intrahandoff technique is also considered in the proposed model so that, in the same cell, the channels are reassigned to replace the host's channels by more reliable free channels as and when it is possible. To observe the effect of communication time on the reliability of the designed network system, an experiment has been conducted for different sessions over the different time periods. An experiment is conducted for the new initiated calls and for the handoff calls.

B. Fitness Function

Based on (1) and (2), the total reliability *RT* of the network system for a communication session is given by

$$R_T = R_B \times R_C. \tag{4}$$

To obtain the best reliability for the designed network system, the reliability *RT* in (4) will be maximized. This function gives the total reliability of a communication session at any time *T*.

C. Algorithm

This section proposes a channel-allocation algorithm to optimize the reliability of the network system using the GA. The algorithm uses a channel-allocation strategy similar to the one in [3] with reliability optimization. The algorithm is given as follows.

1. *Input the total number of channels and the MHs.*
2. *Assign channels to each cell based on the initial demand.*
3. *Input generation_no. // for how many generations to carry on the experiment.*
4. *Initialize generation_index* = 0. *// used as the index*.
5. *Initialize Max_system_reliability* = 0.
6. *Create the initial population*.
7. *Allocate channels to hosts based on the resource planning model.*
8. *Repeat Steps 9–14 until generation_index = generation_number*.
9. *Perform the genetic operations.*
10. *Score the population based on the reliability fitness function. // based on* (4).
11. *Select the best superchromosome as the current superchromosome*.
12. *Output current_ system_reliabilty resulted in the current generation*.
13. *Increment generation_index*.
14. *If* (*current_system_reliability* > *Max_system_reliability*) *Max_system_reliability* = *current_system_reliability*.
15. *Output Max_system_reliability*.

The aforementioned algorithm starts with the initialization of the maximum reliability (Max_system_reliability) of the network system to zero. The maximum reliability that is scored based on the fitness function will be the reliability of the system in the current generation, and the best superchromosome will be selected as the current superchromosome. This process is repeated until the algorithm reaches to the last iteration. Steps 1–7 take a constant time. The complexity of the algorithm depends on the number of iterations and the operations performed within the iteration. The time for the crossover depends on the size of the chromosome and the population size. If the size of the population is *n*, it will be on the order Θ (*n*). Fitness calculation is elementary addition and subtraction; therefore, the time taken in this step is constant. Thus, the complexity of the algorithm will

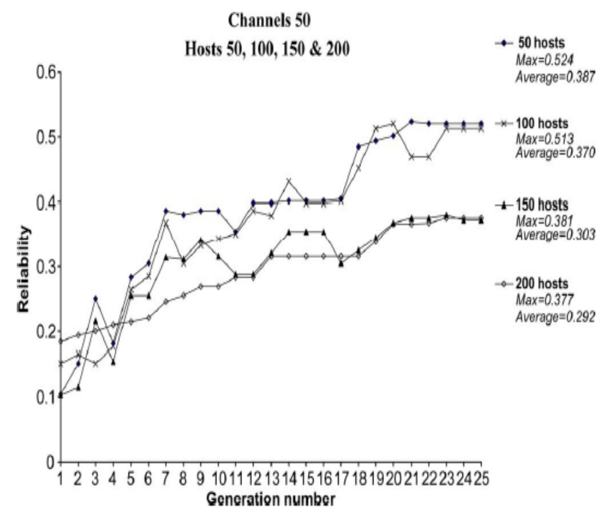

Fig. 5. Fifty channels with varying numbers of hosts.

be of the order of Θ(*nN*), where *N* is the number of iterations.

IV. EXPERIMENTAL EVALUATION

In this section, the performance of the proposed algorithm is evaluated. The experiment is conducted up to 25 generations. It has been observed that the solution converges by 25 generations.

1) Simulation Parameters: The simulation parameters used in the experiment are listed as follows.

- The simulated cellular network consists of 20 cells.
- The total number of channels and hosts in the network are varying.
- The reserved channels, for all the experiments, are 30% of the total number of channels and are distributed among the cells in proportion to the distribution of the MHs. For example, in the experiments with 50, 100, 150, and 200 channels, the reserved channels are 15, 30, 45, and 60, respectively.
- The handoff probability is considered to be 30%, which is in conformity with that of the reserved channels [3]. The results are represented in the performance graphs, where the *x*-axis represents the generations, and the *y*-axis denotes the reliability value.

The experiment is conducted for random values (ranges) of BS failures λ and channel failures μ. The maximum value obtained over the generations is taken as the solution. The input values are as follows.

- $\lambda = 0.1 - 0.3$, and $\mu = 0.4 - 0.8$;
- Number of channels: 50, 100.
- Number of hosts: 50, 100.

An experiment is performed for various sessions over the different time instances. The graphs for the experiment are shown in Figs. 5–8.

We treat the aforementioned experiment for Session 1.

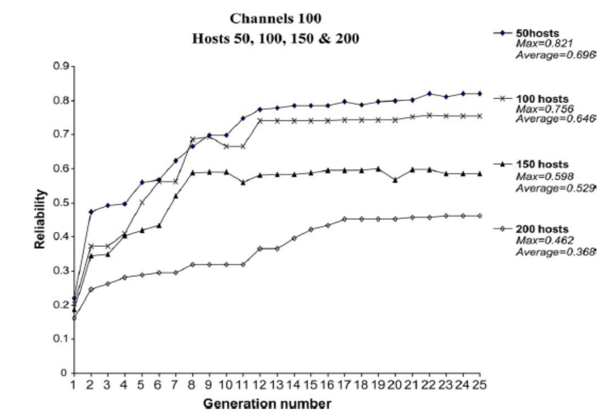

Fig. 6. One hundred channels with varying numbers of hosts.

Results that were obtained for Session 1 are summarized in Fig. 9.

Similarly, the experiment is conducted with the same simulation parameters for other sessions (i.e., on different time instances). The results are summarized in the graphs in Figs. 10–12.

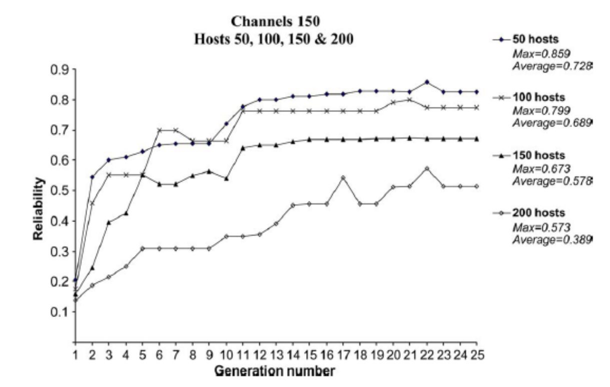

Fig. 7. One hundred fifty channels with varying numbers of hosts.

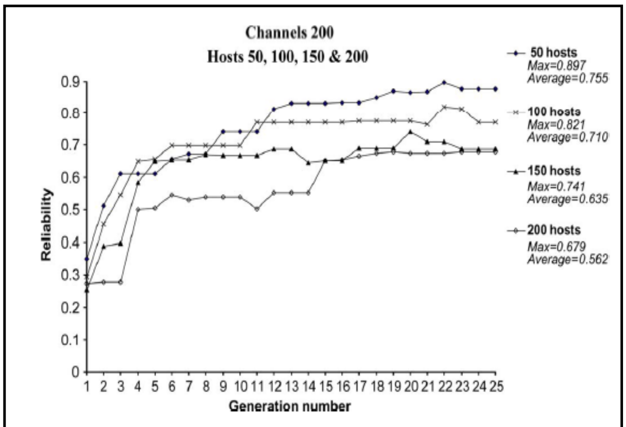

Fig. 8. Two hundred channels with varying numbers of hosts.

The average reliability values of all the four sessions are shown in Fig. 13.

Furthermore, we conducted the experiment by varying the values of λ and μ. First, it is conducted when $\lambda = 0.1 - 0.3$ and $\mu = 0.5 - 0.9$. Simulation has been carried out again for the four sessions, and the average value is shown in the graph in Fig. 14.

The next experiment is conducted when $\lambda = 0.2 - 0.4$ and $\mu = 0.4 - 0.8$. The simulation results for the four sessions and the average value are shown in the graph in Fig. 15.

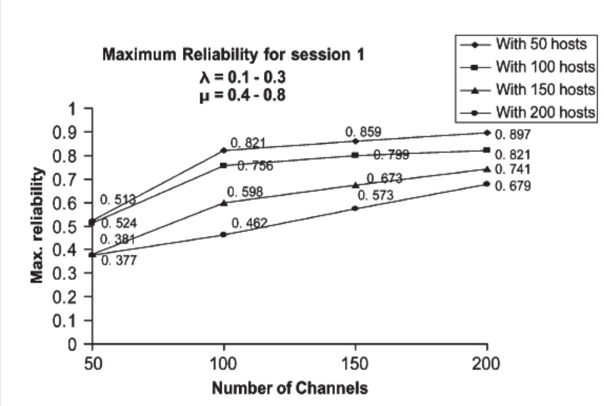

Fig. 9. Results of Session 1.

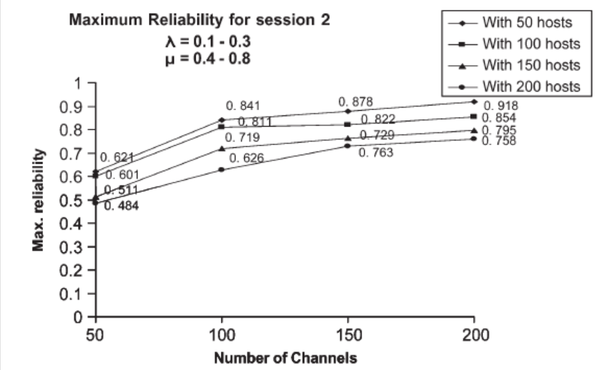

Fig. 10. Results of Session 2.

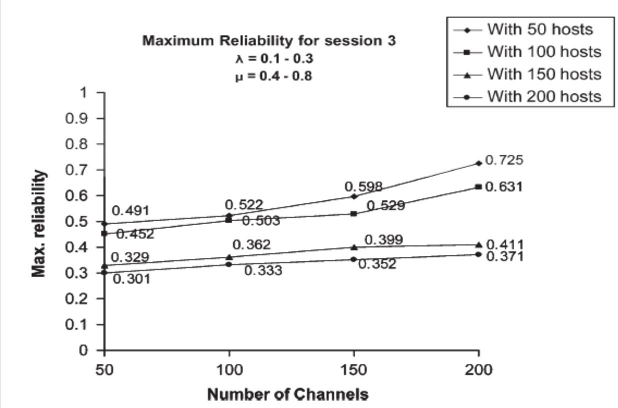

Fig. 11. Results of Session 3.

Another experiment is conducted with $\lambda = 0.2 - 0.4$ and $\mu = 0.5 - 0.9$. The average value obtained with the simulation for the four sessions is shown in the graph in Fig. 16.

V. OBSERVATIONS

Before making our concluding remarks, the following observations have been derived from the results obtained in Section IV.

A. Observations

• Both the maximum reliability value and the average reliability value increases over the generations, as shown in Figs. 5–8.

• It is evident that the proposed model increases the network reliability up to 85% and 89% (see Figs. 7 and 8), respectively and, in some sessions, up to 91% (see Figs. 9–16). Thus, in general, the reliability values increase with the proposed model.

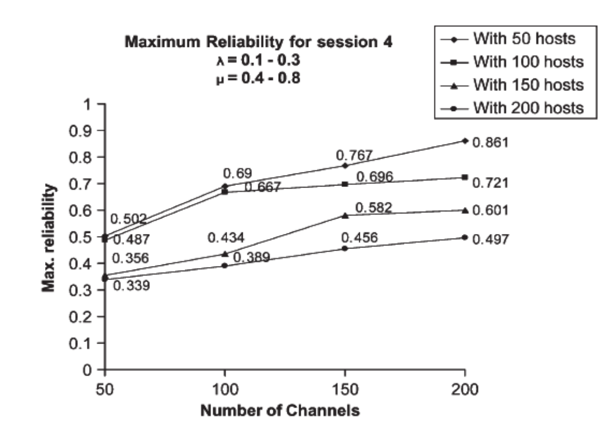

Fig. 12. Results of Session 4.

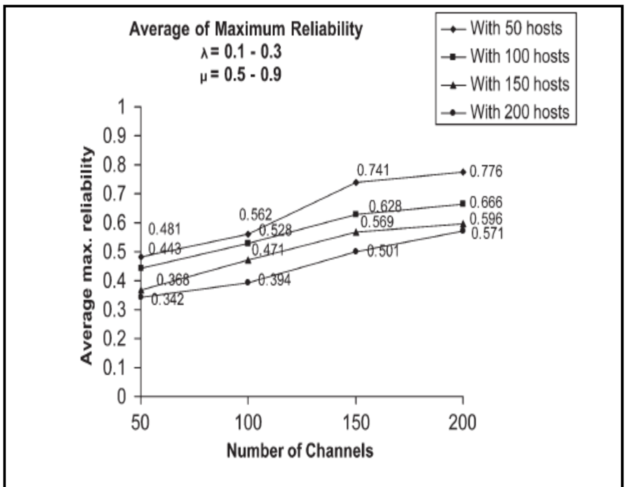

Fig. 14. Average results of the four sessions.

• There is an obvious maximization in the reliability values over the successive generations.

• Although the channels and MHs are randomly distributed through the cells, and some cells may have fewer channels and more hosts than the other cells, the efficient use of the GA results in better reliability.

• In some cases (e.g., Figs. 5 and 6), although the number of channels is small compared with the number of hosts, good results are still obtained.

• For a fixed range of λ, μ and the number of hosts, the increase in the number of channels results in a corresponding increase in reliability (see Figs. 9–16), because increasing the number of channels gives more chances to fetch better channels.

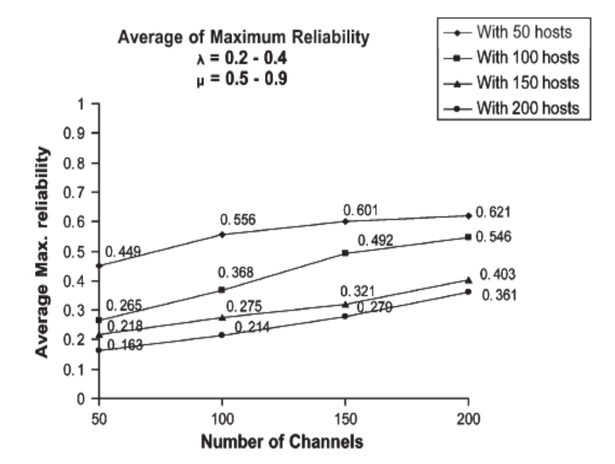

Fig. 16. Average results of the four sessions.

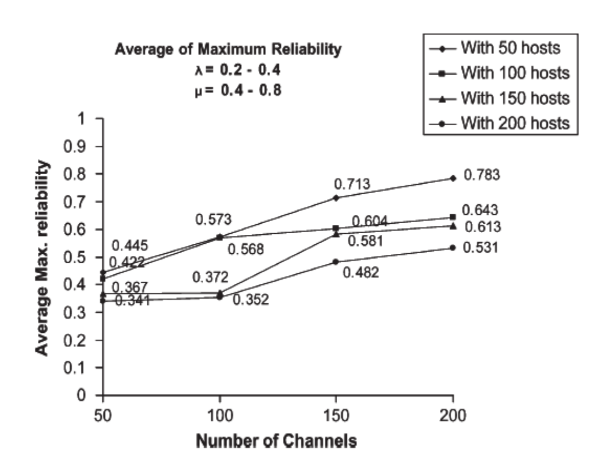

Fig. 15. Average results of the four sessions.

• Convergence in reliability values is notable when the number of MHs is very high compared with the number of available channels.

• It is also notable, for a fixed number of channels and hosts that the increase in λ and μ results in lower system reliability, which is quite obvious (see Figs. 13–16).

VI. CONCLUSION

In this paper, a reliability-based model that uses the GA to optimize the reliability in mobile computing network has been proposed. The proposed model is an effective approach to make the network connections more reliable. It has been observed that the well-managed and efficient usage of the better channels (with lower failure rates) and delivering them to the MHs greatly increases network reliability. The performance of the proposed model has been evaluated by conducting the simulation experiment. It is found that, over the generations, both maximum reliability and average reliability increase, and the result converges after certain generations. The model cannot be compared with any other method, because no other work conducts the channel allocation based on reliability values. The proposed model can be incorporated with other similar models to increase their reliability and effectiveness. In the future, we intend to observe the effect of increasing the reliability on the other quality-of-service parameters of the network system.

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