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Energy Efficiency of a Network per Service

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***Abstract*—We investigate in this paper the assessment of the energy efficiency of a wireless access network per service category. We consider five categories of service, two categories with high traffic: streaming and web browsing, and three other with lower traffic: download, voice and other minor data services. We introduce two scenarios, one where some services are mandatory, it is typically the case of Voice which is mandatory to be provided due to legal constraints, and another one where there is no mandatory service. We used our Shapley-based sharing model introduced in previous works to share the total energy consumption of the access network among the service categories, and then derive the energy efficiency of each service category as the ratio of its traffic volume (measured in the network) and its energy consumption assessed with our Shapley-based model. We applied the models on a real dataset extracted from an operational network in Europe, and analyze the energy efficiency of each considered service category.**

***Index Terms*—Wireless Networks, Energy Efficiency, Services, Shapley value**

I. INTRODUCTION

Internet traffic is growing exponentially over the years, mainly due to the democratization of smartphones and tablets and the increase of content. According to Cisco [1], overall IP traffic will grow at a compound annual growth rate (CAGR) of 23 percent from 2014 to 2019. In order to keep or improve the users' Quality of Experience (QoE), network operators densify their networks, which could result in an exponential increase of the energy consumption as well. It is therefore crucial to find means to mitigate the energy consumption increase both for economical and ecological purposes.

This concern fostered lots of investigations on the topic of networks energy efficiency optimization.

Sun et al. [2] formulate a joint optimization problem to maximize the user-centric energy efficiency in OFDMA-based Cloud-RAN (C-RAN) systems, subject to users uplink transmit power and Remote Radio Head fronthaul capacity constraint. Based on Gaussian quantization, the authors show their proposed algorithms can improve the user-centric energy efficiency obviously, compared with other optimal algorithms.

Yang et al. [3] analyze the optimal power control for energy efficiency of device-to-device (D2D) communication underlaying cellular networks. Using stochastic geometry and convex optimization, the authors give the power control that maximizes the D2D energy efficiency, and show that it is monotonously decreasing with the density of cellular and D2D users, due to interference.

In [4], Mugume et al. investigate the impact of small cells deployed by users on the spectral and energy efficiency of mobile networks. The authors define three scenarios according to the ratio of networks' base stations versus users' base stations. The authors recommend to densify the network when this ratio is low in order to improve the spectral and energy efficiency of the network.

To maximize the energy efficiency while guaranteeing QoS for 5G wireless networks, Cheng et al. in [5] propose the statistical delay-bounded QoS-driven green power allocation schemes to maximize the effective power efficiency (EPE), which is defined as the effective capacity per unit power, under joint average and peak power constraints. The novelty of their work is the definition of a new metric for energy efficiency, i.e., the effective power efficiency, as well as taking into account both average and peak power constraints in the optimization problem.

Li et al. in [6] propose an Energy Efficiency-based Decision Making for cognitive radio networks, which considers residual energy and probability of obtaining spectrum resources. The authors compare their model to a random decision making and show that the former outperformed the latter in regard with the spectrum utilization rate and proportion of allocated users. The model is energy-efficient in that it takes into account energy constraints in the selection of secondary users which participate in the sensing process. No energy efficiency metric has been defined in this paper.

These investigations focus on the global energy efficiency of the network and show that there is a direct relationship between energy efficiency and traffic. As traffic is directly related to services, and given that more and more services are available on the mobile network, the assessment of the energy efficiency per service becomes crucial. This would help network operators to have a more detailed view on the energy cost of their network per service, and so easily define their economical and ecological objectives and strategies. This paper is a contribution in that direction.

We consider a wireless access network providing five categories of service: Streaming, Web, Download, other minor data services and Voice. We model the energy efficiency per service category considering two scenarios, one where some services are mandatory, it is typically the case of Voice which is mandatory to be provided due to legal constraints, and another one where there is no mandatory service. We used our Shapley-based sharing model introduced in [7], [8] to share the

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total energy consumption of the network among the service categories, and then derive the energy efficiency of each service category as the ratio of its traffic volume (measured in the network) and its energy consumption assessed with our Shapley-based model.

The remainder of this paper is organized as follows. In section II, we introduce our models for assessing the energy efficiency of a network per service category. Section III shows some applications of our model, run on a real dataset taken from an operational European network. Section IV eventually concludes the paper.

II. ENERGY CONSUMPTION OF THE NETWORK

We describe in this section a general methodology to assess the power consumption of a given network. The methodology should be valid for all possible architectures: classical reference architecture, centralized radio access, virtualized radio architecture, etc. A typical network is composed of a number of blocks, as illustrated in Fig. 1 for instance. A block is a set of elements with a common general function from the architectures point of view. For example, for radio access networks, we can define two main blocks: the block of base stations and the block of controllers, when applicable. End users should also be considered as one or more blocks. The partition of one block to sub-blocks should be possible following the need and the coherence of the model. Each block or sub-block is composed of a list of elements. An element may be a network component, a server or a terminal that is used to deliver the service to the end user. One base station is for example an element.

The global power consumed by an element k is composed of two parts, according to [9], as illustrated in Fig. 2:

- A fixed consumption P_k^f depending on the long-term evolution of the traffic load (it is constant on small time scale, for example for a given configuration).
- A variable consumption $P_k^v = (P_k^{max} - P_k^{idle})\ \rho_k$ depending on the load of the equipment at the time scale of the flows.

P_k^{max} is the maximum power element k consumes at full load, P_k^{idle} its idle power consumed at zero load, and ρ_k its traffic load. The preponderance of each part varies depending on each element and its technology. In some practical current cases, the variable part is negligible. However, it is important to keep it in all models to build. We should recommend from the green point of view to reduce the fixed part consumption and to transfer all the consumed power to the variable component to satisfy the paradigm zero watt at zero traffic.

Therefore, the power consumption of element k at instant t is given by:

$$P_k(t) = P_k^f(t) + (P_k^{max}(t) - P_k^{idle}(t))\ \rho_k(t) \qquad (1)$$

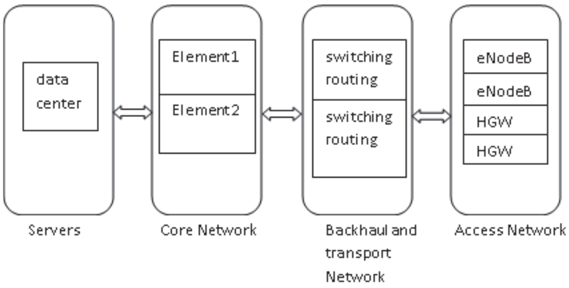

Fig. 1. Per block network decomposition.

We derive the total power consumed by a block as the sum of the powers consumed by each of its elements, that is:

$$\begin{aligned} P(t) &= \sum_{k=1}^{K} P_k(t) && (2)\\ &= \sum_{k=1}^{K} P_k^f(t) + (P_k^{max}(t) - P_k^{idle}(t))\ \rho_k(t)) && (3)\end{aligned}$$

where K is the number of elements in the considered block. So, the energy E consumed by a block over the time period ΔT is

$$\begin{aligned} E &= \int_{\Delta T} P(t)dt && (4)\\ &= \sum_{k=1}^{K} \int_{\Delta T} P_k(t)dt && (5)\end{aligned}$$

As the total energy consumption of the block is the sum of the energy consumptions of its elements, Eqn. (5), and given that the energy consumption of an element consists of a fixed $(\int_{\Delta T} P_k^f(t)dt)$ and a variable $(\int_{\Delta T} (P_k^{max}(t) - P_k^{idle}(t))\ \rho_k(t)dt)$ component, then the total energy consumption of the block consists of a fixed $(\sum_{k=1}^{K} \int_{\Delta T} P_k^f(t)dt)$ and a variable $(\sum_{k=1}^{K} \int_{\Delta T} (P_k^{max}(t) - P_k^{idle}(t))\ \rho_k(t)dt)$ component as well.

The total energy consumption of a block represents the aggregate energy consumption of all the provided services, such as voice, data, video streaming, online gaming, etc. In order to model the energy efficiency per service of the block , it is crucial to assess the contribution of each service in the overall energy consumption of the block. This is tackled in next section.

III. ENERGY EFFICIENCY PER SERVICE CATEGORY

In this paper, we consider the block of the wireless access network. So, the aim is to assess the energy efficiency of a wireless access network per service category. According to the ETSI standard “ETSI TS 203228” [10], the energy efficiency of a network over a period T is the ratio of its traffic volume (measured in bit over T) and its energy consumption (measured in Joule over T). The energy efficiency of the network is expressed in bit/Joule.

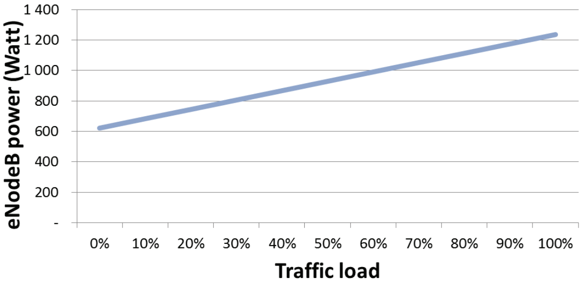

Fig. 2. Power consumption of a 4G base station.

Based on the ETSI definition of a network energy efficiency, we introduce a new metric for modeling the energy efficiency of a given category of service. This metric should be valid for all services to be defined such as voice, data, video streaming, online gaming, etc, and for all possible architectures: classical reference architecture, centralized radio access, virtualized radio architecture, etc. Our new metric will be proposed for normalization. So, let β_i denote the energy efficiency of service category i.

$$\beta_i = \frac{V_i}{E_i} \tag{6}$$

where V_i is the traffic volume of service category i, and E_i is its energy consumption. The traffic volume of service category i, V_i, comes from measurements run on the investigated network. As of the energy consumption of a given service category, it has to be assessed from the energy consumption of the network. In fact, energy measurements provide the global energy consumption of the network, that is, the aggregate energy consumption of services. So, it is worth to elaborate a model for assessing the energy consumption of a given service from the global energy consumption of the network.

As showed in the preceding section, the energy consumed by the wireless access network is composed of a variable and a fixed component, denoted by E^v and E^f, respectively.

Then the energy E of the wireless access network is given by:

$$E = E^v + E^f \tag{7}$$

Let E_i denote service category i energy consumption, with variable and fixed components E_i^v and E_i^f, respectively. We have:

$$E_i = E_i^v + E_i^f \tag{8}$$

We first focus on the variable component of the energy consumption of service category i, i.e., E_i^v. The variable energy consumption of the network is shared among the service categories proportionally to their traffic proportions as this energy component is due to the traffic. So,

$$E_i^v = \varphi_i \times E^v \tag{9}$$

where φ_i is the traffic proportion of service category i, given by:

$$\varphi_i = \frac{V_i}{\sum_{k=1}^{N} V_k} \tag{10}$$

where N is the number of service categories.

As of the fixed energy component, since it is consumed irrespective of traffic, one can share it in many ways. Let ϕ_i denote the share of service category i in the fixed energy consumption of the network, thus we have:

$$E_i^f = \phi_i \times E^f \tag{11}$$

Two straightforward approaches for assessing ϕ_i consist in sharing the fixed energy consumption among the service categories either equally or proportionally to their traffic proportions. The first approach logical is that the fixed energy consumption of the network is independent of the traffic, whereas the second approach point out the fact that it is related to the number of equipment in the network, which is itself due to the network densification causes mainly by services with high traffic, so, it would be fairer to share the fixed energy consumption proportionally to the traffic proportions.

Considering a uniform sharing, the share ϕ_i of service category i in the fixed energy consumption is given by:

$$\phi_i = \phi_i^u = \frac{1}{N} \tag{12}$$

As of a proportional sharing, the share ϕ_i of service category i is given by:

$$\phi_i = \phi_i^v = \varphi_i \tag{13}$$

We introduced in [7], [8] a new sharing model based on the game theory concept, the Shapley value, that is fairer in the sharing than the uniform and proportional approaches. In fact, the uniform sharing is unfair towards services with small traffic comparing to a proportional sharing, while the latter is unfair towards services with high traffic comparing to the former. Our Shapley-based sharing model is a trade-off for all the services irrespective of their traffic. In this model, we consider two scenarios. One where Voice is a mandatory player due to legal constraints, and one another where there is no mandatory player in the game. We find in each scenario the following expressions for ϕ_i:

For the game without a mandatory player,

$$\phi_i = \Big(\sum_{s=1}^{N} \frac{1}{s\binom{N}{s}}\Big)\varphi_i + \Big(\sum_{s=2}^{N} \frac{\big(\binom{N-1}{s-2} - \binom{N-1}{s-1}\big)\binom{N-2}{s-2}}{\binom{N-1}{s-1}\binom{N-1}{s-2}s\binom{N}{s}}\Big)(1-\varphi_i) \tag{14}$$

For the game with a mandatory player, the share of the mandatory player is,

$$\phi_{i*} = \Big(\sum_{s=1}^{N} \frac{1}{s\binom{N}{s}}\Big)\varphi_{i*} + \Big(\sum_{s=2}^{N} \frac{\binom{N-2}{s-2}}{\binom{N-1}{s-1}s\binom{N}{s}}\Big)(1-\varphi_{i*}) \tag{15}$$

where subscript $i*$ stands for the mandatory player.

The share of a non-mandatory player is,

$$\phi_o = \Big(\sum_{s=2}^{N} \frac{\big(\binom{N-1}{s-2} - \binom{N-1}{s-1}\big)\binom{N-2}{s-2}}{\binom{N-1}{s-1}\binom{N-1}{s-2} s \binom{N}{s}}\Big)\varphi_{i*} + \Big(\sum_{s=2}^{N} \frac{\binom{N-2}{s-2}}{\binom{N-1}{s-1} s \binom{N}{s}}\Big)\varphi_o + \Big(\sum_{s=3}^{N} \frac{\big(\binom{N-1}{s-2} - \binom{N-1}{s-1}\big)\binom{N-3}{s-3}}{\binom{N-1}{s-1}\binom{N-1}{s-2} s \binom{N}{s}}\Big)(1 - \varphi_{i*} - \varphi_o) \quad (16)$$

where subscript o stands for a non-mandatory player.

Based on these models, we compute and analyze next the energy efficiency of a real operated network per service category.

IV. NUMERICAL APPLICATIONS

We now turn to the evaluation of our models for assessing the energy efficiency of a network per service category. We consider Orange France network. The period of the study covers two years, representing a mature 2G/3G network with early LTE deployments and associated traffic increase. We measure all voice and data services that are transmitted in the network with the following classification of services: two large ones, namely streaming and web browsing, and three smaller ones: download, voice and other minor data services. Fig. 3 shows their traffic proportions as taken from the real dataset. We only consider the traffic and energy consumption of the 3G/UMTS sub-network (the network of NodeBs and RNCs).

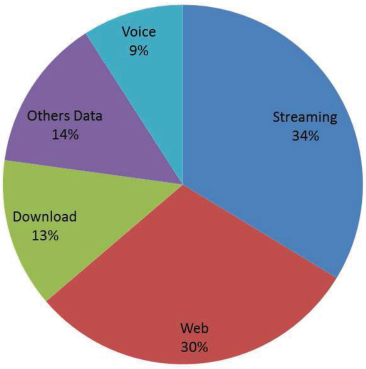

Fig. 3. Traffic proportions per service category.

A. Energy consumption of the network per service category.

In [7], [8], we showed that our Shapley-based sharing model outperforms uniform and proportional sharing approaches, based on the criterion of minimum variance. Hence, in the following, we are going to consider the Shapley-based sharing approach only.

Fig. 4 shows the energy consumption of the network per service category. We notice that the share of Voice significantly increases when it is a mandatory player, passing from 14% to 26% of the fixed energy consumption. This comes from the fact that the mandatory nature of Voice means the network has been deployed for providing this service mainly. Hence, it should contribute more in the fixed energy consumption of the network than in the scenario where it is not considered as mandatory. It is worth to note that the Shapley-based model put more weight in the sharing on services having a high traffic, except for Voice when it is a mandatory player for the reason explained above.

We then derive the energy efficiency of each service category from the traffic proportions and energy consumption shares, considering the two scenarios described above and using Eqn. (6).

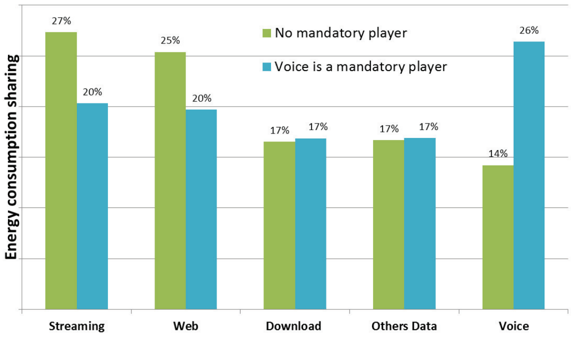

Fig. 4. Energy consumption per category of service.

B. Energy efficiency of the network per service category.

Fig. 5 shows the energy efficiency of the network per service category. Based on the traffic proportions of the service categories, we use our Shapley-based model to assess the share of each service category in the energy consumption of the network. In the figure, we consider two scenarios. A scenario where all the services are optional, i.e., none of them is mandatory to be delivered, and a scenario that is more realistic and corresponds better to the real world. In fact, Voice is typically mandatory to be delivered due to the regulation. Therefore, it is not an optional service but a mandatory one. Hence, we consider this specificity of Voice in our model. Naturally, Voice is more energy efficient when it is not considered as a mandatory player since its contribution in the fixed power consumption is 14% instead of 26%. We notice that the energy efficiency of the service categories is increasing with the traffic proportions. Hence, service categories with high traffic like Streaming and Web are more energy efficient than service categories with lower traffic like Download, other minor data services and Voice. Data services are further more energy efficient when Voice is a mandatory player.

V. CONCLUSION

We investigated in this work the assessment of a wireless access network energy efficiency per service category, based on ETSI definition of a network energy efficiency. We used our Shapley-based sharing model introduced in a previous work to share the total energy consumption of the network among the defined service categories, and then derive the energy

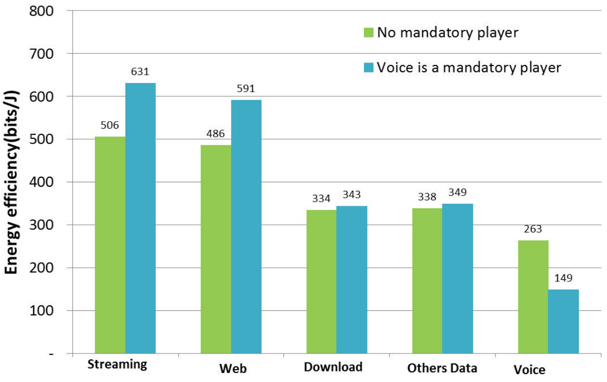

Fig. 5. Energy efficiency per category of service.

efficiency of each service category as the ratio of its traffic volume (measured in the network) and its energy consumption assessed with our Shapley-based model.

We considered two scenarios: one where Voice is mandatory to be provided, in line with what happens typically in real operated networks, and another one where there is no mandatory player.

Our next work will focus on conducting the same investigation on the equipment level. Then, we will extend the models to the end-to-end path, from the content location in a datacenter for instance to the end user, that is, we will consider all the blocks of the network. Finally, we will propose the models for normalization.

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