AI empowered Smart User Association in LTE Relays HetNets

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***Abstract*—Relay nodes (RNs) deployment with wireless backhaul in future mobile networks is considered a promising solution to enhance the indoor coverage region of regular base stations, overcome shadowing dips, and provide a very high capacity and Quality of Service (QoS). Relay node cell footprint is limited by low transmission power which may not allow it to carry a significant share of the traffic load, thus undermining the gains of emerging ultra-dense heterogeneous networks (HetNets). Hence, cell association in a relay-enhanced scenario is a key design task, and has become a very interesting research topic over the past few years. This paper develops artificial intelligence empowered self-organizing network (SON) solution to optimally distribute users among relays and macro cells in an automated way such that holistic network performance is optimized. Contrary to existing studies, this work presents a novel idea of traffic service class based cell individual offset (SCIO) to further enhance the gains achieved from deployment of relay nodes. Employing an LTE system level simulator, for relay-enhanced scenario with a traffic mix having distinct QoS requirements, we observe that reinforcement learning based strategy coupled with SCIOs can yield significant gain in terms of users satisfaction scores, cumulative system payload throughput and reduction in signaling overhead when compared with the genetic algorithm based scheme and current industrial practice of fixed CIOs.**

***Index Terms*—Relays, HetNets, 5G, Heterogeneous Networks, CIOs.**

I. Introduction

Fueled by the needs of high data throughput, reduced latency and improved indoor coverage, network densification through small cells (SCs) is emerging as a promising paradigm to bring the idea of infinite capacity and zero latency to reality in cellular networks [1]. Next generation networks such as 5G, composed of umbrella cells (macro cells) and hot-sport cells (small cells), are envisioned to be based on heterogeneous architectures orchestrated by self organizing networks [1]. Such networks will offer continuous/ubiquitous connectivity through the macro-cell layer with tailored additional capacity through the small cell layer. Deploying more base stations (BSs), or cells, within the same geographical region increases the spatial spectral efficiency and offers more capacity due to the shrunk BS footprints. At the same time, mobile networks are witnessing and explosive growth in data demand, driven by content rich applications (according to Cisco, video content will be 82% of global Internet traffic in 2021) with 80% of traffic being indoor. To this end, industry pundits have identified the crucial role of indoor SCs to cater for this traffic and amass the incurred profit, with an ambitious forecast of SCs spread. However, to date, mass deployments of indoor SCs remain elusive. The main hinder associated with the deployment of SCs is the provisioning of a backhaul connection to the core network. Such backhaul connections are very exigent in terms of capacity, latency, and reliability and often come at a very high cost. Another key challenge is efficient management of this complex dense HetNet in a cost effective way when 70 millions SCs are expected to be deployed by 2025. Connecting the SC BSs to the macro base station via wired backhaul links is the most common scenario. Such SC BSs, also called pico base stations, are deployed by the operators and require high-quality and low latency backhaul connection since they are aimed to cater large number of users with commercial grade QoS. Currently, the only wired solution that offers the required attributes is direct optical fiber; however, these are rarely available network wide and deploying such a solution would require cumbersome trenching and laying fiber at an inhibitive and very costly scale. Hence desirable alternative is a wireless backhaul solution. SCs employing wireless backhaul, also called relay nodes (RNs), leverage the underutilized spectrum that is not useful for the front haul. There is no need for excavations to install fiber and the location of the small cell can be easily changed to improve the service.

Some recent papers have studied performance of various LTE relay configurations [2]–[6] and observed that relay deployment achieves significant gains over conventional macro only deployment. However, even with a targeted deployment where these relays are placed in high-traffic zones, most users will still receive the strongest downlink signal from the tower-mounted macrocell due to the disparity in the downlink transmission powers of the macro cells and relays. Therefore, there lies the opportunity of biasing the serving station assignment toward RNs through cell individual offsets (CIOs) to expand relay cell range and, thus, increase the gains achievable by RNs. Most works in the literature on CIO have considered picocell deployments like [7], [8] with wired backhaul. Few works like [9]–[11] have focused on optimizing CIO for relay based networks with wireless backhaul. However, they do not consider class based CIOs to exploit diversity in traffic service profiles of users as we have proposed to do.

Moreover, it is important to model the relation between the front-end activity of the relay and the signalling overhead, an aspect that is missing from current literature, to quantify the gains and losses incurred by introducing a relay in the network. The gains are mainly the improved capacity for the

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users while the losses are mainly the signalling overhead due to S1 interfaces in the Uu interface of the macro cell. The relay backhaul is encapsulated in the air interface channel of its donor macrocell and hence the backhaul capacity of the relay node depends on the radio channel capacity of the macrocell. The present study considers jointly the SC radio access and the wireless backhaul that is encapsulated in the macro cell radio access. In particular, we investigate following research questions pertinent to relays based HetNets:

- How to autonomously manage wireless backhauling based relay HetNets in a cost effective manner?
- How can we stretch the capacity of the heterogeneous network by exploiting the diversity of services that are not born equal?
- How can we do that while complying with current network interfaces and procedures?

In light of aforementioned challenges, this paper presents an AI based SON solution complemented with service class based CIO paradigm. The contributions of this paper can be summarized as follows:

1) We propose an AI based learning solution that dynamically adapts relays to traffic, radio, and network changes for improving network-centric and user centric performances. Another key novelty is that unlike state-of-the-art practice of using same CIO for all UE traffic classes, it leverages the novel concept of service class based CIOs that is aware of disparity in traffic profiles of users for further capacity enhancement.
2) Based on the current network conditions, the proposed solution makes it possible to prioritize one of the following objectives: Maximization of the geometric mean of the users payload throughput, the number of satisfied users or the mean satisfaction score of all users and solve formulated optimization problem using reinforcement learning (RL) and genetic algorithm (GA).
3) We perform a comparative analysis of proposed solution, through multi-tier system level 3GPP compliant rigorous simulations. Four performance metrics are considered to evaluate network-centric and user-centric performances. Results indicate reinforcement learning based solution with SCIOs achieve maximum performance in all performance metrics.

II. System Model

Network topology considers at least one randomly deployed indoor relay in the coverage area of a macro cell. Three separate frequency bands are considered; one for UE to macro link, one for UE to relay link and one for relay to macro link. Macro cells use directional antennas with three sectors per site while relays employ directional antenna for wireless backhaul and omni directional antenna for front haul links. An LTE like OFDMA based system with resources divided into physical resource blocks (PRBs) of fixed bandwidth, is assumed. For conciseness, the downlink direction is chosen for the analysis. Relays connect to the macro cells from which they receive strongest signal strength. The set of users connected to cell c is determined by the user association criterion:

$$\mathbb{U}_j := \{\forall \mathrm{u} \in \mathbb{U} \mid j = \arg\max_{\forall c \in \mathbb{C}} (P_u^c + P_{SCIO,u}^c)\} \quad (1)$$

where $\mathbb{C}$ is set of all macro cells ($\mathbb{M}$) and relays ($\mathbb{R}$) in the network i.e., $\mathbb{C} = \mathbb{M} \cup \mathbb{R}$, P_u^c is the true reference signal power in dBm received by user u from cell c and $P_{SCIO,u}^c$ in dB is the SCIO that is primarily used to offset lower transmit power of relays to transfer more load to them depending upon the traffic class of the users. There are two SCIOs per BS (two for each macro and relay) corresponding to the two traffic classes (VOIP/FTP) considered in this paper without loss of generality. VOIP users will use corresponding SCIOs in association decision and FTP users will users their respective SCIOs. The signal to noise and interference ration (SINR) γ_u^c of user u when associated with a macro cell m is defined as the ratio of reference signal received power P_u^m by user u from cell m to the sum of reference signal received power by user u from all macro cells i such that $\forall i \in \mathbb{M}/m$, and the noise variable κ:

$$\gamma_u^m = \frac{P_u^m}{\kappa + \sum_{\forall i \in \mathbb{M}/m} P_u^i} \quad (2)$$

Here P_u^m is given by:

$$P_u^m = P_t^m G_u G_u^m \delta \alpha (d_u^m)^{-\beta} \quad (3)$$

where P_t^m is the transmit power of macro cell m, G_u is the gain of user equipment, G_u^m is the gain of transmitter antenna of the macro cell m as seen by the user u, δ is the shadowing observed by the signal, α is the path loss constant, d_u^m represents the distance of user location of u from macro cell m, β is the pathloss exponent. Likewise SINR γ_u^r achievable by user when connected to relay r is given as:

$$\gamma_u^r = \frac{P_u^r}{\kappa + \sum_{\forall i \in \mathbb{R}/r} P_u^i} \quad (4)$$

The rate achievable by the user when connected to macro cell m is given as:

$$T_u^m = \omega_{mu} \log_2 (1 + \gamma_u^m) \quad (5)$$

where ω_{mu} is the available bandwidth on macro to UE link. Similary when connected to relay, end-to-end rate for this two hop link is given as [2], [6]:

$$T_u^r = \left(\frac{1}{\omega_{ru} \log_2 (1 + \gamma_u^r)} + \frac{1}{\omega_{mr} \log_2 (1 + \gamma_r^m)} \right)^{-1} \quad (6)$$

where γ_r^m is SINR of wireless backhaul link between relay r to which UE is connected and that relays's donor macro cell m:

$$\gamma_r^m = \frac{P_r^m}{\kappa + \sum_{\forall i \in \mathbb{M}/m} P_r^i} \quad (7)$$

and ω_{ru} and ω_{mr} are the bandwidths assigned to relay to UE and macro to relay links respectively. The S1 (control/user) signaling overhead (in terms of PRBs) for all UEs connected to relay is subtracted from total number of PRBs assigned

for each respective relay to macro wireless backhaul link to analyze the impact of UE service classes on backhaul signalling load. In this work, we focus on a fixed relay that targets indoor users and on manipulating the front-end of the relay (i.e., the radio access towards indoor users). Hence, optimization of donor cell selection is out of scope of current work.

III. AI Approaches

Two optimization techniques have been utilized (i) reinforcement learning and (ii) genetic algorithms. Three problem formulations (P1, P2, P3) are devised depending upon variant of the objective function: (i) P1 that maximizes number of satisfied UEs (ii) P2 that maximizes geometric mean of UE payload throughputs and (iii) P3 that maximizes logarithmic sum of satisfaction scores.

A. Reinforcement Learning Approach

In reinforcement learning approach, BSs (macro as well as relay nodes) optimally, learn their SCIOs depending upon network conditions. This is formulated as a Q-learning process which consists of a set of states and actions and aims at finding a policy that maximizes the observed rewards over the interaction time of the agents. All BSs are agents that explore their environment, observe their current state, and take a subsequent action according to their individual decision policy. Each BS maintains an individual Q-table based on its acquired knowledge. The goal of every BS is to find an optimal policy for every state in such a way that the cumulative reward is maximized. The Q-learning problem can, thus, be formulated as follows:

Agents: All BSs in the network

States: Any agent can be in any of the two states:

$$s^c = \begin{cases} 1 & \text{, if } \frac{1}{|\mathbb{C}|}\sum_{\mathbb{C}}\frac{1}{|\mathbb{U}_c|}\sum_{\mathbb{U}_c} 1(T_u^c \geq T_{u,th}) \geq \bar{\omega} \\ 2 & \text{, otherwise} \end{cases} \tag{8}$$

where $\mathbb{U}_c$ is set of all users in cell c, T_u^c is achievable payload throughput of user u in cell c, $T_{u,th}$ is minimum required throughput for user u, $\bar{\omega}$ defines the QoS KPI that operator wants to maintain, and 1(.) denotes indicator function.

Action: The actions of a cell are set of possible SCIO settings represented by the vector $a^c = [CIO_{c,1}^{VOIP}, CIO_{c,2}^{VOIP}, CIO_{c,3}^{VOIP}, ..., CIO_{c,|o|}^{VOIP}, CIO_{c,1}^{FTP}, CIO_{c,2}^{FTP}, CIO_{c,3}^{FTP}, ..., CIO_{c,|o|}^{FTP}]$ where O is set of possible CIO offsets.

Reward: The reward estimated by cell c in state s^c when taking action a^c is computed as follow depending upon the problem formulation (P1, P2 or P3):

$$r^c = \begin{cases} \text{P1, P2 or P3} & \text{, if } \frac{1}{|\mathbb{C}|}\sum_{\mathbb{C}}\frac{1}{|\mathbb{U}_c|}\sum_{\mathbb{U}_c} 1(T_u^c \geq T_{u,th}) \geq \bar{\omega} \\ -1000 & \text{, otherwise} \end{cases} \tag{9}$$

where

$$P_1 = \frac{1}{|\mathbb{C}|}\sum_{\mathbb{C}}\frac{1}{|\mathbb{U}_c|}\sum_{\mathbb{U}_c} 1(T_u^c \geq T_{u,th}) \tag{10}$$

$$P_2 = \prod_{\mathbb{C}}\prod_{\mathbb{U}_c}((T_u^c)^{1/|\mathbb{U}_c|})^{1/|\mathbb{C}|} \tag{11}$$

$$P_3 = \sum_{\mathbb{C}}\sum_{\mathbb{U}_c}\log(\frac{T_u^c}{T_{u,th}}) \tag{12}$$

Q-Table: The Q-table will be updated according to the following, when an action a^c is taken by agent (BS):

$$Q_{t+1}^c(s_t^c, a_t^c) = Q_t^c(s_t^c, a_t^c) + \alpha(r_{t+1} + \gamma \max_{a^c} Q_t^c(s_{t+1}^c, a^c) - Q_t^c(s_t^c, a_t^c)) \tag{13}$$

where $\alpha = 0.5$ is the learning rate and $\gamma = 0.9$ is the discount factor, Q_t^c is the Q-table of cell c at time t, and Q_{t+1}^c is the new Q-table with updated entry according to action taken (a^c).

B. Genetic Algorithm

Genetic algorithms represent a class of algorithms within the field of artificial intelligence, which is derived from the natural evolutionary systems and are one of the important heuristic algorithms available for solving complex combinatorial problems. Genetic algorithms use methods found in the evolutionary process such as survival of the fittest, population mutation, death and migration process. Using these processes, the genetic algorithm moves through the solution spaces trying to find the feasible solution space. This makes it an attractive choice given the fact that for a multi-variable problem with a large variable count and enormous search space, knowledge of feasible solution space is extremely rare. It is also important to note that the genetic algorithm starts from a random parameter set in the solution space, therefore, for each run the time to find the feasible space is different. However, once found, the algorithm can quickly move towards the optimal solution in the feasible space. A generic pseudo code for the genetic algorithm is presented in [12]. The GA is utilized to solve following optimization problems:

$$\text{GA-P1}: \max_{P_{SCIO,u}^c} \frac{1}{|\mathbb{C}|}\sum_{\mathbb{C}}\frac{1}{|\mathbb{U}_c|}\sum_{\mathbb{U}_c} 1(T_u^c \geq T_{u,th}) \tag{14}$$

$$\text{GA-P2}: \max_{P_{SCIO,u}^c} \prod_{\mathbb{C}}\prod_{\mathbb{U}_c}((T_u^c)^{1/|\mathbb{U}_c|})^{1/|\mathbb{C}|} \tag{15}$$

$$\text{GA-P3}: \max_{P_{SCIO,u}^c} \sum_{\mathbb{C}}\sum_{\mathbb{U}_c} -\log\frac{T_u^c}{T_{u,th}} \tag{16}$$

all subject to:

$$\frac{1}{|\mathbb{C}|}\sum_{\mathbb{C}}\frac{1}{|\mathbb{U}_c|}\sum_{\mathbb{U}_c} 1(T_u^c \geq T_{u,th}) \geq \bar{\omega} \tag{17}$$

Four performance metrics are considered:

- **Net Payload (NP):** It is the sum of payload throughputs of all UEs in the network given as:

$$\text{NP} = \sum_{\mathbb{C}}\sum_{\mathbb{U}_c} T_u^c \tag{18}$$

- **Average Backhaul Signaling Overhead (SO):** This is the signalling load generated by all users connected to relays compared to the payload generated by the same users. It is given as:

$$\text{SO} = \frac{1}{|\mathbb{U}_r|} \sum_{\mathbb{U}_r} \frac{S_u^{r,m}}{T_u^{r,m}} \tag{19}$$

Where $S_{r,m}$ is signaling load of all users connected to relay r ($\mathbb{U}_r$) that is using wireless backhaul of macro cell m, $T_{r,m}$ is sum payload throughput of all users connected to relay r that is using wireless backhaul of macro cell m.

- **Percentage of Unsatisfied Users (PUU):** This is the percentage of users that do not reach their minimum required throughput of all users in the network. It is given as:

$$\text{PUU} = \frac{1}{|\mathbb{U}|} \sum_{\mathbb{C}} \sum_{\mathbb{U}_c} 1(T_u^c \leq T_{u,th}) \tag{20}$$

- **Average Satisfaction Score (SS):** This is a calculated score that compares the gap between the achieved throughput and the minimum requirement. It is important to distinguish (or classify) the level of dissatisfaction of users; for instance, a user achieving 90% of the target is much more satisfied than the one achieving 20%. It is given as:

$$\text{SS} = \frac{1}{|\mathbb{C}|} \sum_{\mathbb{C}} \frac{1}{|\mathbb{U}_c|} \sum_{\mathbb{U}_c} \frac{\min(T_u^c, T_{u,th})}{T_{u,th}} \tag{21}$$

IV. Simulation Results

Simulation results leverage RL approaches with three objective functions (RL-P1, RL-P2, RL-P3), GA approaches with three objective functions (GA-P1, GA-P2, GA-P3), macro only and the best performing Fixed SCIO settings found by trying all possible fixed SCIO settings.

A. Simulation Settings

We generated typical macro and relay based network and UE distributions leveraging LTE 3GPP standard compliant network topology simulator in MATLAB. The simulation parameters details are given in Table I. We consider a sectored cellular network wherein each of the macro base station has three cells and each cell has one indoor relay placed at an arbitrary location. Snapshot of network topology at a random instant is shown in Fig. 1 wherein circles represent outdoor UEs, square represent indoor UEs, green color specify satisfied UEs, red color denote unsatisfied UEs, dark blue triangles denote relays while light blue diamonds represent macro BSs. The network topology consists of 7 sites with wrap around technique. Thus, though there are 21 macro cells (and 21 relays) in total, the wrap around technique mitigates the boundary effect and helps us to simulate interference as in infinitely large network. UE's are distributed non-uniformly in all the sectors (25 UEs per cell on average) with 50% indoors and 50% outdoors. To model realistic networks, UEs were distributed non-uniformly in the coverage area such that a fraction of UEs were clustered around randomly located relays in each sector. Monte Carlo style simulation evaluations were used to estimate average performance of the proposed solution. Without loss of generality, we considered two UE traffic requirement profiles corresponding to 56 kbps (VOIP) with 160 bytes payload packet size and 2048 kbps (FTP) with 1000 bytes payload packet size. S1 control overhead (S1-U: User Plane and S1-C: Control Plane) calculation for relay to macro wireless backhaul is implemented in accordance with [13]. VOIP traffic throughput requirement is low (56Kbps for VOIP) but creates large S1-U signaling overhead while converse is true for FTP traffic with large throughput requirement (2048 kbps). VOIP users throughput is capped at maximum (56 kbps).

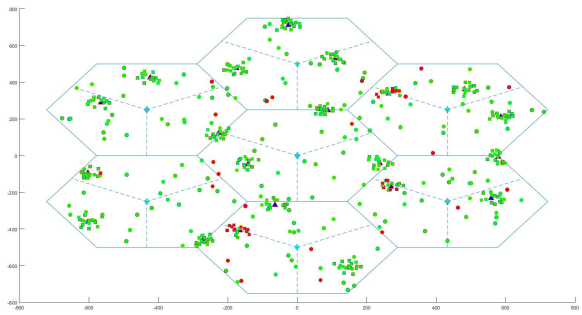

Fig. 1. Snapshot of Network Topology

TABLE I
Simulation Parameter Settings

System Parameters	Values
Number of Macro Base Stations	7 with 3 Sectors per Base Station
Relays per Sector	1 (All Indoor)
Number of UEs per Sector	25
LTE System Parameters	Frequency = 2 GHz, Bandwidth = 20 MHz for all three links, ISD: 500m, Topology= Hexagonal
UE Traffic Classes	Voice: Required Throughput 56 kbps, Payload: 160 bytes FTP: Required Throughput 2048 kbps, Payload: 1000 bytes
Macro Cell Parameters	Tx Power: 46 dBm, Tilt: 12^0
Small Cell Tx Parameters	Tx Power = 30 dBm, SCIO = -20 to 20 dB
Schedular	Round Robin
Macrocell Antenna	Directional Antenna with 17 dBi gain
Relay Antenna	Backhaul: Directional Antenna pointing towards closest Macro Cell Fronthaul: Omni Antenna
QoS Throughput Threshold ω	90%
Path loss Model [14]	Macro to UE Link: – LOS scenario: PL LOS (R)= 103.4+24.2log10(R) where R is distance in km. – NLOS scenario: PL NLOS (R)= 131.1+42.8log10(R) – LOS Probability function: Prob(R)=min(0.018/R,1)*(1-exp(-R/0.063))+exp(-R/0.063) – Lognormal shadowing standard deviation: 10 dB – In case of an indoor UE, an additional wall penetration loss of 18dB has to be considered. Macro-Relay Wireless Backhaul link: – LOS scenario: PL LOS (R)=100.7+23.5log10(R) Indoor Relay access antenna - UE link: – Relay to UEs inside the same cluster building: L= 127+30log10(R) – Relay to UEs in different cluster buildings: L= 128.1+37.6log10(R) – Lognormal shadowing standard deviation: 10 dB for link between relay and relay UE, and 8dB for other links – The penetration loss of the walls separating buildings is 18dB.

B. Results with SCIO Approach

Fig. 2 plots the cdf for Macro-Relay backhaul signaling overhead with total network payload throughput (NP) illustrated in the legend of this figure. It is observed that in terms of total network payload throughput, all variants of optimization objectives outperform best fixed SCIO settings as well as macro only scenarios (for macro only, NP is 0.59 Gbps). The maximum total network payload

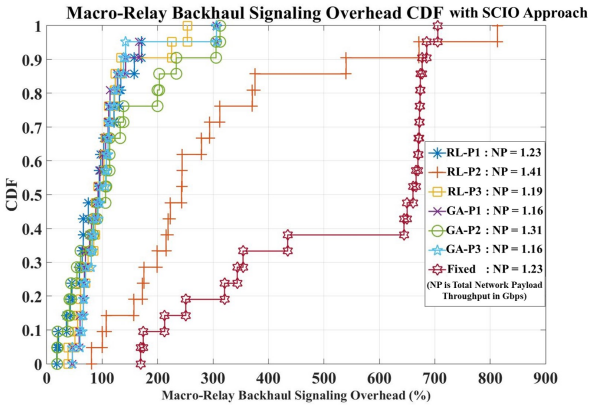

Fig. 2. Macro-Relay Backhaul Signaling Overhead CDF

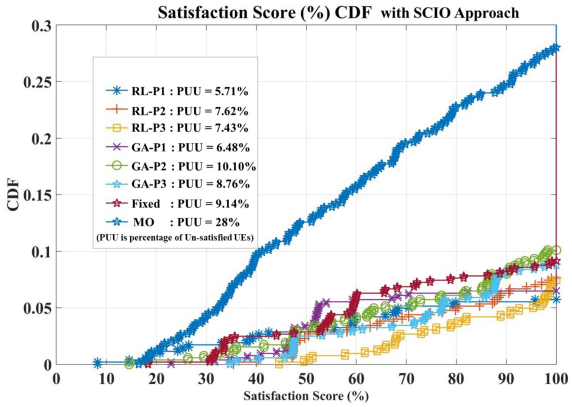

Fig. 3. 30th Percentile Satisfaction Score CDF

occurs with RL-P2 and GA-P2. The reason being P2 problem formulation includes maximization of geometric mean of UE payload throughputs in its objective function. As a result, both AI techniques (RL and GA) strive to find such SCIOs that results in increase in overall UE payload throughputs. While looking at the CDF, we observe that considerable signaling overhead is observed for best fixed settings which for this case was observed when VOIP UEs are aggressively shifted to indoor relays and FTP to outdoor macro BSs. Since VOIP UEs have small packet size, their S1-U signaling overhead ratio is very high around 85% which considerably increases signaling overhead of Macro-Relay backhaul link. Moreover, RL-P2 and GA-P2 achieved maximum payload throughputs at cost of higher signaling overheads.

Fig. 3 plots upto 30th percentile of satisfaction scores CDF for the UEs with percentage of un-satisfied UEs (PUU) illustrated in the legend of this figure. By looking at PUU values, it is observed that RL-P1 and GA-P1 achieve lowest percentage of un-satisfied UEs due to inclusion of the satisfaction ratio in their objective functions. Hence, both RL-P1 and GA-P1 find such combinations of SCIOs that reduce number of unsatisfied UEs in whole network. A UE is marked as satisfactory if it's achievable payload throughput is at least equal to its required throughput (56kbps for VOIP and 2048 kbps for FTP). From the cdf curves for the 30th percentile of satisfaction scores for the UEs, it can be seen that with the macros only scenario, UEs attain less satisfaction scores as compared to relay schemes. With macro only around 28% UEs have satisfaction score less than 100% (un-satisfied) and 72% are satisfied. RL-P3 scheme owing to its objective function outperform all others with 7% UEs having satisfaction score less than 100% (un-satisfied) while 93% UEs are satisfied (100% satisfaction score). If we compute complimentary CDF, we observe with macro only, around 88% of UEs have satisfaction score greater than 50% while with RL-P3, 99% of UEs have satisfaction score greater than 50%.

C. Results with single CIO per BS and cell reselection priority

The aforementioned results in Fig. 2 and 3 are valid when SCIO approach is implemented in the network. In current 3GPP standardized networks, multiple biases per cell can be signaled to UEs through the concept of dedicated CIO signaling and Access Group method [15]. However, as viable alternative, we also evaluated results considering single CIO per BS (Macro/Relays) coupled with the cell reselection priority. The CIO can be used by a cell to attract or deter all users equally while the cell reselection priority is a dedicated parameter to a particular user to influence the cell selection decision. Cell reselection priority is used to prioritize specific RF carrier depending upon service being used by UE (VOIP Class/FTP Class). The Subscriber Profile ID for RAT/Frequency (SPID) is an index standardized in 3GPP referring to user information (e.g mobility profile, service usage profile) that can be used for this purpose. These can be jointly used to minimize the signalling messages required to achieve the desired selection of all users while distinguishing between different user services and complying with current network standards. As earlier, two optimization techniques have been utilized (i) Reinforcement Learning and (ii) Genetic Algorithm. For brevity, results with only P2 variant i.e., maximization of geometric mean of UE payload throughputs are presented here. Four schemes are considered: Reinforcement Learning (RL), Genetic Algorithm (GA), Fixed CIO settings (Fixed) and Macro Only (MO). Both RL and GA optimize CIO values for macros and relays within range of 0 to 20 dB as well as RF carrier (RF1 for outdoor macro, RF2 for indoor relays) priority in cell selection for each of the two classes of UEs present (VOIP class / FTP class).

Fig. 4 plots the cdf for Macro-Relay backhaul signaling overhead with total network payload throughput (NP) illustrated in the legend of this figure. It can be observed that RL based scheme outperforms GA, Fixed CIO settings as well as macro only scenario (for macro only, NP is 0.67 Gbps). It is interesting to observe that fixed

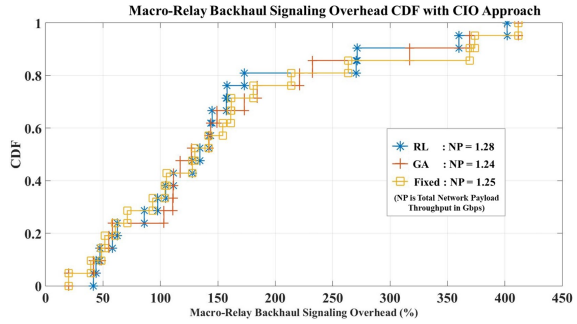

Fig. 4. Macro-Relay Backhaul Signaling Overhead CDF

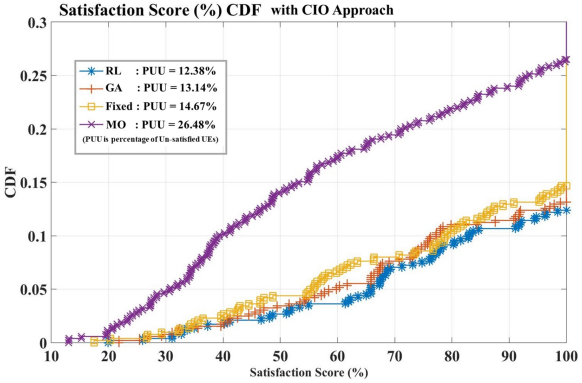

Fig. 5. 30th Percentile Satisfaction Score CDF

CIO setting perform better than GA scheme. However this observation will be misleading if we don't consider other metrics because as per cdf curves in Fig. 4 and 5, fixed CIO scheme achieves better sum payload throughput albeit at cost of increased signaling overhead and number of unsatisfied UEs. As per Fig. 4 and 5, we observe that RL scheme perform best followed by GA scheme. By comparing these with SCIO approach, it is concluded that SCIO based strategy outperform state-of-the-art CIO approach in all performance metrics considered in this work.

V. Conclusions

In this paper, we have presented a novel concept of AI empowered smart relays with wireless backhaul that exploit the diversity of the traffic profiles of UEs to maximize the total system payload throughput, users satisfactions scores and reduced singling overhead. Three optimization problems are formulated and solved using reinforcing learning strategy and genetic algorithms. Simulation results show the novel idea of service class based CIO coupled with reinforcement learning based strategy yield significant gains in terms of user-centric and network centric performance measures as compared to genetic algorithm based scheme and current industrial practice of fixed CIOs. The proposed work can help operators increase in revenue as result of increase in capacity, QoE, and ratio of payload/signalling. Same network infrastructure can generate "free" gain that does not require experts time for network optimization since AI can achieve it with zero-touch. Further work in this area will investigate complexity analysis and optimality gap of proposed schemes. Moreover, existing work will be coupled with load balancing schemes within the relay-enhanced macro cell and transforming optimization problems from reactive to proactive using big data.

Acknowledgement

This material is based upon work supported by the National Science Foundation under Grant Numbers 1619346, 1559483, 1718956 and 1730650. The statements made herein are solely the responsibility of the authors.

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