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# Network Sharing to enable sustainable communications in the era of 5G and beyond

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***Abstract*—The transition towards the era of 5G and beyond is currently fostered by the extensive penetration of extremely demanding communication services, characterized by the need for exchanging increasingly larger traffic volumes with tight throughput and latency constraints. Nevertheless, the consequent massive densification of radio access networks (RANs) entails remarkable sustainability concerns, related to the staggering increase of energy demand and to the costly deployment of new infrastructure that, being dimensioned for future peak demands, may result underutilized for long periods of time. Furthermore, new potential vulnerabilities emerge that may impair the provisioning of resilient communication services. In this context, sharing network resources among different mobile operators (MOs) may play a key role to improve energy efficiency and to enhance resilience of future mobile networks. We hence investigate the potential benefits derived from the sharing of network infrastructure (primarily Base Stations with their portion of spectrum) among different MOs, comparing different areas, from a urban densely populated environment to a rural region. Based on real mobile traffic data, we design data-driven strategies to dynamically offload traffic among Base Stations owned by different MOs, allowing the switch off of unneeded resources. Our results shows that network sharing (NS) is effective in achieving huge energy saving and significant reduction of the electricity bill. Furthermore, proper configuration settings of the offloading strategies allow to trade off between sustainability goals and Quality of Service, hence enabling a feasible deployment of 5G scenarios and a sustainable evolution towards 6G.**

## I. Concept

The deployment of 5G networks is expected to provide excellent quality of service (QoS) to extremely high numbers of devices, to enable flawless services during user mobility, and to enhance energy efficiency with respect to previous communication technologies [1], [2]. Currently, the 5G technology is in its initial commercialization stage [2]. However, we are still witnessing relevant challenges in the actual realization of the 5G era, that is characterized by the widespread penetration of extremely demanding communication services, based on the massive Machine Type Communication, Ultra Reliable Low Latency Communications, enhanced Mobile Broadband service categories, and requiring edge caching and computing to support smart mobility [3]. Such services come with huge bandwidth requirements and tight delay constraints, and entail the need for exchanging increasingly larger traffic volumes. Whereas the extensive densification of radio access networks (RANs) aims at coping with this challenging scenario, sustainability concerns arise due to the consequent huge increase of network energy consumption and to the installation of new infrastructure that, being dimensioned for future peak demands, may result underutilized for long periods of time. Furthermore, mobile operators (MOs) face increasingly higher expenses, both in terms of operational cost (OPEX), due to the growing energy demand, and capital expenditures (CAPEX), due to the need for integrating new expensive network components based on 5G technology in their current infrastructure. Finally, new potential vulnerabilities emerge that may impair the provisioning of resilient communication services, entailed by the fast expansion of the network and by possible overload on the energy grid.

In this context, sharing network resources among different MOs may play a key role to improve energy efficiency and to enhance the resilience of future mobile networks [3], [4], [5]. The purpose of our research activity is investigating the potential benefits in terms of sustainability and resilience derived from the sharing of Base Station (BS) usage among different MOs. In particular, we aim at implementing network sharing (NS) to achieve a number of objectives: (i) to improve the energy efficiency of RANs; (ii) to reduce the OPEX due to the network energy demand; (iii) to limit the CAPEX faced by MOs to install new proprietary network nodes based on 5G technology; (iv) to enhance network resilience in case of power outages due to electric grid overload, cyber attacks, natural disasters, or emergency situations.

We hence consider a portion of the mobile access network, focusing on a densely populated urban environment. We assume that the capacity provided by Base Stations (BSs) owned by different MOs can be shared, based on predefined agreements, as long as the coverage of the shared BSs is overlapping. Furthermore, besides the traditional electric power grid, a local renewable energy supply, consisting of a set of photovoltaic panels and some battery units, may be envisioned to power a subset of the BSs. We design data-driven strategies to dynamically offload traffic between BSs, possibly powered by renewable energy, that are installed on the same site and belong to different operators (as it often happens), in order to consolidate traffic on few network nodes and periodically deactivate unneeded network resources, to enable more sustainable and resilient RANs.

The objective of this study consists in evaluating the performance of these strategies in reducing the network energy consumption, decreasing operational cost, limiting CAPEX, and enhancing the network resilience to power outages, to enable a feasible deployment of 5G scenarios and a sustainable evolution towards 6G. Clearly, an effective analysis should be performed based on real and up-to-date mobile traffic data, in order to derive reliable outcomes about network sharing that result actually representative of a rapidly evolving scenario. To this extent, the NetMob23 Dataset presented in [6] results extremely suitable to perform our research.

## II. Network sharing

Our study aims at investigating the potential benefits of applying data-driven strategies that allow the dynamic offload of traffic between BSs owned by different MOs, in order to consolidate traffic on few BSs and switch off network nodes that (after the offload) are not carrying any traffic. We hence assume that a subset of the network operators agree to make the capacity of their own BSs available to host the traffic offloaded from neighbor BSs belonging to other operators. Network nodes are grouped in clusters, each consisting of multiple BSs that are placed in the same installation site and belong to at least two different operators. The traffic load of each BS can be assumed to be either statistically known from historical measurements, or predicted according to machine learning (ML) based forecast techniques. At each time step, the algorithm implementing the offloading strategy focuses on each BS cluster, to make decisions about traffic offloading according to the following baseline criteria: (i) whenever one of the BSs in the cluster has sufficient available capacity to accept the offloading of the traffic of the least loaded active BSs in the cluster, the traffic is offloaded and the BS that has become idle is switched off; (ii) the procedure is repeated for the BS that has become the least loaded active BS in the cluster. If multiple BSs can accept the offloading of the least loaded active BSs in the cluster, the procedure selects the one that provides the largest energy saving. Additional offloading strategies can be derived from this baseline version. For example, the traffic offloading may be always performed towards BSs owned by the same predefined operator, instead of considering the convenience in terms of energy saving. Moreover, in presence of renewable energy supply, BSs featuring the highest solar energy availability could be preferably selected to host traffic offloaded from other cluster BSs. In addition, decisions about traffic offloading can be taken keeping into account specific QoS requirements of different traffic classes, with the purpose of reserving a reasonable amount of network resources for critical services. In particular, critical services can be prioritized in case of network resource scarcity during power outages, and BSs featuring high bandwidth capacity may be preferably selected to host delay sensitive traffic offloaded from other BSs. Finally, offloading decisions can be made based on the mobile technology that characterizes BSs. For instance, NS approaches may consider that whereas an operator shares the resources of its own LTE BSs, another operator makes its own 5G BSs available for network sharing purposes. Algorithms that take into account mobile technology of available network nodes to perform traffic offloading decisions in a NS framework are pivotal to trade off a feasible deployment of 5G networks and the need for limiting CAPEX faced by MOs to install new communication infrastructure required to evolve towards 5G scenarios.

Our work focuses on the demonstration of the NS potential to save energy and to reduce CAPEX and OPEX for a feasible and sustainable deployment of 5G networks. We evaluate the performance of the proposed NS algorithms via simulation, estimating the energy saving and operational cost reduction with respect to the baseline scenario in which network resources are not shared among MOs. The benefits yielded by NS are compared among various area types, from a urban densely populated environment to a rural region, and considering several different configuration settings of the traffic offloading strategies. However, the availability of an extensive set of recent data on mobile network operations opens many possibilities for further relevant research directions, in relation to the contribution that NS may give to resilience in 5G and beyond networks and to the definition of a path toward net-zero networks. Indeed, on the long term our research activity aims at evaluating additional key performance indicators to assess the impact of NS on the network operation. In particular, the average fraction of shared bandwidth capacity per operator and the average fraction of offloaded traffic volume per operator will be computed, to evaluate the effect of different contribution levels by the MOs on achieving NS benefits. In addition, we will evaluate to what extent NS allows to never activate a subset of BSs, confirming that the deployment of a portion of redundant network nodes can be avoided and the related cost can be saved by MOs. Furthermore, the effect of the traffic prediction error due to the limited precision of ML algorithms on the performance of NS strategies will be measured. Finally, performance metrics to evaluate the system resilience will be derived, focusing on the contribution of NS to increase the RAN self-sufficiency during power outages, and on the capability to guarantee minimum levels of QoS for critical services.

## III. Methodology

We now present the case study scenario considered in our work, also detailing how the mobile network deployed in the investigated urban area is modeled. Furthermore, we describe the traffic offloading strategy that is applied to enable the sharing of the network infrastructure among different MOs.

### A. Case study

We start our analysis considering the simple case in which two MOs provide mobile access service to their customers within the same coverage area, where a number of LTE BSs are installed. The NS is enabled by the implementation of a traffic offloading strategy that is detailed in Section III-C.

To estimate the BS energy consumption we adopt the power models detailed in [7] for LTE technology, considering a Radio Remote Head (RRH) BS. Real traces of normalized mobile traffic from the NetMob dataset, provided by a French mobile operator, are used to model the BS traffic demand [6]. The traffic patterns cover a period of 77 days, with samples collected every 15 minutes with a spatial resolution of 100×100 m$^2$, and represent more than 60 different mobile services. Real data about the geographical distribution of sites hosting mobile BSs, with information about the adopted mobile technology and the owner network operator (Bouygues, Free Mobile, Orange, SFR) for each BS are retrieved from public datasets made available by the Agence Nationale des Fréquences (ANFR) [8]. Finally, energy cost is estimated based on real electricity market prices [9].

### B. Modeling the mobile network

For our analysis we consider the city of Lyon, France. Fig. 1 depicts the traffic volume distribution over the entire city, with warm shades closer to red indicating higher normalized traffic volumes and cold nuances corresponding to low loaded areas. Furthermore, the actual location of the BSs owned by the same MO for which NetMob traffic traces are provided is represented by black dots. Let us denote this operator $Op_1$. BSs clearly appear more densely deployed in the city center, whereas a lower BS density characterizes the peripheral and

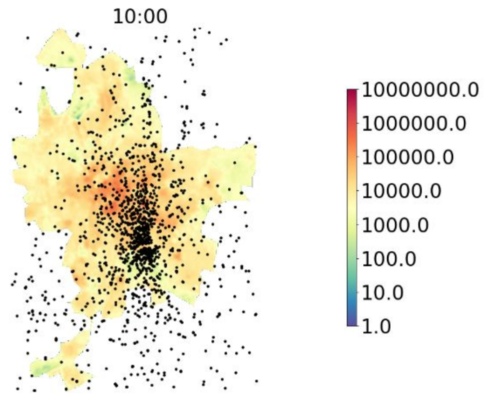



Fig. 1: Sites of $Op_1$ BSs and traffic load intensity in Lyon.

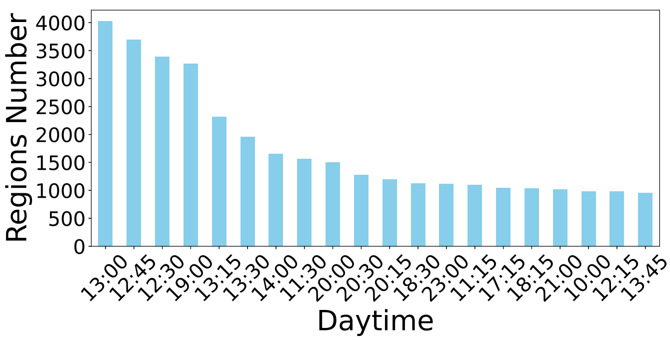



Fig. 2: Top 20 time slots with highest video streaming traffic in the city of Lyon.

suburb areas. Within this region, we identify three restricted areas on which our analysis is focused, corresponding to a urban area in the city center, a suburban area, and a rural area. Each area is square in shape, and it is derived from the aggregation of $n \times n$ contiguous tiles, each sized $100 \times 100$ $m^2$, for which traffic traces are available based on NetMob dataset. We then consider the location of actual BSs installed within the defined area that are owned by operator $Op_1$.

In the NetMob dataset, mobile traffic data is in the form of time series representing the traffic volume generated within each tile with 15-minute time steps. In order not to disclose the sensitive information of the actual volume of traffic served by the mobile network operator, the traffic volume is normalized by a same random value, still resulting fully comparable across space and time [6]. Notice that in our work we consider traces of downlink traffic generated by the most representative services (i.e., Video Streaming, Social Media, App Store, Web Browsing, Cloud, Music, and Game), corresponding to 29 different types of applications. We now need to derive realistic traces of the traffic volumes handled by the $Op_1$ BSs located in the considered areas, hence mapping the traces of traffic volumes distributed over the $n \times n$ tiles to each of the BSs from $Op_1$ included in the considered area. To this aim, we exploit an Euclidean distance based strategy. Let us denote $L = \{L_1, L_2, \ldots, L_{n \times n}\}$ the set of $n \times n$ traffic time series available for a given area, and $B = \{B_1, B_2, \ldots, B_m\}$ the set of $m$ BSs owned by $Op_1$. Each traffic volume corresponding to the time series $L_i$ from tile $i$ is mapped to the nearest BS $B_j$ such that the Euclidean distance $d_{ij}$ is minimized. Finally, the traffic trace representing the actual traffic volumes handled by each BS $B_i$ is derived from the aggregation of the traffic data series associated to that BS according to the presented method. Notice that the aggregated traffic trace is further scaled up by a factor $f_C$ that is proportional to the actual BS bandwidth capacity, making the conservative assumption that the peak of the aggregated normalized traffic volume should correspond to 90% of the overall estimated BS capacity. In addition, based on the ANFR data [8], we consider the BSs from a different mobile operator, that we denote $Op_2$, installed in the same considered area. Each of these BSs is assigned an aggregated traffic volume trace based on the same processing method presented above.

### *C. Traffic offloading strategy*

To enable the sharing of the network infrastructures among $Op_1$ and $Op_2$, a traffic offloading strategy is applied to every pair of co-located BSs owned by different operators. Two BSs from different operators are assumed to be co-located if they are placed sufficiently close to each other to provide a nearly overlapping coverage ($\geq 95\%$) over the same area, hence assuming their distance results smaller than 50 $m$, 100 $m$ and 472 $m$ in the urban, suburban and rural areas, respectively. A preliminary agreement is assumed among operators envisioning that the traffic offloading can be performed either from operator $Op_2$ to operator $Op_1$, or vice versa. According to the proposed offloading strategy, at every time step a check is performed to identify the BS that is characterized by the highest residual capacity. Let us assume this BS is owned by $Op_1$. If its current residual capacity is sufficient to host the traffic volume handled by the other BS, owned by $Op_2$, this traffic volume is shifted to the $Op_1$ BS, provided that its capacity is not saturated above a threshold that we denote $C_{th}$. The $Op_2$ BS can hence be deactivated to save energy.

## IV. Traffic data characterization

We now present some results about the characterization of the traffic traces available from the NetMob dataset for the city of Lyon. The considered traffic traces corresponding to 29 different types of applications can be classified in the following main service types: Video Streaming (53.2%), Social Media (19.5%), App Store (12.6%), Web Browsing (6.2%), Cloud (4.6%), Music (2.5%), Game (1.3%).

*Pre-processing analysis:* We first analyse the raw traffic traces, i.e. those representing the traffic patterns per each tile in the entire city of Lyon. In particular, considering different service types, we start considering the distribution of the traffic peaks of each provided traffic trace over a sample day. For the sake of brevity, we only report results derived from the characterization of Video Streaming, since this type of mobile service is responsible of the largest contribution to the overall traffic demand. As it can be observed from Fig. 2, the traffic peaks for the Video Streaming service result mostly concentrated either during late afternoon and evening time or during the lunch break, whereas they are less frequently observed during the rest of the day. Conversely (data not reported), peak times for other services like Social Media

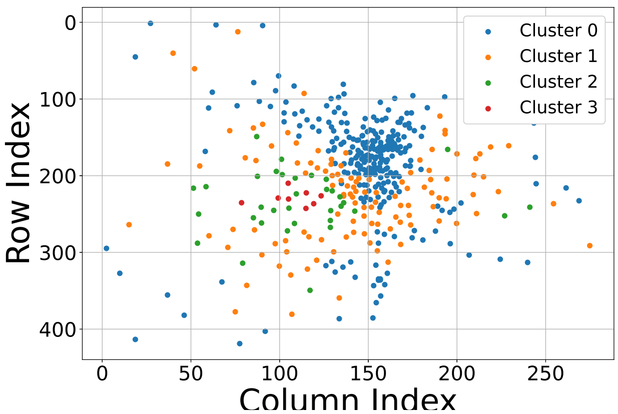



Fig. 3: Spatial distribution of BS clusters.

TABLE I: BS clusters

| Cluster ID | **0** | **1** | **2** | **3** |
|---|---|---|---|---|
| Number of BSs | 265 | 118 | 34 | 8 |
| Normalized traffic volume per BS | 0.31 | 3.33 | 30.91 | 288.63 |

TABLE II: Intra-operator BS distance

| | **Orange** | **Bouygues Telecom** | **SFR** | **Free Mobile** |
|---|---|---|---|---|
| Distance [m] | 791 | 733 | 697 | 832 |

applications result concentrated in the central hours of the day. This trend appears consistent with a user demand reflecting the human behavior that is typically found in a region more likely dominated by residential rather than business traffic demand.

*Post-processing analysis:* After having derived the traffic profiles associated to each BS from $Op_1$, and considering each service type, BSs are classified in four different clusters based on the traffic volume corresponding to the considered service handled by each BS. Focusing on Video Streaming, the average traffic volume per BS in each cluster $i+1$ results about 10-fold larger than cluster $i$. Table I reports the number of BSs observed in each cluster and the normalized average traffic volume per BS, whereas Fig. 3 depicts how the BSs classified in different clusters are distribuited in the city of Lyon, with x-axis and y-axis indicating the row and column indexes of the tiles. Clusters 2 and 3 includes few BSs handling high or extremely high traffic volumes and resulting very sparsely distributed, hence suggesting a limited potential for network sharing. Several BSs are grouped in Cluster 1, characterized by much lower traffic volumes that, jointly with a denser BS distribution that more likely entails an overlapping coverage with close-by BSs, make these BSs more promising for NS application. The largest potential for NS is yielded by BSs from cluster 0, collecting a huge number of extremely low loaded network nodes that are densely deployed likely to provide additional capacity during peak traffic demand, especially in the city center.

## V. Network sharing analysis

Our performance analysis is conducted via simulation over a period of one week, with time step duration of 15 minutes. The size of each of the identified areas is $20 \times 20$ tiles ($4\ km^2$), in order to include a reasonable number of BSs in our investigation. The BS density results 11.75 BSs per $km^2$ in the urban area, 4.5 BSs per $km^2$ in the suburban area, and 1.75 BSs per $km^2$ in the rural area. Furthermore, 5, 4, and 3 pairs of co-located BSs owned by two different operators are identified in each area, respectively, with average distance between the co-located BSs within each pair of 7.7 $m$, 17.6 $m$, and 252.8 $m$.

### *A. Network sharing potential*

We provide a preliminary evaluation of the NS potential analysing how the BSs from different MOs are distributed in the city of Lyon. Table II reports the average intra-operator BS distance, corresponding to the average distance between each BS and the nearest BS belonging to the same operator. A lower average distance reflects a more clustered pattern of BS distribution, possibly indicating a focus of the MO on a denser BS deployment in the Lyon region, like in the case of SFR. Table III shows the average inter-operator Huff Model probability for spatial interactions between BSs of different operators, reflecting the likelihood that the BSs owned by a given operator are located near the BSs belonging to another operator. The Huff Model is typically adopted in spacial analysis to evaluate the probability for a user to visit a site, based on the distance of the site, its attractiveness, and the relative attractiveness of alternatives. Based on the Huff Model, the probability that a BS at location $x_i$ will interact with any BS in set $Y$ due to its closeness -we denote this probability $P(x_i \to Y)$- is derived as follows:

$$P(x_i \to Y) = \frac{M_1}{M_1 + \sum_{j=1}^{N} \left( \frac{M_2}{(d_{ij}+\epsilon)^\lambda} \right)} \tag{1}$$

where $P(x_i \to Y)$ is the Huff Model Probability that a BS at location $x_i$ will interact with any BS in set $Y$, $M_1$ is the number of BSs for the first operator, $M_2$ is the number of BSs for the second operator, $d_{ij}$ is the distance between the BS at location $x_i$ and the $j^{th}$ BS in set $Y$, $\epsilon$ is a small constant added to avoid division by zero, typically $\epsilon = 1 \times 10^{-10}$, $\lambda$ is the sensitivity to distance parameter in the Huff Model, and $N$ is the number of BSs in set $Y$.

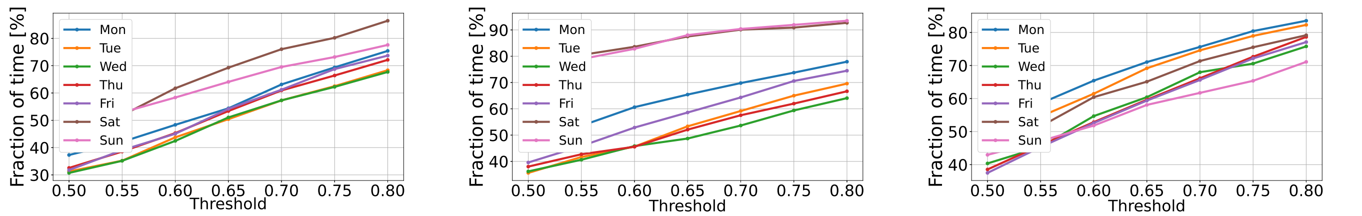
Furthermore, the mean Huff Model Probability for all BSs in set $X$ interacting with any BS in set $Y$, that we denote $P_H$, is derived as follows:

$$P_H = \frac{1}{R} \sum_{i=1}^{R} P(x_i \to Y) \tag{2}$$

where $R$ is the number of BSs in set $X$.
Rather similar values of Huff Model probability are observed for different pairs of MOs, reflecting analogue spatial closeness as well as similar potential for NS that may derive from the cooperation between any pair of operators in this region.

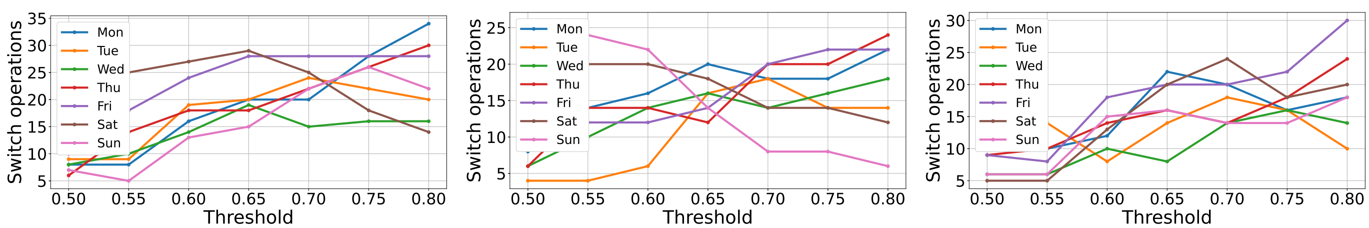
### *B. Performance evaluation*

In each of the defined areas we consider all the installation sites hosting a pair of co-located BSs owned by two sample



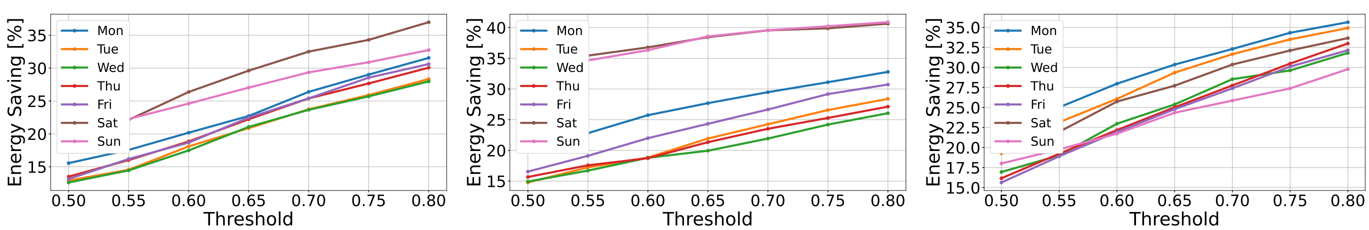

(a) Urban area (b) Suburban area (c) Rural area

Fig. 4: Fraction of time slots during which NS can be applied ($f_T$) in a sample BS pair under different settings of the threshold $C_{th}$ per each day of a sample week, considering three different area types.




(a) Urban area (b) Suburban area (c) Rural area

Fig. 5: Occurrences of BS switching on/off operations in a sample BS pair under different settings of the threshold $C_{th}$ per each day of a sample week, considering three different area types.




(a) Urban area (b) Suburban area (c) Rural area

Fig. 6: Energy saving for a sample BS pair under different settings of the threshold $C_{th}$ per each day of a sample week, considering three different area types.

TABLE III: Huff Model probability for all pairs of MOs.

| | Huff Model Probability |
|---|---|
| **Orange-Bouygues Telecom** | 0.473 |
| **Orange-SFR** | 0.463 |
| **Orange-Free Mobile** | 0.558 |
| **Bouygues Telecom-SFR** | 0.492 |
| **Bouygues Telecom-Free Mobile** | 0.531 |
| **Free Mobile-SFR** | 0.505 |

operators, i.e., $Op_1$ (Orange) and $Op_2$ (Bouygues Telecom). Based on the traffic variations over time, we investigate the fraction of time slots during which the NS strategy can be applied, that we denote $f_T$. To evaluate how the configuration settings of the threshold $C_{th}$ may impact on the NS performance, Fig. 4 reports $f_T$ for increasing values of the threshold on the saturation of the BS capacity hosting the offloaded traffic, $C_{th}$, with each curve representing a different day of the week (with Monday corresponding to Day 1), for three sample BS pairs from the urban, suburban and rural areas (with distance between BSs within each pair resulting 0 $m$, 70.4 $m$, and 420 $m$, respectively). In general, $f_T$ increases as the threshold $C_{th}$ grows larger, achieving values up to more than 90%. Furthermore, in the urban area and, more evidently, in the suburban area, lower values are observed during most weekdays, likely reflecting higher traffic demand with respect to the weekend, during which the NS can be successfully applied for longer period of times, even under low settings of $C_{th}$. Conversely, in the rural area, lower variability among days is observed, and no neat difference emerges between weekdays and the weekend. Notice that even under $C_{th}$ as low as 50%, NS can be applied for at least one third of the day in any area, with a peak of almost 80% in the suburban area. These results highlight how MOs, that are typically concerned about the risk of overloading the network capacity, can be granted huge flexibility and a sufficient safety margin in operating NS. Indeed, even conservative settings of $C_{th}$ still enable the deactivation of unneeded radio resources for long periods, likely entailing significant gains in terms of energy consumption reduction and operational cost saving.

Notice that our results (data not reported) show that a remarkable fraction of time slots in which one of the two co-located BSs within each pair can be switched off is highly overlapped for different pairs of BSs in the same area. This trend suggests that there may be periods of the day, possibly featuring off-peak demand, or certain usage patterns that make NS more universally feasible across different BS sites.

Similarly, we analyse the effect of $C_{th}$ settings on the frequency of BS switching on/off. Fig. 5 depicts the occurrence of BS activation/deactivation operations for increasing values of $C_{th}$ during the different days of the week in the three area types. The behavior of this metric results more variable with respect to $f_T$ and less consistent over different days. Hence, a typical trend of $f_T$ as the value of $C_{th}$ becomes larger cannot easily been identified. This variability over different days is likely due to different traffic patterns, that may feature either several short periods of low traffic or few longer off peak periods. In addition, our results show that remarkable values of $f_T$ can be achieved at the price of frequent BS switching on/off operations, especially in the urban area, with up to 34 BS switching on/off operations per day, that may result quite high values that operators are likely not willing to accept. Clearly the high short-term variability that is typical of video traffic, that is dominating in the mobile traffic profiles, may contribute to the observed high BS switching frequency when NS is applied. These raised critical aspects should definitely be taken into account in defining the proper threshold configuration, since it may be convenient to limit the maximum allowed frequency of switching operations or to introduce some hysteresis by setting two different thresholds on the BS capacity for the BS activation and deactivation operations, respectively, in order to avoid too frequent switching operations, hence preserving the BS from faster degradation. Furthermore, a time varying configuration of the threshold $C_{th}$ may be advisable, since different values of $C_{th}$ may lead to frequent BS switching on/off operations only during specific days, due to more frequent traffic variations likely occurring around specific values of the threshold. For example, low settings of $C_{th}$ should be avoided in some days, like on Sunday, since they may lead to significantly higher frequency of switching on/off operations, hence contributing to a faster deterioration of the BS.

### C. Energy and cost saving

The application of NS strategies allows to achieve relevant energy saving, of up to more than 40% with respect to the case in which no NS is applied, depending on the offloading strategy configuration settings. Fig. 6 depicts the energy saving that can be obtained for a sample BS pair in the considered area types when NS is applied under different $C_{th}$ settings, for each day of the week. The savings raise as the threshold $C_{th}$ is set to higher values, with relevant variability observed over different days, confirming that NS effectiveness is influenced by traffic load and user behavior. Like for $f_T$, in the rural area no difference is observed in the trend of energy saving between weekdays and the weekend. Interestingly, at least 10% (and up to about 30%) of energy can be saved in any area type even under the most conservative threshold settings, highlighting the potential of NS to trade off sustainability goals and QoS requirements.

Considering all the BS pairs that are suitable for NS in the areas under evaluation and assuming $C_{th} = 0.8$, NS allows to save up to 4.2 $MWh/km^2$, 4.1 $MWh/km^2$, and 2.8 $MWh/km^2$ per year in the urban, suburban and rural areas, respectively. Assuming an average electricity price of 0.174 €$/kWh$, more than 737 €$/km^2$, 705 €$/km^2$, and 479 €$/km^2$ can be saved per year in the corresponding areas. Considering the estimated distribution of different area types in France [10], scaling up these savings to the entire area of mobile network deployment over the whole country served by the considered MOs results in a remarkable reduction of the electricity bill, amounting to more than 300 million euros per year.

## VI. Open challenges and future work

Starting from these promising results, the potential challenges and limitations that may prevent a widespread adoption of Network Sharing among different MOs should be further investigated. Indeed, although the flexibility provided by Open RAN may remarkably contribute to enable a feasible implementation of NS, relevant research efforts should be devoted to address technical interoperability issues. Moreover, MOs may need to overcome several regulatory and legal constraints that may hinder the extensive deployment of NS based communication infrastructures. Finally, suitable business models should be properly deployed to define how cost and revenues can be fairly distributed among MOs, also based on the different penetration level of new mobile technologies in different MO networks, and on the variable fraction of network resources that MOs are willing to share.

As future work, we first plan to expand our study considering a larger set of BSs, and evaluating more complex scenarios with multiple MOs. In addition, we will analyse the influence of varying the fraction of resources shared among MOs and evaluate how the traffic prediction error may affect the system performance during the real time application of algorithms. Furthermore, we aim at investigating the potential role of Network Sharing in enhancing the deployment of resilient communication infrastructures. In particular, we plan to identify possible critical services whose traffic needs to be prioritized in case of scarcity of network resources, during the application of algorithms, either under normal system operation or during power outages, in order to keep a reasonable amount of network resources reserved for these critical services. Finally, we will investigate how the integration of some local renewable energy supply to power a subset of the BSs, besides the traditional electric power grid, can contribute to enhance the feasibility of network sharing and to achieve its potential benefits.

## VII. Conclusion

Our study highlights the potential of network sharing to enable a feasible deployment of 5G scenarios and a sustainable evolution towards 6G. In particular, our preliminary results show that sharing the network infrastructure among different operators is effective in reducing the network energy consumption by up to more than 40%, entailing further benefits in terms of reduction of the electricity bill, especially in urban environments. However, a proper dynamic tuning of the parameter settings of the strategies is definitely required in order to adapt the operation to the location dependent BS density as well as to the traffic demand variability in space and over time, hence enabling MOs to achieve the desired trade off between energy reduction, cost saving, and QoS.

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