An Enhanced Genetic Algorithm to Optimize Network Parameters for Soft Handover in Universal Mobile Telecommunications Systems

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Abstract — In the Radio Access Networks guaranteed service levels and performance management are crucial factors because of limited licensed spectrum support of cognitive Mesh mobility and multimedia services. One way to enhance the performance of Radio Access Networks is by selecting appropriate network parameters and parameter optimization. Optimum network parameters can be selected by minimizing its corresponding predefined cost function with respect to key performance indicators and best proposed optimization algorithm. In our approach, enhanced Search and Optimization based Genetic Algorithm is used to optimize UMTS Soft Handover (SHO) Overhead network parameters with proposed (Window Add, Window Drop) to increase capacity and control downlink transmission power through minimizing its cost function with selection, crossover and mutation operations. Enhanced UMTS System Level Simulator with JGAP (Java Genetic Algorithm Package) and Bonn-motion mobility scenario tool is used to optimize network parameters with respect to its proposed cost function (KPI’s) and compared with other existing intelligent optimization Algorithms (Ant colony optimization, Bee Colony Optimization, Particle Swarm Optimization (PSO)). Simulation results shows that the performance of UMTS long term Evolution with modified GA is almost same as Bee colony optimization and outperforms when compared with PSO and Ant colony optimization.

Keywords - UMTS, Enhanced Genetic Algorithm, KPI, Network Parameter optimization.

I. INTRODUCTION

Centrifugal Wireless communications has been seen an eminent growth and will certainly continue its outstanding developments due to the support of new interactive real-time multimedia applications with advanced microelectronic devices. Wireless communications has seen an eminent growth and will certainly continue its outstanding developments due to the support of new interactive real-time multimedia applications which are solely targeted to support digital voice communications with low efficient transmission rates [1]. The major problem with existing IEEE 802.11 wireless networks is the capacity reduction due to collisions among multiple simultaneous transmissions which degrades the performance of the network [2]. UMTS popularity comes with its air interface. UMTS air interface supports heterogeneous networks through GRAN (Generic Radio Access Network). It connects to wide range of networks, such as the internet (packet switched networks), ISDN, GSM (Circuit Switched Networks), or to another UMTS network. The functional diagram of UMTS is shown in Fig. (1), consists of three modules namely User Equipment (UE), Universal terrestrial radio access Networks (UTRAN), and core network. User terminal in UMTS is called UE, which is responsible for communicating with radio interface to transmit voice and data in the form of radio signals. A UE has to support an interface to UICC (Universal Integrated Circuit Card) for insertion of USIM, Service provider information, network registration and deregistration, Location update, Support of both connection-oriented and connectionless services, basic identification of terminal capabilities, Support for emergency calls and support for executing authentication and encryption algorithms. UTRAN is located in between Uu and Iu interfaces which is the “revolutionary” part of UMTS system because of its services provided to manage and control the WCDMA radio resources. Apart from it, UTRAN creates and maintains RAB (Radio Access Barrier) to provide communications in between UE and the core network.

Fig. (1). UMTS Architecture

UTRAN consists of multiple Radio Network Subsystems (RNS) and each RNS contains one RNC (Radio Network Controller) and a collection of Node-B’s. Main functionality of RNC is to manage Radio Resource Management (RRM) and control UTRAN functions. RRM contains algorithms for handover control, power control, admission control and packet scheduling with code.
management. Two RNC’s are communication through Iur interface and the communication in between RNC and Node-B are through Iub interface which carries both signaling and traffic information. Unstable achieved QoS, channel capacity allocation decisions to different traffic types need to be adaptive to the achieved QoS and fast enough to follow these changes [3]. The data coming from Iu-Cs and Iu-PS are multiplexed with Iur, Iub and Uu interfaces to reach UE. The main functionality of Node-B’s are to establish the physical implementation of the Uu and Iub interface and implement WCDMA radio access channels to transfer information from transport channels to the physical channels based on the arrangement determined by the RNC. Each Node-B contains several logical entities called cells. A cell is the smallest radio network entity having its own cell-ID (for radio network topology) and scrambling code (cell logging) used by UE to determine cell identity. Each cell may have several TRX (carriers) and a separate Primary Common Control physical Channel (PCCPCH) containing Broadcast channel (BCH) for broadcasting information to UE’s. Physical channels with Uu interface are used to carry transport channels actual information may be either common or dedicated in nature. Mobile operators can use multiple 5 MHz band with a carrier space of 200 KHz to increase capacity and can provide Bandwidth on Demand (BoD). The functional overview of core network is shown in Figure 1 whose main functionality is not directly related with radio access technology LTE-A to meet the IMT-A requirements [3]. Iu-PS provides interface in between RNC and SGSN (Serving GPRS support Node) to communicate with packet-switched networks whereas Iu-CS provides interface in between RNC and MSC/VLR to communicate with circuit-switched networks. Asynchronous Transfer Mode (ATM) is used as UMTS core transmission i.e. Switched traffic is handled by ATM Adaptation Layer-2 (AAL2) or AAL5 for packed switched networks.

The generic protocol model of the UMTS is divided into three layers namely radio network layer, transport network layer and system network layer in horizontal separation with two planes namely user and control planes in vertical separation. Control planes are used to control connections whereas user planes are used to transmit user data from higher layers [4]. Transport network layer provides transport services for all UMTS network elements to communicate with different interfaces. Radio network layer is responsible for interworking between UE and CN on all radio bearer related aspects. The rest of the paper is organized as follows. Section II explains about related work i.e., brief overview of UMTS soft handover with related network handover parameters, Key Performance indicators with predefined cost function for SHO overhead with downlink transmission power (DLTxPower), Interference above thermal noise level (SIR) capacity and Call Block Ratio(CBR) to optimize SHO overhead network parameters (Add window, Drop window). Section III briefly explains about Enhanced Genetic Algorithm and proposed Work to minimize cost function. Section IV explains about simulation results of SHO Overhead network parameter optimization with comparison to other intelligent optimization algorithms.

II. RELATED WORK

In this section, we first introduce some preliminaries, and present the problem formulation.

A. UMTS Soft Handover

UE measures radio link quality through power on intra-frequency cells of same Node-B’s and neighboring Node-B’s. Once RRC Connection is setup with CELL_DCH (Dedicated Physical Channel) state. Subsequently, it sends a measurement report (Event 1A, Event 1B, and Event 1C) to RNC, which helps to create and update Active Set to determine the best radio link of neighbor cell in same Node-B or different Node-B for handover. This paper is restricted to soft handovers network parameter optimization and various types of soft handover are shown in Fig. (2).

Fig. (2). UE Handover Scenario in UMTS.

In traditional ad-hoc networks, route path in between source and destination are selected irrespective to its operating channel due to static spectrum allocation [5][6].
Soft handover is the process of maintaining at least more than one radio link to communicate with UTRAN through Active Set. SHO is employed in cell boundary areas where cells have overlap. Active Set contains the list of cells where user information will be transmitted from all these cells. Monitored list contains a list of cells who’s Ec /No power is not sufficient to add into Active Set report. In Intra-RNC Soft Handover UE has radio links to at least more than one Node-B’s which are connected to same RNC. In Inter-RNC Soft Handover and UE is connected to more than one base station of different RNC’s. Where one RNC will act as Serving RNC (SRNC) and others will act as drift RNC’s. Serving RNC will combine and split the data from drift RNC’s through Iur interface and communicate with core network through Iu interface which shows SHO as transparent to core network. In Softer handover, UE has radio links for more than one sector within same base station which is shown in Fig. (2). In Uplink rank processing is used to compare and combine multi-path reception of data from different sectors of same base station in softer handover. Whereas data will be compared and combined at SRNC once it receives from different DRNC’S (inter-RNC) or different Node-B’s (intra-RNC’s) in soft handover.

Soft Handover process is divided into three phases namely measurement, decision and Execution. Firstly, UE measures at Primary-CPICH (common pilot channel) and sends to RNC which decides to update Active Set with one of three events namely.

\[ \text{Ec/Io} = \frac{\text{Received Signal Code Power (RSCP)}}{\text{Received Signal Strength Indicator (RSSI)}} \]  

(Event 1A) = Addition of new cell

(Event 1B) = removal of cell,

(Event 1C) = replacement of existing cell

Based on proposed algorithm explained in (1) and Fig.3 with Active Update Set to UE. Execution Phase decides mobile station to enter or leave into new cell. Hence, SHO is mobile assisted, with the criteria and the decision algorithm located in the RNC.

**SHO Active Set Update (Event1-A)**

If \(((\text{Ec/Io})_i > (\text{Ec/Io})_j) \&\&( (\text{Ec/Io})_i > \text{UHB of RR}) \&\&( (\text{Ec/Io})_j > \text{UHB of RR}) \&\& ( (\text{Ec/Io})_j == \text{Monitored Set}) \&\& ( (\text{Ec/Io})_i == \text{Active Set}) \)

{  

   // UHB= Upper Hysteresis boundary  

   Event 1A \leftrightarrow \text{ True; } // \text{ RR= Reporting Range}  

   Add Cell-J from Monitored to Active Set.  

   UE is in Soft handover. (Connected to both cell-i and cell-j).  

}  

(1)

// Event 1-C.—Cell Replacement at Active Set.

If \(((\text{Ec/Io})_i > (\text{Ec/Io})_j) \&\&( (\text{Ec/Io})_i < \text{UHB of RR}) \&\& ( (\text{Ec/Io})_j > \text{UHB of RR}) \&\& ( (\text{Ec/Io})_j \&\& ( (\text{Ec/Io})_i == \text{Active Set})) \)

{  

   Event 1C \leftrightarrow \text{ True; }  

   Replace cell-j with cell-i in Active Set.  

}  

(2)

//Event 1B—- Cell drop from Active Set

If \(((\text{Ec/Io})_i > (\text{Ec/Io})_j) \&\&( (\text{Ec/Io})_i < \text{UHB of RR}) \&\& ( (\text{Ec/Io})_j > \text{UHB of RR}) \&\& ( (\text{Ec/Io})_j \&\& ( (\text{Ec/Io})_i == \text{Active Set})) \)

{  

   Event 3 \leftrightarrow \text{ True; }  

   Remove Cell from Active Set.  

}  

(3)

// Formulae for calculating Event 1A and Event 1B

Cell whose Ec/Io of P-CPICH is largest at the UE can serve as a reference with downlink power allocation from Admission Control. The active set consists of cells, whose received pilot power has higher than pilot power of best cell minus the value of add window. Reporting Range parameter, R, and the hysteresis value, H is used for calculating add and drop window size which is shown in (3). Drop Window is slightly larger than the difference between Event 1A hysteresis and Event 1B Hysteresis value. In general, overhead (extra Connections) increases with increase in add window. Wide SHO( Large Add Window ) Area results unnecessary branch addition, which reduces capacity and increased SHO overhead, where as too small SHO (Add window ) area results reduced UL macro-diversity gain and frequent Active Set Update ( Increased Signal Overhead). window Add can improve the connection quality of the UE especially for high data transmission in Uplink through different cells of Active Set and recombinated at SRNC whereas, in downlink scenario from Node-B to UE, extra power has to be needed due to multiple links from different BS’s with Window Add value which leads to interference with co-channel or adjacent channel. Hence there is a trade-off in between increase and decrease of SHO_Window_add power level because, high overhead causes larger downlink transmission power( causes interference) and lower overhead will reduce the uplink quality and increases signal overhead which leads to higher UE call blocking rate [6][7]. Whenever Drop window is too large, outdated cells will be in Active Set, uplink and downlink capacity will be reduced. On other hand, whenever both add window and drop window is small,
frequent HO occurs, which increases signaling overhead and causes Ping-Pong effect. Hence a cost function for SHO overhead should be defined and optimized with best optimization algorithm to select appropriate add window and drop window parameter values to minimize SHO overhead and improve network performance.

B. Cost Function with Key Performance Indicators

Network Optimization is divided into three phases namely performance measurements, performance analysis and Network Tuning. In initial phase, measurement reports from network elements (UE, Node-B, and RNC) are collected and KPI’s are defined through counters at OSS (Operation Support Subsystem). Number of administrative messages sent over the link by which a mobile node is directly attached to the Internet should be minimized, and the soft messages should be kept as small as possible Packet drops may be occur due to Packet re-ordering problem at the destination [8][9]. Key Performance Indicators are the quantities measured to evaluate the resource utilization per cell (DL power usage, Channel Elements usage) or to measure general performance of the UTRAN elements. Performance-related data for specific business target is collected at Node-B’s and RNC’s mobile switching centers (MSC) to GPRS support nodes at regular intervals of time and transferred to performance management systems through predefined XML reports. KPI values are generated with its corresponding counter values received from network elements. In second phase key performance indicators are analyzed to check target service levels and to find performance degradations areas. Based on collected and analyzed KPI’s from UMTS network parameters (Window Add, Window Drop) will be optimized either manually or with intelligent randomized optimization algorithms whenever business targets are not achieved or network performance is getting degraded. In third phase, RRM parameters will be updated based on performance measurements, KPI’s with defined cost function optimization. SHO is a part of RRM (Radio Resource Management) which is supposed to increase capacity or coverage and QoS by defining optimum static and dynamic parameters [8]. Even though, SHO reduces packet drops (enhances throughput) due to multiple connections resource utilization (SHO overhead) is very high compared with HHO because of simultaneous transmissions from multiple BS’S. Hence, optimum power channel capacity and load control should be maintained in order to maintain optimum network performance which can be done by defining and minimizing cost function with efficient optimization algorithm. In simplest case, cost function C is defined as combination of key performance indicators based on the measurement reports collected from various network elements (UE, Node-B and RNC).

Cost Function C = F1 (KPI1) +……. + Fi (KPIi)  

\( C = \sum_{i=1}^{n} F_n \)  \( \sum_{i=1}^{n} F_n (KPI) (P_0,……,n-1) \)  

(5)

Where \( (p_0, p_1, p_2,……,p_n) \) = Network parameters.

Hence \( C = \sum_{i=1}^{n} F_n (P, t) \)  

(7)

Based on (4) (5) and (7) Generic cost function is defined as function of KPI’s which in turn is the function of network parameters \( (P0,……,n-1) \). Hence cost function is defined as function of network parameters with respect to time as shown in (6). Optimization of cost function is not straight-forward in live networks because of variation of traffic types and load distribution which varies with respect to time. Hence, optimization algorithm has to adapt to such variations in the network and able to track these changes based on the network measurements. Once dominant transmit power connection is established, the transmit powers for SHO connections should be allocated with the difference of CPICH power of connected base station with CPICH power of best downlink base station.

III. PROPOSED GENETIC ALGORITHM

Genetic algorithm is powerful stochastic, probabilistic based search and optimization algorithm that iteratively transforms a set of mathematical objects called population, based on principles from evolution theory with associated fitness value by Darwinian natural selection, crossover and mutation operations. The aim is to provide maximum or minimum optimal solution for defined cost function. The algorithm usually starts with randomly generated initial population \( M(0)) \) [11]. Secondly, fitness value \( u(m) \) for each individual ‘m’ in the current population \( M(t) \) with cost function is computed and saved. Thirdly, Selection probabilities \( p(m) \) for each individual \( m \) is defined in \( M(t) \), so that \( p(m) \) is proportional to \( u(m) \). Fourthly, generate \( M(t+1) \) by probabilistically selecting individuals from \( M(t) \) to produce offspring via genetic operators. Algorithm will run until it reaches to global optimized value with newly generated population as input for generic operator. The basic terms used in GA are shown in Figure.4 and operation of Genetic Algorithm is explained in Figure.5.

Probability \( P(x) = f(x_i) / \sum_{j=1}^{n} f(x_j) \)  

(8)

Expected Count \( E_i = n * P_i (x) \)  

(9)

Where \( n \) = Number of individuals in population.

Compare (Fitness1, Fitness2)

Where \( x= \) size of population.

\( x_1, x_2 , x_3,......x_n \) is individuals in population

// Selection Procedure

If \( (f(x_i)>f(x_j)) \)  

(10)
In this paper, binary encoding is used to convert the individuals (chromosomes + fitness value) of population. In GA, Pair of individuals from the population will be selected based on probabilistic manner weighted as shown in (10) their corresponding fitness and designated as parents.

Figure (4). Basic terms in Genetic Algorithm

In this approach, Roulette-wheel technique is used for selecting best individuals from the population for crossover and mutation. Each individual in the population is assigned space on the roulette wheel proportional to the individual’s relative fitness. The wheel is spun each time a parent is required [10]. Individuals with the largest spaces on the wheel have the greatest chance of being selected and, therefore, the greatest probability of passing on their characteristics to the next generation. Equation (11) explains about the procedure to select the individuals of best fitness value for crossover and mutation. Children, a pair of offspring are generated from the selected pair of parents with crossover and mutation operations which is shown in Figure.5. Crossover occurs with a probability based on random selection and the combining of two parent’s genetic information. Array of population with individual, chromosome and fitness value is considered as generation. In general, Selection operation is applied first to population and crossover, mutation are applied to outcome of selection operation. In our approach, crossover and mutation are applied first and selection operation is applied to outcome of crossover and mutation operation. One advantage with our approach is, new offspring will be generated first and best offspring will be selected subsequently. One way is by replacing the previously generated population with newly generated population where memory is efficiently utilized. In Second approach, generated populations are buffered like array of generations and sorted with individuals of best fitness value. Optimization will be faster in second approach compared with first because of pool of data generations. Offspring-1 receives the chromosomal substring that precedes the cross-site in parent-1 and the substring following the cross-site in parent-2. Offspring-2 gets the remaining genetic information not given to child 1. The two produced offspring’s share the characteristics of the parents as a result of these recombination operators. Other recombination operators are sometimes used but crossover is the most important. Recombination (e.g., crossover) and selection are the principle way that evolution occurs in a GA optimization. In this approach, crossover is applied as a combination of both single-point and multipoint crossover. In GA, crossover probability and mutation probability are the deciding factors to optimize the cost function [11] i.e. time taken to optimize the cost function directly depends on crossover and mutation probability values. In this, probability for crossover and mutation are considered as 0.2. In Mutation, allele of gene within the same selected parent is changed based on the probability whereas; next generation will be replaced with previous old generation. In general, two different approaches are used to buffer population or generations. Eventually, it is important to select appropriate termination approach to sack the flow of algorithm. In general, GA can be terminated with different methodologies. In our approach, combination of population convergence and number of iterations are used to terminate the algorithm which is shown in Fig.(5).
Initially, default random network parameters (Window Add, Window Drop) are set and its performance is monitored through Key performance Indicators from UMTS network. Once the KPI’s of Downlink transmission power, signal-to-noise ratio and Pilot-CPICH KPI’s are calculated, its performance will be compared with target business service levels. Whenever, UMTS network performance gets degrading or its KPI thresholds are less than required target thresholds, GA runs to optimize SHO overhead cost function and tunes the optimized predicted network parameters to UMTS network. Firstly, chromosomes are randomly generated with predefined range. Fitness value is generated with SHO cost function using randomly generated chromosomes. Binary encoding is used to encode the individual (chromosome + Fitness). Population Size plays an important role in GA optimization. Whenever the size of the population is small, its convergence time is less and vice-versa is true. With less population size, there is a possibility of local convergence which leads to local optimization. Hence, selection of population size is crucial for GA optimization performance. Firstly, two population sizes 500, 1000 are considered, compared with respect to their convergence time, number of iterations and considered as population size to be 1000.

IV. SIMULATION RESULTS

Enhanced UMTS System level Simulator (ns-2.1b9a) with Bonn-Motion mobility Scenario Generation Analysis tool and JGAP (Java Genetic Algorithm Package) is used to minimize SHO Overhead cost function with modified Genetic Algorithm.

On the other hand, other intelligent based algorithms like Bee Colony optimization, Ant colony optimization and Particle Swarm Optimization with our predefined SHO cost function are used to simulate and compare the performance of UMTS network with modified GA. Network topology is considered with 25 micro cells which are arranged as grid within building blocks and crossroads with Omni-antennas and base stations in outside building. Manhattan Grid Mobility Model is used as scenario with 1000 users and mobility speed as 2 Km/h. are analyzed and compared. Subsequently, downlink transmission power, Signal-to-interference ratio and block or bit-error-rate are re-calculated for each active connection in uplink, downlink and check the performance of overall UMTS network at first time frame.

Predicted optimized network parameters generated from different optimization algorithms (GA, ANT, BEE) are used to tune the network in subsequent timeframes whenever, its target service levels are not achieved due to capacity limitation or frequent SHO (small Window Size) or frequent Active Set update. Optimization Algorithms (GA, ANT, BEE) run until required QoS (Quality of Service) of overall UMTS network performance is achieved.

Finally, GA simulation results are analyzed and compared with other intelligent optimization algorithms with respect to performance of UMTS network due to SHO overhead. Overview of SHO E-UMTS simulated network is shown in Figure 6. It consists of Node-B’s, cells, active and in-active users. When network is simulated, at each and every timeframe its downlink TxPower, SIR (Signal to Interference Ration) is monitored. SHO Cost Function will be optimized using GA, whenever its QoS is below target levels. Cost Function optimization for each and every optimization algorithm (ANT, BEE, PSO) will be performed individually and compared with GA. Moreover,
it is important to select best GA operator for most effective performance results. Figure.7, explains about time taken to optimize cost function with different GA operators (Selection, crossover and mutation). Firstly, leftmost two graphs of Fig.(7) explain about comparison of two popular GA selection operators with population size 500 and 1000. Top left most graph compare Roulette-wheel selection and tournament selection with population size as 500 and bottom left graph compares same roulette-wheel selection and tournament with population size 1000. As shown in Figure.7, it is clear that in both cases roulette-wheel outperforms compared with tournament selection. Even though, time taken to optimize roulette-wheel with population size 500 is relatively less compared with roulette-wheel with population size 1000, it is good to select roulette-wheel with population size 1000 because larger population size has fewer tendencies for local convergence and local optimization. Hence, in our approach Roulette-wheel with population size 1000 is considered for selection operation. Top rightmost graph of Fig.(7) explains about comparison of crossover operator with different probabilities (0.2, 0.4). From graph, it is clear that crossover with 0.2 probability reaches to optimal point quickly compared with 0.4 probability. This is because, high crossover probability results in frequent crossover of individuals which takes longer convergence time. Hence, crossover with 0.2 probability is considered for crossover operation. Bottom rightmost graph of Figure.7 explains about comparison of mutation operation with probability 0.2, 0.4 and selected 0.2 in our approach. The total numbers of iterations are considered as 100. From Figure.8, one can say that optimum SHO value for GA is achieved approximately at 18th iteration, and 20th iteration for BEE whereas it has taken almost 35 iterations for PSO and 50 iterations for ANT Optimization algorithm. Hence the time taken to optimize SHO overhead cost function with GA and BEE are almost same and relatively less compared with ANT and PSO optimization algorithms. Whenever, target levels are not achieved due to interference and call blocking, optimization algorithm will run with cost function and key performance indicators. Predicted network parameters from cost function will assign to network until it satisfies required target service .indicators with modified Genetic Algorithm shows increase in network capacity and decrease in downlink TxPower to satisfy required business targets which enhances the overall performance of radio access network compared with other Once cost function is minimized with maximum fitness or object function from corresponding optimization algorithm (GA, BEE, PSO and ANT), its corresponding network parameters (Window Add, Window Drop) will be predicted and tune to UMTS network.

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Predefined cost function is proposed for Soft handover network parameter optimization and modified genetic Algorithm is used to optimize object function and reduce SHO overhead. In addition, other intelligent optimization algorithms (BEE, PSO, and ANT) are used to optimize the same predefined SHO cost function and compare with GA simulation performance results. Predicted optimized network parameters (SHO Window Add and Window Drop) from GA, BEE, ANT and PSO are assigned to simulated network and monitor the performance of network. Optimization performs until cost function of soft handover network parameter optimization reaches to optimal or best value for all algorithms in different simulations scenarios. Results shows that proposed modified GA optimization algorithm performance is almost same as Bee Colony optimization and better than ANT and PSO techniques which reduces uplink and downlink blocking ratio compared with non-optimized simulations of blocking ratio. Downlink TxPower gets reduced with optimized simulations compared with non-optimized simulations. This results in minimization of interference with neighbor cells and increase in capacity of radio access network. In future, network parameters for SHO gain will be studied in detail and try to implement in existing

V. CONCLUSIONS

Predefined cost function is proposed for Soft handover network parameter optimization and modified genetic Algorithm is used to optimize object function and reduce SHO overhead. In addition, other intelligent optimization algorithms (BEE, PSO, and ANT) are used to optimize the same predefined SHO cost function and compare with GA simulation performance results. Predicted optimized network parameters (SHO Window Add and Window Drop) from GA, BEE, ANT and PSO are assigned to simulated network and monitor the performance of network. Optimization performs until cost function of soft handover network parameter optimization reaches to optimal or best value for all algorithms in different simulations scenarios. Results shows that proposed modified GA optimization algorithm performance is almost same as Bee Colony optimization and better than ANT and PSO techniques which reduces uplink and downlink blocking ratio compared with non-optimized simulations of blocking ratio. Downlink TxPower gets reduced with optimized simulations compared with non-optimized simulations. This results in minimization of interference with neighbor cells and increase in capacity of radio access network. In future, network parameters for SHO gain will be studied in detail and try to implement in existing
optimization algorithms with proposed predefined cost function.

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