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Energy-efficient SON-based user-centric backhaul scheme

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***Abstract*—Energy efficiency in future networks is a global and paramount requirement driven by the desire to reduce networks' carbon footprint and energy bills, as well as extend the battery life of devices. Ultra-dense small cell deployment is a key enabler of such networks as it addresses the energy efficiency aspect of its radio section. However, the small cell backhaul mark of energy consumption is one order of magnitude higher than that of macro cells, and as such a new "green" challenge is born. A long-term solution to the many-fold requirements of the future backhaul would be and end-to-end fibre based network or wireless technologies that are still under-development. In the meantime, a hybrid backhaul network is developing to fill in the performance requirement gaps, where different technologies address different aspects. In this work, we offer an energy-efficient approach to the new user-centric backhaul concept in a heterogeneous and hybrid backhaul network. The approach is automated and it successfully mediates between three conflicting optimisation objectives: network, users, and energy key performance indicators.**

I. Introduction

Future (5G) networks are expected to cater for the explosive rise in devices and exigent quality of experience without causing a significant increase in energy consumption. Small cells represent an indisputable enabler of such networks for many reasons [1]. Small cells also endorse energy efficiency as they economise on transmit power requirements, owing to the proximity of transmitters and receivers. The RAN centralisation, C-RAN, transforms the small cells into remote radio heads (RRH) while keeping the baseband processing in a distant centralised pool. The potentials of C-RAN for economising on energy are quite attractive as this architecture reduces operational expenditures of RRHs and improves possibilities of putting RRHs to sleep [2]. Nonetheless, C-RAN architecture comes with exorbitant requirements on the fronthaul; the backhaul part that links the RRHs to the baseband pool, with throughput in excess of 10 Gbps and latency less than 1 msec for a basic LTE scenario [1].

On these grounds, direct optical fibre links are reckoned as the only fronthaul viable solution existing today. Nevertheless, optical fibre networks have limited reach worldwide and often an unclear roadmap for expansion [3]. The usage of the extremely high frequency (EHF) wireless spectrum band represents a serious contender to fibre-based network, as it offers ample capacity with controlled latency and resilience. The currently discussed millimetre-wave (mmWave) spectrum falls in this category and, recently, ETSI has started looking at the D-band (141-174.8 GHz) with potential capacity of 50 Gbps [4]. Nonetheless, EHF transmission industry is still in its early phase and faces many challenges [5]. As such, the currently available EHF-based backhaul solutions may not be sufficient for 5G networks, and better performing EHF solutions may not be readily available for the 5G launch.

Under these circumstances, a heterogeneous backhaul network is key for enabling 5G timely launch. Such a backhaul employs different technologies to expand and reach each small cell. Although none of these solutions is capable of addressing fully all the needs of the 5G backhaul; nevertheless, jointly, they form a viable temporary hybrid solution. Energy consumption of small cell networks' backhaul is 10 times higher that that of macro-cell networks according to [6]. In case of deploying more than one last-mile link per small cell for the purpose of boosting the backhaul performance, the energy consumption would plunge even more. Inasmuch, energy efficiency is a new backhaul requirement, in addition to the traditional capacity, latency, resilience, and security constraints.

The energy efficiency in a 5G network of small cells with multi-last-mile connections is thus the focus of this work. We present a two-layered approach for user-centric backhauling that aims at economising backhaul energy consumption by minimising the number of active last-mile backhaul links. The first optimisation layer is centralised at the backhaul aggregation point which has access to data from all connected small cells. It uses a sliding window approach to deactivate the maximum possible number of backhaul connections in view of the carried traffic and users' satisfaction. The second optimisation layer is distributed and occurs at the small cells. Following the available backhaul connection(s) and corresponding constraints, small cells dynamically adjust the advertised attribute-based bias factors in order to influence users' cell selection in a way that improves their experienced quality as in [7]. Users traditionally attach to the cell with highest received signal power; a bias factor (or offset) is usually used in small cells to step-up the received signal measured by the user and bias her selection. The proposed scheme in this work reaches quality of experience (QoE) targets while reducing the energy consumption by up to 21.9% and maintaining the total system throughput.

The rest of the paper is structures as follows. Section II looks at the state-of-the-art research on backhaul energy efficiency. Section III describes the system model and the proposed algorithm. Section IV presents the results obtained using the energy-efficient user-centric backhaul scheme with analysis and insights. The paper is concluded in Section V.

II. State-of-the-art energy-efficient backhaul

Developing an energy-efficient 5G backhaul entails understanding first the energy consumption of available solutions. Three deployment scenarios are considered in [6]: fibre-to-the-node (FTTN) with VDSL2[1] to the cell, microwave, and a hybrid solution of fibre-to-the-building (FTTB) and microwave. It is shown that the first deployment scenario is more energy efficient than the one that employs microwave only, whereas the hybrid scenario outperforms both in an ultra-dense small cell network, capitalising on existing fibre infrastructure. In another work, mmWave for backhaul is investigated from an energy consumption point of view by comparing different spectrum bands and deployment scenarios [8]. As expected, provisioning wireless backhaul frequencies at lower frequencies results in higher energy efficiency. An earlier EU FP7 project, BuNGee, proposes a joint design of backhaul and access networks, by using heterogeneous radio elements and a cognitive radio backhaul approach that is enabled by SON capabilities [9]. They propose a green-oriented implementation of the cognitive backhaul [10] in which user association is geared towards prioritising RRHs with higher load, when possible, to allow a higher number of RRHs to be in sleep mode, thus, economising energy. Motivated to design green networks, authors [11], propose an ICIC[2] resource allocation scheme that is energy-aware, thus, improving energy efficiency (by up to 50%) at the expense of reduction in spectrum efficiency. Authors in [12] first study the energy impact of various backhaul technologies under two scenarios: uniform device distribution and hotspot. They show that mmWave is the most efficient solution and that the backhaul could consume up to 78% of total energy if provisioned using sub-6 GHz technology in a hotspot scenario. Next, they elaborate an energy-aware cell-association scheme based on cognitive heuristic algorithm with two objectives. It first exploits the available context-aware information to find the path with the least number of hops, in order to minimize the backhaul energy consumption. Then it selects the less loaded backhaul route in order to achieve load balancing. The proposed algorithm is shown to consistently improve energy efficiency, especially in a hotspot scenario (42% amelioration). This work is the first to study the energy efficiency in a dense network with multiple last-mile links per small cells.

[1]Very-high-bit-rate digital subscriber line.

[2]Inter-cell interference cancellation.

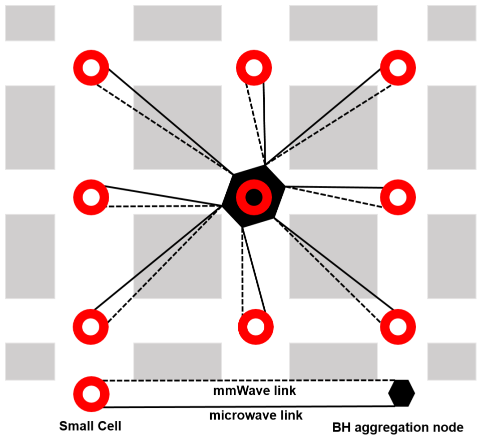

Fig. 1. The system model represents an ultra-dense-network Manhattan-grid-like with nine small cells belonging to one cluster, defined by the backhaul aggregation node. Each cell may have a mmWave and/or a microwave backhaul link to the aggregation node.

III. System model

The modelled system is a representation of an ultra-dense-small-cell-network that follows a Manhattan grid as shown in Figure 1. The nine small cells have multi-last-mile options to attach to the aggregation point in a star topology. The centralised optimisation intelligence that runs in the aggregation node aims to minimise the number of last-mile links over all connected small cells, as represented in Figure 2. The constraints for this optimisation problem are two-fold. Firstly, the recorded quality of experience (QoE) of attached users should remain within a user-define threshold. Second, the amount of traffic load carried per last-mile link should exceed a user-defined minimum. The proposed algorithm uses the sliding-window concept to avoid system instability and ping-pong effect between ON/OFF status of last-mile links. Moreover, the centralised intelligence prioritises candidate last-mile links for activation and deactivation based on corresponding degradation of QoE and reduction in throughput, respectively. In addition, the algorithm allows for the definition of the number of last-mile links that may be activated or deactivated simultaneously. A time-to-trigger parameter is also associated with each last-mile link to avoid the ping-pong effect of a specific link.

A distributed self-optimisation scheme runs, in parallel, on every small cell based on the user-centric-backhaul (UCB) concept in [7]. The UCB lets small cells optimise a set of bias values $\beta_1, \beta_2, \beta_3\}$ that reflect their different end-to-end constraints/capabilities, including capacity and resilience. A high capacity-based bias value β_1 indicates that the cell is capable of ensuring end-to-end high capacity to potential users, whereas a low resilience-based bias value β_2 is associated with high end-to-end outage probability, thus, discouraging users with stringent resilience requirements. On the other hand, users

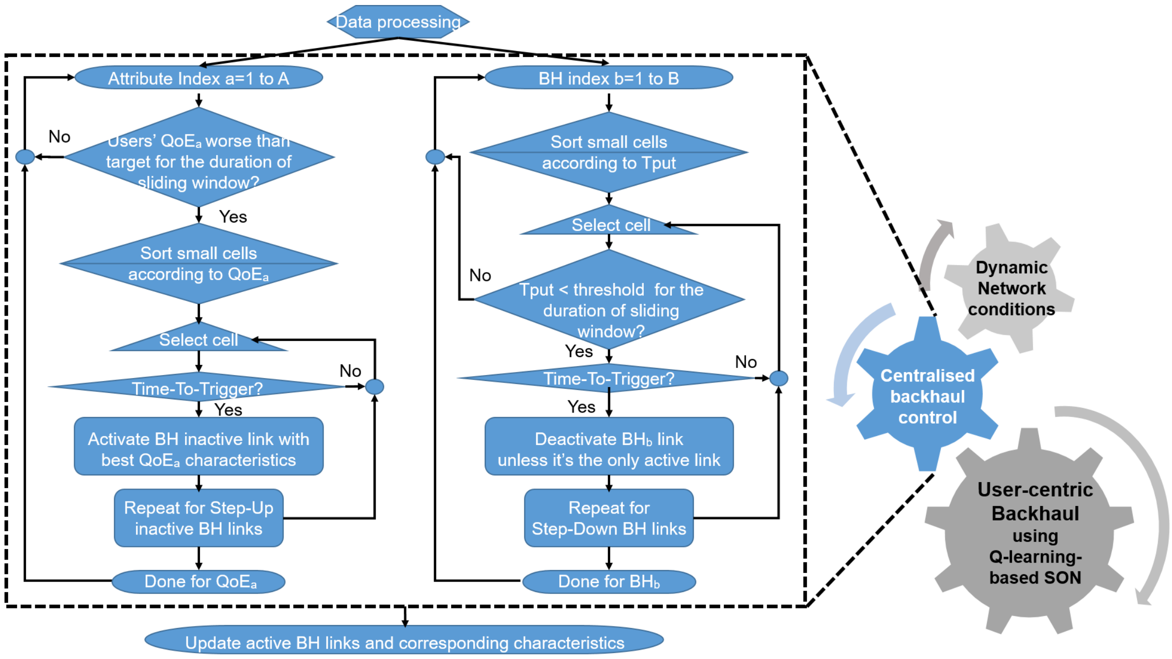

Fig. 2. The proposed energy-efficient backhaul allocation scheme takes care over two major steps. The first is the centralised optimisation that reduces the number of active links while respecting users'QoE. The second is a distributed SON mechanism that optimises the user-cell association pattern based on backhaul status and users' needs.

have relative weights $\omega_1, \omega_2, \omega_3\}$ to different quality attributes, determined by the device capabilities, the user preferences, and the application used. For instance, virtual reality and augmented reality applications require very high throughput, thus, would associate a high weight on throughput-related attributes. A mission-critical application, however, would have high weights on reliability and latency instead. Consequently, each user will calculate his/her user-centric bias value B_u with respect to each candidate cell, based on his/her defined weights and the cells' broadcast bias values ($B_u = \sum_b \beta_b \times \omega_{u,b}$). This leads to a user-centric virtual perspective of the network cells' footprints, tailored to each user's needs.

The UCB scheme adjusts the biasing of users' cell selection in accordance with the status of the backhaul links. Thus, a cell c that lost its high-throughput last-mile link will automatically lower its throughput-based bias factor. In parallel, neighbouring cells that retained their high-throughput links, would increase further the corresponding bias factor to attract throughput-greedy users that were previously served by cell c. This coordination between the centralised and distributed optimisation mechanisms insures stability in the system, and preserves the focus on users' QoE.

IV. Case Study

The system described in Figure 1 is reproduced in Matlab and the proposed energy-efficient backhauling scheme in Figure 2 is simulated. Small cells have two optional last-mile backhaul links: microwave and mmWave, in line with the wireless backhaul solution described in [13]. A traditional microwave (in the 28 GHz band) has limited capacity but high availability (99.999%) over distances within two kilometres is considered. A mmWave radio link with 250 MHz channels is less resilience but offers high capacity. Combining both links can be used to boost capacity by an additional one Gbps while securing 99.999% availability for high priority traffic and control information. The energy efficiency of the system is measured as the ratio of the effective throughput over the consumed energy. The former is derived using Matlab simulations based on the described method. Energy consumption of the last-mile backhaul links in the system is derived in the following paragraph.

A. Backhaul energy consumption model

The energy consumption of wireless backhaul links is directly related to the incurred transmit power S_{TX} necessary to achieve the target received signal-to-noise ratio (SNR). The SNR is defined as $\sigma = \frac{S_{\text{RX}}}{N}$, where N is the thermal noise power in the channel and S_{RX} is the received signal which is assumed to follow distance-based propagation loss such as: $S_{\text{RX}} = K \cdot S_{\text{TX}} \cdot d_c^{-\alpha}$. In the latter expression, d_c is the reach of the last-mile wireless link connecting small cell c, and α is the propagation exponent. The constant K is the product of the propagation constant and antenna gain (affected by the cable loss). Following the approach in [8], the energy consumption (in Joules) of a wireless backhaul link b can be expressed as follows:

$$E_{b,c} = [S_{\text{TX}} \times \eta + \epsilon] \times T = \left[\eta \cdot \frac{N \cdot \sigma}{K_b} \cdot {d_c}^{\alpha_b} + \epsilon\right] \times T \quad (1)$$

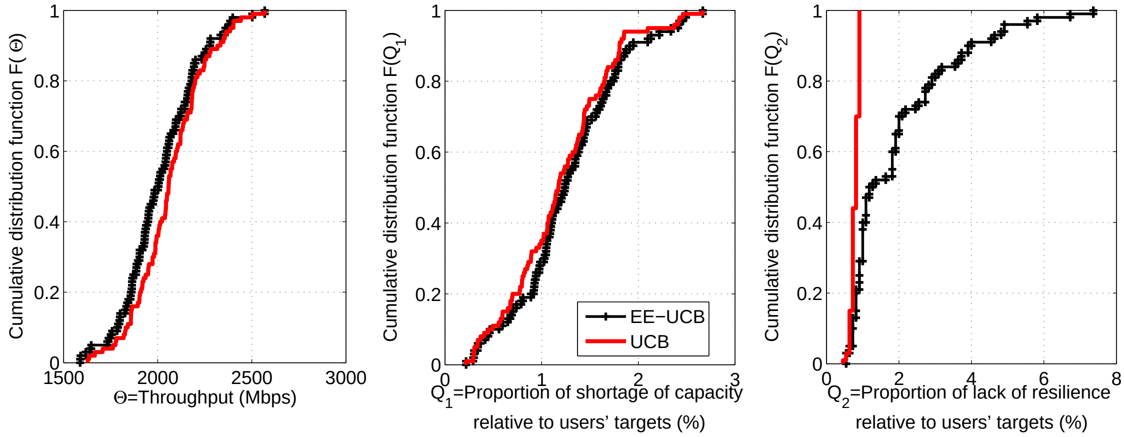

Fig. 3. The left=most figure shows the cumulative system application-layer throughput. The middle figure shows the gap between the users' required and achieved throughput. The right-most figure shows the difference between required and achieved latency.

The parameter T represents the time duration (in seconds) over which the link is active. As the propagation characteristics (K and α) vary with respect to the operational frequency, the energy consumption of links in each of the traditional microwave (e.g., at 28 GHz) and mmWave (e.g., at 60 GHz) bands would differ significantly, even when the travelled distance is the same.

The energy efficiency of the backhaul is measured as the amount of data (in Mbits) transmitted per Joule of backhaul energy. This can be expressed as follows:

$$\Gamma_{b,c} = \frac{\Theta_b}{\left[\eta \cdot \frac{N \cdot \sigma}{K_b} \cdot {d_c}^{\alpha_b} + \epsilon\right]} \tag{2}$$

where, Θ_b is the throughput in Mpbs carried over the backhaul b of small cell c, hence, $\Gamma_{b,c}$ is measured in Mbits/Joule.

B. Results and analysis

The proposed scheme (EE-UCB) is compared to the UCB scheme which each cell has two last-mile links (L1 at 23GHz and L2 at 60GHz) that are always on. The cells are identical in terms radio parameters such as transmit power, allocated spectrum, antenna height and type, etc. Users are distributed randomly in the network and their required quality targets are generated randomly with different quality expectations (see Table I). Over 100 runs, the location of users (and their corresponding shadowing) is dynamically changed to reflect actual users' behaviour. Moreover, the available throughput of the last-mile backhaul of each cell is randomly varied, per run, around its nominal capacity to reflect dynamic changes in the backhaul network. The availability of the last-mile link is also randomly altered, based on the nominal outage probability of the corresponding technology. The network and users' key performance indicators (KPI) are recorded for every run, by capturing the cumulative effective network throughput and the users' satisfaction with respect to achieved throughput and resilience. In addition, a record is kept of all active last-mile links over the 100 runs. The parameters adopted in these simulations are summarised in Table I.

TABLE I
MAIN SIMULATION PARAMETERS ADOPTED IN SIMULATIONS.

	L1	L2
Central frequency (GHz)	28	60
Transmit power-S_{TX} (mW)	147	675
α	4	4
η	7.84	7.86
ϵ (W)	71	71
Nominal throughput (Mbps)	300	1000
Nominal availability (%)	99.999	90
Radio parameters/Users parameters		
Number of users	180	
Cell radius (m)	80	
Bias factor range (dB)	0-9	
Nb. of resource blocks per cell	50	
Target user SINR(dB) - low	0	50% of users
Target user SINR(dB) - high	5	50% of users
Required user availability - high	90	50% of users
Required user availability - low	99	50% of users

Three KPIs are shown in Figure 3: (i) the total network throughput - a network KPI, (ii) the throughput shortage as experience by users with high priority re-capacity - a user KPI, and (iii) the resilience shortage as experience by users with high priority re-resilience - another user KPI. Network throughput (i) witnesses a slight degradation of 2.44%, on average, as shown in the left most graph. Users' QoE experiences a degradation of 0.08% and 1.16% with respect to throughput-based and resilience-based performance criteria (middle and right-most graphs), respectively. On the other hand, the number of active last-mile backhaul links has dropped from a constant 18×100 in the UCB scenario to 1571

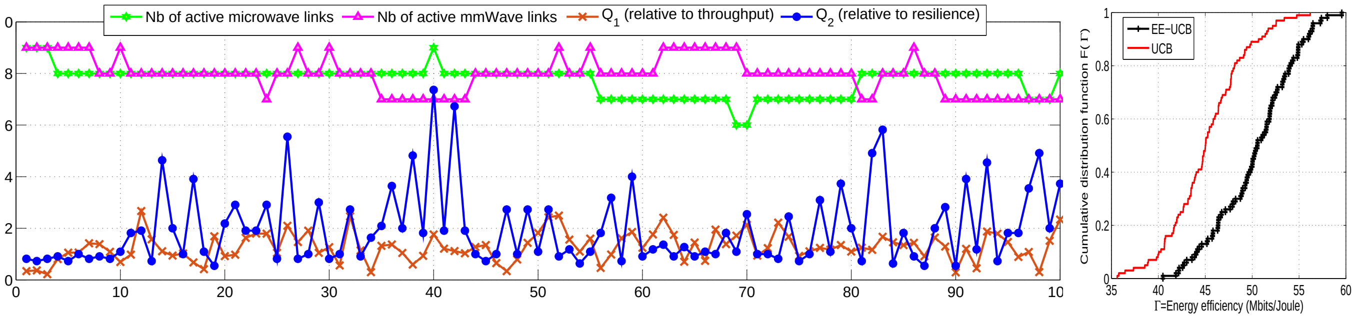

Fig. 4. Leftmost: Number of active last-mile links (microwave and mmWave) shown in parallel with the throughput-based (Q_1) and latency-based (Q_2) QoE degradation (proportion of shortage of capacity and lack of resilience relative to users targets (%), respectively) over 100 runs. Rightmost: Cumulative distribution function of energy efficiency for both schemes over the 100 runs.

over the recorded period, indicating a reduction of 12.72%, as shown in Figure 4 (left).

The impact of last-mile reduction on QoE degradation is evident in Figure 4 (left), as the QoE gap increases when the number of active links decreases. In the shown example, the maximum accepted gap for both throughput-based and resilience-based QoE is 1% and the sliding window size is three for both. Effectively, whenever a QoE degradation larger than 1% is recorded over three consecutive periods, the algorithm attempts to activate the key last-mile link that would improve the QoE. This is done by identifying the worst performing cell with respect to the bad QoE and then activating its QoE-rich last-mile. For instance, if the unsatisfactory QoE were resilience, then the microwave link would be activated; and if it were capacity, then the mmWave would be activated. If the least performing cell has both links active, then the algorithm would move up in the sorted list of cells until it finds a suitable link to activate. In parallel, the algorithm uses the sliding window method to identify last-mile links that are lightly loaded and would attempt to deactivate the one with lowest load to save energy. The correlation between the number of active links and the users' QoE is clearly seen in Figure 4 (left); more importantly the system seem to manage better quality with less active last miles, with time. This is can be deduced by looking at the number of active links and corresponding QoE between iterations 10 to 40 and 70 to 100. The number of active links is reduced from a mean of 16 to 15 while the capacity-based QoE remains at a mean of 1.3% and the resilience-based QoE is improved from 2.3% to 2.2%.

The cumulative distribution function of the effective energy efficiency index is show in the rightmost graph of Figure 3. The EE-UCB scheme has clearly improved the energy efficiency of the system with an overall improvement of 11.4%. The difference between the reduction in number of active links and the improvement of energy efficiency is due to the difference in energy consumption between microwave and mmWave links and the corresponding impact of the last-mile reach. In brief, the proposed algorithm has effectively improved the energy efficiency of the backhaul network by 11.4% at the cost of slight degradation in total throughput of 2.44% and 1.16% users' QoE.

C. Sensitivity analysis

In this section, we study the impact of different user-defined parameters on the performance of the proposed algorithm. Settings and results from all tested scenarios are summarised in Table II, in which Scenario A is the basic scenario presented in the previous section. Each scenario, other than Scenario A is simulated over 50 runs. First, the effect of changing the minimum accepted load on the last mile backhaul is investigated. When the minimum load is decreased from 20% to 10% between Scenarios (A and A1) and (A4 and A4.1), the resulting throughput and QoE degradation is reduced as well as the energy efficiency gain, as can be seen in Table II. However, the improvement in quality and throughput is more important than the reduction in energy efficiency gain. On the other hand, when the load threshold is increased to 30% in Scenario A2, the energy efficiency gain is improved but higher degradation in throughput and QoE is recorded.

Next the effect of varying the accepted QoE gap is studied. The accepted QoE gap is changed to 5% in Scenario A3, resulting in further reduction in total throughput and degradation in users' QoE, compared to the basic Scenario A with 1% setting. However, the gain in energy efficiency has significantly improved (21.9%). The same behaviour can be seen when comparing Scenarios A2 and A2.1. On the other hand, reducing the accepted QoE gap to 0.5% has the opposite effect, and the gains of the proposed algorithm become limited, as shown with Scenario A4.

The role of the sliding windows sizes is assessed next, by reducing the activation sliding window separately (Scenario A5) or both activation and deactivation windows (Scenario A6). The results show less stable behaviour of the proposed algorithm with more frequent toggling between ON/OFF status without considerable gain in energy efficiency nor network or users' KPIs. It is thus not recommended to reduce the size of the sliding window beyond the basic setting.

Last, we look at the effect of increasing the number of simultaneous toggling ON or OFF of last-mile links. In the basic Scenario A, only one last-mile link is activate or deactivated at one time. In Scenarios A7 and A4.2, the

TABLE II

SENSITIVITY ANALYSIS SCENARIOS. THE REDUCTION IN THROUGHPUT AND INCREASE IN Q_1, Q_2, AND ENERGY EFFICIENCY ARE RELATIVE TO THE UCB RESULTS.

	A	A1	A2	A2.1	A3	A4	A4.1	A4.2	A5	A6	A7
Maximum QoE1 gap (%)	1	1	1	2	5	0.5	0.5	0.5	1	1	1
Maximum QoE2 gap (%)	1	1	1	2	5	0.5	0.5	0.5	1	1	1
Minimum last-mile load (%)	20	10	30	30	20	20	10	20	20	20	20
Max number of toggle up	1	1	1	1	1	1	1	2	1	1	2
Sliding window size UP	3	3	3	3	3	3	3	3	2	2	3
Sliding window size DOWN	3	3	3	3	3	3	3	3	3	2	3
Reduction in throughput (%)	2.44	1.27	3.24	4.38	5.69	1.67	0.66	1.76	2.65	3.43	2.8
Increase in Q_1 (%)	0.08	0.02	0.1	0.11	0.11	0.06	0.01	0.06	0.13	0.09	0.06
Increase in Q_2 (%)	1.16	0.21	2.42	2.92	1.78	1.17	0.14	0.53	1.4	1.36	0.61
Increase in energy efficiency (%)	11.4	8.33	14.67	17.89	21.9	7.52	4.5	8.83	8.79	9.85	12.3

number is increase to two simultaneous possible switches. The results of users' QoE related to resilience is twice improved and energy efficiency is also increases by $\sim 10\%$, while resulting in minimal degradation in network KPI. This setting allows two links to be activated simultaneously, hence, improves the resilience-related quality of experience of users, as resilience is the bottleneck of the network (as seen in all scenarios in Table II). On the other hand, deactivating two links simultaneously reduces further the energy consumption. In parallel, the throughput-related QoE constraints limits this occurrence, resulting jointly in improved energy efficiency (ratio of slightly lower throughput over significantly reduced energy consumption).

V. CONCLUSION

In this work, we have proposed an energy-efficiency-aware implementation of the user-centric backhaul concept. The scheme uses a two-steps optimisation approach: the first is centralised and the second is distributed. The centralised step strives to reduce the number of active last-mile links while respecting the user-defined quality-related constraints. The distributed step optimises the settings of the broadcast quality-related bias factors of all cells in the system according the ON/OFF status of their last-mile links. An energy saving of up to 21.9% is achieved with minor degradation in network and users-based KPIs. We have also conducted a sensitivity analysis to assess the role of different algorithm parameters on the results. As such, we have demonstrated that the proposed algorithm may be tuned to achieve the desired KPIs while still saving on backhaul energy for all tested quality targets. The stability of the algorithm is also investigated and guidelines for choosing the size of the sliding windows and the number of simultaneous last-mile activations are defined.

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