A HYBRID GAPSO OPTIMIZATION APPROACH

Lutfi Mohammed Omer Khanbary

Computer Science and Engineering Department, Faculty of Engineering
Aden University, Aden, Yemen.

ABSTRACT

In this work, the hybrid techniques of genetic algorithm (GA) and particle swarm optimization (PSO) are presented. PSO and GA are two population-based heuristic search methods that can be applied to the channel allocation optimization problem. GAPSO is based on a mixture of particle swarm optimization (PSO) and genetic algorithms (GA). Individuals of a new generation are produced in GAPSO by PSO in addition to crossover and mutation operations as in GA. In order to reduce the number of blocked calls and handoff failures in the mobile network, the Hybrid GAPSO algorithm is used to allocate tasks to resources efficiently. The proposed strategy optimizes the channel allocation using the GAPSO.

KEYWORDS

channel allocation; evolutionary algorithm; genetic algorithms; particle swarm optimization.

1. INTRODUCTION

Evolutionary computation has inspired new resources for solving optimization problems, such as channel allocation in mobile systems. Unlike traditional computer systems that can perform accurate calculations but have brittle operations, evolutionary computing provides a more robust and efficient approach to solving complex real-world problems [1]. Many evolutionary algorithms, such as genetic algorithm (GA) [2, 3], genetic programming, particle swarm optimization, evolutionary programming and evolutionary strategies, have been proposed. They are less likely to get stuck in local minima because they are heuristic, stochastic, and based on populations composed of individuals with specific behavior that resembles biological phenomena. Because of these similarities, evolutionary computation has become an increasingly important field.

The assignment of channels for simultaneous use in different cells has a direct impact on the throughput of such systems. The efficient use of radio spectrum also determines the 'cost-of-service,' as reducing the number of base stations can result in a lower cost-of-service. Thus, the channel assignment problem is concerned with allocating channels to base stations in such a way that each base station is assigned a predetermined number of channels in order to minimize adjacent channel interference [4-6]. Because there is no simple efficient solution to this optimization problem, many channel allocation strategies have been proposed in the literature [7-12].

Genetic algorithms are well- known examples of evolutionary algorithms. GAs are stochastic hunt procedures grounded on the mechanism of natural selection, genetics, and elaboration. Since they contemporaneously estimate numerous points in the space, they're more likely to find the global result of a given problem. In addition, they use only a simple scalar performance measure that doesn't bear or use secondary information, so they're general- purpose optimization styles for

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such problems. Two major primary areas in which GAs have been employed are optimization and machine learning [2].

Particle swarm optimization (PSO), an evolutionary computation technique, has recently been proposed. PSO, like GA, starts with a population of random solutions. It arose from observations of animal social behavior such as bird flocking, fish schooling, and swarm theory. PSO assigns a randomized velocity to each individual based on their own and their companions' flying experiences, and the individuals, known as particles, are then flown through space. It has constructive particle cooperation; particles in the swarm share information with one another. PSO's potential has been demonstrated through successful applications to a variety of optimization problems [6, 13, 14].

The remainder of the paper is organized as follows. Section 2 discusses the channel assignment problem. Section 3 provides a brief overview of both the GA and Particle Swarm Optimization (PSO) techniques. Section 4 displays the related work. Section 5 elaborates on the GAPSO model. Section 6 presents experimental results to evaluate the model's performance study, followed by some comparative study observations in Section 7. Section 8 contains the concluding remarks.

2. CHANNEL ASSIGNMENT IN MOBILE COMPUTING

As the number of mobile users has increased significantly, the number of mobile devices (hosts) has also increased significantly. The number of mobile hosts unable to connect to the destination (so-called blocked hosts) has increased due to increased load and limited infrastructure. This problem is addressed in two ways. The first is to expand the number of channels while reducing costs. The other approach is to use it efficiently by making the most of the available infrastructure to achieve the best results. The channel allocation problem deals with the distribution of frequency channels between mobile hosts. Mobile channel reuse and handoff are two key concepts in channel allocation. Cells are based on the reuse of channels or frequencies, i.e. the use of the same frequency by different mobile phone users who are separated from each other by a minimum distance without interfering with each other (co-channel interference) [15].

Handoff, also known as handover, is a key idea in cellular networks. When a user switches from one base station (BS) to the neighboring one while still communicating, it is called handoff. The call will now be forwarded to a new channel. The newly established channel could be in a separate cell (intercell handoff) or in the same cell (intracell handoff). These are significant problems in microcellular systems where the cell radius is small. In any cellular system, handoff techniques are important because they irritate the mobile user if they lose connection while switching between cells. Blocking a newly initiated call is better than interrupting an existing one. Handling handoff is critical in mobile computing, as a loss of connection can occasionally result in the need to restart an application from the beginning. Handoffs that effectively handle traffic fluctuations while maintaining high utilization are managed using various techniques [16, 17].

3. GENETIC ALGORITHMS AND PARTICLE SWARM OPTIMIZATION

The hybrid GAPSO utilized in this proposed work combines GA and PSO. The combination of PSO and GA can result in an algorithm that is superior to either method alone [18, 19]. This section introduces the basic ideas of GAs and PSO.

3.1. Basic Concepts of Genetic Algorithms

The survival of the fittest and natural selection are modeled by genetic algorithms. The solutions are shown as chromosomes in GA. The fitness values of the chromosomes are assessed, and a ranking is derived from the best to the worst. Through the repetition of three genetic operators—selection, crossover, and mutation—the GA creates novel solutions by imitating the natural selection of living things. To create new children (new chromosomes), the better chromosomes are first chosen to become parents. The survivor of the fittest, or chromosomes with higher fitness, is selected with higher probabilities than chromosomes with lower fitness. The relative ranking of the fitness values is typically used to define the selection probabilities. The crossover operator combines the parents' chromosomes to create new offspring after the parent chromosomes have been chosen. Stronger individuals may be chosen more frequently, which could result in a decline in population diversity and a tendency for new solutions to become very similar after several generations. This could cause population stagnation. In order to prevent population stagnation, mutations serve as a mechanism to introduce diversity [2, 20].

In addition to choosing the population size and the maximum number of iterations, there are other parameters that need to be considered for GA. One is the fitness-based selection process and probability assignment mechanism. Different selection techniques might call for various probability assignment mechanisms in order to maintain a balance between the new population's diversity and the advancement of solutions. The selection of the roulette wheel and the tournament are the two most popular ones. The crossover probability and crossover method come in second. Since simple crossover methods tend to produce unusable or infeasible chromosomes for many complex optimization problems, there is a large literature reporting number of crossover methods. Finally, because the mutation method and mutation probability have the potential to introduce new elements into the chromosomes and preserve population diversity, they must be chosen.

The basic structure of the GA is shown below.

```
GA( )
{
    Initial population ;
    Evaluate population ;
    While termination criterion not reached
     {
         select solutions for next population ;
         perform crossover &mutation ;
         evaluate population ;
     }
}
```

3.2. PSO basic Concepts

Computer science and social sciences are the two core areas on which PSO is built. PSO also uses the concept of swarm intelligence, which is the characteristic of a system that leads to coherent global functional patterns through the collective behavior of simple agents interacting locally with their environment. PSO takes into account the swarming behavior of swarms of fish, birds or bees as well as human social behavior, from which the concept comes. PSO is an easy-to-use population-based optimization tool that can solve a variety of feature optimization problems. The main advantage of PSO as an algorithm is its fast convergence, which performs well against a variety of global optimization techniques, including Genetic Algorithms (GA), Simulated Annealing (SA), and others [2, 20]. Representing the problem solution in the PSO particle is crucial for the effective use of PSO as it directly impacts its performance and viability [21].

Velocity update and position update are the two main operators of the particle swarm. Each particle is accelerated toward both the global best position and its previous best position during each generation. Each iteration determines a new velocity value for each particle by calculating the distance from the global best position, the distance from the previous best position, and the current velocity. The new velocity value is then used to determine the next position of the particle in the search space [22]. The pseudocode of the PSO algorithm is shown below [24].

PSO ( )
{
Initializing the swarm by giving initial and random values to each particle.
For each particle perform (the following)
{
Calculating the fitness function
If the value of the fitness function is better than the best fitness value (Pbest) in the history then
Set the current value as the new best
Choosing the particle with the best fitness value of all the particles as the (Gbest).
Update the velocity of each particle as

$$v_j^{k+1} = w \cdot v_j^k + c_1 \cdot r_1 (Pbest_j^k - x_j^k) + c_2 \cdot r_2 (Gbest^k - x_j^k)$$

Updating the position of each particle as

$$x_j^{k+1} = x_j^k + v_j^k . \Delta t$$

}
Until the solution converges
}

In the above pseudo code

v_j^k is the velocity of particle *j* in iteration *k*

Pbest is the best solution (position) has been achieved so far for each individual.

Gbest is the global best value for the swarm.

x_j^k is the current position of particle *j* in iteration *k*

w is inertia weight and is varied from *0.4* till *0.9*.

r_1, r_2 are random numbers between 0 and 1.

c_1 , c_2 are acceleration factors that determine the relative pull for each particle towards *Pbest* and *Gbest*, usually $c_1 = c_2 = 2$.

Δt is the time step, *usually =1*.

Figure 1 shows the flowchart for particle swarm optimization algorithm.

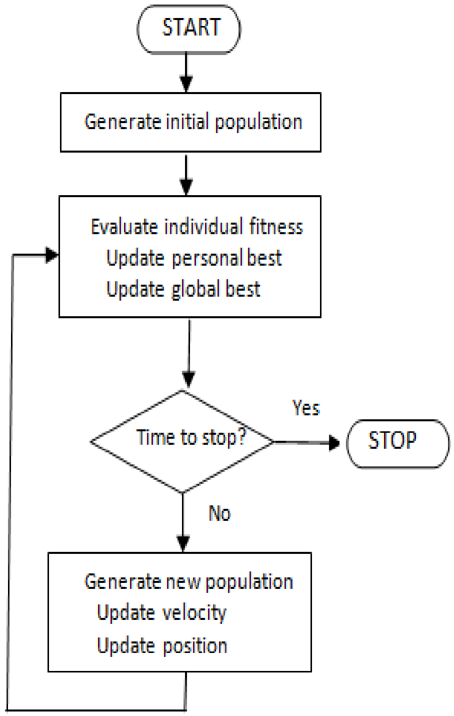

Figure 1. Flowchart for Particle swarm optimization algorithm

4. Related work

A channel allocation model to maximize the consumed power is proposed by [17] using GA. A power management solution is offered to determine the most energy efficient channel allocation in a mobile network. A performance evaluation simulation study shows how accurate the proposed method is.

[25] is dedicated to maximizing the secrecy capacity in V2V-subjected mobile communications. Specifically, it first optimizes the secrecy capacity of vehicular user equipment (VUEs) and then optimizes the sum proportional fairness function for both VUEs and cellular user equipment (CUEs). The optimization problem is solved by applying the genetic algorithm (GA).

In [18], a partial computation offloading technique is proposed to reduce the overall energy consumption of SMDs and edge servers. Genetic simulated annealing-based particle swarm optimization (GSP) is a hybrid metaheuristic algorithm that formulates and solves a nonlinear constrained optimization problem to obtain a near-optimal solution.

A PSO-based method is offered to optimize channel utilization in a mobile computer network and thereby reduce the frequency of call blocking and handoff errors in mobile network systems. The PSO algorithm achieves a fast convergence rate and finds a better solution without getting trapped in a local maximum [23].

A faster convergence rate and a better solution without local maximum trapping were achieved by the proposed and applied hybrid GAPSO scheme to the design of recurrent neural/fuzzy networks in [19].

The hybrid of GA and PSO is introduced in detail in the following section.

5. THE GAPSO MODEL

Below are some of the points and assumptions that the proposed model takes into account. Since the elements of a mobile network (base stations, links, etc.) are prone to malfunction; BSs may crash or stop sending or receiving data. As a result, the allocation process is delayed when the BS of neighboring cells crashes during the free channel search process. This is because the neighboring cell does not respond to the borrowing cell's channel request. It can be assumed that the cells respond to neighboring channel requests with different times [26].

By minimizing interference between transmissions over the same channel, the channel allocation algorithm can reduce the likelihood of interfering with an ongoing transmission and wasting bandwidth. In the FTCA model, we proposed a channel allocation strategy that utilizes an effective co-channel technique [16]. Furthermore, hosts are transmitted over a reserved channel pool [27]. The proposed work has adopted the same. Figure 2 shows the flowchart of the GAPSO algorithm.

The GAPSO algorithm starts by generating a random population and specifies the number of iterations as an algorithmic parameter. The first half of the defined iterations of the GA algorithm are applied to the initialized population; If the number of iterations is (n_i), the GA algorithm is repeated (n_i /2) times. Since the performance of the GA algorithm depends primarily on the technique used to encode solutions into chromosomes and particles, what the fitness function measures, and the size of the population – i.e. the number of iterations – (n_i /2) iteration is used to reduce the complexity of the proposed algorithm [28].

The GA algorithm uses GA operators to incrementally improve the solutions (chromosomes) at each iteration (i.e., crossover, mutation, and selection). The PSO algorithm receives the resulting chromosomes in the second half of the specified iterations. The chromosomes are called particles in the PSO algorithm, and each time the algorithm is run, the particles get progressively better. The particle chosen as the symbol for solving the problem has the lowest fitness value.

A predetermined number of iterations is used to initialize the hybrid GAPSO algorithm. During the first iteration, a solution is randomly launched. After the first iteration, a set of new populations is generated and recursively improved using the previous solutions to generate a set of proposed solutions. The first component of the proposed algorithm is represented by the GA algorithm

In order to identify the best solution among the solutions produced by the GA algorithm, the solutions returned by the GA algorithm are fed into the PSO algorithm along with the remaining calculated iterations. The PSO algorithm refers to the solutions as particles.

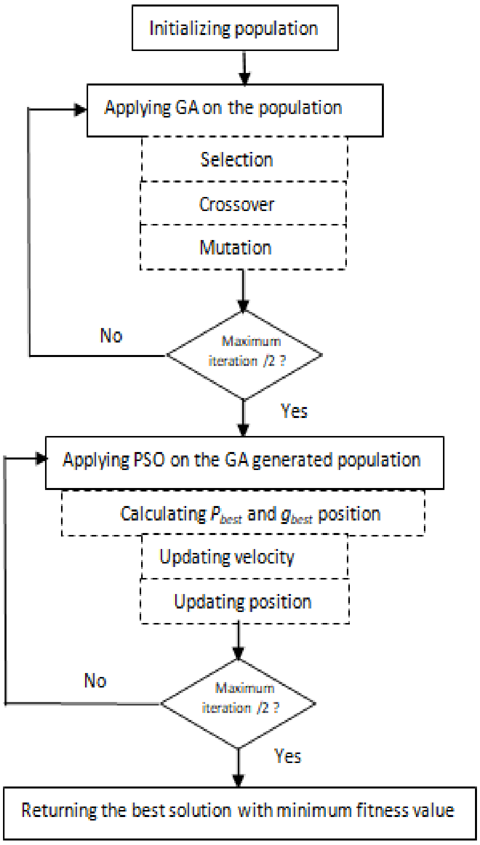

Figure 2. GAPSO algorithm flowchart

5.1. Explanation of the Model

Every cell has a set of reserved channels that are handed over right away to the mobile host that is crossing over (to handle handoff). However, the cell will look for a new channel concurrently. It will assign the new channel to the crossed-over mobile host as soon as it receives it, preserving the reserved channel pool. A cell can lend the same channel to any of its neighbors by using the co-channel interference strategy. Figure 3 depicts a cellular system with a seven-cell pattern.

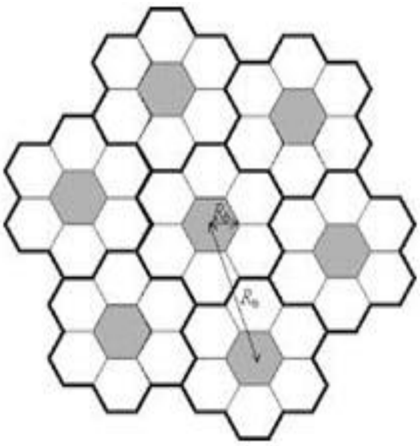

Figure 3. A seven-cell pattern cellular structure.

The following are some of the GAPSO modules in use.

5.1.1. Initial population

The hosts are initially spread among the cells in proportion to each cell's capacity, and the channels are allocated to each cell according to its initial demand. As a result, the values are obtained for every chromosome array.

5.1.2. Encoding

To simulate the designed model, the following encoding is used.

- *A chromosome represents every cell.*
- *A chromosome is a 14-length array.*
- *The number of blocked hosts in the cell is indicated by the first location of the chromosome array.*
- *The number of free channels in the cell is indicated by the chromosome array's second location.*
- *The data regarding the channels lending to six neighboring cells can be found in the following six locations.*
- *The information regarding the channels that are borrowed from six neighboring cells is found in the final six locations.*
- *A cell's chromosome forms a 7 × 14 matrix with the chromosomes of its six neighboring cells.*
- *The combined information from all 7 x 14 cells is that of the entire network.*
- *The 7 x 14 cells are used for all GAPSO operations.*

5.1.3. Selection

Since the issue at hand is dependent on the population's total number of blocked hosts and free channels for each generation, a threshold value is selected based on past experience gauging the population goodness of the channel allocation problem. The network system's performance has been enhanced by the use of the threshold selection operator.

5.1.4. Fitness function

This model uses the following fitness function.
Fitness = blocked_hosts – reserved_channels – prime_channels.

6. COMPARATIVE EXPERIMENTS

Extensive experiments are conducted to evaluate the performance of the algorithms by comparing the results of the PSO scheme and the GAPSO algorithm. Each scenario has a variable time step and a finite running time. In such dynamic systems, variable time step is a feasible solution for reducing search space for problems with large search spaces. Using the convergence/diversity balance mechanism, it creates a robust algorithm for dynamic optimization that not only improves stability and convergence, but also improves the accuracy of results by reducing the optimization time and achieving better performance. Different hosts and channels are used in this experiment. The simulated cell system consists of one hundred hexagonal cells. In the simulation study, both GAPSO and PSO were applied to the same parameters such as traffic load, number of channels, etc. to fairly compare the two algorithms.

6.1. Comparison of Call blocking

Calculating the *average call blocking* with different numbers of hosts and channels is done through experiments. The graphs of performance are displayed in Figures 5-7.

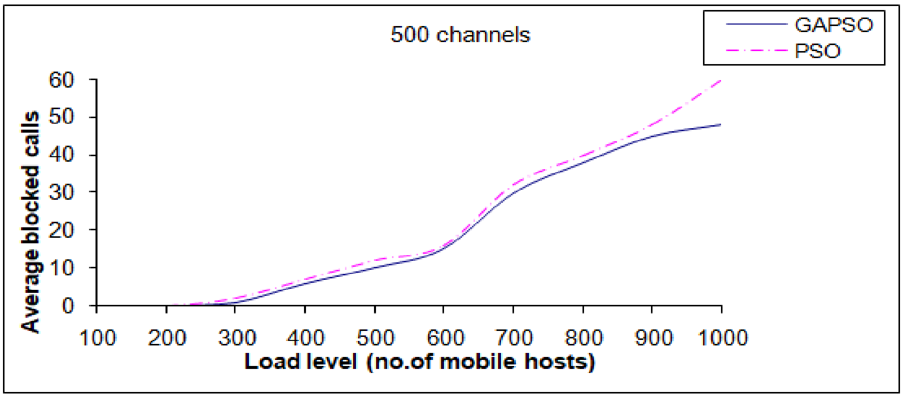

Figure 5.Call blocking with 500 channels and different numbers of hosts

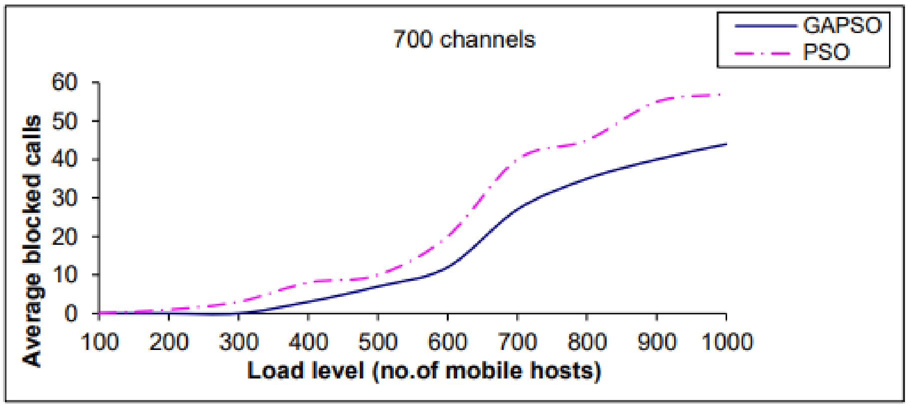

Figure 6. Call blocking with 700 channels and different numbers of hosts

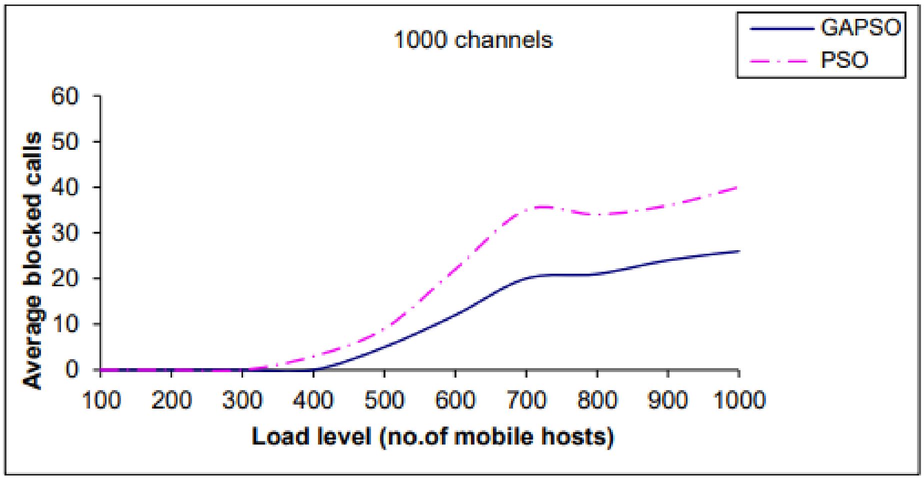

Figure 7. Call blocking with 1000 channels different numbers of hosts

6.2. Comparison of Handoff Failures

Experiments are conducted to determine typical *handoff failure rates* across different host and channel sets. The performance graphs are shown in Figures 8-10

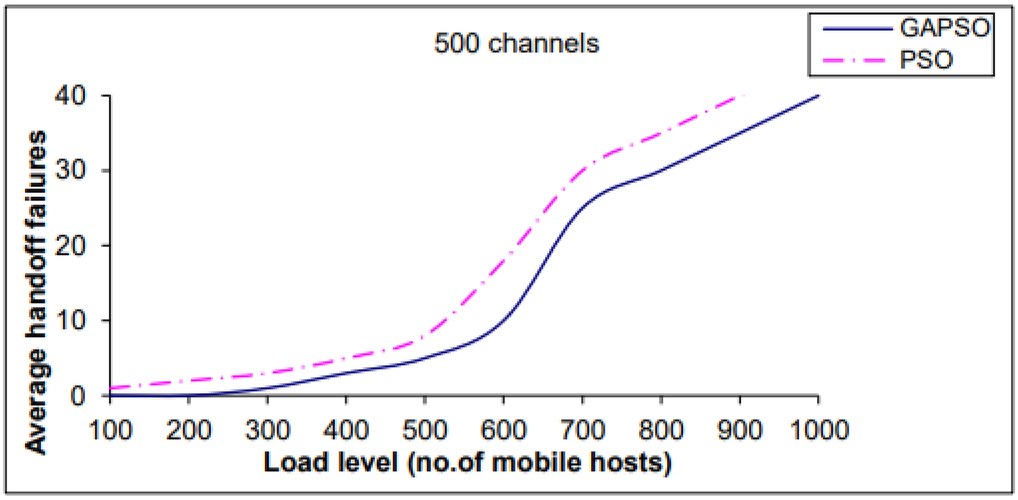

Figure 8. Handoff failures with 500 channels and different numbers of hosts

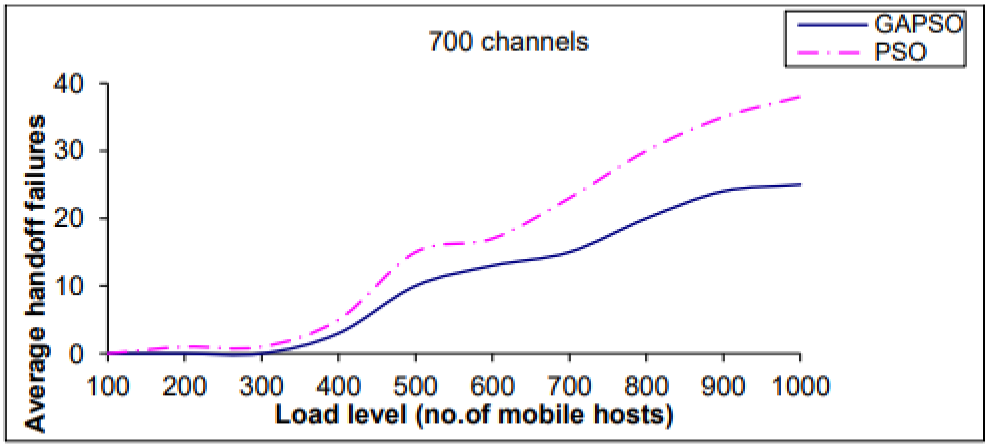

Figure 9. Handoff failures with 700 channels and different numbers of hosts

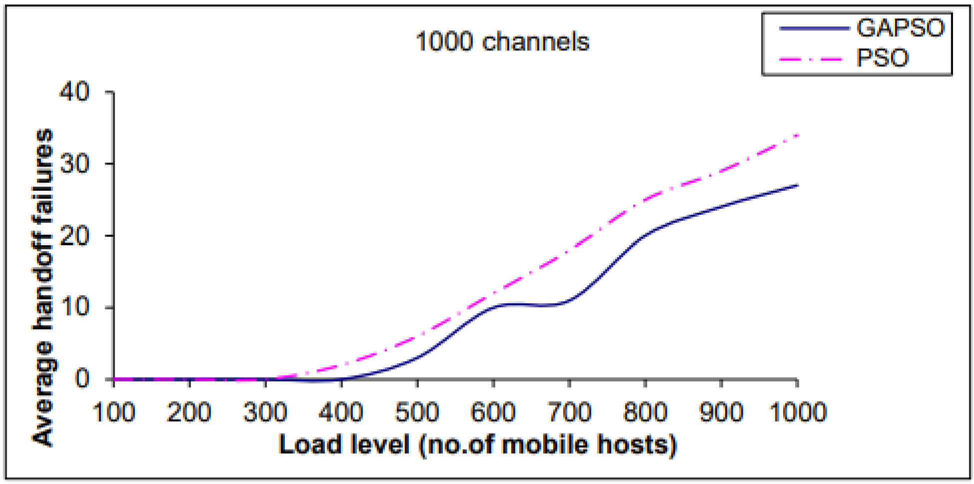

Figure 10. Handoff failures with 1000 channels and different numbers of hosts

7. OBSERVATIONS OF COMPARATIVE STUDY

Based on the performance graphs found in section 6, the following observations have been made.

- As shown in Figures 5–10, the GAPSO method performs better than the PSO-based algorithm in terms of both call blocking and handoff failures.
- As seen in Figures 5–10, both the GAPSO and the PSO based algorithms reduce blocked calls and handoff failures by increasing the number of channels.
- Both GAPSO and the PSO algorithms give near results under light-medium loads, but under heavy load the GAPSO algorithm outperforms the PSO, as shown in Figures 5-10.
- The effective use of the search for available channels to preserve the reserved channel pool prevents the increase in handoff failures beyond a predetermined maximum.
- Due to the initial random distribution of the mobile hosts and channels among the cells, handoff failures and channel blocking occur even when the number of channels exceeds the number of mobile hosts. It's possible for some cells to have more mobile hosts than channels.

8. CONCLUSION

This paper presents the hybrid GAPSO algorithm's optimization of a channel allocation problem. The mobile network channel allocation problem is addressed with an effective solution. Because the hybrid strategy prevents the search process from prematurely convergingto local optima and allows for better exploration of the search process, the GAPSO is more dependable in providing higher quality solutions with reasonable computational times. The suggested plan is a useful strategy for reducing the likelihood of a block in the mobile network. It is also discovered from the simulation experiments that the number of handoff failures in the network decreases with each generation and that the outcome converges after a predetermined number of generations. An experimental comparison study with the current scheme demonstrates how effective it is at preventing blocked calls and handoffs.We have applied the GAPSO to the channel allocation problem, but the same approach is supposed to produce better results for other problems as well. The interested readers and researchers are encouraged to apply the GAPSO approach to various problems and observe the improvement in the performance of the system.

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AUTHOR

Lutfi Mohammed Omer Khanbary has done B.E (Electrical & Electronics Engineering) degree from Faculty of Engineering, Aden University, Yemen in 1995. He completed his M.Tech degree from SCSS, Jawaharlal Nehru University (JNU), New Delhi, , India in 2006 Also, he completed his Ph. D. from SCSS, JNU, New Delhi, India in 2009. Currently he is working as an Associate Professor in Department of Computer Science and Engineering at Faculty of Engineering, Aden university, Aden, Yemen. His current research interests include mobile computing, network management, evolutionary computation, and performance evaluation of computer networks.