A Multiple Attribute User-Centric Backhaul Provisioning Scheme using Distributed SON

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***Abstract*— The backhaul network is a critical challenge towards the success of 5G and corresponding difficulties are many-fold, such as network coverage expansion, very high bandwidth, ultra-low latency and energy consumption, at a minimum cost. No single backhaul solution can address all these requirements but, on the other hand, not all of the backhaul links require the same set of stringent requirements. To this end, we propose a novel scheme that capitalises on the diversity in both performance requirements and backhaul capabilities to maximise the system-centric as well as user-centric performance indicators. The user-centric backhaul provisioning scheme uses multiple attribute decision making (MADM) for the user-cell-backhaul association criteria in a way that intelligently associates users with available cells based on corresponding dynamic radio and backhaul conditions while abiding by users requirements. Radio cells broadcast multiple bias factors, each reflecting a dynamic performance indicator of the end-to-end network performance such as capacity, latency, resilience, energy consumption, etc. A given user would employ these factors to derive a user-centric cell ranking that motivates it to select the cell with radio and backhaul capabilities that conform to the user requirements. Reinforcement learning is used by the radio cell to optimise the bias factors for each performance indicator in a way that maximises the system performance and users end-to-end quality of experience (QoE). Preliminary results based on a case study show considerable improvement in users QoE when compared to state-of-the-art user-cell association schemes.**

***Index Terms*— Backhaul, user-centric, user-cell association, SON, reinforcement learning, multiple attribute decision making**

I. Introduction

Ultra dense small cell networks are deemed an ipso facto catalyst of 5G deployment owing to the proximity of cells to users, hence, low power operation which results in energy efficiency and high area spectral efficiency. The first challenge is to connect these blossoming small cells to the core network which entails expanding the backhaul in breadth and depth to reach them. Moreover, the exigent performance requirements of 5G networks in terms of throughput in the order of Gbps and latency less than a millisecond, are reflected on the backhaul and are often more stringent. Direct fibre optic links (dark fibre) may be considered as the best choice in delivering this performance category, however, they are not widely available and are inhibitive and cumbersome to lay down to every small cell. Copper-based links, based on digital subscriber lines (xDSL), are generally available but have limited capacity and relatively higher latency. Wireless links are fast to deploy since they do not require trenching; these are either licenced or unlicensed. Licenced wireless backhaul links provide reliable connections but limited capacity due to overcrowding of the spectrum and the relative cost (e.g., microwave or in-band backhauling). Unlicensed wireless links have in general ample bandwidth and capacity but are less reliable (e.g., sub-6GHz due to interference, or millimetre wave due to challenging propagation conditions). Incumbent cellular networks rely on a mix of wired and wireless links to form the existing backhauls and it is envisaged that the 5G backhaul will similarly be heterogeneous.

Disruptive radio access network (RAN) technologies such as Cloud-RAN and splitting of data and control planes are also characteristics of 5G networks. Consequently, the 5G RAN is heterogeneous with a mix of macro-cells (high power) and small cells, different radio access technologies (RAT), different forms of Cloud-RAN, and data/control planes management. Each of these cells would have different backhauling needs and would generate different levels of traffic towards the backhaul. In addition, advanced radio features such as coordinated multi-point processing (CoMP), carrier aggregation, and massive multiple input multiple output (MIMO) transmission would also impact the requirements on the backhaul links. Consequently, the 5G backhaul requirements vary with respect to the type of connected radio cell and some scenarios are more or less lenient on given aspects than others.

Diversity in requirements also exists from the user's perspective. Indeed, eight 5G service use-case families have been identified, "ranging from delay-sensitive video applications to ultra-low latency, from high-speed entertainment applications in a vehicle to mobility on demand for connected objects, and from best effort applications to reliable and ultra-reliable ones such as health and safety" [1]. These services will be delivered across a wide range of devices with different capabilities, such as amplification, MIMO, and battery-life. Hence, each user has different performance targets, where some prioritise latency (e.g., e-health) others value energy efficiency (e.g., smart metre) or high throughput (e.g., video conferencing).

According to the broad variety of users' requirements, RAN requirements and backhaul network capabilities, a cell-centric backhaul may not be the best option for service provisioning. To this end, a novel user-centric backhaul is proposed in which users associate with cells that satisfy their service requirements from both RAN and backhaul sections of the network. The novel association scheme is based on virtual cell footprints that are tailored for each user according to his QoE requirements and the network availabilities and constraints. The potential gain that can be obtained from user-centric backhauling, exploiting the heterogeneous backhauling options, promises to reduce the performance gap between 5G backhaul network expectations and realistic backhaul solutions, while capitalising on the existing infrastructure.

The rest of the paper is organised as follows. We first provide a background on state-of-the-art user-cell association schemes

in Section II. In Section III we present our novel user-centric backhaul scheme in a case study and conclude in Section IV.

II. State-of-the-art user-cell association

Traditionally, user-cell association in both idle and active modes is based on the signal strength received by the mobile device, for all cellular generations. In idle mode, the mobile measures all available downlink (DL) signals from the cells in the authorised network, and once it decodes the cell identification data, ranks the potential cells based on the strength of the DL common channel. The mobile device attempts to access the identified potential serving cells, starting from the highest ranking cell, until one of them grants access. In active mode, the mobile device periodically measures the DL signal strength of the serving cell's neighbouring cells and reports it to the RAN, which uses the data to rank potential candidates for handover.

Such ranking and selection mechanisms are suited for networks designed to ensure one prime serving cell within the network coverage area, and where most mobile devices are operated by humans with similar quality of service (QoS) expectations. In the presence of heterogeneous networks (HetNets), composed of umbrella-type macro-cells overshadowing multi-RAT small cells, and diverse users' requirements, such a simplistic decision-making becomes obsolete and inefficient.

A. Cell range extension for heterogeneous network

Small cells have very low transmitted power compared to macro-cells; this would result in most users ranking the macro-cell highest, hence, missing out on the extra capacity provided by the small cell layer. A workaround to this problem is the cell range extension (CRE) mechanism, whereby a cell range extension offset (CREO) is broadcast by small cells to bias their ranking and attract users to select them [2]. Authors in [3] propose to use Q-learning, a reinforcement learning technique, for users to optimise user-centric bias values that would reduce the number of users in outage in the system. Q-learning is employed again in [4], as a self-optimised network (SON) technique, by cells (small and macro) to adjust dynamically their corresponding CREO values and the ICIC mechanism leading to improvement in users' throughput.

B. Multiple attribute decision making in user-cell association

While CRE addresses the challenge of biassing users to various network layers and may also be used for load balancing; it is nonetheless unaware of the different capabilities of various cells and diverse requirements of different users. A novel call admission control algorithm addresses this gap in [5], in which various types of call requests with various QoS parameters are considered in a multi-RAT environment. The scheme aims to offer the required QoS to new calls without degrading the existing calls' quality while prioritising handover calls. Another user-centric joint call admission control scheme is proposed in [6], in which RAT selection is based on user preference (e.g., cost, data rate, security, and battery consumption), using fuzzy MADM technique.

C. Backhaul-aware cell range extension

Mechanisms introduced so far ignore the backhaul conditions in the call admission procedure. However, the backhaul may be the new bottleneck of next cellular generations, thus, call admission schemes that are blind to the backhaul status may effectively be shifting the problem from the radio to the backhaul. Hence, they are essentially neither solving the user QoE problem nor the network efficient utilisation problem of next generation networks.

In our previous work, [7], we propose extending the usage of CRE to have it reflect the end-to-end available capacity of the cell, including the backhaul. Q-learning is used to dynamically adjust the CREO of each cell with the aim of maximising the system throughput while avoiding users' assignement to cells with congested backhaul links leading to 15% improvement in users' QoE. In another work, [8], CRE feature is used to reflect the backhaul delay of the corresponding cell and influence users' selection accordingly. Similarly, a joint radio-backhaul delay objective is targeted in [9] in which authors consider a two-tier HetNet with wireless backhaul (out-of-band). CRE is again employed and the CREO is centrally optimised to attract users to select cells with minimum end-to-end delay.

III. A multiple attribute user-centric backhaul-aware user-cell association

Backhaul-aware cell selection is a promising research direction for solving the holistic user-network association problem instead of shifting the bottleneck from radio to backhaul, as presented in Section II. However, none of the current works fully capitalises on users QoS diversity nor on distributed SON. Our novel scheme, the user-centric backhaul, addresses these two shortcomings as explained here.

Next generation cellular networks are heterogeneous, thus, there are numerous candidate cells for users to connect to at any point and more options to backhaul to the core network. The 5G network operators' prime objective is still to maximise their revenue; hence, they want to maximise the users' QoE to increase their market share while minimising the network expenditure. While the radio side was the focus of incumbent cellular networks' optimisation, 5G comes with broader challenges and new opportunities. Network optimisation can no longer be conducted in network chunks but should target end-to-end performance, hence the critical role of an intelligent user-cell-backhaul association scheme that maximises the utilisation efficiency of the network in parallel with users' QoE as a first goal.

A. System model

In the novel scheme, the radio cells have knowledge of the dynamic status and capabilities of their connected backhaul links and the corresponding radio channels. Cells employ this information jointly to optimise a set of CREO factors that reflect different constraints/capabilities of the end-to-end network. A high capacity-based CREO indicates that the cell is capable of ensuring end-to-end high capacity to potential users, whereas a low latency-based CREO is associated with high end-to-end latency, thus, discouraging users with stringent delay requirements. Similarly, a low resilience-based CREO indicates that the cell has high outage probability, due to weather-dependant wireless backhaul link, for instance. Other bias values may correspond to the level of energy efficiency, cost per bit, relative security, etc. On the other hand, users have relative weights to different QoEs, affected by the device capabilities, the user preferences, and the

application used. With delicate settings of these CREOs, it is possible to optimise the user-cell-backhaul matching exercise in a way that satisfies the users' QoE while respecting the network's conditions. This leads to a user-centric virtual perspective of the network cells' footprints, tailored to each user's needs, as proposed in this paper.

We present a case study in which the user-centric backhaul scheme is simulated assuming three user attributes: throughput, latency, and resilience. Dynamic capabilities and constraints of each backhaul link are randomly generated and periodically changed to reflect the backhaul status with respect to these three attributes. The system considered consists of one macro-cell with three sectors and 21 small cells in fixed locations. Small cells use Q-learning to self-learn three optimised CREOs that indicate three joint radio/backhaul capabilities and constraints: throughput, latency, and resilience. Each small cell is assumed to have only one backhaul link and macro-cells are assumed to aggregate the backhaul traffic of all small cells over an ideal backhaul. Users are randomly generated and uniformly distributed with higher concentration in hot-spots (centred around the locations of small cells). QoE requirements and corresponding weights of users are also randomly generated.

The system is simulated over 100 runs; in each run the users are randomly re-distributed with the reassignment of QoE requirements and weights, and the backhaul capabilities and constraints are regenerated randomly. In the proposed algorithm, we capture the variation of the network conditions through a Monte Carlo approach in which, within each of the 100 simulated runs, different snapshots of the system are considered with the users' movements, activities, shadowing conditions, in the serving and interfering neighbouring cells are changed, resulting in realistic radio access network variations. In addition, the backhaul link status is randomly varied to reflect changes in a realistic transport network. Similar to current LTE cell selection schemes, we assume that the effect of fast fading (multi-path fading) is averaged out by defining a minimum duration over which a cell should rank best before being selected. Hence, fluctuations due to fast fading will not change the setting of the CREOs which is desired to avoid system instability. These simulation considerations are in-line with the work conducted in [7] and readers are encouraged to refer to this document for more details. The performance of the user-centric backhaul (User-centric-BH) is compared to four other scenarios, under identical network and user conditions, as follows:

- SINR-based user-cell association (SINR-based).
- Backhaul-aware CRE (capacity), as in [7] (BH-aware-CRE)
- CRE with fixed bias=6dB (Fixed CREO=6dB).
- CRE with fixed bias=12dB (Fixed CREO=12dB).

The results of each scenario are captured over the 100 runs and the corresponding cumulative distribution function of each key performance indicator (KPI), listed below, is generated. The first KPI is the cumulative throughput of all served users in the system as shown in Figure 1 (Left); that is the sum of all served users $u \in |\mathcal{U}|$ achievable throughput T_u as defined in (1), where $|\mathcal{U}|$ is the cardinality of the set of al users int he system.

$$T(\mathbf{B}) = \sum_{c=1}^{|\mathcal{C}|} \sum_{u=1}^{|\mathcal{U}_c|} T_{c,u} \tag{1}$$

where, T is a realisation of the cumulative system throughput, $\mathbf{B}$ is the realisation of the optimised set of CREOs, $|\mathcal{C}|$ is the cardinality of the set of cells (small and macro) in the system, $|\mathcal{U}_c|$ is the cardinality of the set of users served by cell c, and $T_{c,u}$ is the instantaneous effective throughput experienced by user u served by cell c. $T_{c,u}$, is based on the actual measured SINR if the backhaul is not a bottleneck. Otherwise, if the captured radio throughput of a cell c exceeds the backhaul capacity by a margin M, then the throughput of all users served by the cell is reduced uniformly by the same amount which is $\frac{M}{|\mathcal{U}_c|}$. Clearly the CRE feature enhances the system throughput as seen by the noticeable improvement between the SINR-based approach and the CRE-based approaches. Besides, the User-centric-BH is second-best in maximising the system throughput lagging behind the Fixed CREO=12dB by 3.3%. Figure 1 (Right) shows another KPI reflecting the proportion of users in outage; these are users that are not permitted in the system due to radio or backhaul unavailability. The Fixed CREO=12dB results in the best outage KPI since users are pushed down to the small cells layer even if such a shift undermines the users' QoE. Both, the BH-aware-CRE and the User-centric-BH are tailored to satisfy users' QoE and may result in outage when the minimum requirement is not possible; 6.5% more users are in outage with the novel scheme compared to the Fixed CREO=12dB.

The left side plots in Figure 2 show the aggregate gap between users' QoE expectations (Q_i) and achieved performance ($\breve{Q}_i$) for users who prioritise the corresponding QoE. The QoE Q_1 indicates the throughput, Q_2 the latency, and Q_3 the resilience. Three KPIs are shown: x refers to the network throughput shortage, y to the excess in latency, and z to lack of resilience, respectively, as shown below.

$$x = 100 \cdot \sum_{c=1}^{\mathcal{C}} \sum_{u=1}^{|\mathcal{U}_c|} \frac{Q_{u,1} - \breve{Q}_{u,1}}{Q_{u,1}}, | \{\breve{Q}_{u,1} < Q_{u,1}, W_{u,1} = W_H\} \tag{2}$$

$$y = 100 \cdot \sum_{c=1}^{\mathcal{C}} \sum_{u=1}^{|\mathcal{U}_c|} \frac{\breve{Q}_{u,2} - Q_{u,2}}{Q_{u,2}}, | \{\breve{Q}_{u,2} > Q_{u,2}, W_{u,2} = W_H\} \tag{3}$$

$$z = 100 \cdot \sum_{c=1}^{\mathcal{C}} \sum_{u=1}^{|\mathcal{U}_c|} \frac{Q_{u,3} - \breve{Q}_{u,3}}{Q_{u,3}}, | \{\breve{Q}_{u,3} < Q_{u,3}, W_{u,3} = W_H\} \tag{4}$$

where, $W_{u,i}$ is the weight that user u associates with QoE i, $Q_{u,i}$, and W_H indicates high priority.

The right-side plots in Figure 2 show the aggregate gap between users' QoE targets and measured performance for those who do not prioritise the corresponding QoE. Three KPIs are shown, x' refers to the throughput shortage, y' to the excess in latency, and z' to lack of resilience, respectively. These are computed as in (2), (3), and (4) with W_H replaced with W_L, indicating low priority. Note that users in outage are considered to have zero measured throughput, 0% resilience, and a latency of 1000msec in all cases.

The KPIs shown in Figure 1 are considered network-centric since they reflect the performance perceived by the network, blind to the users' preferences. Whereas, KPIs shown in Figure 2 are user-centric since they evaluate how close the network is capable of delivering the specific QoE requested by users, compared to their particular targets. Although from a network perspective, the Fixed CREO=12dB seems the most attractive solution, it fails to deliver on all aspects of users' QoE, hence, would lead to users' dissatisfaction and potential churn.

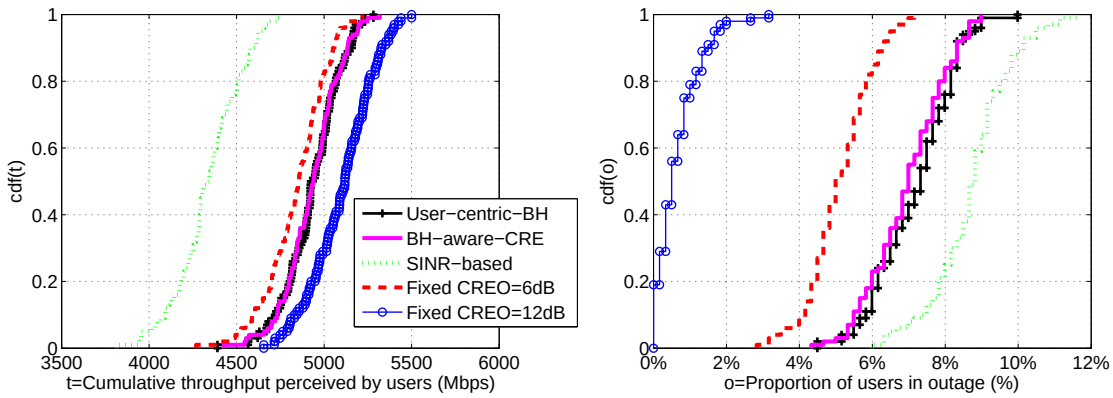

Fig. 1. (Left) Cumulative users' throughput: CRE-based schemes outperform the SINR-based scheme and the novel User-centric-BH lags behind the maximum throughput scheme by 3.3$. (Right) Proportion of users in outage: 6.5% more users are in outage with novel scheme.

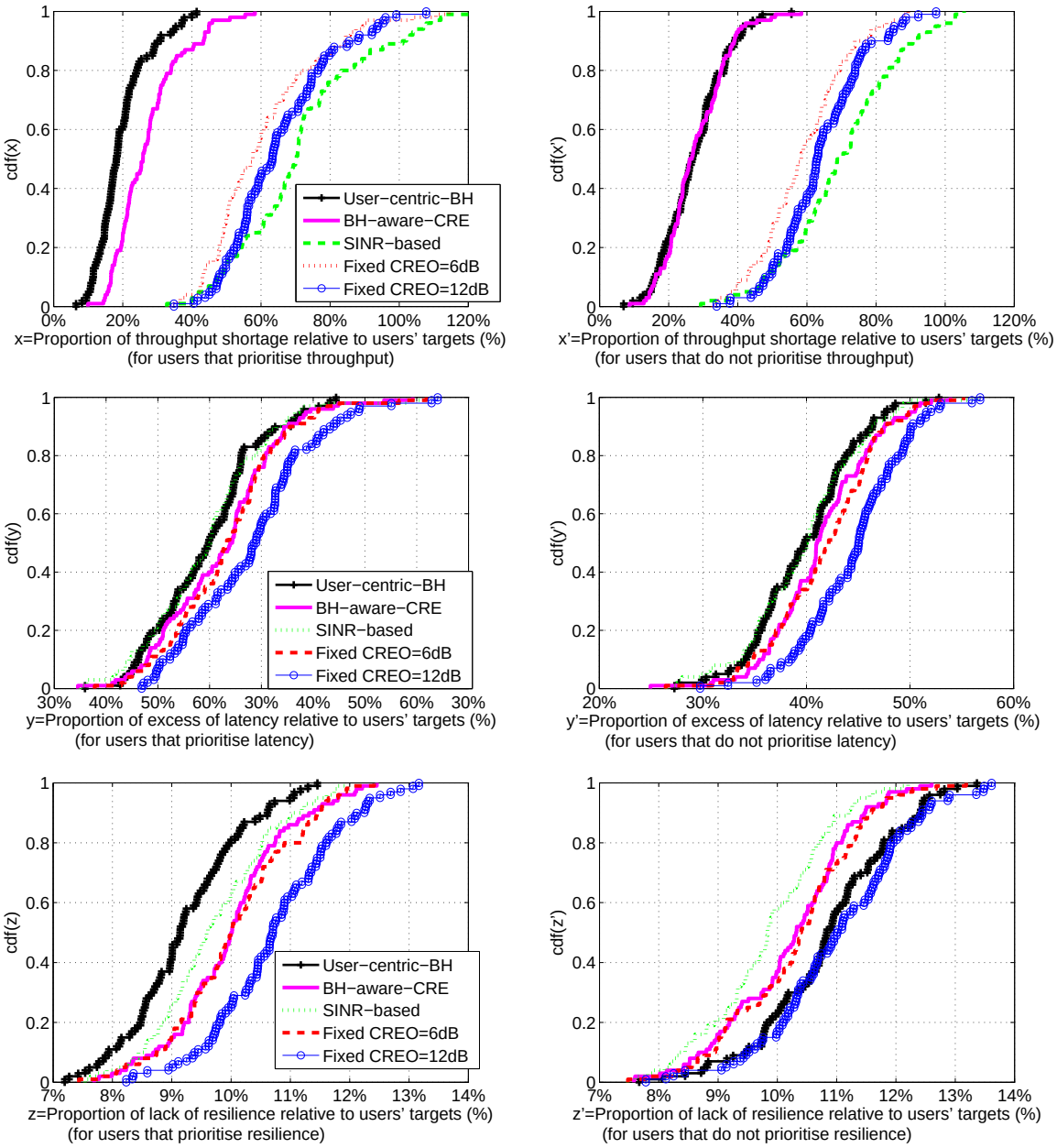

Fig. 2. User-centric KPI measuring the shortage or excess of measured QoE relative to user defined target for: throughput (x,x'), latency (y,y'), and Resilience (z,z'). The left-side figures show the QoE gap of users that prioritise the indicated QoE; the right-side figures show the QoE gap of those who do not prioritise the indicated QoE. The novel approach is the only one that distinguishes users' priorities and outperforms all others in terms of user-centric KPIs.

The novel scheme succeeds in maximising the throughput-based QoE of users who value this criterion, as seen in Figure 2 top-left; whereas for those users that do not prioritise throughput, the performance is similar to the BH-aware-CRE (Figure 2 top-right). In other words, the novel scheme allocates throughput-rich resources to users who value this criterion, instead of wasting them on those who do not. Moreover, the novel scheme is the only one that maximises simultaneously all users' QoE, including latency and resilience-based, as seen in Figure 2 middle-left and bottom-left.

1) Analysis and insights: Assessing the effectiveness of an optimisation scheme may only be performed after identifying adequate and representative performance metrics. Authors in [10] highlight the critical role of user-centric QoE metrics in 5G, in addition to network-centric metrics. The results shown in Figures 1 and 2 are averaged and summarised in Table I for clarity. There are five network-centric metrics: $\overline{t}$ and $\overline{o}$ corresponding to the mean values in Figure 1, and $\overline{o_x}$, $\overline{o_y}$,and $\overline{o_z}$ corresponding to the proportion of unsatisfied users with respect to throughput, latency, and resilience, respectively. In addition, six user-centric performance metrics are shown: $\overline{x}$, $\overline{x'}$, $\overline{y}$, $\overline{y'}$, $\overline{z}$, and $\overline{z'}$ which reflect the mean values from Figure 2.

The cumulative throughput, $\overline{t}$ and the proportion of users in outage $\overline{o}$ consistently improve with increased CREO value as can be deduced from comparing the SINR-based scheme to the Fixed CREO=6dB and 12dB. This is an expected outcome since higher CREO values push more users to the small cell layer hence increase the usage efficiency of the available spectrum. Thus, from a high system-level perspective, the Fixed CREO=12dB comes across as the best scheme. However, when we look closely at the number of satisfied users, the image changes as the User-centric-BH reduces the number of unsatisfied users for both throughput and latency aspects, and is second-best in reducing the number of users connected to the network with less than desired resilience. The SINR-based scheme retains the highest number of users on the macro-cell which, in our simulations, is assumed to have an ideal backhaul link with ultra low latency and highest resilience. Consequently, the SINR-based scheme is evidently a close contender in improving resilience and latency. However, it results in the least cumulative throughput due to the saturation of the macro-cell and lack of motivation for the users to select the small cells. In brief, from a holistic network perspective, the User-centric-BH achieves the best results since it maximises the proportion of satisfied users, from all aspects, at the mere cost of 3.3% throughput reduction.

Analysing the user-centric metrics reveals further the strengths of the User-centric-BH. Indeed, a user that targets 500Mbps throughput is considered equally unsatisfied for any achieved throughput less than the target in the computation of the system-centric KPI o_x. However, the same user is more satisfied in reality if the achievable throughput is within 90% of the target as opposed to 50%, for instance. This critical difference in QoE is captured in the user-centric KPIs x and x', which measure the gap between the target and actual throughput. The same applies to the other QoE aspects represented by the KPIs y, y', z, and z'. The User-centric-BH is best or second best with a minor difference (0.2% with respect to $\overline{y}$) when examining the user-centric metrics $\overline{x}$, $\overline{y}$, and $\overline{z}$ for users that prioritise the respective QoE. In fact, the SINR-based scheme is naturally the safest for improving latency and resilience, only because the macro-cell is assumed to deliver all users' requirements in this respect (ideal backhaul assumed). However, any other macro-cell backhaul assumption would negatively sway the actual users' latency and resilience when the SINR-based scheme is adopted, irrelevant of backhaul constraints of the small cells and users' needs.

Moreover, when examining closely the User-centric-BH and the BH-aware-CRE respective performances in maximising the throughput-based QoE, the sensitivity of the novel scheme to distinguish the users' preferences becomes evident. Both schemes aim to reduce the gap between the users' target and achievable throughput, and they succeed to do so as shown by the corresponding lowest values of $\overline{x}$ and $\overline{x'}$. However, where the BH-aware-CRE achieves similar results for all users, with high or low priority to throughput-based QoE (27.13% and 27.77%, respectively), the User-centric-BH reduces further the gap for users who associate high values to throughput resulting in 19.56%, and 27.43% for users who value it less.

On the other hand, it is interesting to note the effect of fixed CREO on the throughput-based metric $\overline{x}$ and $\overline{x'}$. The SINR-based is indeed a fixed null setting of the CREO, and has the worst performance, as expected since it does not take advantage of the offered capacity on the small cells. What is more interesting is that the Fixed-CREO=6dB outperforms the 12dB setting; the latter scheme forces users to select the small cells despite the fact that there is available capacity on the macro-cell with better backhaul throughput conditions. This indicates that the optimum value for the CREO, per cell, is constantly changing, bounded by the two extreme values: 0 and 12.

In summary, the User-centric-BH delivers on the optimisation objectives that we set from both network and user perspectives. Moreover, the novel scheme is sensitive to users' preferences, hence results in an efficient resource allocation that satisfies diverse users' needs while simultaneously maximising the network's performance. Optimising 5G networks proves to be largely more complex than incumbent cellular generations due to the new user-centric dimension that is gaining a pivotal role in measuring the network's performance. The proposed novel scheme succeeds in sustaining network-centric metrics with a marginal degradation of 3.3% in total throughput while improving users' QoE on all targets: throughput (70%), latency (9.6%), and resilience (14.2%) when compared to the maximum throughput delivering scheme. It would certainly be interesting to evaluate this scheme when more than three users' QoE attribute are targeted; however, one can deduce that with the User-centric-BH scheme, at least, the same performance of the state-of-the-art schemes may be expected. Moreover, comparing the results from [7], which considers one QoE attribute, to the results presented here with three QoE attributes shows that the user-centric metrics have inarguably improved, indicating that the User-centric-BH scheme will outperform the state-of-the-art.

From a different angle, the results can be interpreted as a guide for estimating the required network upgrades. If the Fixed CREO=12dB scheme is adopted, the network is deemed to lag behind the users' QoE throughput, latency, and resilience targets by 64%, 44% and 11%, respectively, on average. Such results would motivate a network operator to upgrade the existing backhaul network to accommodate the users' requirements. On the other hand, if the novel User-centric-BH scheme were to be adopted, the network gap is reduced by 70%, 9.6% and 14%, thus reducing the required network extensions and highlighting the bottleneck which is latency in the given example. The

TABLE I

TABULATED RESULTS FROM CASE STUDY COMPARING THE AVERAGE METRICS ACHIEVED BY EACH OF THE TESTED SCHEMES.

		User-centric-BH	BH-aware-CRE	SINR-based	Fixed CREO=6dB	Fixed CREO=12dB	Delta(%)
Cumulative throughput perceived by all served users (Mbps)	$\overline{t}$	4933	4930	4337	4840	**5101**	3.3%
Proportion of users in outage (%)	$\overline{o}$	7.1	7.0	8.72	5.10	**0.65**	6.5% of users
Proportion of unsatisfied users with respect to throughput (%)	$\overline{o_x}$	**5.01**	5.02	6.44	6.79	8.11	N/A
Proportion of unsatisfied users with respect to latency (%)	$\overline{o_y}$	**6.96**	7.2	6.97	7.44	7.97	N/A
Proportion of unsatisfied users with respect to resilience (%)	$\overline{o_z}$	12.10	12.13	**11.83**	12.45	13.37	2.3%
Proportion of throughput shortage relative to users targets (for users that prioritise throughput) (%)	$\overline{x}$	**19.56**	27.13	70.85	60.49	64.81	N/A
Proportion of throughput shortage relative to users targets (for users that do not prioritise throughput) (%)	$\overline{x'}$	**27.43**	27.77	69.75	58.87	63.90	N/A
Proportion of latency excess relative to users targets (for users that prioritise latency) (%)	$\overline{y}$	39.79	41.17	**39.72**	41.78	44.01	0.2%
Proportion of latency excess relative to users targets (for users that do not prioritise latency) (%)	$\overline{y'}$	39.81	41.39	**39.69**	41.78	44.57	0.3%
Proportion of lack of resilience relative to users targets (for users that prioritise resilience) (%)	$\overline{z}$	**9.21**	10.00	9.70	10.04	10.73	N/A
Proportion of lack of resilience relative to users targets (for users that do not prioritise resilience) (%)	$\overline{z'}$	10.84	10.21	**9.84**	10.31	11.01	10.16%

insights drawn from the achievable metrics with the User-centric-BH are critical for operators to plan the network optimisation manoeuvres and focus the spending on key network aspects that would unlock the users' perceived QoE. Such an approach distinguishes the performance gaps due to resources mismanagement from those that can not be circumvented by intelligent user-cell-backhaul association, hence reveals the hard limits of the network.

IV. CONCLUSION

We have presented a novel concept of user-centric backhauling, which exploits the diversity of the radio and backhaul networks as well as that of the users QoE expectations. The novel concept is based on a multiple attribute user-centric backhaul-aware user-cell association scheme which builds on the cell range extension feature. The novelty lies in the multiple cell range extension offsets used to reflect the different network end-to-end (radio and backhaul) performance aspects. We present a case study in which the novel concept is simulated assuming three key performance indicators: capacity, latency, and resilience. The small cells use reinforcement learning to optimise the value of each CREO in a way that the system throughput is maximised while users' QoE is also maximised. The results show a QoE improvement of 70%, 9.6% and 14% with respect to throughput, latency, and resilience, respectively, at the cost of 3.3% degradation in cumulative throughput.

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