ENERGY OPTIMIZATION USING EVOLUTIONARY ALGORITHMS FOR LTE NETWORKS

G. Sindhuja
PG student, Department of Electronics and Communication Engineering,
Pondicherry Engineering College,
Puducherry, India
sindhujaganesh17@pec.edu

V. Saminadan
Professor, Department of Electronics and Communication Engineering,
Pondicherry Engineering College,
Puducherry, India
saminadan@pec.edu

Abstract: LTE is well positioned to meet the requirements of next-generation mobile networks– both for existing 3GPP/3GPP2 operators and 'green fielders'. It will enable operators to offer high performance, mass-market mobile broadband services. In this paper, an optimization technique based on evolutionary algorithm is consideredto achieve improved energy saving in LTE network. Simulation results obtained show significant improvement in energy efficiency and QoS in terms of throughput and end to end delay.

Keywords: *Base station (BS) sleeping strategy, Long Term Evolution(LTE), QualityofService (QOS),Genetic Algorithm (GAs),Bee Colony Optimization (BCO).*

I. INTRODUCTION

Smart grids are new modern electricity grids that are widely seen as a means to upgrade the electrical infrastructure and enhance energy savings and to help optimize the green goals of consumers by reducing greenhouse gas emissions and optimally adjusting the consumed energy. It allows massive integration of intermittent renewable sources, and it offers the possibility to deliver electricity more cost effectively with active involvement of the customers in procurement decisions. On the other hand, mobile networks already contribute around 10% of the total carbon emitted by the information and communication technology (ICT) sector, and this is expected to increase every year due to the extensive growth in the numberof subscribers and service usage times [3]. Studies show thatover 70%–80% of the power is consumed by base stations(BSs). Several studies have been proposed to save energyin radio access networks of the recent fourth-generation Long-Term Evolution (LTE) by turning off BSs during off-peak hourswhen data traffic is low [4 and optimal procurement of energy from the smart grid. Indeed, an active BS in idle status (no transmission) consumes more than 50% of the energy dueto circuit processing, air conditioning, and other factors.Many algorithms and heuristic approaches have been proposedto reduce the number of active BSs, depending on differentcriteria based on varied QoS metrics.

II. LTE NETWORKS

Mobile communication has become an everyday commodity. In the last decades, it has evolved from being an expensive technology for a few selected individuals to today's ubiquitous systems used by a majority of the world's population. The task of developing mobile technologies has also changed, from being a national or regional concern, to becoming an increasingly complex task undertaken by global standards-developing organizations such as the Third Generation Partnership Project (3GPP) and involvingthousandsof people [6]. Mobile communication technologies are often divided into generations as shown in Figure 1.11G being the analog mobile radio systems of the 1980s, 2G the first digital mobile systems, 3G the first mobile system to handle broadband data and 4G being the next in wireless evolution.

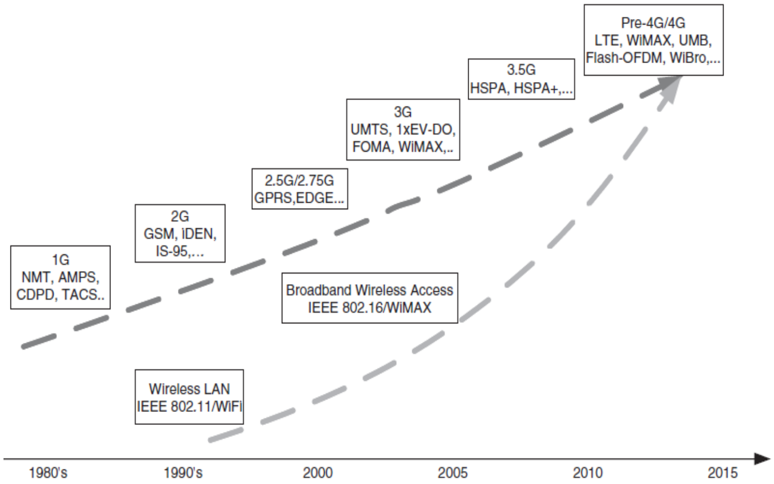

Figure. 1.1: Evolving of technology to 4G wireless

2.1 Architecture

The architecture of LTE is shown in Figure 2.1.

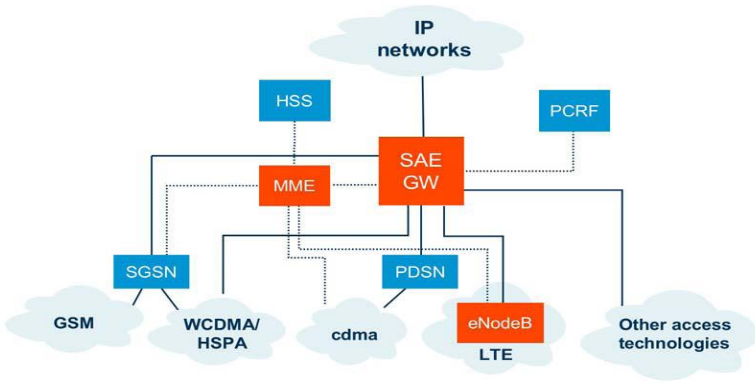

Figure.2.1 Flat architecture of Long Term Evolution and System Architecture Evolution

2.2 Highlights about LTE:

- Peak data rate[DL:100Mbps, UL- 50Mbps]
- Peak spectrum efficiency[DL- 3 to 4 times release 6 HSDPA, UL- 2 to 3 times release 6 enhanced uplink]
- C-plane capacity[supports 200 users per cell in the active state for spectrum allocation up to 5 MHz]
- Mobility support[supports mobility across the cellular network for various mobile speeds up to 350 km/h]
-

III. GENETIC ALGORITHMS

Genetic Algorithms are nondeterministic stochastic search/optimization methods that utilize the theories of evolution and natural selection to solve a problem within a complex solution space. Figure3.1 shows the genetic loop. The principle and the steps involved in GA are discussed below.

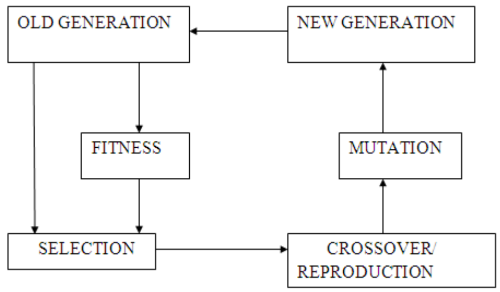

Figure3.1:Genetic loop

Working Principle of Genetic Algorithms (GAs)

Algorithmically, the basic genetic algorithm (GAs) is outlined as below:

Step I [Start] Generate random population of chromosomes, that is, suitable solutions for the problem.

Step II [Fitness] Evaluate the fitness of each chromosome in the population.

Step III[New population] Create a new population by repeating following steps until the new population is complete.

- [Selection] Select two parent chromosomes from a population according to their fitness. Better the fitness, the bigger chance to be selected to be the parent.
- [Crossover] With a crossover probability, cross over the parents to form new offspring, that is, children. If no crossover was performed, offspring is the exact copy of parents.
- [Mutation] With a mutation probability, mutate new offspring at each locus.
- [Accepting] Place new offspring in the new population.

Step IV [Replace] Use new generated population for a further run of the algorithm.

Step V [Test] If the end condition is satisfied, stop, and return the best solution in current population.

Step VI [Loop] Go to step II

Figure3.2 shows the GA flowchart.

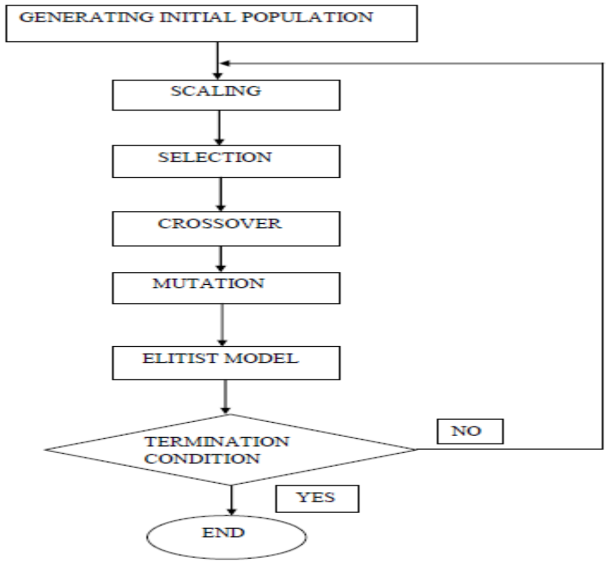

Figure.3.2: Flow chart of Genetic Algorithm

IV. ANT COLONY OPTIMIZATION TECHNIQUE

The main underlyingidea of ACO, loosely inspired by the behavior of real ants, is that of a parallel searchover several constructive computational threads based on local problem data andon a dynamic memory structure containing information on the quality of previouslyobtained result.

V. THE BEES ALGORITHM

Swarm Intelligence (SI) is defined as the collective problem-solving capabilities of social animals.SI is the direct result of self-organization in which the interactions of lower-level components create aglobal-level dynamic structure that may be regarded as intelligence.

As a result of combination of these elements, a decentralized structure is created. In thisstructure there is no central control even though there seems to be one. A hierarchical structure is usedonly for dividing up the necessary duties; there is no control over individuals but over instincts. Thiscreates dynamic and efficient structures that help the colony to survive despite many challenges.

Bee-Inspired Algorithms

Bee Colony Optimization (BCO) was proposed to solve combinatorial optimization problem.BCO has two phases called forward pass and backward pass. A partial solution is generated in theforward pass stage with individual exploration and collective experience, which will then be employedat the backward pass stage. In the backward pass stage the probability information is utilized to make the decision whether to continue to explore the current solution in the next forward pass or to start thenneighborhood of the new selected ones. The algorithmconsists of the following bee groups: employed bees, onlooker bees and scout bees as in nature.Employed bees randomly explore and return to the hive with information about the landscape. Thisexplorative search information is shared with onlooker bees.

VI. SIMULATION RESULTS AND DISCUSSIONS

Network simulation is a technique where a program models the behavior of a network either by calculating the interaction between the different network entities (hosts/routers, data links, packets, etc) using mathematical formulas, or actually capturing and playing back observation network.A *network simulator* is a software program that imitates the working of a computer network. In simulators, the computer network is typically modeled with devices, traffic etc. and the performance is analyzed.The simulation is performed using network simulator 2.35(NS 2.35) software. The simulation parameters are given in table 4.1.

Table 4.1 Simulation Parameters

PARAMETERS	VALUES
Simulator	NS2
Wireless MAC	802.11
Antenna type	Omni-Directional
Antenna Coverage	550m
No. of Nodes	60
Traffic type	Constant Bit Rate, File Transfer Protocol
Packet Size	1500 Bytes

The simulation scenario for the genetic algorithm is shown in Figure.4.1. The same scenario is also considered for ant colony optimization. This network consists of 60 nodes. In the scenario, given below, the green color nodes represent user equipment whereas blue color node denotes the base station. The simulation was carried out using Ns2 simulator. In order to be able to calculate the results from the simulations, the data has to be collected somehow. Ns2 supports two primary monitoring capabilities: trace and monitors. The traces enable recording of packets whenever an event such as packet drop or arrival occurs in a queue or a link. The monitors provide a means for collecting quantities, such as number of packet drops or number of arrived packets in the queue.

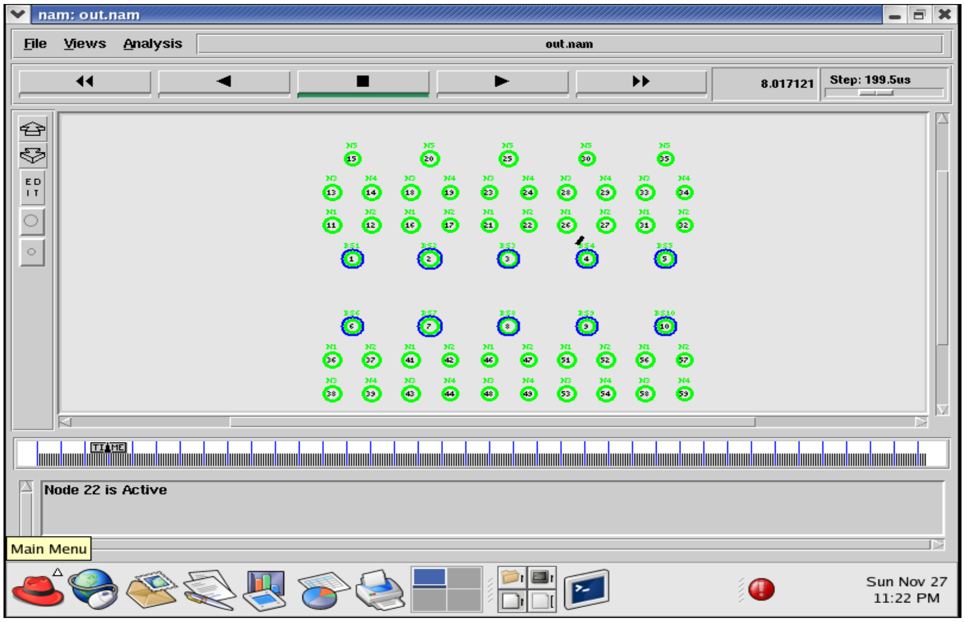

Figure.4.1:Simulation scenario for genetic algorithm

Figure.4.2 and 4.3 show the output graph of throughput VS Time and End to end delay VS Time for Genetic algorithm.

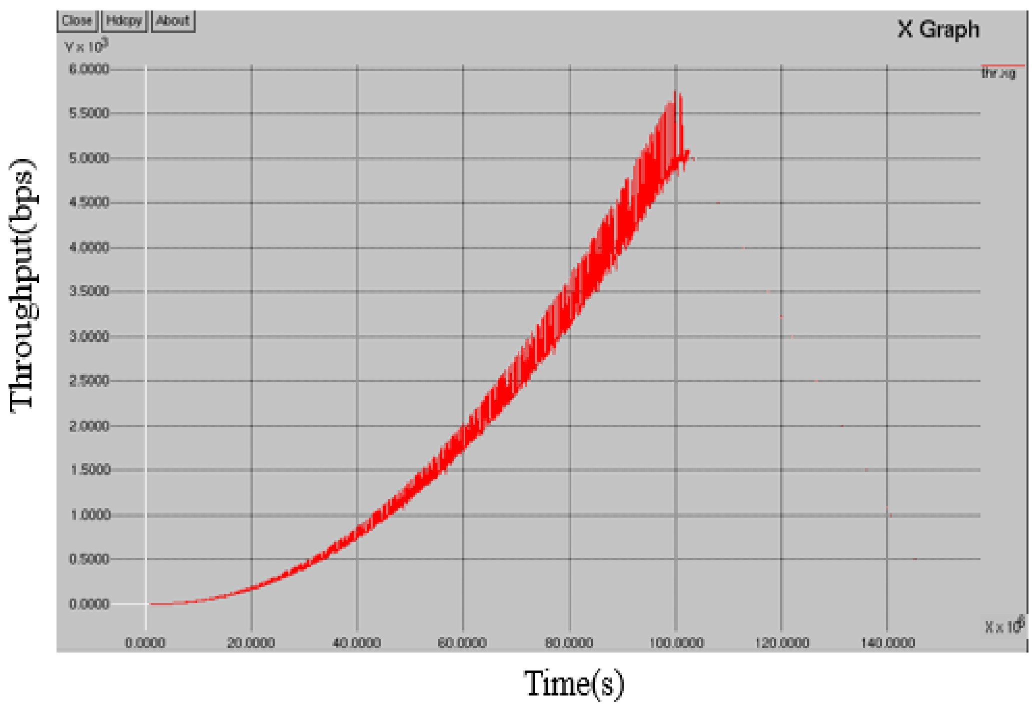

Figure.4.2: Throughput VS Time for genetic algorithm

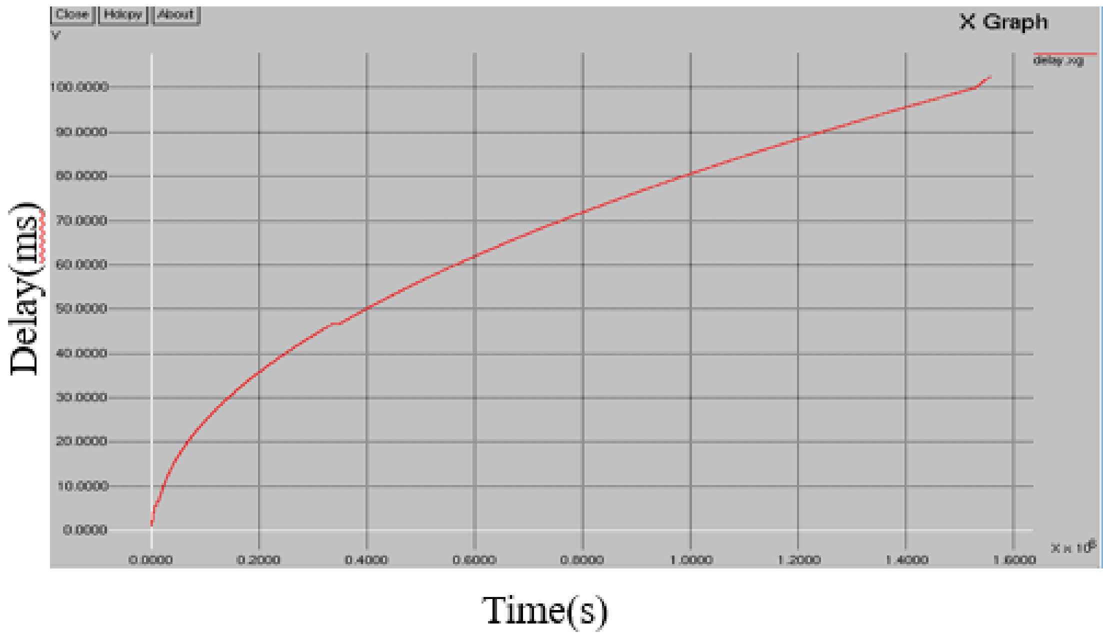

Figure.4.3:End to End delay VS Time for genetic algorithm

Figure .4.4 and 4.5show throughput VS Time and end to end delay VS time for Ant Colony Optimization.

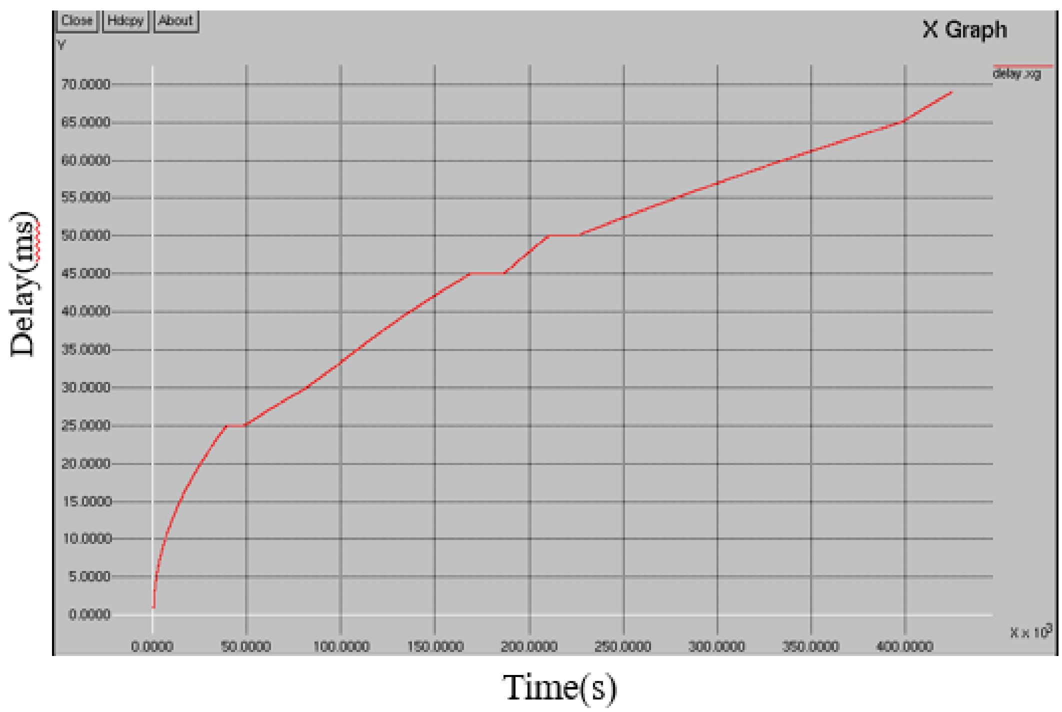

Figure.4.4: Throughput VS Time for Ant Colony Optimization

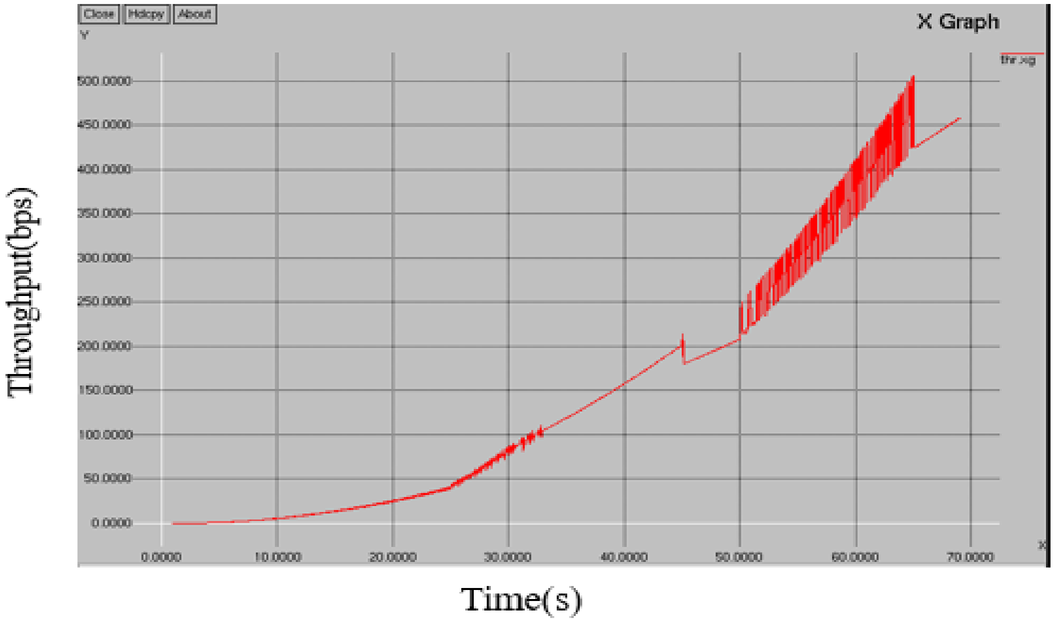

Figure.4.5:End to End delay VS Time for Ant Colony Optimization

Figure4.6,4.7and 4.8compare the performance of genetic algorithm and Ant Colony Optimization in terms of throughput, delay and energy consumption respectively.

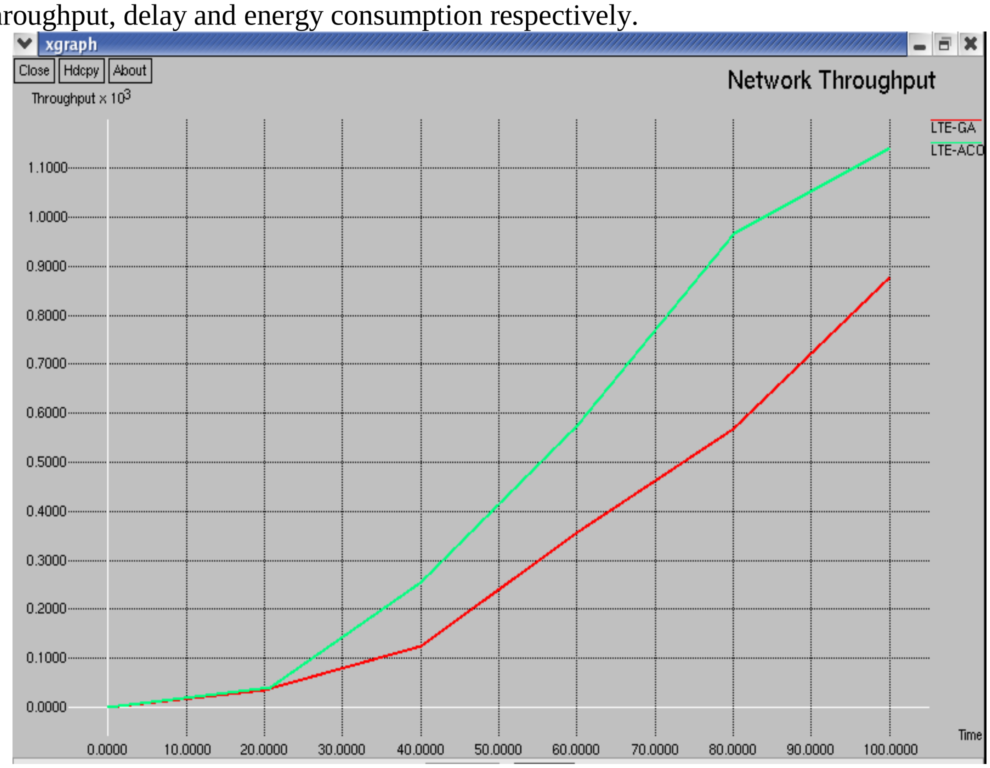

Figure .4.6: Comparison of throughput for genetic algorithm and Ant Colony Optimization

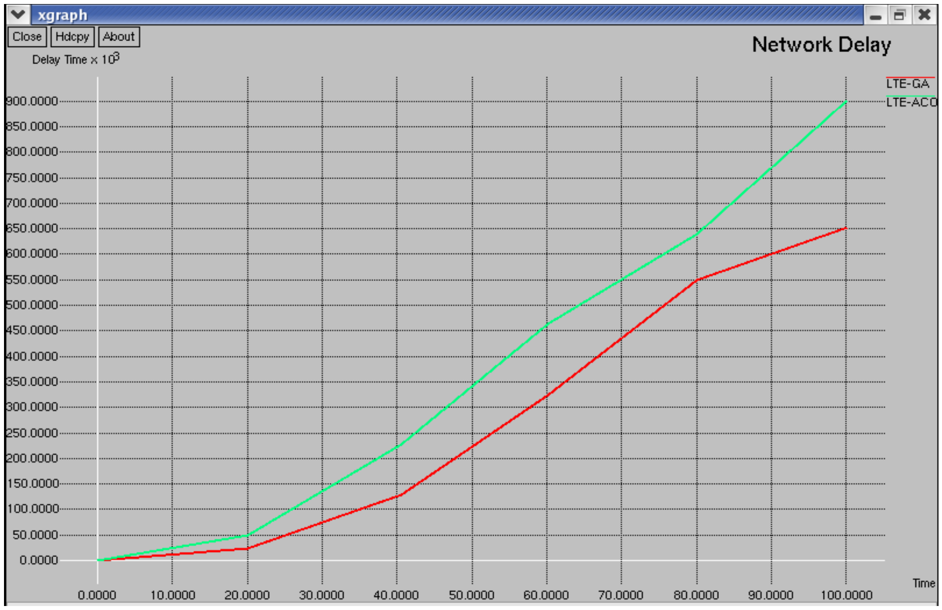

Figure4.7: Comparison of delay in genetic algorithm and Ant Colony Optimization

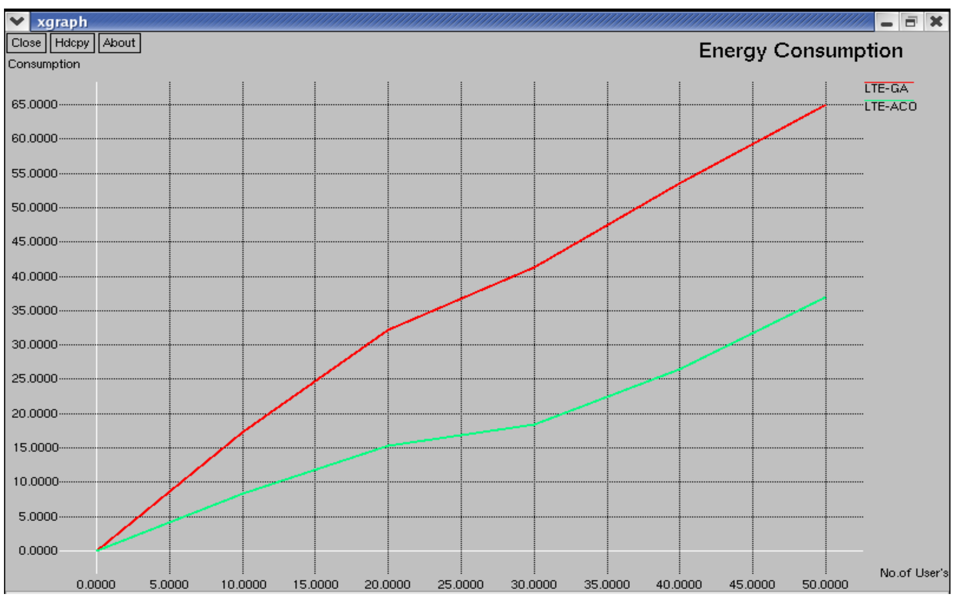

Figure.4.8: Comparison of energy consumption in genetic algorithm and Ant Colony Optimization.

It can be observed from the above figures that ACO outperforms genetic algorithm in terms of throughput and energy consumption. From fig. 4.6,it can be observed that ACO achieves higher throughput than GA because it selects the best base station to serve the UE. This enables that the UE is connected to the BS with strong downlink signal. This leads to higher throughput in ACO when compared to GA. However the End to End delay is higher for ACO as can be seen from fig. 4.7, because the optimization algorithm determines the shortest path to find the fittest BS. This process is not considered in GA.

CONCLUSION

In this project, we have combined the BS sleeping strategyand evolutionary algorithms to achieve energy savings for LTEnetworks without affecting the required QoS.We also showed that, due totheir random evolution process, evolutionary algorithms (i.e.,ACO) can be exploited not only to solve the nonconvexmultiobjective problems but to outperform other deterministicapproaches as well.

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