Multihop Cellular Network optimization using genetic algorithms

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Abstract- Future cellular systems demand higher throughput as an important requirement, along with smaller cell sizes to characterize the performance of network services. This paper purposes a way to optimize the multihop cellular network (MCN) deployment in LTE-A/Mobile WiMAX broadband wireless access systems. A simple way to optimize the MCN is to associate direct and multihop users based on maximum channel quality and allocate the resources blocks dynamically based on traffic load balancing as adjustment variables. The changing traffic demands require dynamic network reconfiguration to maintain proportional fairness in achieving the throughput. A self optimizing network based on genetic algorithm (GA) is made to adaptively resize the cell coverage limit and dynamically allocate resources based on active user demands. A policy control scheme to control resource allocations between direct and multihop users can be either fixed resource allocation (FRA) or dynamic resource allocation (DRA).

Key words-coverage; capacity; multihop cellular network; genetic algorithms;

I. INTRODUCTION

An essential requirement of next generation wireless networks deployment is to achieve dynamic system reconfiguration by combining network planning with radio planning. However, wireless deployment face changing situations, due to time variant traffic demands, due to occurrence of faults, due to mobility and due to varying radio system parameters necessitates the feature of self organizing networks. The concept of self organizing networks will adaptively configure resource management techniques supported with enhanced monitoring of the network for intelligent decision making. Currently deployed cellular networks are based on overlapping base stations (BSs) to provide network services like voice and data to large number of end user devices (MSs) by allocating the resources by prioritizing the quality of experience (QoE). However, this kind of deployment by its own cannot satisfy future demands of wireless systems without further deployment of BSs, especially in a reasonably large or densely populated areas. A newly proposed LTE-A/Mobile WiMAX approach is to employ relay stations (RSs) as intermediate nodes to establish multihop transmission areas between MSs and their corresponding BSs to enhance the QoE is termed as multihop cellular networks (MCNs). However, depending on the size of their coverage areas, this can be called as fixed RSs to provide coverage within the donar BS to enhance the channel quality and to provide a cost effective operational solution than BSs.

In addition, the relay deployment allows flexible and fast network rollout, which is particularly important at the initial stage of system testing, where an extensive deployment of BSs may not be economically viable. Although, each BS cell is assigned with finite number of resource blocks and preinstalled RSs are available to regulate traffic from hot cells to cool cells to balance traffic load among highly loaded cells and lightly loaded cells. An important aspect of deploying a relay station in a cellular network is to fully evaluate its network performance on a practical view point. However, relay deployment done with various objectives such as increased throughput and enabling high spectral efficiency extension needs possible changes to system parameters with intelligent decision making. Fast changing system conditions require quick convergence and faster adaption needs to minimize the search space to reach the required optimality condition without affecting network performance. An evolutionary approach using genetic algorithms (GA) is adopted for this. The related works are briefed in section II. The network model with problem formulation is discussed in section III provides. The proposed approach using GA is briefed in section IV. The simulated analysis is given in section V with conclusion in section VI.

II. RELATED WORKS

To achieve spatial diversity without requiring multiple transceiver antennas on the same node is to use multiuser diversity. In an environment, when many users fade independently, at any time there is a high probability that one of the users will have a strong channel. By allowing only that user to transmit, the shared channel resource is used in a most efficient way and the total system throughput is maximized in the MCN network.

Ng and Yu in [1] studied a utility maximization problem for the joint optimization of relay node selection with resource allocation in a cellular network. The key assumptions of the solution are to optimize an infinite number of resources in the network. But, this assumption may not hold in practice. Yu et al. in [2] provides a two-tier assignment variant to model MCN with the assumption that the RSs and BSs are uncapacitated. A clustering approach with fixed number of RSs and BS are considered, so that the top-level assignment can be treated by a p-median to reduce the cost of BS/RS. Lin et al in [3] gives a location planning for RSs with bandwidth allocation to satisfy traffic demands. The benefits of cooperative relaying to achieve higher data rate with cell coverage at different power levels are provided as solution. Sheen et al. in [4] provides the downlink performance limits in a fixed number of relay scenarios to provide fixed bandwidth allocation and fixed throughput allocation using genetic algorithms. Niyato et al. in [5] provides an optimization of RS placement and bandwidth reservation under random arrivals and departures of mobile users in the extended service area. A stochastic programming formulation for RS placement and a markov decision process for random arrivals of users are used to obtain the solutions. Yu Ge et al. [6] investigated the selection of optimal RSs for a vehicular network in maximizing the network capacity.

The proposed approach combines the work of Sheen et al and Niyato et al, but here we optimize jointly the relay user channel quality with resource allocation to balance the traffic load between the BS and the RS users using policy control of either fixed resource blocks strategy or dynamic resource blocks strategy to enhance the network performance.

III. MCN Network Model and Problem Forumulation

A MCN single cell structure with one BS, six RSs and random MSs distribution in a particular cell area is shown in Figure.1. In a wireless access network, the strict line-of-sight (LOS) requirement cannot be assumed. In this case, RSs can be placed for access providing good channel quality with sufficient resource allocations to satisfy the user demands. A MCN network does not interfere with each other as long as the RSs are placed far apart from each other with combined TDD and FDD. However, users using the multihop RSs are located on the same frequency spectrum with the BSs, sharing the sub channels in a time multiplexed fashion while not exceeding the sub channel resource allocations of RSs using OFDMA transmission. Each user specifies their uplink and downlink demands, and the system can allocate the required resource blocks based on traffic load between the BS and each RSs.

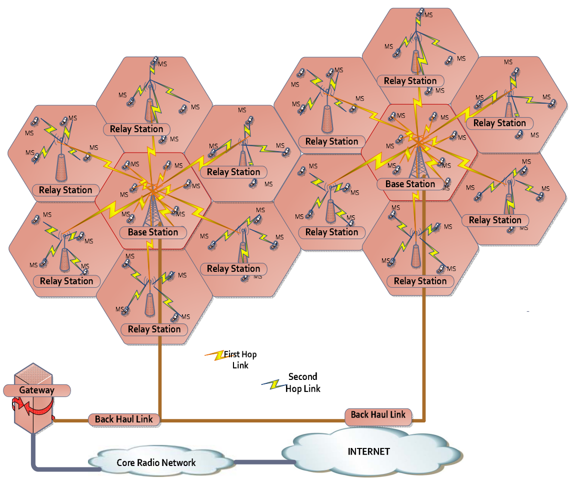

Figure 1. MCN with one BS, six RSs connecting to core packet network

A MS is allowed to communicate with either the BS or RS based on maximum channel quality using adaptive modulation and coding (AMC). The separation distance between the transmitter (BS/RS) and the receiver (RS/MS) will affect the throughput by selecting a particular AMC transmission mode. The SNR thresholds and the net data rates for the AMC transmission modes are known to the system for making decisions about user association with either BS or RS. The maximum SNR user is provided with good channel quality and sufficient resource allocations to obtain the required throughput.

A BS is located at the center of the cell with 'D' as the cell radius and RSs are deployed to improve the cell performance. The position vector of the RS is $\overrightarrow{r_{x,y}}$ giving the location inside the cell and represented as $R_{i,j}$ with index i giving the associated BS and index j pointing to the RS. The position vector of the MS is given by $\overrightarrow{M_{m,n}}$. The MSs are assumed to be distributed over the cell region Ω_i. The cell is provided with K sub channels resources inside the cell as the design criteria in which the RSs are deployed to enhance the network performance. The resource allocation to users constitutes the BS-RS sub channel resources and BS-MS sub channel resources. The resource allocation for the multihop is restricted to two hops.

The path and shadowing losses are separately treated from small-scale fading. For the path loss, the LOS and nonline-of-sight (NLOS) models for the suburban macro cell COST 231 extended Hata model as adopted in [7], that is

$$L_{path}^{LOS}(d) = 23.8 \log_{10}(d) + 41.9\, dB \qquad (1)$$

$$L_{path}^{NLOS}(d) = 40.2 \log_{10}(d) + 27.7\, dB \qquad (2)$$

Where d is the separation (in meters) between transmitter and receiver. The LOS model is used for the BS-RS link because RSs are often located over rooftops, whereas the NLOS model for the BS-MS and RS-MS links. For shadowing loss, a simplified model given in (3) is mainly adopted for verifying the effectiveness of the proposed method in a shadowed environment. A sectored antenna pattern is assumed for cell for propagation, as in [8] are adopted. In this setup, an MS is said to be in a shadowed area if the LOS between BS (RS) and MS is blocked by an obstacle. No shadowing loss is imposed on the BS-RS link. MS are equipped with one omnidirectional antenna, whereas the BSs and RSs are equipped with both omnidirectional and sectored antenna configurations.

$$L_{shadow}(\vec{m}) = \begin{cases} \delta\, dB, if\ \vec{m}\, is\, in\, a\, shadowed area \\ 0\, dB, otherwise \end{cases} \qquad (3)$$

The proposed MCN optimization problem can be modeled as a weighted graph G = (V, E). There are three types of vertices in the graph, i.e., V = (B $\cap$ R) $\cup$ M, where B represents the candidate BS, R represents the candidate RSs and M represents the MS. For each m $\in$ M and b $\in$ B, there is an edge between them if the channel gain g (m, b) between m and b is greater than or equal to a given threshold

δ_1 for direct data transmission. For each m ∈ M and r ∈ R, there is an edge between them if the channel gain g (m, r) between m and r is greater than or equal to a given threshold δ_2 for multihop data transmission. Therefore, graph G in this case is a bi-partite graph, where there is no edge within R or M themselves. Every m ∈ M is associated with a resource requirement of C_m. The candidate BS sites each have a resource limit of $CB_{m,n.}$ which caps the total amount of resources of its connected MSs/RSs. The candidate RS sites each have a resource limit of $CR_{m,n}$, which caps the total amount of resources of its connected MSs.

A user selecting the direct hop transmission provided with a sub channel allocation based on the resources of the BS $CB_{m,n}$ given with the load of the BS. A user selecting the multihop transmission provided with a sub channel allocation based on the resources of RSs $CR_{m,n}$ given with the load of RSs. The channel gain and the traffic load pattern are jointly optimized over the design area $\Omega = \bigcup_{i=1}^{K} \Omega_i$ to maximize the system spectral efficiency (SE) under different QoE criteria and load balancing between different RSs and the BS. Let L_Ω and S_Ω be the aggregate offered load and the maximum SE over the design area. The system throughput T_Ω is then defined by

$$T_\Omega = \frac{S_\Omega}{L_\Omega} \qquad (4)$$

The objective is to search for the optimal set of channel gains λ_g for either direct users g (m, b) or multihop users g (m, r) in the design area and the resource allocation μr varying based on load balancing so that the throughput T_Ω is maximized. The load balancing given in (5) used for admission control with resource sharing.

$$Load\,balancing\,L_\Omega = \frac{\beta_\Omega(resource\,blocks\,allocated)}{\alpha_\Omega(total\,resource\,blocks)} \qquad (5)$$

A policy control scheme is devised to evaluate resource allocations. In fixed resource allocation (FRA), the resources are equally shared between the BS and RSs with load balancing. In dynamic resource allocation (DRA), the resources are reconfigured with load balancing between the BS and the RSs.

IV. Optimization Algorithm

It is easy to see from (4) that T_Ω is a highly nonlinear function of λg and $\mu_{r,}$ given QoE criteria and generally, an analytic close-form solution is not available. In this section, a GA-based optimization algorithm is devised to solve the optimization problem. Simply applying general and conventional genetic operations without specific heuristics could not be able to exploit the automatic search power of evolutionary algorithms. There is an increasing need for customizing evolutionary methods to closely incorporate the feature of a problem. The individual representation and genetic variations are specifically designed suited to the characteristics of the problem. Furthermore, incorporate a population adjustment method to enhance its search ability.

The iteration operations are applied to the population to approach the optimum. The fitness of an individual is defined as one with maximum channel gain with minimum load factor in a particular design area of BS or RSs. Thus, there can be many tied solution with the same fitness but not necessarily the same set of activated BS or RSs and associated MSs. Although this neutral diversity is not observable at the fitness level, it plays an important role in expanding the genotypic search space. The adaptive population size scheme allows a system to dynamically enhance neutral search during different stages of the evolution by population size adjustment.

The population of individuals is evolved with adaptive size in the generational node to approach the optimum. The process starts with randomly generating a population P_0 of given size, and other configuration parameters from section V. Next, each individual's fitness in this initial population is evaluated. Then, the process enters a generational iteration as follows.

Step 1. Randomly pair up individuals of population P_t

Step 2. Crossover each pair of individuals to generate $|P_{t\,|}$

Step 3. Repair the offspring of previous step

Step 4. Mutate the offspring

Step 5. Repair the output of previous step

Step 6. Evaluate offspring

Step 7. Calculate the next population size $|P_{t+1}| = f(|P_t|)$

Step8. Choose by truncation selection the next population P_{t+1} from the competition pool consist of $|P_t|$ parent and $|P_t|$ offspring individuals

Step 9. Go to first step1 if termination criterion is not met.

The iterative process stops when the best fitness in the population has remained the same for stagnation threshold individual evaluations. This termination condition will signal if the evolution stagnates. A measure of how fast the algorithm leads the process to a possibly global/local optimum before stagnation by recording the number of individual evaluations elapsed so far.

V. Numerical Results

In our numerical results, the cell radius is set to be 1000 m, the cell is divided into grids with each side equal to 20 m, and all stations (BS, RSs and MS) are located at the grid intersection points as shown in Figure.2. MSs = 100, carrier frequency of 2.5 GHz, total spectrum = 20 MHZ divided into 100 resource blocks, subcarrier channel bandwidth = 180 kHz. The minimum required SNR greater than 10, 16-QAM with ½ coding for 10 dB, 16-QAM with ¾ coding for 12 dB, 64-QAM with 2/3 coding for 16 dB, 64-QAM with ¾ coding for 21 dB. Transmission power of BS is 46 dBm and transmission power of RS is 43dBm. Standard deviation for shadowing (σ) = 8 dB and Noise power (N_o) is (-102) dBm.

Antenna height of BS is 30 m, Antenna height of RS is 15 m and Antenna height of MS is 2m. The service request is for data traffic type of 512 kbps.

Figure.3 shows the dynamic resource allocation case between the RS and the BS based on the active users with load balancing. The user changing the position will require dynamic reconfiguration to allocate the resources. Figure.4 gives a comparison of single hop throughput with multihop throughput. The performance of the optimized network reported by the simulation results is considerably higher than the single hop network performance. Furthermore, fairness is also improved since the CDF of user throughput becomes almost a step function, implying that all users enjoy the same data rate. Figure.5 shows the simulation to illustrate the convergence behavior of the proposed GA. The convergence of the proposed GA algorithm is quite insensitive to the control parameters (P_0, β, P_{mut}) if they are selected to within a proper range of values. In this case the initial population size $|P_0|$ to 200 and the termination stagnation threshold s to 10,000 (evolution is terminated if the best fitness of the population remains unchanged for 10,000 evaluations). The population size is limited between 100 and 500 when it is varied for maximum and average fitness.

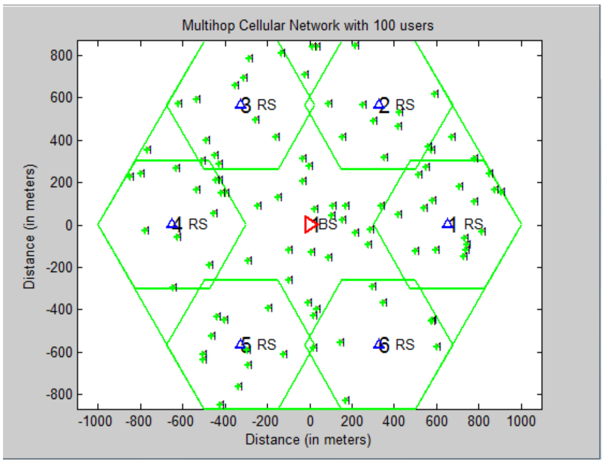

Figure 2. MCN with 1 BS, 6 RS and 100 users

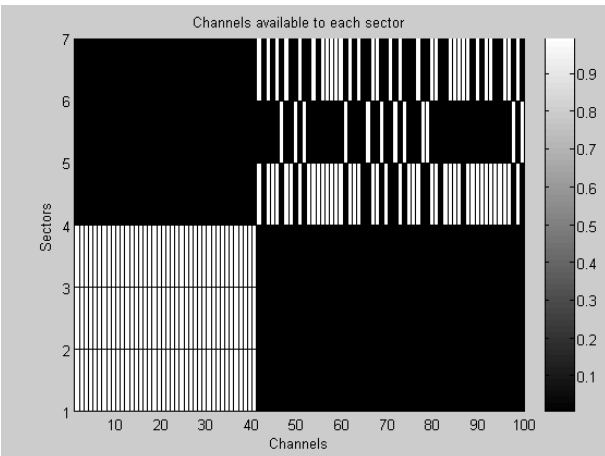

Figure 3. Dynamic resorce allocation with 100 resource blocks

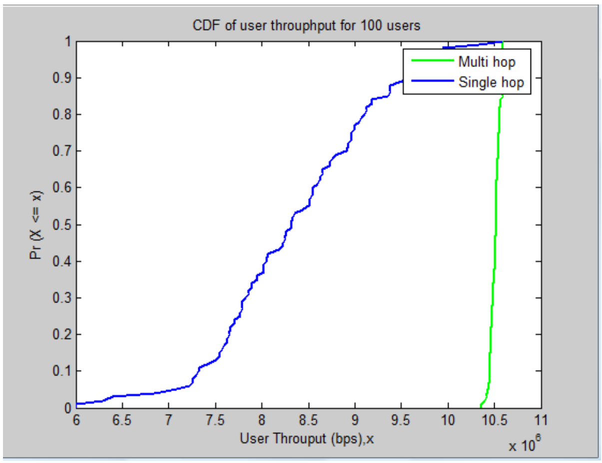

Figure 4. Multiuser througput for single hop and multihop with 100 users

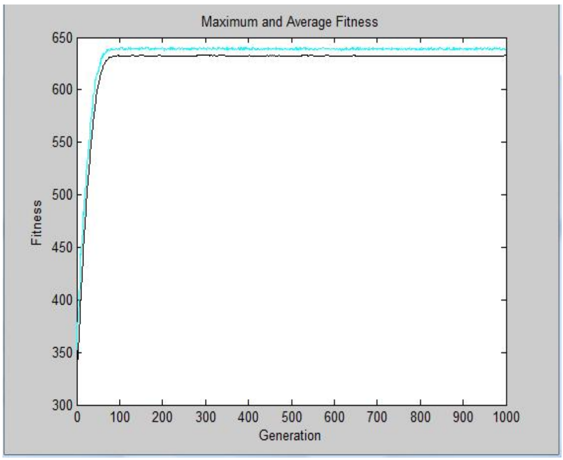

Figure 5. GA for convergence of generations using adpative population size approach.

VI. CONCULSION & FUTURE WORK

A single cell optimization for MCNs investigated. The algorithm proposed uses GA to a high dimension problem, as a good candidate for dynamic system reconfiguration. The system reconfigurations considered includes 100 users with 100 resource blocks. The numerical results shows MCN provide significant throughput with respect to single hop throughput system by properly optimizing the resource allocation with load balancing. The approach can be extended to a multicell environment with inter channel interference cancellation to give further throughput improvement for a more practical scenario. A comparison with other evolutionary algorithms like tabu search in terms of convergence time also can be done to test practical suitability. .

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REFERENCES

[1] T.C-Y.Ng and W.Yu, "Joint optimization of relay strategies and resource allocations in cooperative cellular networks," *IEEE Journal on Selected Areas in Communications*, vol. 25, no. 2, pp. 328-339, Feb 2007.

[2] Y.Yu, S.Murphy, and L.Murphy, "Planning base station and relay station locations in IEEE 802.16j multi-hop relay networks," in *IEEE Consumer Communications and Networking Conference (CCNC)*, 2008, pp. 922-926.

[3] B.Lin, P.-H.Ho, L.-L.Xie, and X.Shen, "Optimal relay station placement in broadband wireless access networks," *IEEE Transactions on Mobile Computing*, vol. 9, no. 2, pp. 259-269, Feb 2010.

[4] W.-H Sheen, S.-J. Lin and C.-C Huang, "Downlink optimization and performance of relay-assisted cellular networks in multicell environments," *IEEE Transactions on Vehicular Technology*, vol. 59, no. 5, pp. 2529-2542, June 2010.

[5] D.Niyato, E.Hossain, D.-I.Kim, and Z.Han, "Relay-centric radio resource managment and network planning in IEEE 802.16j mobile multihop relay networks," *IEEE Transactions on wireless communications*, vol. 8, no. 12, pp. 6115-6125, Dec 2009.

[6] Y.Ge, S.Wen, Y.-H Ang, and Y-C.Liang, "Optimal relay selection in IEEE 802.16j multihop relay vehicular networks," *IEEE Transactions on Vehicular Technology*, vol. 59, no. 5, pp. 2198-2206, June 2010.

[7] "Part16:Air Interface for fixed and mobile broadband wireless access systems: multihop relay specification," , IEEE Std. P802.16j/D9, Feb 2009.

[8] D.R.Basgeet and Y.C.Chow, "Uplink performance analysis for a relay based cellular system," in *IEEE VTC-Spring*, 2006, pp. 132-136.