

Towards A Sustainable Green Design for Next-Generation Networks

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Towards A Sustainable Green Design for Next-Generation Networks

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Abstract The evolution in the Information and Communications Technologies industry results in excessive energy consumption and carbon dioxide emission in the wireless networks. In this context, energy efficiency in mobile networks has been attracting considerable attention as green communications and operational expenditures reduction depend on it. Although the Internet of Things is to be supported by devices that are low-energy consuming, the power consumption of the huge number to be connected for several applications and services demand significant attention. To offer insights into green communications, this paper reviews various energy efficiency improvement techniques. Also, we consider a hybrid model in which the main grid power and dynamically harvested green energy from renewable energy sources can be leveraged to support the energy demand of the radio access network. In this regard, we reformulate the energy consumption model and consider an energy-efficient power allocation algorithm for green energy optimization. Numerical results show that with resource allocation algorithm exploitation, the energy efficiency can be enhanced. Besides, the amount of the grid energy consumption can be considerably minimized, resulting in the greenhouse gas emissions reduction in the wireless networks.

Keywords 5G · 6G · cloud RAN · dense networks · energy efficiency · energy harvesting · green communications · green energy · power consumption · wireless network.

1 Introduction

The advancement in the Internet of Things (IoT) technology enables a huge amount of low-energy consuming devices to be deployed for different applications and services. The aggregate energy of the IoT devices becomes significant when the supported number is considered. Besides, wireless networks consume excessive energy and emit considerable carbon dioxide (CO₂). This is even more challenging in the off-grid sites [1]. Furthermore, the fifth-generation (5G) networks are intended to be green networks with improved energy efficiency (EE) and low CO₂ emissions compared to the fourth-generation (4G). Likewise, research efforts are now towards the sixth-generation (6G)

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networks that are envisaged to offer better performance than the existing networks. In general, to enhance the system performance, the current and future networks usually rely on innovative technologies and network densification in which more base stations (BSs) are deployed. Network densification mainly focuses on ways of meeting the required capacity and coverage [3, 4]. Nevertheless, its implementation brings about an upsurge in power consumption [5]. This can be attributed to the huge number of the required BSs. It is noteworthy that BSs consume most of the network energy [6, 7]. The energy consumptions of various components such as the signal processing circuits, power amplifier (PA), analog-to-digital converter (ADC), feeders, antenna, cooling, and power sources of macro, micro, and pico BSs are illustrated in Fig. 1. So, apart from high energy bills, high energy consumption has led to an increase in the carbon footprint [1].

Moreover, it should be noted that the upsurge in the carbon footprint and other greenhouse gases (GHG) such as nitrous oxide, ozone, and methane in the atmosphere contributes to climate change. In the radio access network (RAN), the CO₂ emission is mainly owing to the off-grid sites that are powered by diesel generators [8]. Therefore, to improve the network EE, both academia and industry are focusing on *green communications* [6–8]. In this context, certain consortiums and projects such as the Green-Touch, Green-IT, and Green Radio project have been focusing on the wireless network's energy consumption and carbon emission reduction through the development of advanced green radio architectures and techniques [7, 9]. For instance, software-based turning solutions have been presented. In this, during idle hours, the network energy can be saved by turning off some carriers. Furthermore, solutions that leverage renewable energy systems such as solar and wind for supplying the BS have been presented. Similarly, by taking into account the local environmental features, energy-saving air conditioning technologies have been adopted. Nonetheless, it is noteworthy that the aforementioned approaches are secondary as they cannot efficiently address the related high power consumption [5]. Therefore, paradigm-modification technologies such as efficient BS redesign, opportunistic network access smart grids, small cell-based heterogeneous network deployment, and energy-efficient wireless protocols/architectures should be considered [6]. Moreover, infrastructural-based change offers a disruptive solution for attending to the power consumption challenges. For instance, centralized BS schemes can be adopted to reduce both the required number of air conditioners and BS equipment rooms [5]. Besides, in dynamic network load conditions, a centralized BS-based approach can exploit resource sharing schemes for the enhancement of the BS utilization rate [1, 10].

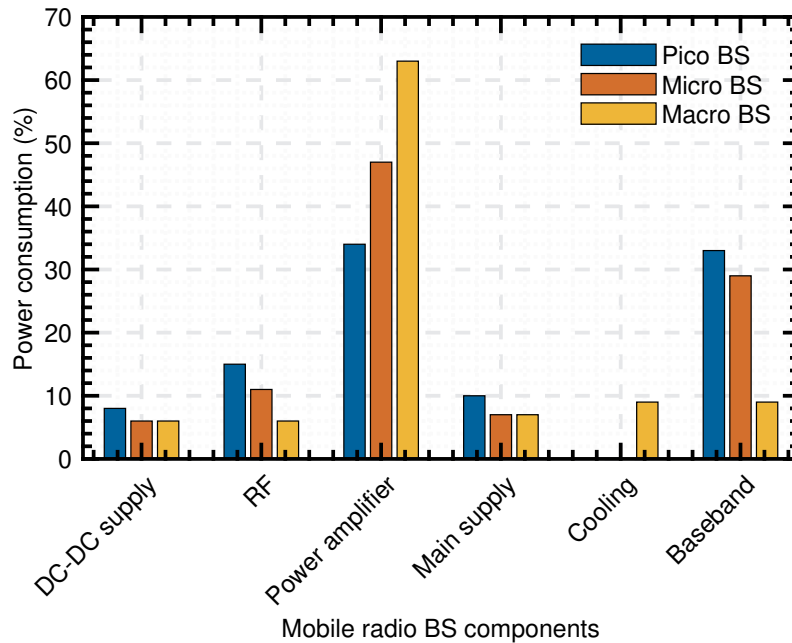


Fig. 1 Typical power consumption for macro, micro, and pico mobile BSs (adapted from [1, 2])

The remainder of the paper is organized as follows. In Section 2, we discuss various efforts towards green radio networks. Section 3 presents the system and power consumption models along with optimization analysis. In Section 4, the numerical results and discussions are presented, and concluding remarks are given in Section 5.

2 Towards Green Radio Networks

In each next-generation network (NGN), capacity increase is usually required at reduced power consumption compared with the preceding counterparts. In this context, innovative techniques are required in the design and operation of wireless networks to prevent energy crunch. Consequently, advancement to sustainable networks will be based on the green BS solutions. In this regard, as illustrated in Fig. 2, green BS should be equipped with renewable (green) sources. Also, to attend to the erratic nature of renewable energy sources, battery storage systems should be deployed. So, the BS can be powered using both renewable energy and on-grid sources. Based on this, energy utilization can be optimized through the exploitation of green energy. Besides, various power cooperation and scheduling algorithms will be required for the selection of appropriate energy source that reduces the aggregate energy consumption [11]. Moreover, the requirement for air conditioning can be eliminated with the deployment of the air-cooled and light-weight BSs that can be deployed outdoor. In this section, we discuss some network EE enhancement techniques.

2.1 Hardware solutions

It is noteworthy that the main power consumption of the BS is at the access and core networks [7]. Therefore, one of the means of achieving energy-efficient wireless systems is to focus on the power consumption of the related hardware. In this context, considerable attention should be paid to the green-based design of the Radio Frequency (RF) chain. Also, as the BS EE mainly depends on the radio transceivers, simplified transceiver architecture implementation is essential. This is also desirable for the effective implementation of Millimeter wave (mmWave) and massive MIMO systems. In this regard, to enhance the hardware EE through energy consumption and system complexity reduction, the transceiver should exploit hybrid analog/digital beamforming and coarse signal quantization schemes [12].

Furthermore, as aforementioned, a substantial amount of energy is consumed by the associated PA of the transceivers. Likewise, their EE is a function of the frequency band, modulation, and operating environment. Besides, the associated high peak-to-average power ratios (PAPR) and linearity requirement of the PAs may result in the BSs inefficiency [6]. Consequently, energy-efficient PAs that are capable of PAPR reduction have been gaining research attention. [6, 12]. For instance, the EE can be improved through the implementation of the switch-mode PAs [6]. Compared with the traditional analog RF PAs, a lesser amount of current is drawn by the switch-mode PAs. This is realized by turning the transistor's output (i.e. on and off) at an high rate, during signal amplification. Similarly, time-domain solutions can be employed to reduce the operating time of the PA. This is achieved through the control signal reduction in the idle-case or low-traffic condition to minimize energy consumption [13]. Another promising approach is flexible PA architectures that are capable of adapting the PAs to the demanded output power [6, 14].

Moreover, the 5G networks are more energy-efficient compared with their preceding networks due to the adoption of disruptive technology in which RANs are implemented using the cloud-based approach. In the cloud-RAN (C-RAN), a range of functions that are normally executed in the BS is shifted to the remote data center [15]. In this implementation, software-defined networking (SDN) and network function virtualization (NFV) play a vital role. Besides, with RAN functional split, light BSs are expected. In this context, the RF chain and baseband-to-RF conversion stages are implemented at the light BSs while resource allocation algorithms and baseband processing are performed at the data center. Apart from the offered high network flexibility, this approach can significantly help in saving energy consumption and deployment costs. Likewise, mobile-edge computing is a promising scheme that not only helps in enhancing the network flexibility but also offers considerable energy savings [3, 12].

2.2 Energy-efficient network planning and deployment

This subsection presents some innovative technologies that have been considered for the planning, deployment, and operation of the network to enhance its EE.

2.2.1 Dense network deployment

To attend to the huge number of connected IoT devices, dense network deployment based on the small cell concepts has been presented to improve the network performance. For instance, dense heterogeneous networks in which massive MIMO is implemented have been gaining significant attention in the 5G network applications. In this regard, to address the associated challenges of the conventional arrays in which the antennas demand expensive and bulky hardware, massive MIMO that comprises hundreds of small antennas are deployed. Unlike the conventional arrays, they are fed using low-cost amplifiers and circuitry and are capable of reducing the radiated power [12]. Nevertheless, a considerable amount of energy is consumed by the huge number of arrays in the MIMO system. Also, another disruptive technology that has been recently gaining significant attention is the intelligent reflecting surface (IRS). The IRSs are passive meta-surfaces and aim at facilitating a smart radio environment by changing the wireless propagation environment into an intelligent reconfigurable space. Based on this, it helps in extending the coverage and ensures massive device-to-device (D2D) communications. Besides, it offers an enabling platform for wireless power transfer. Also, as IRSs components are passive and are not incurring extra power consumption, they are anticipated to be a good path towards green and sustainable NGNs [16].

2.2.2 Relay system

Relay nodes are usually deployed between the source (e.g. BS) and the destination [e.g. user equipment (UE)] to save energy while enhancing the network performance. In this regard, they provide short transmission paths between the network elements. So, they help in reducing the related path loss. Besides, owing to their low transmission power, they are also capable of reducing inter-cell interference [13].

2.2.3 Cell zooming and self-organizing networks

Cell zooming is based on the cell size adjustment in accordance with the traffic load. For instance, when an increase in the number of UEs brings about cell congestion and some UEs cannot be effectively served, the congested cell has to zoom in. Also, the neighboring cells that are not congested will zoom out to offer coverage for UEs of the congested cell. Moreover, in a scenario where the neighboring cells can offer coverage to the UEs in the concerned area without the need for the congested cell being zoomed, to reduce energy consumption, the congested cell can go into a sleep mode operation [13]. Moreover, to facilitate network utilization/deployment based on the traffic conditions, self-organizing cells can be implemented. The self-organizing cells can autonomously be activated/deactivated based on the traffic requirements to reconfigure, optimize, and heal themselves, making them a key scheme for enhancing the EE [12]. For instance, it can be used for energy partitions for effective associations between the powered-off and the powered-on BSs. Based on this, the associated energy configuration can be rearranged [6].

2.2.4 Traffic offloading technique

Apart from the offered enhanced capacity, offloading technique implementation is a promising solution for improving the network EE. In this context, multiple radio access technologies (RATs) like cellular, Bluetooth, and Wi-Fi can be leveraged by the user devices to enable traffic offloading using various strategies like local caching and D2D communications. It should be noted that traffic offloading techniques offer an enabling platform for enhancing the system EE. For instance, when neighboring devices transmit directly between themselves, the required transmit power is lower compared with that of communication through a remotely located BS [3, 12].

2.3 Cell switching

In cellular networks, cell switching (on/off) has been widely employed due to its ability for the required power consumption reduction. The energy-saving capability is achieved by switching off idle wireless devices and resources. This approach is contingent on the related traffic load conditions. For instance, certain cells can be switched off (inactive cells) in a particular area with low traffic. Based on this, the remaining active cells will then be used to support the required radio coverage and service in the area. For effective coverage, the transmission power of active cells may need to be increased [13].

2.4 Resource allocation

There are notable efforts regarding a paradigm change from the usual throughput optimization to EE-optimized systems to further improve the network performance. Consequently, the communication system EE can be enhanced through the allocation of the system radio resources for maximizing the EE rather than the throughput. A notable way of achieving this is through the enhancement of the aggregate information that is reliably transmitted per Joule of consumed energy. Also, different advanced resource allocation algorithms can be employed for EE maximization [12].

2.5 Energy harvesting (EH) and transfer

The wireless EH is a promising scheme for improving the EE and reducing the total GHG emissions of the wireless networks. Besides, based on the supported ubiquitous connectivity, it has been considered as one of the enablers for future networks. In general, the wireless EH is grouped into dedicated and ambient EHs [3, 17].

2.5.1 Dedicated EH

In the dedicated EH, energy is purposely transmitted from dedicated sources to the corresponding EH devices. It is noteworthy that it requires additional power consumption as a result of its being based on the deployment of dedicated energy sources. Based on this, an ambient EH offers promising means of reducing the dependency of the networks on the grid power supply [3, 18].

2.5.2 Ambient EH

The ambient EH is a group of energy that is harvested from renewable sources like wind, solar, thermoelectric effects, and electro-mechanical. Moreover, other examples of the ambient EH are energy that is obtained from ambient RF signals that are generated by various BSs, radio networks, Wi-Fi networks, and TV [3, 18]. For instance, mmWave input power can be converted by a 60-GHz energy harvester into storable DC power. The stored energy can either be consumed right away or be employed for charging the batteries or storage capacitors [19]. Consequently, energy recycling is facilitated by the employment of ambient EH [12]. Also, apart from the offered longer operation lifetime, ambient energy implementation eliminates the associated issue of battery replacement [3, 18].

Generally, the NGN BSs are anticipated to be supported by grid sources and renewable energy sources. In this context, as illustrated in Fig. 2, they will be supported by a hybrid energy system. In this system, the renewable energy sources' erratic nature will be addressed by the EH battery. The hybrid scheme will mainly focus on the optimization of energy utilization. In this regard, green energy utilization will be maximized to minimize the use of grid energy. It should be noted that it is highly imperative to implement various scheduling techniques to attend to multiple available energy sources. Besides, they are also required for transmission power joint control. This will facilitate total energy consumption minimization through the choice of an appropriate energy source. Moreover, the implementation of power cooperation schemes can enable optimal green power-sharing among the BSs to ensure a sustainable wireless network [1, 11].

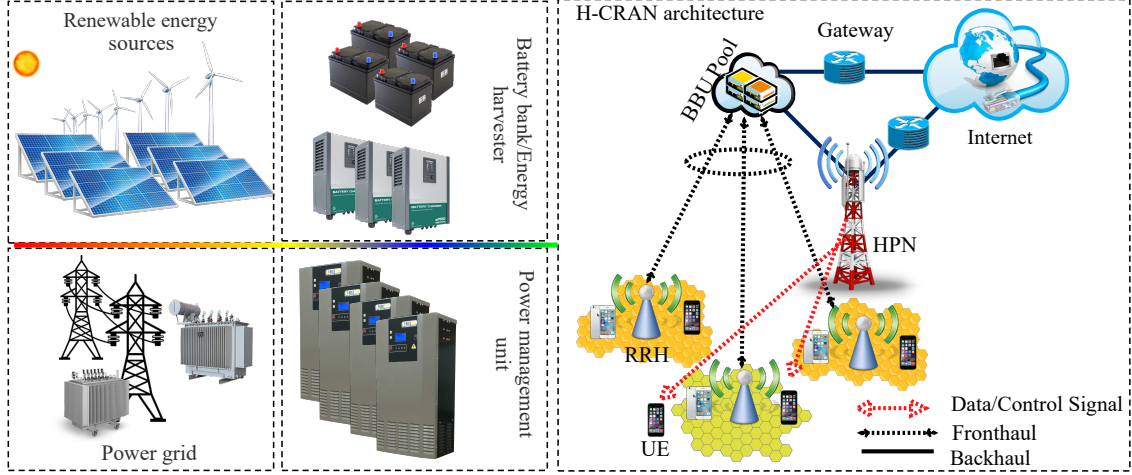


Fig. 2 Hybrid power solution for heterogeneous cloud RAN (H-CRAN) (adapted from [1, 3, 20]).

3 System and Power Consumption Model

We consider a heterogeneous cloud RAN (H-CRAN) in which M BBUs, N remote radio heads (RRHs), and one high-power node (HPN) are deployed to lessen the associated limitations of the fronthaul network that links the BBU pool to the RRHs as illustrated in Fig. 2. So, a set of RRHs is denoted with $\mathbb{N} = \{1, 2, \dots, N\}$. Also, we assume a set of users $\mathbb{U} = \{1, 2, \dots, U\}$ in the network. Therefore, U_l denotes \mathbb{U} being served using the l th RRH. Besides, we assumed a BBU pool that is equipped with some high-speed processors given by $\mathbb{C} = \{1, 2, \dots, C\}$ for supporting the required processing by the RRHs. Moreover, at each BS, the transmit power can be defined as [1, 21]

$$P_{l,tx} = \mathbb{E}[|s_l|^2] \leq P_l, \quad l \in \mathcal{L} = \{1, 2, \dots, L\}, \quad (1)$$

where P_l represents the transmit power budget of the BS, and s_l denotes the transmit signal at the l th BS.

Moreover, the PA efficiency and other power-consuming modules like the BBU pool and cooling system have to be considered to effectively describe the BS power consumption. Likewise, the H-CRAN fronthaul link power consumption has to be considered. Furthermore, the power consumption of the BS components such as direct-current (DC)-DC converter, PA, main supply (MS), RF small-signal transceiver, active cooling (ACO), and baseband engine (BB) is based on parameters like the transmission bandwidth, the radio chain/antenna number, and the power. Consequently, the BS power-consuming parts are contingent on their design. Also, they vary from one BS type to another. The maximum power consumption of a typical BS is given by [1, 2, 22, 23]

$$P_{BS} = \frac{P_{BB} + P_{RF} + P_{PA}}{(1 - \sigma_{DC})(1 - \sigma_{MS})(1 - \sigma_{ACO})} \quad (2)$$

where σ_{DC} , σ_{MS} , and σ_{ACO} , represent the loss factor for the DC, MS, and ACO, respectively. The power consumption of the RF, BB, and PA denoted as P_{RF} , P_{BB} , and P_{PA} , respectively can be expressed as [1, 24]

$$P_{RF} = D \frac{W}{10\text{MHz}} P'_{RF}, \quad (3a)$$

$$P_{BB} = D \frac{W}{10\text{MHz}} P'_{BB}, \quad (3b)$$

$$P_{PA} = \frac{P_{\max}^{PA}}{D\eta(1 - \sigma_{\text{feed}})}. \quad (3c)$$

where, D is the number of BS antennas, W signifies the bandwidth, η denotes the PA efficiency, σ_{feed} represents losses that are related to the feeder cable, P_{\max}^{PA} indicates the maximum transmission power (full load), P'_{RF} and P'_{BB} represent certain basic consumptions.

Furthermore, a unified model can be employed to represent the power consumption for several BSs. The model uses the transmit power piecewise linear function to approximate the power consumption of the evolved node B (eNB) and it is given by [1, 21, 23]

$$P_l^{\text{eNB}} = \begin{cases} P_0 + y \cdot \Delta_p \cdot P_{\max} & \text{if } 0 < y < 1 \\ P_{\text{sleep}} & \text{if } y = 0 \end{cases} \quad (4)$$

where P_0 denotes the power consumption at the zero load (minimum non-zero output power), P_{sleep} is the power consumption by the BS in the sleep mode (i.e. $P_{\text{sleep}} < P_0$), y represents the scaling parameter that signifies the l th BS normalized cell traffic load (i.e. $y = 0$ and $y = 1$ indicate an idle and a fully loaded system, respectively), and Δ_p is the load-dependent linear power model slope.

Moreover, it is noteworthy that unlike (4), (1) offers no room for sleep mode. As given in (4), when there is no data to be received or transmitted, a sleep mode operation will be employed by the eNB. Also, it is noteworthy that $P_{\text{sleep}} < P_0$. Consequently, considerable energy will be saved when the eNB operates in sleep mode as it enables certain main units of the eNBs to be switched off in the no-load condition.

Furthermore, the model for the long-term evolution (LTE) given in (4) cannot be directly applied to the C-RAN and H-CRAN. Because some of their components are shared while others are centralized, they are different from traditional architecture. Based on this, an improved model that should consider the main components like the BBU pool, RRH, fronthaul, and HPN is required. Hence, the C-RAN modified power consumption model can be defined as [1]

$$P_{C\text{-RAN}} \sum_{r \in \mathcal{R}} \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} (P_r^{RU} + P_i^{CU} + P_j^{FH}) \quad (5)$$

where P_j^{CU} , P_i^{RU} , and P_k^{FH} represent the power consumptions of the centralized unit, the remote unit, and the fronthaul, respectively.

Additionally, consider a heterogeneous cloud RAN (H-CRAN) in which the RRHs are employed for delivering high data rates while the HPN is used to ensure seamless coverage, from (5), the per RRH and HPN total power consumption of the remote unit can be expressed, respectively as [25]

$$P(\mathbf{a}, \mathbf{p}) = \eta \sum_{k \in \mathcal{K}} \sum_{n \in \mathcal{N}} a_{n,k} p_{n,k} + P^{CU} + P^{FH} \quad (6a)$$

$$P_M(\mathbf{a}^M, \mathbf{p}^M) = \eta^M \sum_{t \in \mathcal{T}} \sum_{m \in \mathcal{M}} a_{t,m} p_{t,m}^M + P^{CU} + P^{BH}, \quad (6b)$$

where η^M denotes the PA efficiency, P^{BH} represents the backhaul link power consumption, n represents the number of UEs that are accessing RRH and can be allocated to the RB set and $a_{t,m}$ denote the RB allocation indicators with either 0 or 1 value, $p_{n,k}$ and $p_{t,m}$ denote the allocated transmit power to the UEs that are accessing RRH and HPN, respectively, $\mathbf{a} = [a_{n,k}]_{(N+M) \times K}$ and $\mathbf{a}^M = [a_{t,m}]_{T \times M}$ denote the RB allocation policies for the RRH and HPN, respectively, $\mathbf{p} = [p_{n,k}]_{(N+M) \times K}$ and $\mathbf{p}^M = [p_{t,m}^m]_{T \times M}$ represent the power allocation policies for the RRH and HPN, respectively.

Moreover, we assume a multiple radio access technology (multi-RAT) wireless network where one grid supplies the entire RATs. Also, let the individual RAT be equipped with a battery. If the capacity of the battery is θ_n^E and the n th RAT harvests $e_m(t)$ energy at time slot t from renewable energy sources, the required energy by the RATs should not be more than the harvested energy that is constrained by [26]

$$\sum_{m \in \mathcal{N}} \rho_{n,m}(t) \leq 1, 0 \leq \rho_{n,m}(t) \leq 1, \forall n \in \mathcal{N}, \quad (7)$$

where $\rho_{n,m}(t)$ denotes the energy demand variable that specifies the required fraction of harvested energy of the n th RAT that is required by the m th RAT counterpart.

In addition, the aggregate grid transmit power have to satisfy

$$\sum_{n \in \mathcal{N}} P_n^{in}(t) \leq P_{\max}, \quad (8)$$

where P_{\max} represents the multi-RAT network's maximum energy consumption.

Therefore, the energy queuing can be expressed as

$$E_n(t+1) = E_n(t) + P_n^{in}(t) + \sum_{m \in \mathcal{N}} q_{m,n} \rho_{m,n} e_m(t) - \sum_{n \in \mathcal{N}} \sum_{m \in \mathcal{M}} x_{n,m}^k(t) p_{n,m}^k(t). \quad (9)$$

where $E_n(t)$ represents the n th RAT energy queue size at time slot t , $q_{n,m}$ is the harvested energy transmission discount from the n th RAT to the m th RAT, $x_{n,m}^k$ is the indicator function for allocating k th RB to m th UE in the n th RAT.

Additionally, the total amount of stored energy in the battery in each time slot is constrained by the capacity of the battery and should satisfy

$$E_n(t) + P_n^{in}(t) + \sum_{m \in \mathcal{N}} q_{m,n} \rho_{m,n} e_m(t) \leq \theta_n^E. \quad (10)$$

Furthermore, for each RRH and the HPN, the sum data rates can be defined, respectively as

$$C(\mathbf{a}, \mathbf{p}) = \sum_{k \in \mathcal{K}} \sum_{m \in \mathcal{M}} \sum_{n \in \mathcal{N}} a_{n,k} B_0 \log_2(1 + \sigma_{n,k} p_{n,k}) \quad (11a)$$

$$C_M(\mathbf{a}^M, \mathbf{p}^M) = \sum_{t \in \mathcal{T}} \sum_{m \in \mathcal{M}} a_{t,m} B_0 \log_2(1 + \sigma_{t,m} p_{t,m}), \quad (11b)$$

where B_0 represents the bandwidth of the RBs, $\sigma_{n,k}$ and $\sigma_{t,m}$ denote the channel-to-interference-plus-noise ratio (CINR) of the n th and t th UEs that are accessing the RRH and HPN on the k th and m th RB, respectively.

Furthermore, for optimization analysis, we consider the H-CRAN that comprises an HPN and densely deployed RRH (L RRHs) with sufficiently large L . Besides, we aim at achieving an optimal RB and power allocation, a and p , respectively, that maximize the H-CRAN EE while considering the related constraints like the fronthaul capacity, minimum data rate requirement, as well as maximum transmission power. Therefore, the H-CRAN EE performance can be defined as [25, 27]

$$\gamma(\mathbf{a}, \mathbf{p}) \approx \frac{L * C(\mathbf{a}, \mathbf{p})}{L * P(\mathbf{a}, \mathbf{p})} = \frac{C(\mathbf{a}, \mathbf{p})}{P(\mathbf{a}, \mathbf{p})}. \quad (12)$$

The H-CRAN EE maximization problem can be reformulated as

$$\begin{aligned} & \max_{\{\mathbf{a}, \mathbf{p}\}} \gamma(\mathbf{a}, \mathbf{p}) \\ & s.t. \quad C_1 : \sum_{m \in \mathcal{M}} \sum_{n \in \mathcal{N}} a_{n,m,k} C_{n,m,k} \geq r_k^{\min}, \forall k \in \mathcal{K} \\ & \quad C_2 : \sum_{k \in \mathcal{K}} \sum_{n \in \mathcal{N}} a_{n,m,k} p_{n,m,k} \leq P_m^{\max}, \forall m \in \mathcal{M} \\ & \quad C_3 : \sum_{k \in \mathcal{K}} \sum_{n \in \mathcal{N}} a_{n,m,k} C_{n,m,k} \leq C_m, \forall m \in \mathcal{M} \\ & \quad C_4 : \sum_{k \in \mathcal{K}} a_{n,m,k} \leq 1, \forall m \in \mathcal{M}, n \in \mathcal{N} \\ & \quad C_5 : a_{n,m,k} = \{0, 1\}, \forall k \in \mathcal{K}, m \in \mathcal{M}, n \in \mathcal{N}, \end{aligned} \quad (13)$$

where r_k^{\min} denotes the required minimum data rate of the k th UE, P_m^{\max} represents the maximum transmission power of the m th remote unit, C_1 , C_2 and C_3 denote constraints regarding the UE minimum data rate, the remote unit maximum transmission power, and the fronthaul capacity, respectively, C_4 and C_5 control the H-CRAN RB allocation. In this regard, C_4 limits each RB allocation to just one UE at a time while C_5 enforces the binary RB assignment.

Furthermore, by following [25, 27], the optimal power allocation, $p_{n,m,k}^*$, can be expressed as

$$p_{n,m,k}^* = \left[\omega_{n,m,k}^* - \frac{1}{\sigma_{n,m,k}} \right]^+, \quad (14)$$

where $[x]^+ \triangleq \max\{x, 0\}$, $\omega_{n,k}^*$ represents an optimal water-filling.

4 Numerical Results and Discussions

This section presents a simulation-based performance analysis of the considered RAN EE with an optimization algorithm. In the considered RAN, we assume 20 MHz system bandwidth with 10 RBs and 6 randomly distributed UEs that are associated with the RRH. Likewise, we assume 3 randomly distributed RRHs and an HPN which are separated from the UEs at propagation distance d (km). Also, the path loss between the RRH and a UE as well as the one between an HPN and a UE are modeled as $140.7 + 36.7 \log_{10}(d)$ and $128.1 + 37.6 \log_{10}(d)$, respectively. Also, in the simulations, the fading is assumed to be independent and identically distributed and the noise power is -174 dBm. The power consumptions and efficiencies of the PAs of the RRHs and HPN are set to 3.5 W and 84 W, and 2 and 4, respectively. Also, 29 dBm and 43 dBm are used for the maximum transmission power of the RRHs and HPN, respectively.

Energy as a function of signal-to-interference-plus-noise ratio (SINR) requirement for the considered scenario is depicted in Fig. 3. It shows that energy consumption increases with the SINR, owing to the required higher transmit power to ensure better QoS requirement. Based on this, the GHGs emissions will be high. When green energy is exploited, the emissions can be reduced significantly in wireless networks. For instance, when no green energy is exploited ($e = 0$) at 3 dB SINR,

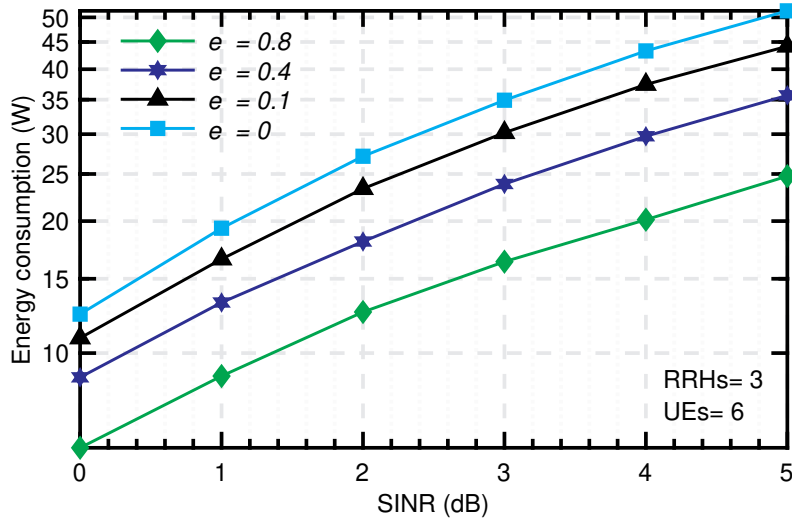


Fig. 3 Grid power consumption versus SINR requirements.

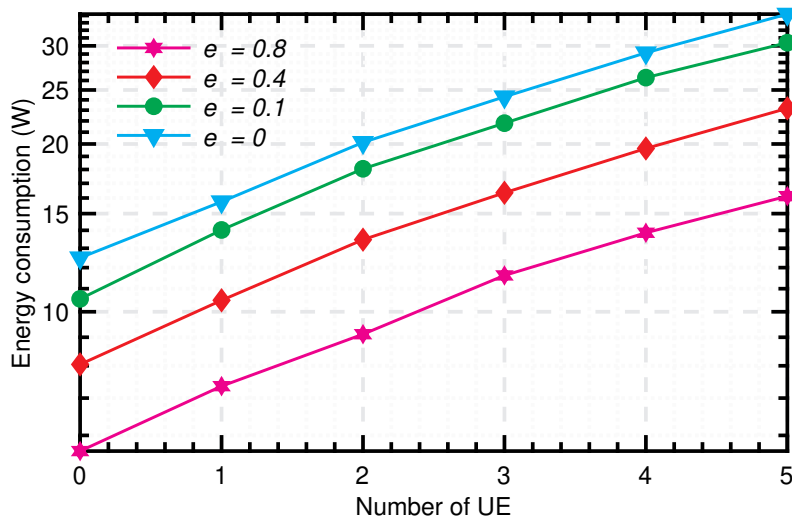


Fig. 4 Grid power consumption versus number of user equipment.

the average energy consumption is 35 W. On the other hand, about 16 W is required at the same SINR, when the harvested green energy has been exploited ($e = 0.8$). Furthermore, we consider the energy consumption of the UEs at 3 dB SINR. As illustrated in Fig. 4, energy consumption increases with the number of UEs, resulting in high GHGs emissions. Also, it is noteworthy that when sufficient green energy is harvested and exploited, the emissions can be reduced.

5 Conclusion

In this paper, we have comprehensively discussed different EE improvement techniques that are promising for green communications. Also, we have reformulated the power consumption and allocation models for the optimization of green energy utilization, taken into consideration the random nature of the harvested energy in the network. Simulation results show that the network EE can be enhanced when the resource allocation algorithm is exploited. With grid energy consumption minimization, the GHGs emissions can be reduced in wireless networks.

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Figures

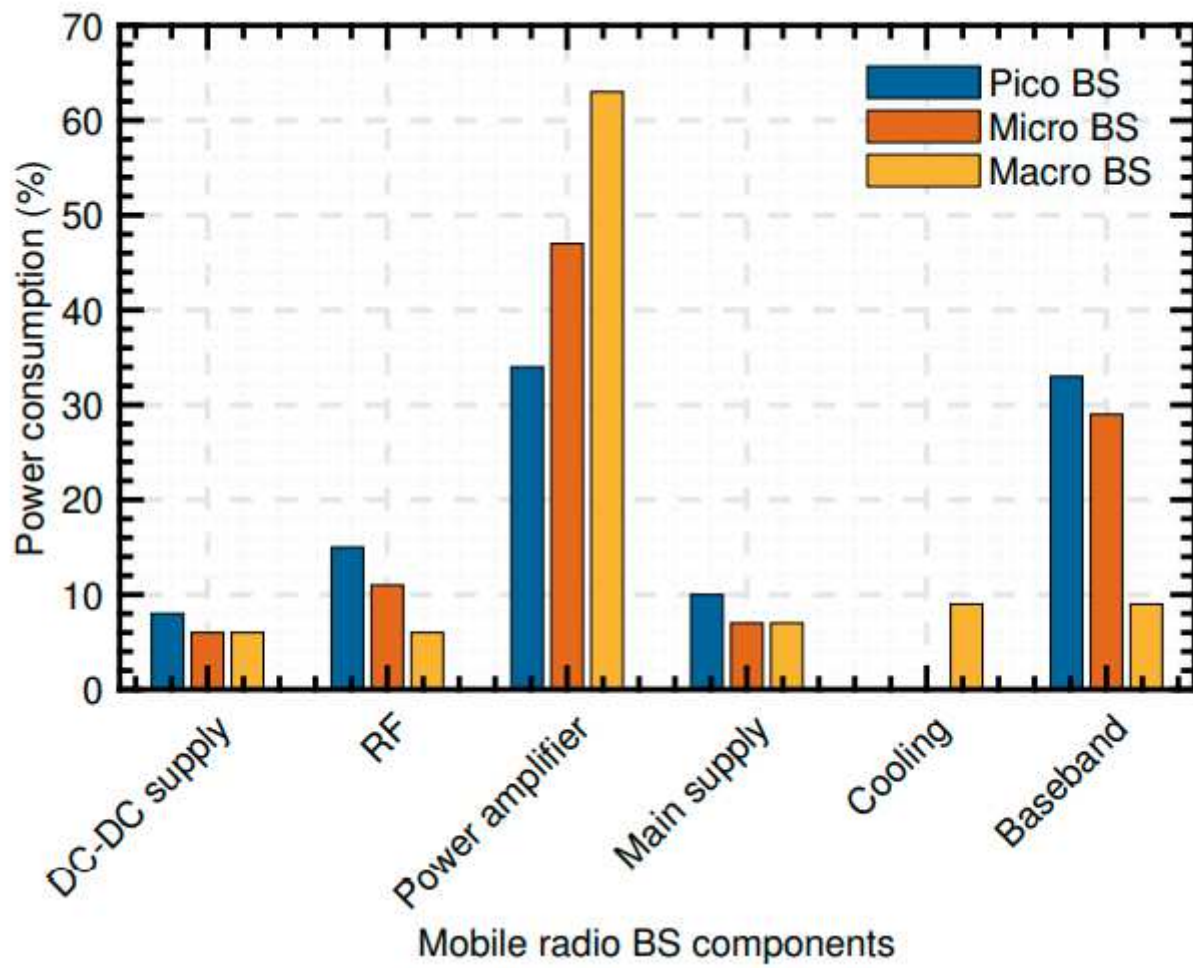


Figure 1

Typical power consumption for macro, micro, and pico mobile BSs (adapted from [1, 2])

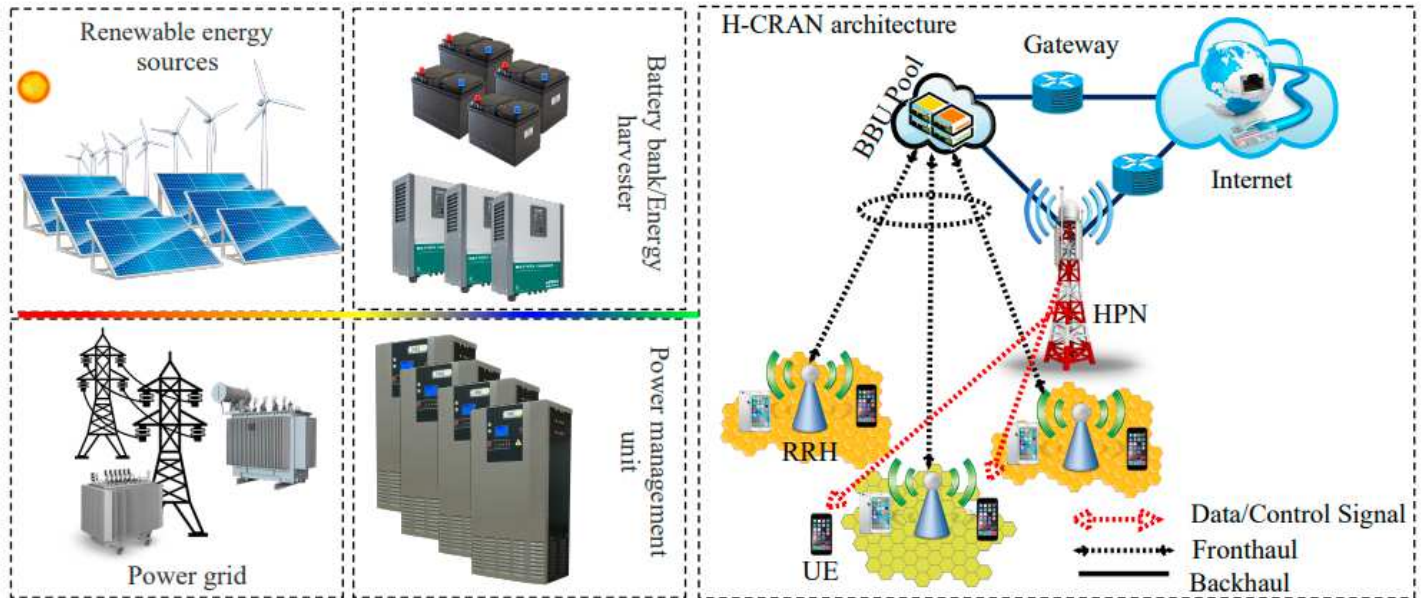


Figure 2

Hybrid power solution for heterogeneous cloud RAN (H-CRAN) (adapted from [1, 3, 20]).

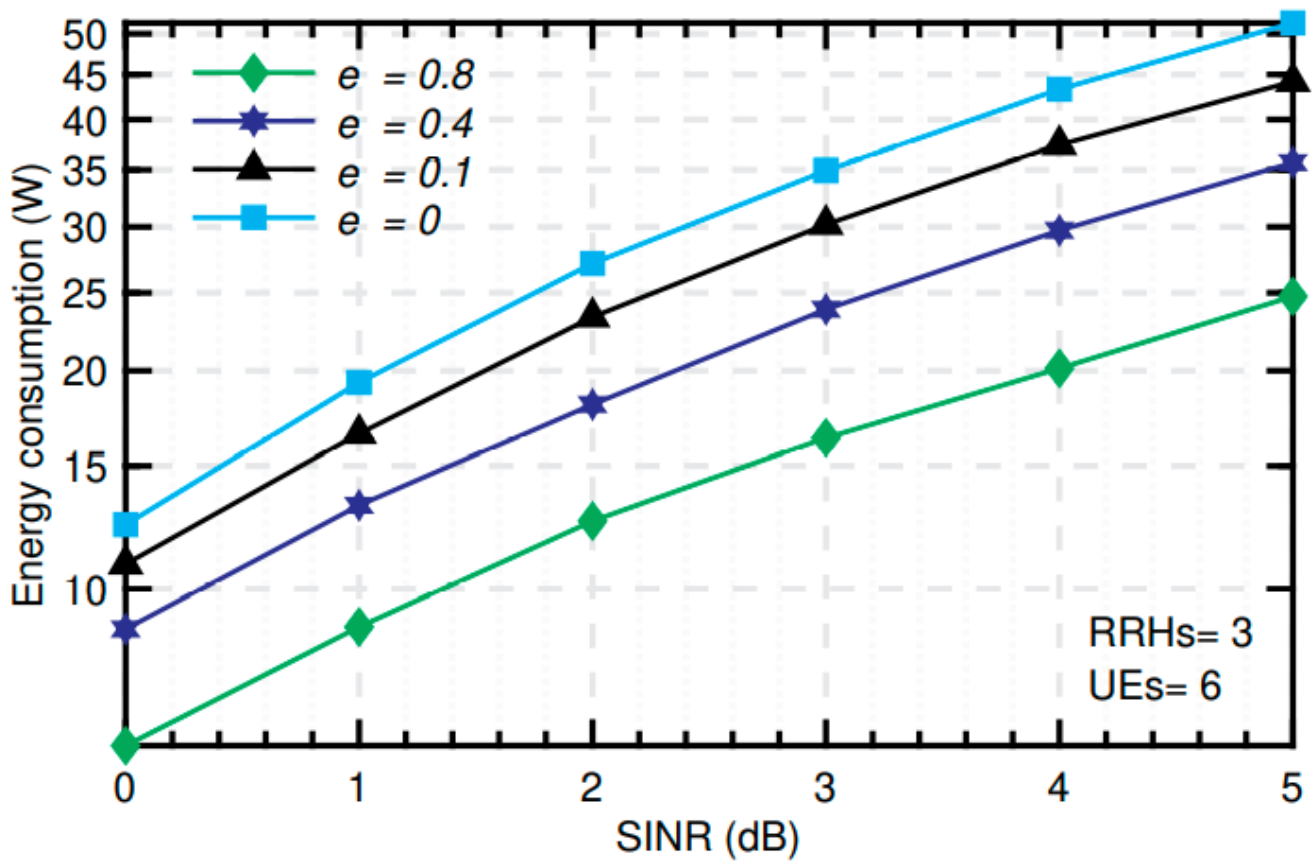


Figure 3

Grid power consumption versus SINR requirements.

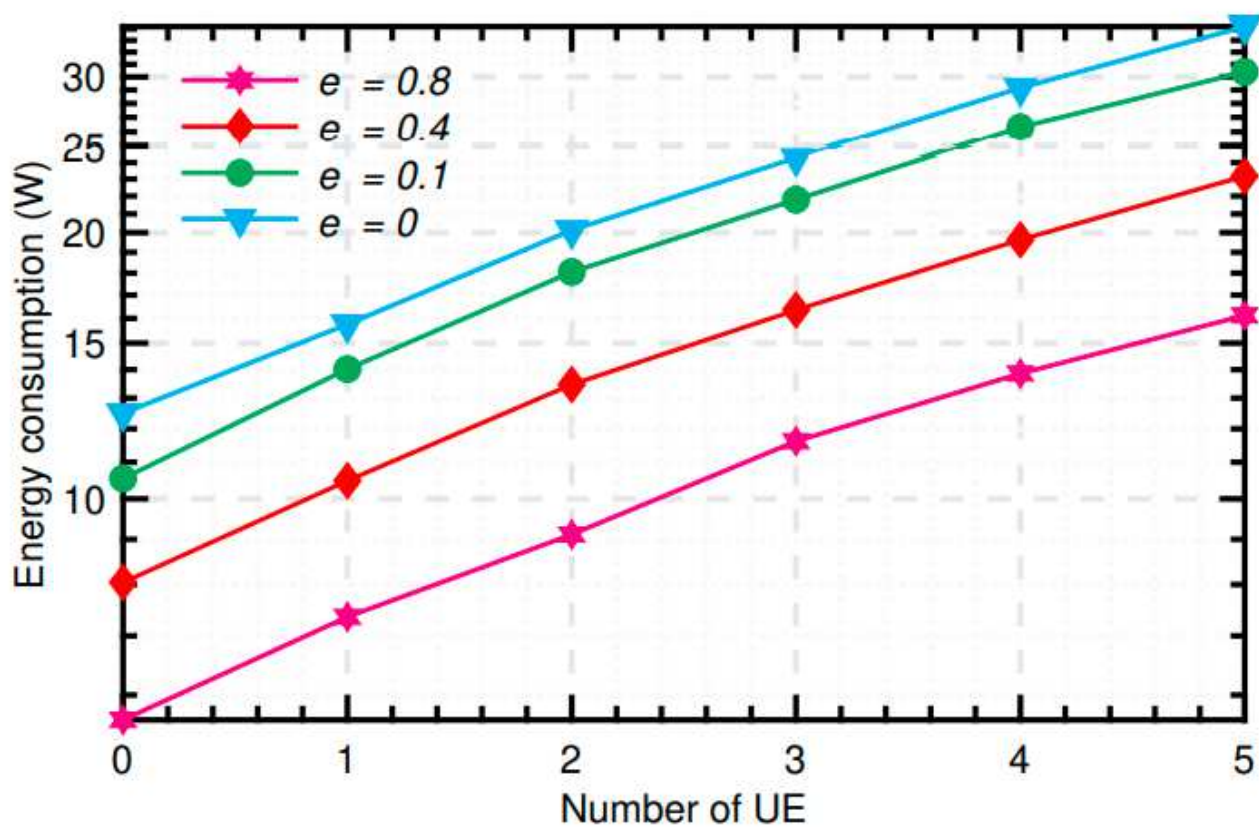


Figure 4

Grid power consumption versus number of user equipment.