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Next-Generation Environment-Aware Cellular Networks: Modern Green Techniques and Implementation Challenges

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ABSTRACT Over the last decade, mobile communications have been witnessing a noteworthy increase of data traffic demand that is causing an enormous energy consumption in cellular networks. The reduction of their fossil fuel consumption in addition to the huge energy bills paid by mobile operators is considered as the most important challenges for the next-generation cellular networks. Although most of the proposed studies were focusing on individual physical layer power optimizations, there is a growing necessity to meet the green objective of fifth-generation cellular networks while respecting the user's quality of service. This paper investigates four important techniques that could be exploited separately or together in order to enable wireless operators achieve significant economic benefits and environmental savings: 1) the base station sleeping strategy; 2) the optimized energy procurement from the smart grid; 3) the base station energy sharing; and 4) the green networking collaboration between competitive mobile operators. The presented simulation results measure the gain that could be obtained using these techniques compared with that of traditional scenarios. Finally, this paper discusses the issues and challenges related to the implementations of these techniques in real environments.

INDEX TERMS Base station sleeping strategy, energy procurement, green networking, renewable energy exchange, smart grid.

I. INTRODUCTION

Cellular networks have substantially evolved over the last three decades and enjoyed widespread popularity and usage. This is due to their access flexibility and ability of providing high data rate traffic with adequate decoding quality [1]. After first analog systems offering only voice services, 2G networks emerged in the 1990s with an initial goal of providing full coverage and smooth connectivity to their subscribers but with a relatively low data throughput. In this case, cellular networks are *coverage dominated*. Later, as the use of 2G systems became more and more widespread, the demand for greater data speeds and improved network capacity was growing in order to meet the requirements of this new life basic need. Therefore, beginning of 2000s and 2010s, 3G and 4G mobile technologies were, respectively, developed to enhance the network performance in terms of throughput and network capacity. The initial goal of improving the individual links has gradually evolved to improve the performance of the entire network as a single entity and cellular networks have become *capacity dominated*. As a result, recent cellular networks have witnessed an unprecedented rise of mobile user demand that is perpetually increasing due to the introduction of new services requiring extremely fast and reliable connectivity. Moreover, there is an important increase of the number of devices connected to cellular networks because of the emergence of the machine-type communication. Indeed, data traffic of cellular networks is increasing at a rate of approximately 1.5 to 2 times a year. Therefore, the cellular networks are expected to handle up to 1000 times more data traffic in 10 years time [1].

Because of the huge number of wireless terminals, in addition to the deployed radio access networks (RANs) necessary to serve them, currently deployed and future generation cellular networks, including the upcoming fifth-generation (5G) will suffer from an enormous growth of energy consumption that will cause negative economical and environmental impacts. It is predicted that if no actions are taken, the greenhouse gas (GHG) emissions per capita for information and communication technology (ICT) are estimated to increase from 100 kg in 2007 to about 130 kg in 2020 [2]. Therefore, there is an urgent obligation to develop new techniques and technologies in order to cope up with the exponential energy consumption growth and correspondingly the carbon emission of emerging wireless networks. From a cellular network operator perspective, reducing fossil fuel consumption is not only for behaving green and responsible towards the environment, but also for solving an important economical issue that mobile operators are facing. Indeed, such energy consumption forces mobile operators to pay huge bills which actually constitute around half of their operating expenditures (OPEX). It was shown in [3] that cellular networks consume around 120 TWh of electricity per year and mobile operators pay around 13 billion dollars to serve 5 billion connections per year.

A new green objective has been added to the list of 5G goals [4] consisting in controlling and mitigating the energy consumption increase in cellular networks [5]. In other words, decoupling this increase from the traffic growth. This objective cannot be achieved by only using the traditional energy-efficient techniques. In fact, many algorithms and techniques were proposed to optimize energy efficiency in wireless communications [6]. However, these methods, which only focus on individual transmission links, will not be sufficient to meet energy efficiency targets of wireless and cellular networks. Therefore, modern green techniques should be involved in order to cost-effectively decrease the negative environmental impacts of cellular network fossil fuel consumption. Hence, in the next two decades, further green evolution of cellular networks will be witnessed in the form of base station (BS) on/off switching, green mobile operator collaboration, renewable energy exchange, and cooperation with smart grid.

The smart grid is widely seen as one of the most important novel means that help manage energy procurement of consumers to achieve green and economical goals. It can considerably help in reducing GHG emissions by optimally controlling and adjusting the consumed energy [7]. Moreover, it allows the massive integration of intermittent renewable sources and offers the possibility to deliver electricity in a more cost-effective way with active involvement of customers in the procurement decision. Many wireless communication and networking technologies were proposed to improve the performance of smart grid [8]. For instance, home automation network technologies are employed to achieve cost-efficient residential energy management in smart grid. Novel efficient and secure wireless communication schemes were also proposed to improve the spectrum efficiency for advanced metering infrastructure in smart grid. Furthermore, wireless sensor networks (WSNs) were introduced as a promising technology that can solve various smart grid problems. However, some research works exploited the potential of smart grid to reduce the carbon footprint of wireless cellular networks. The introduction of the concept of smart grid as a new tool for managing energy consumption in cellular networks is considered as an important technological innovation that would significantly contribute to the reduction of mobile carbon dioxide (CO_2) emissions.

Therefore, the BS sleeping strategy can also constitute a promising solution contributing to the reduction of cellular network energy consumption and GHG emissions. A basic on/off switching example consists in turning off lightly loaded BSs while serving its corresponding subscribers via neighbor BSs in order to maintain the required quality of service (QoS). Several advanced on/off switching algorithms have been proposed in the literature aiming to minimize energy consumption under different scenarios and constraints. For instance, in [9], the energy-delay tradeoff is investigated when optimizing the BSs' statuses. Algorithms for BS on/off switching for renewable energy powered networks have been given in [10] and [11]. Another study has been presented in [12] where a traffic load balancing framework has been proposed to achieve tradeoffs between two network utilities; namely the average traffic delivery latency and the green energy utilization. Software-defined radio access network architecture are exploited for this purpose.

Mobile operators are increasingly deploying renewable energy generators on the sites of their base stations (BSs) to cope with negative impact of fossil fuel consumption. Due to the randomness in renewable energy generation and power consumption, each BS may have a surplus or a shortfall of energy at any given period of time. Hence, this energy surplus or deficit has to be sold to or procured from the electricity grid, respectively [13]. Another more self-reliant solution is to enable energy sharing between BSs in the sense that BS with energy surplus can support other BSs with energy deficiency instead of procuring the remaining energy from the smart grid. In this way, mobile operators owning renewable energy sources can limit their dependency on the electrical grid and hence, reduce their energy cost and corresponding CO_2 emissions. In [14], an overview on the design and optimization of renewable energy in cellular networks is presented. The advantages of powering future cellular networks are analyzed and the future research challenges are discussed.

Another approach that can contribute to the carbon footprint and huge energy bills reduction is the green mobile operator collaboration. This concept, introduced in [15], suggests cooperation between competitive service providers in order to achieve green targets. The fundamental idea was to completely turn off the equipment of one service provider and serve the corresponding subscribers by infrastructure belonging to another mobile operator under some fairness constraints. Although this technique has not been extensively applied in real environments, its impact is expected to provide important energy savings. Therefore, further research should be carried out in this direction in order to prove the efficiency of this technique and encourage mobile operators to cooperate together not only for green but also for profitable goals.

The main concepts that will be discussed in this article have been highlighted. In the following sections, we elaborate more on these techniques and their intersections with the green requirements of future 5G cellular networks. Their environmental and economical impacts are also discussed. Finally, we focus on the challenges related to their standardization and applications in real environments.

The rest of the paper is organized as follows: Section II analyzes energy consumption and CO_2 emissions of cellular networks. In Section III, the potential of smart grid in OPEX and carbon footprint reduction is investigated. Section IV deals with the BS energy exchange mechanisms. The mobile operator collaboration is presented in Section V. Section VI focuses on the future issues and implementation challenges of the proposed green solutions. Finally, the paper is concluded in Section VII.

II. ENERGY CONSUMPTION AND GREENHOUSE GAS EMISSIONS ANALYSIS IN CELLULAR NETWORKS

Improving energy efficiency of cellular networks and curtailing their CO_2 emissions will be one of the most critical key challenges of next-generation networks as mobile traffic demand is continuing rising in a rapid way over the coming years. Global traffic is growing around 65% year-on-year as shown in Fig. 1 and presented by Cisco in their global mobile traffic forecast [16].

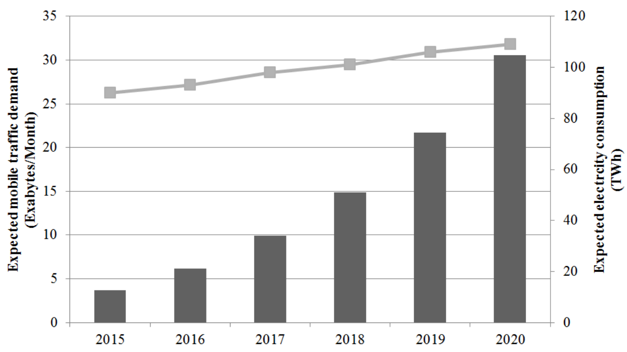
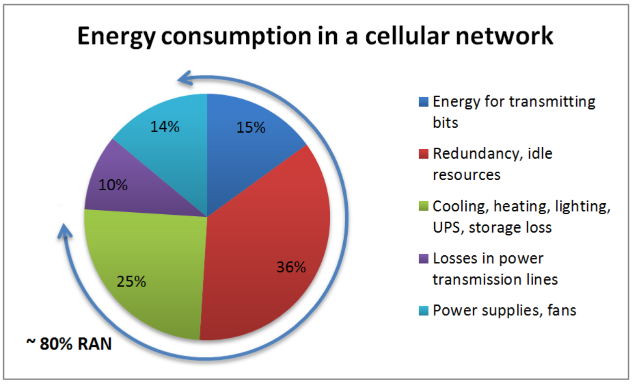
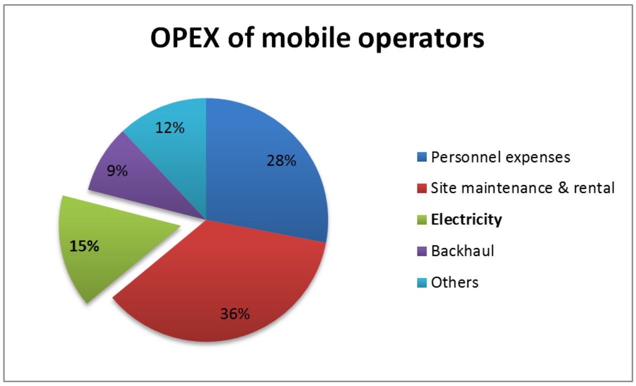


FIGURE 1. Expected mobile traffic demand (gray bars) and energy consumption (gray line).

Given the enormity of the current traffic usage and taking into account the substantial increase expected in the next decade, the corresponding energy consumption is also expected to significantly increase, if no action is taken, as many technical reports and studies predict [3], [5], [17]–[19]. The global growing energy consumption in cellular networks in terms of electricity usage in live networks has been measured over the past decade as illustrated in Fig. 1. It is shown that global energy consumption in cellular networks is expected to increase by around 20% from 86 TWh in 2015 to 109 TWh in 2020 [19].



(a)



(b)

FIGURE 2. Energy consumption in cellular networks (a) repartition of energy consumption (b) repartition of OPEX.

The most power greedy component in cellular networks is the RAN with around 80% of the total consumed energy as shown in Fig. 2(a) [17]. The RAN is deployed to serve this huge number of subscribers located everywhere and can connect at anytime. However, it has been shown that for a typical cellular network, 50% of the deployed BSs serve only 15% of the total traffic, while 5% of the sites serve 20% of the traffic [18]. These statistics reveal that most of the deployed BSs are under-utilized and networks are over-dimensioned since they are usually planned to ensure connectivity during high-traffic situations. The figure also shows that only 15% of the total energy allocated to cellular networks is used to perform for essential task, namely transmitting data. The rest is consumed by idle nodes and for cooling, heating, and lighting, etc. On the other hand, energy costs represent about 15% of the OPEX of mobile operators as illustrated in Fig. 2(b) and can reach up to 50% in some scenarios, e.g., high-number of off-grid sites [20]. Therefore, controlling energy consumption has become an increasingly important consideration.

GHG emissions rise is another key challenge faced not only by mobile operator but also by the global society.

The Intergovernmental Panel on Climate Change (IPCC) of the United Nations held in 2014 indicates that GHG emissions need to be reduced to 40-70% below 2010 levels by 2050 in order to limit global warming to below two degrees Celsius [21]. This objective will require the integration of existing and also innovative solutions. Although the ICT's part in the overall GHG emissions is expected to slightly increase in the next decades, it is predicted that ICT has an enormous potential to enable energy savings and consequently, GHG emissions reduction across different domains. In [22], it is indicated that ICT may enable reduction of about 15% of the global GHG emissions in 2030 thanks to i) the maturity of mobile broadband, ii) the emergence of diverse Internet-of-Things (IoT) applications enabling efficient energy management, and iii) the improvements of network software by adapting network functionality to evolving traffic behavior and enhancing the spectral efficiency gains.

Many industrial actors believe that in spite of the huge growth of mobile traffic, it is possible to flatten or decouple the corresponding network energy consumption and hence, reduce the mobile operators' OPEX and achieve GHG reduction [17], [18]. In the next sections, we propose and investigate three innovative solutions that contribute, in our point of view, in achieving these green objectives. Afterwards, we discuss the challenges that could be faced when implementing these solutions in practice.

III. SMART GRID FOR CELLULAR NETWORKS

A. MOTIVATION AND BACKGROUND

The new smart electrical grid has integrated several wireless communication technologies in order to streamline the electricity generation, transportation, and distribution. By integrating advanced sensing techniques in addition to communication and control features in its power grid operation, smart grid can significantly enhance the management of energy procurement of different electricity procurers: residential, commercial, industrial facilities, and in particularly future cellular networks. Indeed, given its characteristics as defined by the U.S. Energy Independence and Security Act of 2007 [23], smart grid offers several benefits to next-generation networks. Smart grid's tools can be exploited by mobile operators in order to optimize their energy procurement, limit their CO_2 emissions, and reduce their energy bills. These tools can be summarized as: i) incorporation of information and control technologies to enhance the generation, distribution, and consumption of energy, ii) optimization of the operation of the grid and consumer devices with full security, iii) integration of distributed and renewable resources, and iv) development of the demand side management (DSM) with the provision of timely and accurate information and control options to consumers.

Smart grid enables the active participation of the consumer, e.g., mobile operators, in the procurement decision and the ability to sell consumer-owned generation and storage resources into the market [24]. The latter feature of smart grid encourages mobile operators, principally with the emergence of heterogeneous networks (HetNets), to possess their own renewable energy architecture by equipping, for instance, their micro and small cell BSs with solar panels or wind turbines [25]. This will provide, fully or partially (depending on the amount of energy that can be generated), the energy needed for their operation with the possibility to sell the extra-generated energy to the market. Some studies have investigated the dynamic cooperation of cellular networks with smart grid [26]. It has been shown in [27] that powering RAN's BSs with a combination of renewable energy sources and the electrical grid helps in minimizing the cost of power consumption while meeting the users' demand. Optimized DSM solutions represents a major step toward green wireless communications. An interesting DSM solution is proposed in [28]. The authors have modeled the cooperation between a cellular network and smart grid as a Stackelberg game. In this game, the multiple energy retailers play the role of leaders that compete together in order to maximize their market share by optimizing their energy prices. The energy price varies depending on different parameters, mainly the needed energy by the cellular network which plays the role of the follower. The cellular network aims to minimize its CO_2 emissions by optimizing the amount of energy to be procured from each energy retailer existing in the smart grid. The authors showed that the real-time pricing (RTP) features offered by smart grid can reduce the OPEX and GHG emissions of cellular networks. In [29], the authors investigated the smart grid advantages for different mobile operators' attitudes towards the environment, i.e., environmentally friendly mobile operators or non-green mobile operators, while considering the BS sleeping strategy applied during low traffic periods. Indeed, a BS could be completely or partially turned off when its activation is redundant. The corresponding user equipments (UEs) could be offloaded to neighbor cells to maintain their connectivity and ensure green communication. In [29], the smart grid DSM and the active BSs combination based on the pollution levels and the energy prices are jointly optimized to achieve cost-effective energy saving while respecting the uplink (UL) and downlink (DL) network QoS. In [30], a new integration architecture for renewable energy-powered cellular networks and smart grid is proposed. This architecture is designed based on the requirements of smart grid, renewable energy systems, and cellular networks. It aims to bring mutual benefits for smart grid and network operators by achieving a tradeoff between the concerns and objectives of each actor. A recent work investigating the scenario of cellular powered by smart grid is presented in [31]. It proposes real-time energy management and robust transmit beamforming designs to curtail energy transaction costs with the smart grid while exploiting locally generated renewable energy.

While cooperating with smart grid, the network state considerably varies and depends on many factors such as the time of the day (peak hour, late night, etc.), day of the week (workday, week-end, etc.), UE density, and UE subscription and behavior profile. For instance, spatial distribution of UEs may frequently change during the day: UEs can connect/ disconnect randomly and their movement in a given geographical area is unpredictable. The channel conditions due to fast fading and shadowing variations constitute an important parameter influencing the QoS and the power consumption. Moreover, the availability of the locally generated renewable energy is uncertain and may increase or decrease with time depending on the energy consumption and generation profile in addition to other environmental and technical effects. Thus, these parameters have to be taken into account in the procurement decision. On the other hand, the designer has to be careful with such optimization as in some cases the multiple daily on/off switching might not be practical in real system implementations, particularly during short periods of time [32]. Therefore, such optimized techniques need to achieve a certain tradeoff between CO_2 emissions reduction and on/off switching oscillations. Fig. 3 depicts a diagram representing the architecture of future green cellular networks simultaneously powered by smart grid and locally deployed renewable energy sources. A smart control center is required to establish the link between the smart grid and the mobile operator in order to optimize the cellular network choices, i.e., BSs to be turned off, amount of energy to procure, amount of extra auto-generated energy to sell, etc.

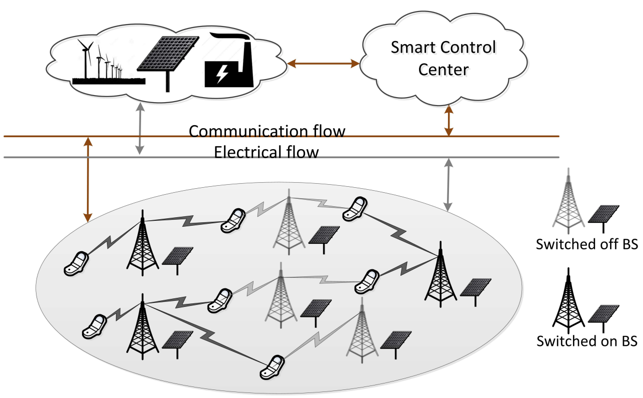


FIGURE 3. Cellular network powered by the smart electrical grid. The optimized energy procurement decision is centrally managed by a smart control center collecting all needed information from cellular networks and smart grid.

B. SELECTED RESULTS AND DISCUSSIONS

In this section, we investigate a scenario of a cellular network powered by smart grid where an optimized energy procurement is performed to minimize the total CO_2 emissions while respecting the network's QoS. An optimization problem is solved every time slot l to determine the best active BSs combination and the corresponding energy procurement decision that maximizes a weighted bi-objective utility $U(l)$ subject to multiple constraints. The objective is to achieve a tradeoff between the mobile operator's profit, denoted by $\mathcal{P}$ and expressed in monetary unit (MU), and a CO_2 emission penalty function corresponding to the network fossil fuel consumption denoted by $\mathcal{I}$ which reflects the friendliness of the mobile operator to the environment [28], [29]. The expressions of $\mathcal{P}$ and $\mathcal{I}$ are given as follows:

$$\mathcal{P}(\boldsymbol{\gamma}) = \underbrace{\sum_{k=1}^{N_U} \gamma_k p_k^{(m)}}_{\text{Service revenue}} - \underbrace{\sum_{s=1}^{N_{\text{BS}}} \sum_{n=1}^{N} \epsilon_s \pi_n q_s^{(n)}}_{\text{Energy consumption cost}}, \tag{1}$$

and

$$\mathcal{I}(\boldsymbol{\epsilon}, \boldsymbol{q}) = \sum_{s=1}^{N_{\text{BS}}} \sum_{n=1}^{N} \epsilon_s \left(\psi_n \left(\frac{q_s^{(n)}}{T} \right)^2 + \phi_n \frac{q_s^{(n)}}{T} \right), \tag{2}$$

where $p_k^{(m)}$ and π_n are price of a service m and the energy price imposed by retailer n, respectively. ψ_n and ϕ_n are the emission coefficients characterizing the CO_2 emissions of the energy source n. N_{BS}, N, and N_U are the number of BSs, the number of external retailers, and the number of connected UEs, respectively. Three decision variables are considered in the optimization framework: $\boldsymbol{\gamma}$, $\boldsymbol{\epsilon}$, and $\boldsymbol{q}$, where $\boldsymbol{\gamma} = [\gamma_1, \cdots, \gamma_{N_U}]$ is a binary vector indicating if a UE k is successfully served or not. A UE is assumed to be successfully served if its UL and DL data rates are greater than or equal to a data rate threshold characterizing a service offered by the mobile operator. The entries of $\boldsymbol{\gamma}$ are determined after executing a resource allocation algorithm applied to the active BSs. A binary vector $\boldsymbol{\epsilon}$ is introduced to indicate the status of each BS. Each element of $\boldsymbol{\epsilon}$, denoted by ϵ_s, is set to one if the corresponding BS is switched on, and vice versa. Finally, the entries of the vector $\boldsymbol{q} = [q_1^{(0)}, \cdots q_1^{(N)}, q_2^{(1)}, \cdots, q_{N_{\text{BS}}}^{(N)}]$ represent the amount of energy procured by a BS from a retailer existing in the smart grid $n \geq 1$ or deployed locally $n = 0$. The optimization problem is solved every time slot l of length T and formulated as follows:

$$\begin{aligned} \underset{\boldsymbol{\gamma}(l), \boldsymbol{\epsilon}(l), \boldsymbol{q}(l)}{\text{Maximize}} \; U(l) = {} & (1-\omega)\mathcal{P}(\boldsymbol{\gamma}(l), \boldsymbol{\epsilon}(l), \boldsymbol{q}(l)) \\ & - \omega \mathcal{I}(\boldsymbol{\epsilon}(l), \boldsymbol{q}(l)), \end{aligned} \tag{3}$$

Subject to: (C1: Energy retailer capacity constraint:)

$$\sum_{s=1}^{N_{\text{BS}}} \epsilon_s(l) q_s^{(n)}(l) \leq Q_{\max}^{(n)}(l), \quad \forall n = 1, \cdots, N, \tag{4}$$

(C2: Local energy capacity constraint:)

$$q_s^{(0)}(l) \leq \alpha_s(l), \quad \forall s = 1, \cdots, N_{\text{BS}}, \tag{5}$$

(C3: BS power requirement constraint:)

$$\sum_{n=1}^{N} q_s^{(n)}(l) = P_s^{\text{BS}}(l)\, T, \quad \forall s = 1, \cdots, N_{\text{BS}}, \tag{6}$$

(C4: QoS constraint:)

$$\frac{N_{\text{out}}(l)}{N_U(l)} \leq P_{\text{out}}, \tag{7}$$

$$q_s^{(n)}(l) \geq 0, \quad \forall s = 1 \cdots N_{\text{BS}} \text{ and } \forall n = 1, \cdots, N. \tag{8}$$

Constraint (4) indicates that the energy consumed by all BSs in the cellular network from energy retailer n cannot exceed the total energy provided by that retailer at time slot l, denoted by $Q_{\max}^{(n)}(l)$, while constraint (5) implies that the energy procured by a BS j from its own energy generated locally can not exceed the amount of energy that can be produced or the amount of energy that can be stored locally at time slot l denoted by $\alpha_s(l)$. Constraint (6) indicates that the amount of energy drawn by a BS from all retailers should be equal to the power needed for its operation, denoted by $P_s^{\mathrm{BS}}(l)$, during a period T. Constraint (7) forces the number of UEs in outage, $N_{\mathrm{out}}(l)$, to be less than a tolerated outage probability threshold P_{out} and constraint (8) is a trivial constraint expressing the fact that the energy drawn is a positive amount. It should be noted that, when a certain retailer n can provide to the cellular network operator enough electricity to power all the BSs in the network, we can set $Q_{\max}^{(n)} = +\infty$ to relax constraint (4) for that retailer, although in practice the amount of energy produced is naturally finite. ω is called the Pareto weight $(0 < \omega < 1)$. When $\omega \to 0$, the mobile operator is said to be selfish as it aims to maximize its own profit $\mathcal{P}$ regardless of its impact on the environment. When $\omega \to 1$, it is considered as an environmentally friendly mobile operator aiming to reduce CO_2 emissions regardless of its own profit. Other values of ω constitute a tradeoff between these two extremes. In other words, ω indicates the mobile operator's attitude towards the environment.

The optimization problem formulated in (3)-(8) is solved periodically in order to optimize energy procurement from smart grid and switch off the underutilized BSs according to the system parameters. For this reason, a periodic computation has to be performed to find the best BS combinations $\boldsymbol{\epsilon}(l)$, the best resource allocation identified by $\boldsymbol{\gamma}(l)$, and, consequently, the corresponding energy procurement decision $\boldsymbol{q}(l)$ needed to achieve green energy consumption at each period lT. However, since two of the decision variables, namely $\boldsymbol{\epsilon}(l)$ and $\boldsymbol{\gamma}(l)$, are binary variables, the formulated problem is a combinatorial non-deterministic polynomial-time hard (NP-hard) problem which makes the optimal and exact solution difficult or even impossible to find [33]. Therefore, low-complex approaches, where at each period of time, try to find the best BS combination that maximizes the utility function expressed in (3) are employed. Two approaches are proposed to jointly optimize energy procurement from the smart grid and the BS on/off switching. The first approach, denoted by A, tries to minimize CO_2 emissions by finding the optimal active BSs combination without taking into account the previous state of each BS. The second approach, denoted by B, aims to keep the same BS active as much as possible in order to reduce the on/off oscillations. The pseudo-code of the proposed approaches are given in Appendix VII and Appendix VII, respectively. The choice of T would vary in time according to the need of the mobile operator. For instance, if the traffic variation is slow (during night), the mobile operator can increase T, e.g., $T = 1$ hour. However, if the traffic variation is relatively fast, the execution period can be decreased to maintain the required QoS, e.g., $T = 1$ minute. Micro-sleep techniques can be used for extremely fast channel and profile variations [34].

TABLE 1. Performance of a cellular network powered by smart grid during 48 hours.

	Traditional	A	B
Profit (MU)	116300	180000	177000
Total consumed energy (MWh)	321	161	164
Self-consumed PV (MWh)	204.6 (63%)	150.6 (93.5%)	134.3 (81.8%)
Fossil fuel (MWh)	22.7 (7%)	0.117 (0.1%)	8 (5%)
Green energy (MWh)	93.7 (30%)	10.3 (6.4%)	21.9 (13.2%)
CO_2 emissions (Kg/hour)	2366	10	833
Average UEs in outage (%)	0.05	0.45	0.52
Average active BSs	16	5.6	5.8
On/off switching	0	2125	860

Table 1 illustrates the performance of a cellular network powered by smart grid during a period of 48 hours. The employed resource allocation and the simulation parameters are presented in [29]. The cellular network is deployed to serve a 4×4 Km^2 coverage area where $N_{\mathrm{BS}} = 16$ BSs are placed uniformly according to the cell radius selected to be 0.5 Km. We assume that the network operator offers three different services with various mobile call models and durations characterized by different DL and UL target data rates varying from 64 kbps for voice calls to 1 Mbps for high data rate applications [35]. On the other hand, we assume that the cellular network can procure energy from two different external retailers $N = 2$: A fossil fuel source, i.e., $n = 1$, denoted by $\mathcal{F}$, and a renewable energy source, i.e., $n = 2$, denoted by $\mathcal{R}$. We consider that $\mathcal{F}$ is able is produce energy that is sufficient to power all BSs of the network while $\mathcal{R}$ is generating green energy that is limited by a certain capacity of generation. The price of $\mathcal{R}$ is considered to be the double price of $\mathcal{F}$. Finally, we assume that the mobile operator owns its private free-of-charge renewable energy that is only produced during the day, e.g., Photovoltaic (PV) source, and can not exceed the storage capacity of the BSs. Both approaches, A and B, are executed for $\omega \to 1$ and such that the percentage of UEs in outage cannot exceed 2%. Note that UEs that are simultaneously connected to the network during the whole day are distributed uniformly over the area of interest and that their number is varying between 10 to 900 UEs for lowest and highest traffic periods, respectively.

We notice that, with both approaches, the network provides almost the same profit and consumes the same energy (around 164 MWh) by activating on average the same number of BSs (between 5 and 6). Thanks to the BS sleeping strategy, the mobile operator is able to save about 50% of the total energy consumption compared to the traditional scenario when all BSs are always kept active. However, it sacrifices more the connectivity of its UEs: around 0.5% outage versus 0.05% in the traditional scenario. In terms of procured energies, we notice that approach A is greener than approach B. Indeed, around 99% of the consumed energy by approach A is procured from renewable energy sources, where 93% of this energy is auto-generated locally via deployed solar cells. However, PV constitutes only 82% of the total consumed energy when approach B is used. This is due to the fact that under this approach, the active BSs are almost the same during long periods of time and thus, they might completely consume their auto-generated green energy and are obliged to procure more energy from the smart grid, i.e., electricity and renewable energy depending on the availability. Nevertheless, one of the advantages of approach B is the reduction of the daily on/off switching. Approach B is able to reduce the daily switching by more than 60% by making 860 transitions instead of 2125 transitions using approach A. Although it pollutes the environment more than approach A, approach B can be considered more practical for mobile operators due to the reduced number of on/off transitions.

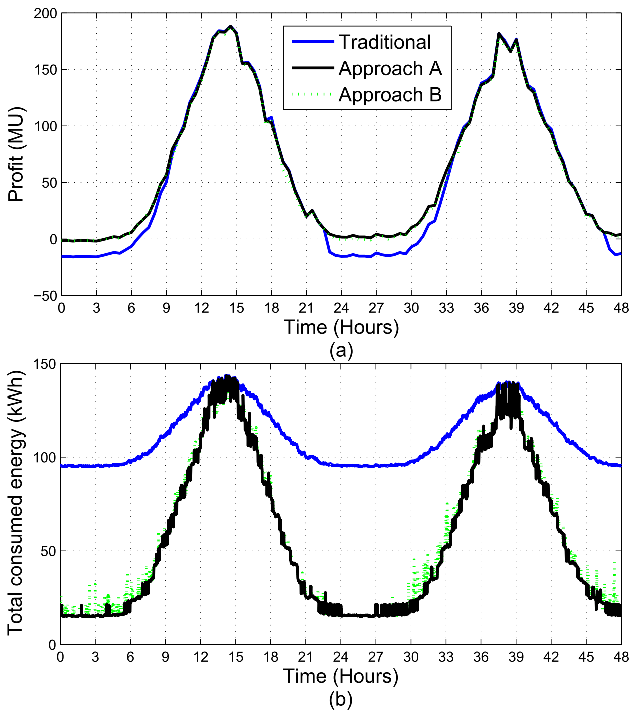


FIGURE 4. Performance of approach A and approach B compared to the traditional scenario: (a) profit of the mobile operator (b) total consumed energy of the network.

In Fig. 4, we investigate the daily strategy of the mobile operator using both iterative approaches A and B. We also compare the obtained results with the traditional case where the mobile operator is keeping all of its BSs active. The figure plots the mobile operator profit in addition to the total energy consumption of the network during 48 hours. We notice that both algorithms achieve almost the same performance in terms of profit which confirms the results presented in Table 1. However, in terms of energy consumption, approach B consumes more energy due to the fact that this algorithm prefers to turn on more BSs than totally modifying the already active BSs combination as it is done with approach A. Indeed, approach B is proposed to reduce the number of on/off switching operation by trying to keep currently active BSs turned on as long as possible. Therefore, instead of switching off all the already active BSs and turning on new BSs to serve the connected UEs, it opts to keep the same BSs combination and activate additional BSs to satisfy the QoS. In Fig. 4(b), we notice the existence of local peaks throughout non-peak hours with approach B. These peaks correspond to the activation of extra BSs to serve new connected UEs at time lT followed by a deactivation of other BSs in $(l+1)T$. It should be noted that both proposed approaches have a higher outage rate than the traditional case as a less number of BSs is activated. However, approach A outperforms approach B by serving more UEs. Indeed, approach A always provides a more efficient BSs combination achieving a higher utility and a lower outage rate.

It should be noted that, in case of higher UL and/or DL data rates, the proposed approaches A and B are still feasible under the unique assumption that the network is well-planned, i.e., the number of BSs and their locations meet the service requirements during the peak periods. If higher data rates are considered then, more BSs will be activated during off-peak periods and hence, more power consumption is required. Consequently, the energy procurement decision will depend on the total energy needs of the network and the renewable energy availability. Furthermore, a reduction of the network operator's profit will be noticed. In summary, the same trend as in Fig. 4 will be obtained with higher power consumption and lower profits during off-peak periods.

Through the examples mentioned earlier, it has been been shown that most of the green objectives can be addressed thanks to the empowerment of cellular networks by multiple retailers existing in smart grid. The expected results from this kind of interactions are, however, subject to many complex factors such as real-time pricing, renewable energy availability, and mobile traffic profile. The foreseen optimal decision for such scenarios is difficult to predict mainly due to the randomness and uncertainty of these factors. Hence, stochastic techniques should be adopted for better assessment of the energy procurement decision.

IV. BASE STATION ENERGY SHARING

A. MOTIVATION AND BACKGROUND

Most mobile operators worldwide are starting deploying renewable energy generators at the sites of their BSs to obtain clean and cheap electricity. These green sources are exploited in conjunction with the traditional electrical grid to power up the BSs. However, their production is highly variable in time and space depending on different environmental and technical factors [36]. Therefore, some BSs may have a surplus energy during certain periods while at other periods, they may be energy deficient. Thanks to the intelligent two-way power flow enabled by the smart grid as described in Section III, the energy deficit may be complemented by purchasing electricity while any surplus renewable energy may be sold back to the grid [37]. However, it will be more cost-effective to share this distributed renewable energy by a common energy infrastructure to collectively serve the energy requirements of all BSs [38]. In other words, the surplus renewable energy at one BS is transferred to another BS by enabling energy sharing between them.

Energy sharing allows more efficient exploitation of locally generated energy across the network and helps in further paring down energy cost by optimizing the procurement from the grid [13], [19], [39]. It is becoming more and more practical to implement mechanisms for energy sharing thanks to the distributed renewable energy generated at BSs sites that can be connected together to create microgrids [40], [41] that collectively serve the energy requirements of all BSs. An example of architecture for microgrid connected cellular networks is proposed in [38]. The architecture uses wind turbines and PV panels as alternative sources of electric power. In this way, a more efficient management of electric resources and a more resilient cellular system architecture are enabled. Results show that there is an important potential to power cellular networks from renewable energy sources. With BS energy sharing, this management of locally generated renewable energy will be more efficient. However, enabling energy sharing within a cellular network requires an effective energy transport mechanism among its BSs. Smart grid infrastructure can virtually transport energy between BSs by selling the extra energy to the grid at one BS and buying the same amount of energy by another BS at a preferential price [13], [39]. The imposed smart grid charge for providing this service is reflected by the difference in the buying and selling prices of the grid which are subject to the pricing policies of the smart grid. In [13], the authors proposed a framework for energy exchange among BSs using smart grid. However, the study does not consider the uncertainty effect associated to renewable energy generation. In [39], an optimized energy management framework is proposed for microgrid-connected cellular BSs that are equipped with renewable energy generators and battery storage. It uses the smart grid as the common energy infrastructure and considers time variations and uncertainty in renewable energy generation in the optimization. The studies show that additional cost saving and CO_2 emissions reduction are achieved thanks to BS energy sharing. Another way to enable energy transfer could be through the use of physical power lines to connect BSs [19]. In this case, the mobile operator will not incur any additional cost for sharing energy and its energy cost will be more independent from the daily variation of smart grid prices. However, this solution is infeasible for long distances due to many factors such as high installation costs, resistive power losses, and restricted access areas. Therefore, it is preferable to install physical power lines between BSs in the same neighborhood to reduce the infeasibility risk. For long distances, the smart grid infrastructure can be used. Hence, we talk about hybrid BS energy sharing.

B. SELECTED RESULTS AND DISCUSSIONS

In Fig. 5, we present a basic example of a hybrid energy sharing scenario where three BSs powered by solar panels and smart grid are considered. We assume that one of them, e.g., BS 1, has a surplus of renewable energy while the others, BS 2 and BS 3, are deficient. We also assume that a physical power line is installed between nearby BSs: BS 1 and BS 2. The available amount of renewable energy α_s, expressed in Joule, and the required power P_s^{BS} in Watt for a safe operation during $T = 1$ second are specified for each BS as highlighted in the figure. To show the potential of energy sharing, particularly the hybrid one, in the reduction of energy cost, we compare four scenarios depending on the level of energy sharing. The first scenario, denoted by ''No share'', corresponds to the traditional scenario where BSs do not exchange energy and the surplus of energy is just sold to the smart grid. The second and the third scenarios, denoted by ''share via SG'' and ''share via Phy-PL'', correspond to the cases where BS energy sharing is possible either via the smart grid infrastructure or the installed physical power line, respectively. The fourth scenario corresponds to the hybrid energy sharing where the exchange of energy can be done via both energy exchange means and it is denoted by ''hybrid share''.

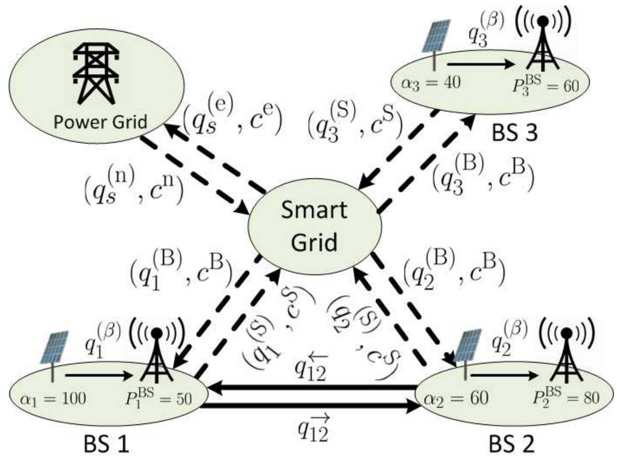


FIGURE 5. Example of energy sharing scenario for three base stations. The energy exchange occurs through smart grid infrastructure (dashed lines) or through installed physcial power links (solid lines).

As indicated in Fig. 5, the amount of extra energy sold back to smart grid at a price of c^{e} is denoted by $q_s^{(\mathrm{e})}$. The amount of energy bought by BS s from other BSs via smart grid is denoted by $q_s^{(\mathrm{B})}$ at a price of c^{B}, while the energy shared by BS s with other BSs is denoted by $q_s^{(\mathrm{S})}$, at a price of c^{S}. In this context, the BSs will sell the energy to the smart grid at a lower price than the price at which they will buy at another location, i.e., $c^{\mathrm{B}} \geq c^{\mathrm{S}}$. The amount of energy obtained by BS s from BS t using a physical power line is denoted by $q_{st}^{\leftarrow}$ while the amount of energy supplied to BS t by BS s is denoted by $q_{st}^{\rightarrow}$. The energy exchange through the power line is free of charge but subject to a loss characterized by the multiplicative factor η where $0 \leq \eta \leq 1$. This loss can take the form of resistive losses that can have a notable effect for longer distances. The amount of energy lost in the conductor in the form of heat during sharing is a function of the amount of energy transferred and the length of the power lines. Finally, we introduce a binary variable A_{st} that takes the value of 1 if a physical power line is installed between BS s and BS t and takes zero otherwise. The following optimization problem is then solved in order to minimize the total energy cost while meeting the BSs' energy requirements:

$$\underset{\substack{q_s^{(n)}, q_s^{(B)}, q_s^{(S)}, q_s^{(e)}, \\ q_{st}^{\rightarrow}, q_{st}^{\rightarrow}}}{\text{minimize}} \sum_{s=1}^{N_{\text{BS}}} c_n q_s^{(n)} + c^{\text{B}} q_s^{(\text{B})} - c^{\text{S}} q_s^{(\text{S})} - c^{\text{e}} q_s^{(\text{e})}, \quad (9)$$

subject to (C1: BS energy requirement constraint:)

$$q_s^n + q_s^{(\text{B})} + q_s^{(\beta)} + \sum_{\substack{t=1 \\ t\neq s}}^{N_{\text{BS}}} A_{st} q_{st}^{\leftarrow} = P_s^{\text{BS}}(l)\, T, \quad \forall\, s = 1, \ldots, N_{\text{BS}}, \quad (10)$$

(C2: Local energy capacity constraint:)

$$\alpha_s - q_s^{(\beta)} - q_s^{(\text{S})} - \sum_{t=1}^{N_{\text{BS}}} A_{st} q_{st}^{\rightarrow} - q_s^{(\text{e})} \geq 0, \quad \forall\, s = 1, \ldots, N_{\text{BS}}, \quad (11)$$

(C3: Energy exchange via smart grid constraint:)

$$\sum_{s=1}^{N_{\text{BS}}} q_s^{(\text{B})} = \sum_{s=1}^{N_{\text{BS}}} q_s^{(\text{S})}, \quad (12)$$

(C4: Energy exchange via physical power line constraint:)

$$A_{st} q_{st}^{\leftarrow} \leq A_{ts} \eta q_{ts}^{\rightarrow}, \quad \forall s, t = 1, \ldots, N_{\text{BS}}, \quad (13)$$

$$q_s^{(n)}, q_s^{(\text{B})}, q_s^{(\text{S})}, q_s^{(\text{e})}, q_{st}^{\rightarrow}, q_{st}^{\rightarrow} \geq 0. \quad (14)$$

The optimization problem formulated in (9)-(14) is similar to the one given in (3)-(8) except that the objective here is to minimize the total cost of energy transactions with the smart grid where one retailer exist. Constraint (12) is added to ensure that the total energy bought by the BSs via smart grid is equal to the total energy sold by other BSs. Constraint (13) indicates that the energy obtained by the BS via physical power lines has to be less than the energy supplied after including the loss effect. Notice that the formulated optimization problem is a linear programming one and can be efficiently solved by off-the-shelf solvers such as CVX [42].

In Fig. 6, we illustrate the total energy cost of the four scenarios described earlier applied to the network model presented in Fig. 5. The total energy cost is computed by solving the optimization problem (9)-(14) while varying the unitary price of the energy procured from the smart grid c_n where one retailer exist. The other energy prices are fixed as follows: $c^{\text{e}} = 0.2$, $c^{\text{B}} = 0.6$, and $c^{\text{S}} = 0.4$ MU. We consider that BS 1 owns a surplus of renewable energy

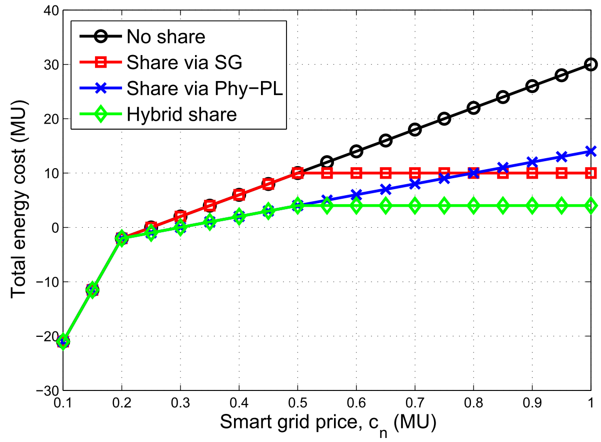


FIGURE 6. **Total energy cost versus the energy price imposed by smart grid c_n for four energy exchange scenarios.**

equal to 50 J while each of the other BSs need 20 J to operate safely. In Fig. 6, it is shown that when the smart grid price is less than the selling price c^{e}, which is a rare event, all the sharing strategies behave similarly. Indeed, the strategy is that all the generated renewable energy is sold to the grid and all BSs procure energy from the smart grid. For higher values of c_n, in the "No share" scenario, the BSs are consuming the generated energy, selling the extra energy if available, and forced to buy electricity from smart grid. However, thanks to energy exchange, the total energy cost can be reduced. For example, in "share via SG" scenario, the energy cost is maintained fixed for high values of c_n. In other words, all BSs do not need to buy from the external smart grid and can exchange energy through the grid as the sharing price is satisfying this condition: $c_n - c^{\text{e}} \geq c^{\text{B}} - c^{\text{S}}$ corresponding to $c_n = 0.5$ MU in our case. In the "share via Phy-PL" scenario, the total energy cost is still increasing since BS 3 is not able to cover its deficiency with renewable energy and is forced to buy electricity from smart grid. However, we notice that this scenario achieves lower cost than "share via SG" for low values of c_n as the sharing is free of charge compared to the virtual one. The potential of hybrid energy sharing is visible in "hybrid sharing" scenario performance that allows the efficient exploitation of the generated renewable energy over the network. In addition, it enables energy cost minimization and GHG reduction. Indeed, hybrid energy sharing offers to the mobile operator more flexibility to manage its energy procurement given different factors, e.g., imposed prices, traffic profile, renewable energy availability, etc. For instance, the uncertainty in the renewable energy generation and the daily traffic generation in addition to the battery capacity represent additional challenges that need to be taken into account in such studies [39]. Regarding the deployment of physical power lines, it should be noted that despite the initial capital investment required for their deployment, the financial gains from energy sharing outweigh the costs in the long-term.

One of the important challenges with renewable energy sharing among BSs is to deal with energy generation and user traffic uncertainties mainly when optimizing the daily energy exchange. This requires at least the knowledge of certain statistics about these uncertainties and then, risk optimization should be taken into account. Indeed, an underestimation or overestimation of the random variables can lead to system outages and/or profit loss.

Another challenge is to address the problem of physical power line installation between different BSs. Connecting each BS with other BSs in a mesh configuration is economically unviable and hence, unpractical for large-scale cellular networks. Nevertheless, the deployment of these power lines is possible for short inter-cell distances scenarios such as in HetNets and ultra-dense networks. In these scenarios, deploying power lines may be more affordable than exploiting the smart grid infrastructure. Therefore, installing permanent physical connections between BSs must be carefully planned. It has to take into account many factors such as the energy generation and requirements at each BS site, the level of interactions with the smart grid, and the energy exchange cost.

V. GREEN COLLABORATION AMONG MOBILE OPERATORS

The research interest in green communications is also moving towards achieving energy saving in multiple mobile operators environment. In such a scenario, additional degrees of freedom for achieving energy efficiency apart from the previously mentioned techniques exist. In general, green collaboration among wireless networks, also known as green networking, refers to techniques employed to improve the energy efficiency of networking and make it more environmentally friendly. It covers processes that directly or indirectly reduce the energy consumption and/or GHG emissions of the networks such as virtualization implementation, devices and data centers consolidation, and efficient server use. The earlier studies related to green networking and virtualization were focused on wired networks [43]. However, in green wireless communications, research work used to investigate the single network scenario without considering the deployed networks of other mobile operators, which leads to suboptimal results. In fact, optimizing the joint performance of different cellular networks serving the same area provides more flexibility for mobile operators to achieve green communications without affecting their revenues and QoS [44]. This new aspect of green networking and virtualization, where multiple cellular networks act as a single virtual network, is introduced to promote mobile operators collaboration in order to ensure energy saving and reduce the CO_2 emissions. Green networking for cellular networks can take a variety of forms according to the agreement arranging the cooperation. They can collaborate as a single network to better manage the energy procurement from smart grid or act as competitive networks where collaboration is based on incentive and roaming price considerations. In the following, we present these two aspects of green mobile operators collaboration.

A. SMART GRID ENERGY PROCUREMENT COLLABORATION AMONG MOBILE OPERATORS

1) MOTIVATION AND BACKGROUND

In this context, multiple mobile operators cooperate together by exploiting the presence of multiple competitive energy retailers existing in the smart grid. Together, the mobile operators cooperate to exert downward pressure on energy prices for the energy purchased from the power retailers. Indeed, thanks to collaboration, mobile operators would exploit the DSM features in smart grid to jointly optimize their energy procurement from energy retailers with lower energy cost. With real-time pricing, the energy prices vary frequently depending on several factors such as the cost of energy supply and the energy demand of mobile operators over time. Hence, mobile operators may join their forces in making energy procurement decision to cope with energy price increase during peak hours. In [45], the authors investigated the case of two mobile operators coexisting in the same geographical area. The mobile operators exploit their collaboration in both energy purchase and wireless load sharing for energy cost saving. The idea is that the two mobile operators are aggregated as a single group to make the day-ahead and real-time energy purchase. They also allow the sharing of their BSs to maximally turn lightly-loaded BSs into sleep mode. It was shown that significant energy cost reduction can be achieved.

2) SELECTED RESULTS AND DISCUSSIONS

Another example showing the benefits of collaboration among mobile operators supplied by smart grid is proposed in [46]. However, in this scenario, the mobile operators are procuring energy from multiple retailers existing in smart grid. In this cooperative scenario, both mobile operators aim to maximize the bi-objective function, given in (3), achieving a trade-off between the mobile operator's profit and their CO_2 emissions. On the other hand, energy retailers focus on maximizing their profits, denoted by U_n^{ret}, by determining the best energy price to impose to the energy procurers. The objective function of the energy providers are given as follows:

$$\underset{\pi_n}{\text{Maximize}}\; U_n^{\text{ret}} = (\pi_n - c_n) \sum_{i=1}^{N_{\text{op}}} q_i^{(n)}, \tag{15}$$

where c_n is the energy generation cost, and N_{op} is the number of mobile operators. Note that high values of π_n improve the revenue of retailer n but they decrease mobile operators' profits and vice versa. Therefore, the optimization of the amount of energy to be procured by mobile operator i, where $i = 1, \cdots, N_{\text{op}}$, from each retailer n, i.e., $q_i^{(n)}$, and the corresponding energy price, i.e., π_n is necessary to achieve a tradeoff between both objectives. Hence, the proposed framework is modeled as a Stackelberg game where mobile operators play the role of followers and retailers in smart grid play the role of leaders. The problem is solved using a backward induction approach and a Nash equilibrium is achieved as shown in [46].

The optimal tradeoff between both utilities, namely mobile operators utility and energy provider utility, is obtained for the following optimal values of the couple $(q_i^{(n)*}, \pi_n)$ given as:

$$q_i^{(n)*} = \left(\frac{1-\omega_i}{\omega_i}\right)\left(\frac{(1-2\chi\psi_n)\pi_n}{4\psi_n^2\chi} + \sum_{\substack{k=1\\k\neq n}}^{N} \frac{\pi_k}{4\psi_n\psi_k\chi}\right) + \frac{(1-2\chi\psi_n)\phi_n}{4\psi_n^2\chi} + \sum_{\substack{k=1\\k\neq n}}^{N} \frac{\phi_k}{4\psi_n\psi_k\chi} + \frac{\sum_{s=1}^{N_{\mathrm{BS}}^{(i)}} \epsilon_{s,i}\left(P_{s,i}^{\mathrm{BS}}T - q_s^{(0)}\right)}{2\phi_n\chi}, \tag{16}$$

where $\chi = \sum_{k=1}^{N} \frac{1}{2\psi_k}$, and,

$$\pi_n^* = \frac{-2\psi_n^2\chi}{\Omega(1-2\chi\psi_n)}\left(\Omega \sum_{\substack{k=1\\k\neq n}}^{N} \frac{\pi_k}{4\psi_n\psi_k\chi} + N_{\mathrm{op}} \sum_{\substack{k=1\\k\neq n}}^{N} \frac{\phi_k}{4\psi_n\psi_k\chi} + \frac{(1-2\chi\psi_n)(\phi_n N_{\mathrm{op}} - c_n\Omega)}{4\psi_n^2\chi} + \frac{\sum_{i=1}^{N_{\mathrm{op}}}\sum_{s=1}^{N_{\mathrm{BS}}^{(i)}} \epsilon_{s,i}\left(P_{s,i}^{\mathrm{BS}}T - q_j^{(0)}\right)}{2\psi_n\chi}\right), \tag{17}$$

where $\Omega = \sum_{i=1}^{N_{\mathrm{op}}} \frac{1-\omega_i}{\omega_i}$. Both expressions are obtained by deriving the Lagrangian of each optimization problem and equating it to zero. The expression given in (16) indicates that the amount of energy procured from a retailer n decreases if its unitary price increases. This is due to the fact that the first-order derivative of $q_i^{(n)*}$ is negative. Furthermore, equation (16) shows that the procurement decision depends on the mobile operator i's attitude towards the environment ω_i. Indeed, as $\omega_i \to 0$, the mobile operator is more and more concerned by its profit and the decrease of the amount of procured energy is more important as π_n increases. However, for an environmentally friendly mobile operator ($\omega_i \to 1$), energy price increase is no more important and the procurement decision is more related to the pollution coefficient factors (ψ_n and ϕ_n) as $\frac{1-\omega_i}{\omega_i} \to 0$ in this case.

In (17), the energy price of retailer n depends on the total amount of energy that will be procured by all mobile operators in addition to other electricity retailer prices π_k, $k \neq n$. Since $1 - 2\chi\psi_n < 0$, we can notice that the unitary energy price π_n increases as mobile operators' energy procurements from retailer n are higher. Fixed-point algorithm can be employed to find the optimal $q_i^{(n)*}$ and $\pi_n{}^*$, $i = 1, \cdots, N_{\mathrm{op}}$ and $n = 1, \cdots, N$. The existence and uniqueness of the Stackelberg equilibrium for similar problems are demonstrated in [28].

In Fig. 7, we assume that two mobile operators ($N_{\mathrm{op}} = 2$) act as a single virtual network applying the BS on/off switching without affecting their UEs' QoS.

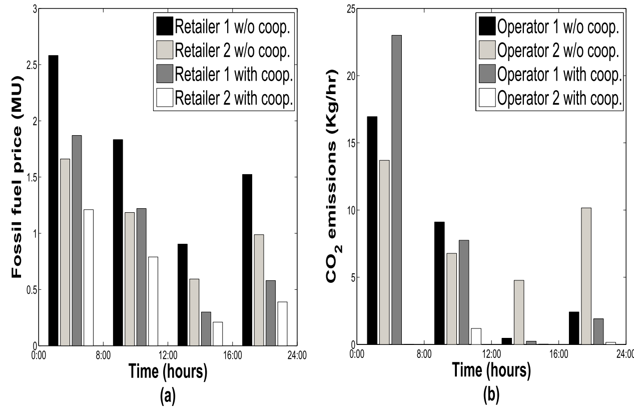


FIGURE 7. Mobile operator collaboration and energy prices reduction.

We assume that network's BSs are equipped with solar panels generating green energy during the day only. The cooperative scenario, denoted by "coop.", is compared to the traditional one, denoted by "w/o coop.", where each mobile operator procures the required energy independently and serves its UEs by its owned BSs only. The simulation parameters are detailed in [46]. Fig. 7(a) plots the fossil fuel prices that are varying during the day depending on the system parameters. They are inversely proportional to the availability of the locally generated green energy. If the energy procurement from the smart grid becomes limited, then, retailers prefer to reduce their prices in order to attract more mobile operators to procure energy. Also, results show that although the BS sleeping strategy is also applied in the non-cooperative mode, its impact in the cooperative mode is more significant. Indeed, notable energy prices and CO_2 emissions reductions are obtained thanks to the collaboration in the procurement decision. For example, during the night, the CO_2 emissions are reduced by about 30% as shown in Fig. 7(b).

B. GREEN COLLABORATION AMONG MOBILE OPERATORS WITH USER OFFLOAD

1) MOTIVATION AND BACKGROUND

This concept of green collaboration is related to the networks virtualization that allows turning off more BSs as compared to the case when each mobile operator is in a standalone setting. In other words, the collaboration is made among multiple mobile operators deploying cellular networks in the same area. It is performed by exploiting the BSs of competitive mobile operators. Hence, mobile operators have the possibility to offload their UEs not only to other owned BSs but also to BSs belonging to other competitive mobile operators. In this way, the networks will benefit by additional possibilities of active BSs combinations in order to achieve energy saving while respecting their UEs' QoS.

Several efforts have been made in literature to study the collaboration among multiple network operators [15], [47]. The authors in [15] evaluated the potential of energy saving in the context of multiple operators collaboration serving the same area. It is shown that significant energy savings can be achieved if collaboration is enabled among mobile operators. In [47], the multi-operator collaboration has been studied from an economical perspective. Notable OPEX reduction is reached thanks to collaboration where a game theoretic approach is proposed to select the active BS combination that minimizes the OPEX of mobile operators.

On the other hand, during collaboration, extra charge should be imposed to mobile operators that exploit other operators' infrastructure to serve their subscribers while their BSs are switched off. In fact, random collaboration may lead to the increase of certain mobile operator's profit at the expense of other competitive operators. This can cause high energy consumption and very low profits for the active network. Therefore, fairness criteria should be introduced for this type of collaboration. Fairness can take different forms such as the collaboration under equal charge allocation where the total cost is equally shared among mobile operators [48]. Another fairness criterion could be the equal share of the collaboration cost where only the cost due to collaboration is counted and equally shared among mobile operators.

In this section, we introduce roaming prices as another criterion for fair collaboration. The roaming price will be defined by mobile operators accepting to share their infrastructure. It will be imposed to other competitive mobile operators who are willing to offload their subscribers. The roaming cost is a possible and applicable solution in this kind of collaboration. Based on their profits before and after collaboration, mobile operators can decide whether sharing their infrastructure is beneficial or not. Thus, the regularization and optimization of roaming prices during collaboration should attract researchers and specialists attention in the coming years. Game theoretical approaches modeling the collaboration among mobile operators should be investigated. In the form of coalitions and/or competitions, the employed models depend on the system environment and mobile operators' objectives.

2) SELECTED RESULTS AND DISCUSSIONS

A multi-operator collaboration framework is proposed in [49], where the optimal active BS combination as well as the roaming prices are obtained using a game theoretic approach. The investigated framework is based on instantaneous network statistics which result in an optimized solution for a single time instant.

TABLE 2. Example of mobile operator collaboration performance.

Number of UEs of Op1	10	70	130
W/o coop. fossil fuel (kW) [Active BSs]	1.5[4.3]	5.1[10.7]	8.5[16]
Coop. fossil fuel (kW) [Active BSs]	1[2.7]	4[7]	6.9[11]
W/o coop. profit (kMU): Op1, Op2	0.10, 0.06	0.98, 0.62	1.86, 1.21
Coop. profit (kMU): Op1, Op2	0.12, 0.08	1.04, 0.68	1.96, 1.30
Roaming price (MU)	5.37	2.84	1.19

Table 2 presents the achieved performance of two collaborative mobile operators while increasing the number of UEs of Operator 1. The simulations are executed following the system model presented in [49] where the profit expression of a collaborative operator i in this context is given as follows:

$$\mathcal{P}_c^{(i)} = \sum_{k=1}^{N_U^{(i)}} \gamma_k^{(i,i)} p_k^{(i,m)} + \sum_{\substack{j=1 \\ j\neq i}}^{N_{\text{op}}} \sum_{k=1}^{N_U^{(i)}} \gamma_k^{(j,i)} \left(p_k^{(i,m)} - p_{ij}\right) + \sum_{\substack{j=1 \\ j\neq i}}^{N_{\text{op}}} \sum_{k=1}^{N_U^{(j)}} p_{ji}\gamma_k^{(j,i)} + R_{\text{op}}\left(N_U^{(i)}\right) - \mathcal{C}_c^{(i)}, \quad (18)$$

where the first term in (18) corresponds to the operator's revenue earned after successfully serving its own UEs. The second term is the revenue coming from UEs served by other mobile operators $j, j \neq i$ after paying the roaming cost p_{ij}. The third term is the gain obtained from serving UEs belonging to other networks $j, j \neq i$ which depends on p_{ji}. Finally, R_{op} is a constant revenue and $\mathcal{C}_c^{(i)}$ is the network energy consumption cost. A mobile operator i accepts to enter in collaboration only if its collaborative profit $\mathcal{P}_c^{(i)}$ is greater than or equal to the non-collaborative profit $\mathcal{P}_u^{(i)}$ corresponding to the difference between its service revenue and the energy consumption cost. Thus, the mobile operators have to solve the following non-homogenous system of linear inequalities to determine the roaming prices satisfying their revenue constraints:

$$\mathcal{P}_c^{(i)} \geq \mathcal{P}_u^{(i)}, \quad \forall i = 1, \cdots, N_{\text{op}}. \quad (19)$$

It should be noted that collaboration is possible only if the system (19) is compatible.

We compare the results of this collaboration scenario with the non-collaborative one where each mobile operator offloads its UEs only to its owned BSs. The roaming price is assumed to be the same for both mobile operators and is determined by solving a non-homogeneous system of two linear inequalities with one unknown variable. This system is determined by comparing the profit of each mobile operator before and after collaboration. Two sets of solutions are determined. If they are disjoints, collaboration is impossible. Otherwise, mobile operators can determine the fair roaming price choice for collaboration. For example, they can consider the price that maintains a close percentage change of mobile operators' profits. In Table 2, we can clearly deduce the importance of collaboration compared to the traditional scenario: on average, more BSs are turned off and energy saving is achieved with a notable increase in terms of profits. Moreover, the roaming price variation is adapted to the UE evolution. The simulation experiments indicate that the percentage of successful collaboration is higher than 95%.

Fig. 8 investigates the impact of generating renewable energy on the collaboration among mobile operators. We introduce a parameter α_{RE} that represents the percentage of green energy generated by Op1 while $100 - \alpha_{RE}$ corresponds to the percentage of green energy generated by Op2. In other words, if $\alpha_{RE} = 0\%$, then only Op2 possesses renewable energy and vice versa. For simplicity, we assume

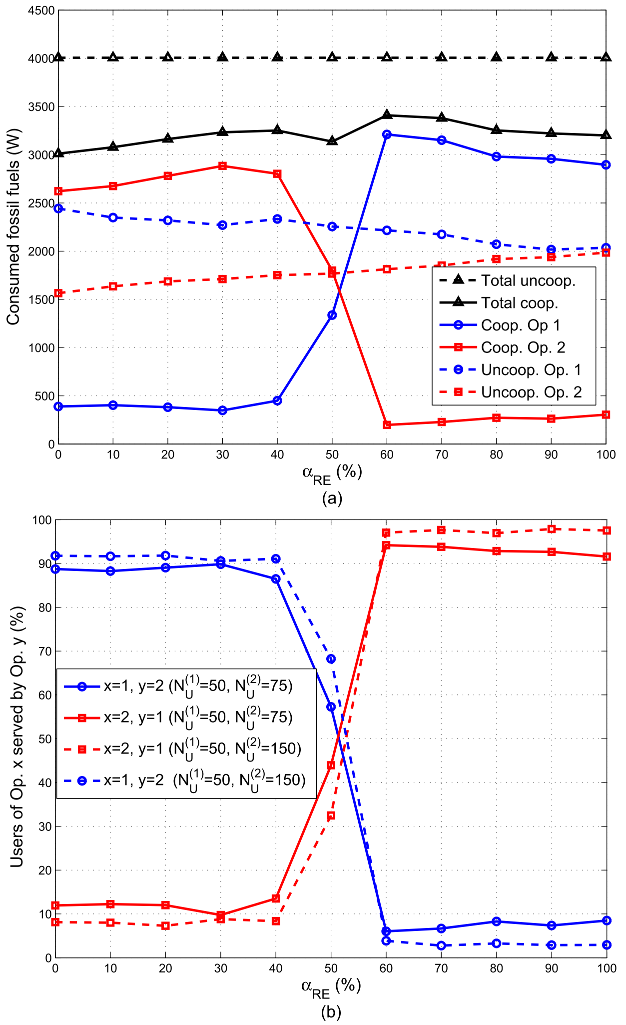


FIGURE 8. (a) Consumed fossil fuels (b) UEs of Op.*x* served by Op.*y* versus the distribution of green energy α_{RE}.

that all BSs owned by a mobile operator have the same amount of green energy. In Fig. 8(a), we plot the consumed fossil fuels versus α_{RE}. We notice that the mobile operator that is controlling renewable energy is able to reduce more of its CO_2 emissions when there is no collaboration. However, while collaborating, most of its BSs are kept active to serve most of the UEs of the competing provider as it is shown in Fig. 8(b) where more than 90% of UEs are offloaded. However, the optimal value for collaboration is $\alpha_{RE} = 50\%$. In this equilibrium, where fossil fuel consumption is at its minimum, all BSs of both mobile operators have the same characteristics and thus, the BS selection set is larger. The curves are unbalanced because of the difference in the number of connected UEs and the number of available BSs per each mobile operator. Note that the roaming price is higher when Op1 is controlling the renewable energy. In fact, as the number of subscribers of Op2 is lower, Op1 is forced to increase the roaming price in order to maximize its profit when collaborating while the inverse can be deduced for Op2. Note that in all our simulations, the network QoS is satisfied for all mobile operators $P_{\text{out}} = 2\%$ and the profits constraints given in (19) in the considered scenarios are satisfied.

In practice, the roaming price cannot be varied instantaneously and dynamically for each combination of channel realizations in the network. It can have a pre-defined fixed average value for a given traffic density or range of traffic densities in the network (e.g., there can be a price during the day corresponding to high density and another during the night corresponding to relatively lower density). This value can be set through collaboration agreements between mobile operators. The results derived in these simulations are averaged over 1000 channel realizations using Monte Carlo simulations. Hence, these results provide insights about the average performance that can be achieved between mobile operators in order to ensure mutual benefit. It is worth mentioning that offloading of traffic to other BSs is transparent to the users since the collaboration process is based on an agreement between mobile operators. Hence, with mobile operator collaboration, a reduction of the uplink transmit power consumption of UEs can be achieved as the density of BSs is higher than the one with non-collaboration case. This is due to the fact that UEs connect to the closest active BSs or the ones that provide better channel quality which will be more abundant in the collaboration scenario.

TABLE 3. Summary of the proposed green approaches.

	Optimized DSM from smart grid	BS energy sharing	Mobile operator collaboration
Energy saving	-	-	✓
Decrease energy prices	✓	-	✓
CO_2 emissions reduction	✓	✓	✓
On/off switching	✓	✓	✓
Applicable with HetNets	✓	✓	✓
Agreement with	retailers	smart grid	competitive operators

VI. FUTURE ISSUES/CHALLENGES

The techniques described in the previous sections present multiple similarities and differences that are summarized in Table 3. If implemented separately, each technique leads to the achievement of certain green gain. For instance, the interactions of mobile operators with smart grid do not contribute to the reduction of total energy consumption of cellular networks but lead to downward pressure on energy prices and optimized exploitation of renewable energy sources. Same remarks are noticed for BS energy sharing which aims to provide a better management of the use of locally generated green energy. On the other hand, the collaboration with other competitive mobile operators allow them to virtualize their infrastructure and hence, better manage their power consumption. All of the techniques will provide more efficient gains if they are jointly implemented mainly with the BS on/off switching. Notice that these techniques can be implemented with recent and future cellular networks including HetNets. However, they face significant challenges that need to be overcome before their practical implementation.

A. CHALLENGES IN THE BASE STATION ON/OFF SWITCHING

In the 3GPP standards [50], provisions have been made for BS on/off switching. Capacity boosting BSs can be put to sleep mode after notifying neighbors and handing over served UEs. Coverage is ensured by coverage BSs, which could be of a different radio access technology (e.g., 2G/3G/4G). In an LTE/LTE-A network, the necessary signaling information can be exchanged over the X2 interface [51]. Additional details on centralized and distributed energy savings procedures, along with the network requirements during on/off modes, are described in [52], which was based on [53] and [54]. However, specific algorithmic details for on/off switching are left for specific implementations by the network operators and/or equipment manufacturers. Consequently, it is possible to achieve energy efficiency in cellular networks by providing a method for switching off, or putting to sleep, capacity BSs that are subjected to light cellular traffic load. When the load increases again, a method is needed for switching on, or waking up, the BSs that are in sleep mode. The wake up process takes place with one BS at a time in the area of a given coverage BS, to maximize energy efficiency by avoiding switching on unnecessary BSs. It is particularly challenging, when several BSs are switched off, to determine which one to switch on without information about the UE positions. Fig. 9 provides a clarifying example. If, in Fig. 9, BS 1 is switched off for example, whereas all the other BSs in the figure are switched on, it is obvious in this case that when the load increases in cells 2-7, then the BS of cell 1 should switched on to offload some of the traffic. However, it would be interesting to consider, in Fig. 9, the situation where BS 1 is switched on, along with BSs 8-19, whereas BSs 2-7 are switched off. If the traffic increases in cell 1, it would be difficult to determine which of the BSs of cells 2-7 should be switched on first.

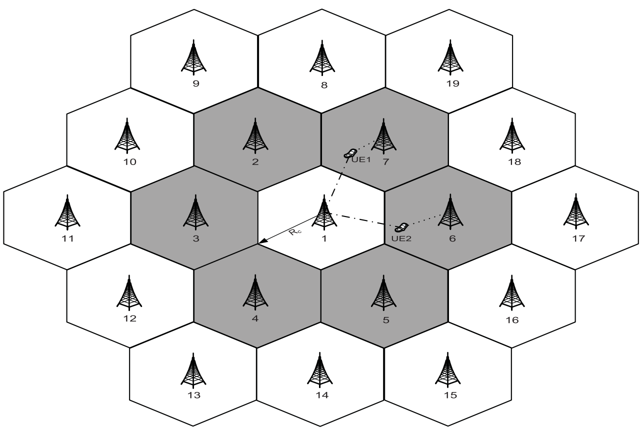


FIGURE 9. BS deployment example.

To avoid unnecessary waste of energy, certain methods are discussed in [55] to enhance the switch on process. They are mostly based on having the BS in sleep mode occasionally transmit some DL signaling to determine the UE in its service area, or perform some UL measurements. In more efficient sleep modes where the BS is not capable of performing these activities, some information about the UE positions is needed. Using measurements from neighboring active BSs would not be sufficient, as positions and link budgets are not fully correlated, and thus the method may have a limited efficiency [56]. Therefore, more complex methods are generally assumed, e.g., the UE location information may be available if UE reports its location information using the global positioning system (GPS) equipment in the UE, or the UE location information can be estimated by network positioning techniques [57], [58]. These localization techniques require additional overhead and signaling, and might involve network entities (e.g., mobility management entity (MME) server) beyond the BSs in the vicinity of the UE considered. Advanced localization (e.g., triangulation) techniques need to be performed by the network for each UE. In case of GPS, this requires the UE to willingly share location information over the application layer, which leads to additional complexity and delay compared to the usual signaling exchanged during handover at the physical/MAC (medium access control) layers.

In [59], the proposed approach suggests the use of information from the coordinated multipoint (CoMP) technique to determine the right BS to switch on, without resorting to advanced positioning techniques. Hence, dynamic BS on/off switching in a distributed manner without centralized control requesting extensive feedback from the network requires additional research investigation and standardization efforts in order to be implemented in a self-organizing manner.

An additional challenge lies in the implementation of BS on/off switching methods in scenarios with dense machine-to-machine (M2M) deployments, commonly referred to in the 3GPP standards as machine-type communications (MTC). Following the proliferation of the internet of things (IoT), MTC devices are expected to be heavily present in future cellular networks. Many of these devices require repetitive network access with reduced data rates, e.g., sensor nodes sending periodic measurements at low bit rates. Possible solutions include reduced signaling for MTC devices such that if it goes into sleep mode, its neighbors could still handle the signaling load. In addition to signaling overhead reduction, another approach is to make use of multiple radio access technologies (RAT) with technology-specific customizations for enhanced performance efficiency. Recent 3GPP activities in this direction include ideas related to a new cellular ultra-low complexity and throughput air interface [60], low cost LTE UE with reduced receive bandwidth to 1.4 MHz (Cat-0 UE category) [61], control and data plane separation over multiple cells that belong to the same or different RATs, and MTC device allocation to different RATs depending on service requirements and RAT capabilities. Other ideas include offloading indoor M2M traffic to user deployed femtocells, e.g., [62]. A potential area of research that could support the drive for green communication networks relies on investigating the interplay between device-to-device (D2D) communications and the BS on/off switching. Indeed, offloading cellular traffic to D2D links whenever possible can help reduce the load on BSs and thus make it easier to place them in sleep mode [63]. In [64], D2D communications between UEs were investigated jointly with BS sleeping strategy. It has been shown that the combined methods lead to energy savings for both the UEs and the mobile operator. The use of heterogeneous macrocell/small cell BSs contributed in allowing traffic offloading on two levels: offloading of macrocell traffic by small cell BSs, and offloading of macro and small cell traffic by D2D communications. The signaling for D2D links should be handled by the active BSs in this case, but the data traffic would not go through the BSs.

Furthermore, the deployment of millimeter wave (mmWave) communications with massive multiple input multiple output (MIMO) antenna arrays would help in enhancing QoS and would allow active BSs to increase their coverage when their neighbor BSs go to sleep mode through dynamic configurations of the large antenna arrays. The design of UEs capable of supporting massive MIMO communications [65] would allow reaping the benefits of massive MIMO when mmWave deployments become commonplace in future networks. Consequently, interesting optimization problems can be formulated to optimize the radio resource management (RRM) in 5G networks in the presence of massive MIMO. Different scenarios can include: single cell cases, multiple cell scenarios with intercell interference mitigation and/or management, RRM optimization in HetNets, scenarios with distributed base stations, relays, and scenarios with D2D communications. Another interesting approach is to investigate the massive MIMO for indoor femtocells, in the presence of mmWave-based WiFi access points (802.11ad), and in scenarios with cellular/WiFi coexistence, for example, the HetNet scenario with possible offloading of users to IEEE 802.11ad access points.

B. CHALLENGES IN THE SMART GRID-BASED SOLUTIONS

Another major challenge is the interoperability between cellular networks and smart grids to enable dynamic powering of cellular BSs from multiple electricity providers. Indeed, coupling smart grids to green cellular networks is still a far reached goal. Although small cell BSs powered by solar panels and wind turbines are becoming commonplace, the more general approach of treating every BS (whether macro or small cell BS) as a micro-grid, generating power from solar panels/wind turbines, and consuming power from energy retailers, while satisfying user QoS requirements and being able to be switched on/off dynamically is a formidable target. This requires significant investments in the cellular networks and smart grids before reaching a stable market deployment phase. Furthermore, standardization in smart grids, and the presence of various communication systems that can contribute to smart grid deployments poses additional challenges. In fact, the National Institute of Standards and Technology (NIST) Framework and Roadmap for Smart Grid Interoperability Standards, Release 1.0, named over 20 IEEE standards among many other IEEE standards that are related to smart grid development, and identified aspects where additional standardization efforts are required. Interoperability between these smart grid standards with the 3GPP standards governing cellular networks should be put in place in order to take full advantage of smart grids in future cellular networks.

C. CHALLENGES IN THE COLLABORATION AMONG MOBILE OPERATORS

Last but not least, an important challenge lies in the collaboration between multiple cellular network operators for the purpose of energy efficiency. Although collaboration among multiple operators is common for international roaming subscribers, it becomes significantly more challenging when implemented in the context of virtual cellular networks with the objective of meeting subscriber QoS requirements while achieving energy efficiency and cost savings for mobile operators. Several possibilities are implemented in the industry for sharing physical network elements such as BS locations, antennas, or network resources such as spectrum and bandwidth [66]. In a Greenfield scenario, mobile operators could even build and roll a new network together, where the shared network infrastructure and operations can be based on the capacity and coverage requirements of both mobile operators [47]. In general, agreements between the infrastructure provider and the various virtual mobile operators using the common infrastructure are signed for guaranteeing an agreed upon level of service. However, the situation becomes more challenging when multiple operators decide to share their physical networks and act as virtual operators to enhance energy efficiency in their respective networks. In fact, operator A having its BS switched off and its subscribers served by operator B needs to pay a roaming price to operator B in exchange of using the resources of network B. This roaming price should take into account that operator A, having its BS switched off, is saving energy at the expense of operator B, whereas operator B is possibly serving subscribers of operator A. Hence, on one hand, the price paid by operator A should not exceed the savings made by that operator when the BS was switched off (otherwise it would be more beneficial to keep it on). On the other hand, the price received by operator B should be fair in terms of ensuring profitability from serving the subscribers of another operator. It should be noted that the situation might be reversed in other parts of the network, with operator B having certain BSs switched off and subscribers served by operator A. Hence, the right balance should be reached in selecting the roaming price, and in setting pricing and billing agreements that can support this dynamic operation of multiple networks as a single virtual network. Preliminary investigations in this direction can be found in [67]. Nevertheless, optimized network operation should also include virtualization at the core network level.

The use of software defined networking (SDN) will support the deployment of network function virtualization (NFV) techniques, which will provide enhanced flexibility, reduced costs, in addition to better scalability and security [68]. Indeed, ongoing standardization studies [69] are focusing on NFV management functions and solutions for mobile core networks. End-to-end management solutions are expected to be included in Release 14 that could be considered the first 3GPP standards release to introduce 5G. Aspects to be covered include the management concept (consisting of architecture and requirements for cellular networks that include virtualized network functions), lifecycle management, configuration management, fault management, and performance management.

VII. CONCLUSION

In this paper, we have investigated modern techniques for green next-generation cellular networks. We have discussed their environmental and economical impacts and provided extensive examples and simulations results to emphasize on their significant advantages. Thanks to inter-mobile operators collaboration, interplay with smart grid, base station sleeping strategy, and energy sharing, fossil fuel consumption of cellular networks can be reduced and/or compensated by renewable energy sources. Hence, mobile operators have the potential to participate in the fight against global warming by reducing their carbon dioxide emissions. These green solutions can be built separately or together depending on the environment and context. The base station sleeping strategy remains the most important technique that should be considered in future networks. In fact, in addition to the significant energy saving that it provides, its joint application with other green techniques allows better renewable energy management, additional cost reduction, and more flexibility during collaboration.

The challenges now are how to implement, in practice, these techniques in order to achieve one of the most important 5G network targets which is environment-aware cellular networks. Therefore, there is a pressing need to develop additional and new approaches in order to encourage telecommunication leaders and regulators to discuss and focus more on such green solutions for possible implementation in next-generation cellular networks.

APPENDIX A
APPROACH A: ITERATIVE ALGORITHM FOR GREEN ENERGY PROCUREMENT WITH MEMORYLESS ON/OFF SWITCHING

The basic idea of the algorithm is to eliminate redundant BSs without affecting the QoS of the total network by respecting (7). In fact, the algorithm which is executed periodically aims to find the optimal BSs combination that reduces CO_2 emissions of the network without affecting the QoS by switching off the maximum number of BSs. Consider N_{BS} BSs deployed in a given area and forming a set $\mathcal{S}$. Initially, we assume all BSs are switched on, i.e., $\boldsymbol{\epsilon} = [1 \cdots 1]$.

Algorithm 1 Approach A

$l = 0$.
loop
  Compute the utility function $U_{\max}$ when all BSs are in the active state ($\mathcal{S}$ contains all BSs and $\boldsymbol{\epsilon}(l = 0) = [1, \cdots, 1]$) and initialize the current iteration with $\mathcal{S}^{\text{iter}} = \mathcal{S}$ and $N_{\text{BS}}^{\text{iter}} = N_{\text{BS}}$.
  Set $U_{s_{\text{op}}}^{\text{new}}(l) = U_{\max}$.
  while $U_{s_{\text{op}}}^{\text{new}}(l) \geq U_{\max}$ **do**
    for $s = 1$ to $N_{\text{BS}}^{\text{iter}}$ **do**
      Eliminate BS s from $\mathcal{S}^{\text{iter}}$ ($\boldsymbol{\epsilon}^{(s)} = [1, \cdots, 1, \underbrace{0}_{s^{\text{th}} \text{ position}}, 1, \cdots, 1]$).
      Allocate resources (Select serving BS and UL and DL RBs) to all users and compute $\boldsymbol{\gamma}^{(s)}$ for the iteration s.
      if $\frac{N_{\text{out}}(l)}{N_U(l)} \leq P_{\text{out}}$ **then**
        Find $\tilde{\boldsymbol{q}}$ by solving the quadratic optimization problem formulated in (3)-(8) given $\boldsymbol{\epsilon}^{(s)}(l)$ and $\boldsymbol{\gamma}^{(s)}(l)$.
        Compute the utility function corresponding to the s^{th} iteration: U_s for the optimal value $\tilde{\boldsymbol{q}}$ as it is given in (3).
      else
        BS s can not be eliminated (we set $U_s = -\infty$).
      end if
    end for
    Find the BS s_{op} that, when eliminated, provides the highest utility ($U_{s_{\text{op}}}^{\text{new}}(l) = \max_s U_s$).
    if $U_{s_{\text{op}}}^{\text{new}}(l) \geq U_{\max}$ **then**
      BS s_{op} is eliminated.
      $\mathcal{S}^{\text{iter}} = \mathcal{S}^{\text{iter}} \setminus \{s_{\text{op}}\}$, $N_{\text{BS}}^{\text{iter}} = N_{\text{BS}}^{\text{iter}} - 1$ and $U_{\max} = U_{s_{\text{op}}}^{\text{new}}(l)$.
    end if
  end while
  No more changes can be made and the final optimal set of active BSs during $l\,T$ is $\mathcal{S}^{\text{iter}}$.
  Set $l = l + 1$ and update the network parameters.
end loop

We consider also N_U users are connected during a period T to benefit from the network services. As a first step, the algorithm computes the data rates of all users and compares them to the data rate thresholds after applying the resource allocation algorithm described in details in [29]. In this way, it identifies the users in outage N_{out} and consequently the value of the vector $\boldsymbol{\gamma}$. Once both vectors $\boldsymbol{\epsilon}$ and $\boldsymbol{\gamma}$ are known and fixed, the optimization problem formulated in (3) becomes a quadratic concave optimization problem that has a unique optimal solution and depends only on one decision variable: the vector $\boldsymbol{q}$. Next, we initialize the optimal utility function as the initial maximum utility $U_{\max} = U(\tilde{\boldsymbol{q}}) = \mathcal{P}(\tilde{\boldsymbol{q}}) - \mathcal{I}(\tilde{\boldsymbol{q}})$, where $\tilde{q}_s^{(n)}$ are the elements of the optimal vector $\tilde{\boldsymbol{q}}$.

Algorithm 2 Approach B

1: **Initialization step** (l=0): All BSs are initialized in the sleep mode ($\boldsymbol{\epsilon}(l=0)=[0,\cdots,0]$).
2: **loop**
3: Compute the utility function $U(l)$ for $\boldsymbol{\epsilon}(l)$ and set $U^{\text{new}}_{s_{\text{op}}}(l)=U(l)$.
4: **if** $\frac{N_{\text{out}}(l)}{N_U(l)} \leq P_{\text{out}}$ **then**
5: **repeat**
6: **for** $s=1$ to N_{BS} **do**
7: **if** BS s is active **then**
8: Turn BS s to the sleep mode and compute $\boldsymbol{\gamma}^{(s)}(l)$.
9: Compute U_s and find $\tilde{\boldsymbol{q}}$ by solving the quadratic optimization problem (3)-(8).
10: **end if**
11: **end for**
12: Find the currently active BS s_{op} that, when eliminated, provides the highest utility ($U^{\text{new}}_{s_{\text{op}}}(l)=\max\limits_{s} U_s$) and satisfies constraint (7) and update $N_{\text{out}}(l)$ if s_{op} exists.
13: **until** No BS can be eliminated.
14: **else**
15: **while** $\frac{N_{\text{out}}(l)}{N_U(l)} > P_{\text{out}}$ **do**
16: **for** $s=1$ to N_{BS} **do**
17: **if** BS s is in a sleep mode **then**
18: Turn BS s to the active mode and compute $\boldsymbol{\gamma}^{(s)}(l)$.
19: Compute U_s and find $\tilde{\boldsymbol{q}}$ by solving the quadratic optimization problem (3)-(8).
20: **end if**
21: **end for**
22: Find the currently inactive BS s_{op} that, when switched on, provides the highest utility ($U^{\text{new}}_{s_{\text{op}}}(l)=\max\limits_{s} U_s$) and update $N_{\text{out}}(l)$ if s_{op} exists.
23: **end while**
24: **end if**
25: $l=l+1$.
26: **end loop**

Then, we eliminate successively one BS, compute the corresponding optimal utility function U_s and compare $\max\limits_{s}(U_s)$ to the previous utility $U_{\max}$ to decide whether eliminating BSs is possible or not. We repeat the same procedure as performed previously but with a reduced number of BSs. Details of the proposed method are presented in Algorithm 1. The algorithm is previously proposed in [70] where the obtained results at the current period lT are independent of the previous BSs' states at the period $(l-1)T$. This can lead to a multiple daily on/off switching. For instance, after only one T, it is possible that all active BSs in the previous period are switched off and new BSs are activated instead. This high amount of on/off oscillations is not practical in real system implementations [71].

APPENDIX B
APPROACH B: ITERATIVE ALGORITHM FOR GREEN ENERGY PROCUREMENT WITH REDUCED ON/OFF SWITCHING OSCILLATIONS

The main limit of Algorithm 1 is that, at each iteration, it starts from the same initial state by assuming that all BSs are switched on, which makes it complex for practical implementation. Therefore, we propose another low complexity approach that starts from the already existing state in the network $(l-1)T$ and evolves to an updated state in lT, which is more convenient from a practical implementation perspective. We adopt the same problem formulation but we try to keep the same BSs active as much as possible, of course, without degrading the QoS. At each new period lT, we keep the same active BSs and verify if the constraint (7) is satisfied. If it is the case, we check if we can turn off some of the already active BSs. If not, we keep the same combination active or we activate additional BSs until having a percentage of users in outage less than P_{out}. When eliminating a BS, the QoS has to be maintained. However, when activating a BS, the QoS may not be satisfied. Thus, additional BSs may also be activated. The new BSs are the ones that provide the highest utility. The proposed algorithm for reduced on/off switching oscillations is given in Algorithm 2. Note that, in line 12 and 22 of Algorithm 2, we are only switching on/off the BS s_{op}, respectively. The previous loops are only dedicated to find the best BS that will be switched on/off. In practice, other BSs keep the same state.

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