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Survey paper

A survey on sleep mode techniques for ultra-dense networks in 5G and beyond

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ABSTRACT

The proliferation of mobile users with an attendant rise in energy consumption mainly at the base station has requested new ways of achieving energy efficiency in cellular networks. Many approaches have been proposed to reduce the power consumption at the base stations in response to the contribution of energy cost to the increase of OPEX of the mobile operators and the rise of the carbon footprint on global climate. As a springboard to the application of sleep mode methods in ultra-dense cellular networks, this paper provides a comprehensive survey of the base station sleep mode strategies in heterogeneous mobile networks from perspectives of modeling and algorithm design. Specifically, the sleep mode enabling strategies and sleep wake-up schemes are reviewed. The base station sleep-mode techniques in ultra-dense networks are further discussed as well as the challenges and possible solutions.

1. Introduction

With the unprecedented growth of Information and Communication Technologies (ICT) over the past two decades, ICT has been estimated to contribute 2 to 2.5% of the global Greenhouse Gas (GHG) emissions [1]. This increase is not unconnected with the way ICT has reshaped our personal and professional lives. This is evident in the massive use of the internet and increased patronage of mobile communication devices and services. Mobile telecommunication is a significant component of ICT in the contribution to climate change. In [2,3], a conducted study estimated the contribution of mobile networks to be 2% of the global CO_2 emissions in 2007 and projected to be 4% in 2020. Fig. 1 represents the global telecoms contribution to greenhouse gas in million metric tons of carbon dioxide equivalent. Recently, there are more than 7 billion mobile subscriptions worldwide, corresponding to a penetration rate of 97%, up from 738 million in 2000 [4].

The introduction of smart mobile devices such as tablets, smart phones, and Internet of Things (IoT) devices, along with the applications such as video live-streaming, conferencing, and image transfers involve enormous volume of data traffic [5]. The huge traffic demand comes with increased energy consumption as evident in recent network standards such as 4G Long-Term Evolution (LTE). In fact, higher traffic-induced energy consumption is imminent in 5G networks and beyond if no energy-efficient methods are employed [6]. The price paid for this enormous growth in data rates and market penetration is a rising power requirement and the growth pattern has driven expansion of cellular base stations [7]. In cellular networks, over 80% of energy is consumed by the Radio Access Network (RAN) [8].

In addition to the overall carbon footprint of mobile communications, the network energy consumption is also a major cost for mobile operators. According to [10], energy cost has been estimated to be about 10%–15% of the total network OPerating EXpenses (OPEX) in mature markets. Moreover, energy cost can amount to 50% of the OPEX in developing market and areas of unreliable electricity grid because of the proliferation of off-grid sites [11]. Until recently, most of the research in mobile communications had been centered on performance metrics such as throughput, spectral efficiency, and Quality of Service (QoS). The rise of global carbon print and mobile operators' OPEX heightens the incentive on research, in both academia and industry, to reduce energy consumption of mobile networks [12,13]. In network beyond 5G, e.g., 6G, the energy efficiency is expected to be increased by 10–100 times, compared with that in 5G network [14–16].

One of the main objectives of the next generation of wireless communications is to save energy consumption over the wireless networks

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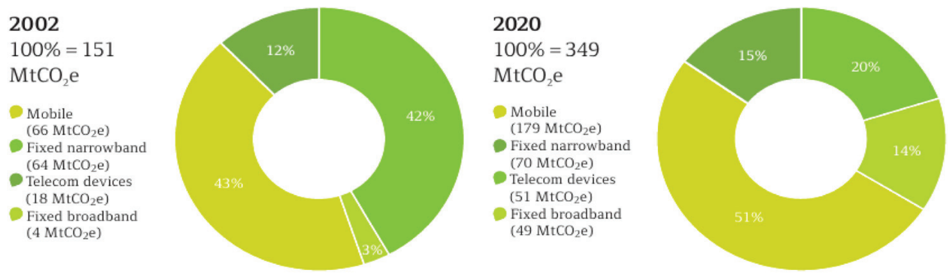

Fig. 1. Global Telecoms footprint [9].

while achieving the 5G promised throughput and quality of service. Energy consumption is one of the highest operating costs used with historically consideration to perform almost every daily tasks. As greener technologies, 5G networks and beyond are expected to save energy by 90% compared to 4G with energy efficiency use case, which enables performing several network services and functions using less power [17]. 5G networks aims at transmitting more data with less power where less wattage will be required. It will be more powerful in terms of how power will be processed. Although 5G networks will improve the energy efficiency, it will require more energy to perform. The potential increase in energy consumption to serve the large number of connected devices and machines leads to making the energy saving even more important in terms of climate change and sustainability.

Conserving energy is important as it allows protecting the environment, saving resources, and reducing bills. Protecting the environment improves the quality of living with fresh and clean air by reducing the environmental pollution, which can be achieved by reducing the CO_2 emission. The increase in energy usage increases the global warming. Consequently, 5G networks are promising to adopt alternative solutions to address the energy consumption trade-off while protecting the environment, thus, decrease the global warming impact. Therefore, energy saving in 5G allows saving the planet by minimizing the chances of increasing the global warming for greener future by optimizing the energy consumption and generating renewable energies [18,19]. Energy saving is primordial for Mobile Network Operators (MNOs), the economy, and the environment for green networks [20].

Ultra-dense networks refer to networks with more cells than active users [21]. With ultra-dense deployment, the network is comprised of large number of small base stations consuming high energy resources, which requires effective solutions for longer sleep mode of the base stations. Power control of the base station corresponds to controlling the power saving mode of the base station by switching among sleep and awake modes [22]. As the wireless traffic represents non-uniform pattern in spatial and temporal domains, sleep mode techniques allow reducing the power consumption of the mobile networks significantly by selectively turning either base stations or their transceivers to the sleep mode. Consequently, the base station operates in two different modes: active mode and sleep mode. In the active mode, the base station is completely on while its transceivers are turned off in the sleep mode. Typically, when some base stations are in the sleep mode, the radio coverage is provided by their adjacent base stations, which remains active in order to guarantee the radio services over the network all the time [23]. Before 5G networks, sleep mode solutions have been used in some of the previous standards and technologies for energy saving purposes including WiMAX, LTE, and wireless sensor networks [24–28]. They have been proven to be promising solutions to increase the energy efficiency and enhance the energy management policies.

In [24,25], sleep modes have been used in IEEE 802.16e for accurate energy management over the Medium Access Control (MAC) protocol [29]. They perform by switching the Mobile Subscriber Station (MSS) from wake mode to sleep mode instead of the base station. MSS switches to sleep mode after the base station approval at the listening window and it keeps alternatively switching from the two modes during the lifetime of its battery. In addition to its mobility, MSS alternates between sleep window, listening window, and wake window, which requires more energy and extend its lifetime. Longer sleep periods lead to longer response delays that the MSS need to wake up. In [26], sleep mode solutions have been applied by switching on–off the Mobile Terminal (MT) radio interface for energy saving purposes in the case of static traffic models. However, scheduling the MTs sleep windows is not practical as it requires realistic traffic models to enhance the switching schedule design of the mobile terminal at uplink and downlink traffic. In [30], the authors proposed a multilevel sleep mode to control the base station operation ON/OFF in order to model and predict the traffic based on the support vector machine algorithm. They aim at addressing the power consumption issues for high traffic networks. Because of the random activity of the users, the authors proposed an optimal base station selection solution to minimize the energy consumption while ensuring high coverage [31]. They aim at determining which base stations to select for sleep mode while respecting the tradeoff between the energy efficiency and the network performance [32].

Moreover, other sleep mode solutions have been developed for wireless sensor networks to enable energy saving. Sleep/wake up solution has been used with the duty cycle protocol to save the nodes' energy and decrease their active time. Duty cycle is one of the saving energy protocols and it refers to the act of switching between sleep and wake modes based on the network activity. Sleep windows can be increased for energy saving purposes while sleep windows can be decreased for response delay reduction purposes, which results in a trade-off between the energy saving and the response delay. Thus, efficient solutions for energy management and sleep scheduling are required in order to save energy while reducing the response delays. In [24,25] analytical models have been proposed to study and evaluate the performance of the sleep mode solutions introduced in the 802.16e standards by analyzing a number of performance metrics including frame response and energy consumption. In [26], waking up scheduling solution has been analyzed in order to optimize the sleeping periods based on arriving packets [33]. It aims at balancing the trade-off metrics by decreasing simultaneously the energy consumption and the response delays. The existing sleep mode solutions have been showing some significant results. However, with the high increase in the number of connected devices and services, advanced sleep mode solutions are needed to accompany the ear and satisfy the future users' requirements.

Moreover, a number of energy efficiency resource allocation techniques have been proposed as optimizing the resource allocation permits reducing the energy consumption of the user devices for Multi-access Edge Computing (MEC) [34] and device to device communication [17]. In [35], the authors proposed a reliable energy efficient technique aiming at minimizing the energy consumption in the Multi-access Edge Computing (MEC) network. By bringing services and computing functions to the edge devices, MEC architecture operates with energy demanding entities called mobile edge hosts, which requires minimizing the energy consumption by the MEC network. The proposed technique aims at minimizing the energy consumption by putting the MEH and the access points under the sleep mode. It optimizes the resource allocation and the number of active base stations in a service delay constraint.

In [36], the authors proposed an energy, performance, and cost-efficient resource management technique, called epcAware, aiming at achieving the network performance while minimizing the energy consumption for the MEC networks. epcAware is a non-cooperative game-based resource allocation technique able to manage energy resources. In [37], the authors proposed an energy-efficient solution based on adaptive resource-block allocation to allow reducing the energy consumption in the 5G green communication. For lower complexity, An adaptive resource-block allocation scheme has been proposed for optimal power control in Device to Device (D2D) communications as high energy consumption leads to rapid battery draining [38]. They proposed a Zone-Based Energy Efficiency (ZBEEn) technique for spectrum shared network [39]. ZBEEn technique performs with one transmitter and multiple receivers via device-to-device transmission located in distinctive zones. It aims at enhancing the battery lifetime of the D2D users using game theory [40]. They also proposed a Sector-Based Radio Resource Allocation (SBRRA) technique to solve the resource sharing problem in D2D communication using cell sectorization [41]. They proposed a Non Orthogonal Multiple Access (NOMA) based approach to enable multiple interference cancellation using sector-based resource allocation [42]. It allows decreasing the power consumption by the regenerators and reducing the system complexity.

In [43], the authors investigated various energy efficiency solutions in several scenarios including device to device communications, ultra-dense networks, and IoT. They mainly focused on security challenges in green cellular networks when operating with relays for energy efficiency purposes. In [44], the authors discussed how some of the energy efficiency solutions can lead to serious security concerns facing the 5G networks as they operate with relays, base stations, and small cell access point. These network elements can be attacked by several types of attacks including bandwidth spoofing. In [45], the authors proposed a saving energy scheme based on game theory to enable idle users to operate as relays to save energy. In [46], the authors proposed an energy saving based Particle Swarm Optimization (PSO) technique to separate the control plan and the data plane in order to minimize the energy consumption by the base station. A joint traffic prediction technique was proposed to allow estimate the network traffic and enhance the quality of the base station sleeping [47].

Several surveys and papers on energy efficient communications techniques were published in the last decades [48–57]. These papers provide existing methods to minimize the power consumption in mobile communication networks, while the aforementioned works focused on the overall approaches at the base stations or from the perspectives of mobile operators and users. Other surveys analyze the energy saving from only one perspective including power consumption models, or sleep mode enabling strategies, or wake up schemes [58]. Therefore, the previous works have mostly focused on the traditional energy saving solutions, and thus they relied on one perspective. Thus, there is a great need for an in-depth survey that analyzes and discusses the different strategies and solutions to improve the power efficiency at cellular networks base stations. In this paper, we discuss and analyze the different proposed solutions of energy-efficient management and sleep mode scheduling in ultra-dense heterogeneous networks, especially in 5G networks. We investigate the energy saving solutions through sleep mode-based strategies from the perspectives of modeling and algorithm design. We discuss the different power consumption models and how to evaluate their efficiency based on a number of energy performance metrics.

With the current expansion trend of base stations, cellular mobile networks are evolving into ultra-dense networks, which raises concern for scrutiny of the existing base stations sleep-mode techniques, their complexity, challenges, and possible solutions in ultra-dense networks. Therefore, this paper analyzes the most recent reviews on energy-efficient sleep mode techniques in 5G and beyond networks [59]. Firstly, we presented and analyzed the base station power consumption for energy saving and system performance. Secondly, we provided an in-depth review of the different wake-up schemes for switching base stations in idle mode to active mode. Then, we discussed some of the applications and challenges of the sleep activation methods in ultra-dense networks. To the best of our knowledge, there is no such paper that covers most relevant models and techniques for energy saving in ultra-dense heterogeneous networks.

Thus, the main contributions of this paper are the following:

(1) Discussion of the need of employing the energy efficiency in 5G networks
(2) Review of the comprehensive models for base station power consumption
(3) Review of the quantifying metrics for energy saving and system performance
(4) Description of the different wake-up schemes for switching base stations in idle mode to active mode
(5) Evaluation of the application of the sleep activation methods to ultra-dense networks and their challenges.
(6) Taxonomy, comparison, and analysis of the different energy efficiency solutions and their possible scenarios of application
(7) Discussion of various open issues, challenges, learnt lessons, and future directions to enable advanced and efficient energy saving techniques

The rest of this paper is organized as follows. In Section 2, we reviewed the achieving network energy efficiency methods. Section 3 represented the base station power consumption models as well as the energy and performance metrics. Section 4 described and discussed the different sleep-mode enabling strategies. Section 5 discussed the advanced sleep mode strategies and how to model them. Section 6 highlighted the sleep wake-up schemes. In Section 7, we discussed some of the applications and challenges of the base station sleep-mode techniques in ultra-dense networks. Section 8 summarized the learnt lessons from exploring the energy efficiency solutions. It discussed the open challenges to be addressed and proposed some of the future directions for research. Finally, a conclusion is given at the end.

2. Reducing energy consumption approaches

Many approaches have been proposed to reduce the energy consumption in cellular networks. These approaches are hinged on minimizing power consumption at different components, equipment, or systems level of the base station. They can be performed through power amplifiers, self-organizing networks, heterogeneous networks deployment, renewable energy sources, and massive MIMO.

2.1. Power amplifier improvement

Power Amplifier (PA) consumes 50% of base station's energy, out of which 80%–90% is dissipated as heat, leaving its total efficiency as 5% to 20% [52]. Studies have been focused on how to improve the amplifier' hardware designs for better energy efficiency. One of the setbacks with the amplifiers is that much energy is wasted at low load traffic times, as the amplifiers are designed to operate at maximum power output necessitated by the desire to maintain good signal quality. Special architectures such as digital pre-distorted Doherty-Architectures and Aluminum Gallium Nitride have the potential of improving the amplifier's power efficiency by over 50% [52,60]. The studies favored the use of switch-mode PAs, over the conventional analog PAs, as they generate no voltage when powered on. Hence, they could boost component-level energy efficiency by 70%. High cost of implementation is another factor to consider in boasting the power efficiency of PAs.

2.2. Self-organizing networks

Another category of approaches in attaining low energy consumption at base station is by Self-Organizing Networks (SON). SON allow reducing the human intervention while increasing the capacity of the network. LTE is the first cellular mobile communication with SON implementation, but it can only work with older radio access technologies. Besides the primary functions of SON, energy saving is reported in [61] as one of the functions provided by SON. It can deactivate the home base station when the User Equipment (UE) is in the coverage of another base station. However, SON based approach represents limited efficiency in reducing the network power consumption at low load condition because the home base station will not be deactivated as long as a UE is present. In [62], the authors take the network traffic into account where SON based network architecture is proposed such as E-UTRAN Node B (eNB) dynamically interacts in mutual cooperation for minimizing the active number of eNBs in the network and thus achieves energy saving. A similar SON based approach was proposed in [63] with the inclusion of multiple Relaying Nodes (RN). These relays coverage areas could be dynamically changed to minimize energy usage. More details about the applications of SON based approaches will be discussed in Section 5.

2.3. Heterogeneous networks deployment

Energy saving at cellular base stations are also accomplished with the current trend of Heterogeneous Networks (HetNet) deployment in cellular mobile communication [64–70]. Since small cells (micro, pico, and femto cells) are low power-consuming base stations, they are deployed with Macro Base Stations (MBSs) to achieve energy efficiency of the overall network [64][1]. In addition, small cells provide the advantage of coverage extension in the areas where macro base stations coverage do not reach and in the network areas requiring higher capacity. Small cells are one type of the cellular base stations, and they refer to Small Base Stations (SBSs). Base stations can be macro or small BS. MBSs perform with large antennas providing low frequency coverage for long distances, miles. SBSs perform with small antennas providing high frequency coverage for small distances, yards. Using SBS in 5G allows transmitting signals to enhance the connectivity at certain areas. In 5G future networks, more small cells will be deployed compared to MBSs [71].

From the perspective of the network operator, heterogeneous networks offer the potential of lower CAPital EXpenditure (CAPEX) due to reduced site build budget and OPEX with low maintenance cost [66]. However, they require good planning to save energy. It has been reported that poorly planned dense deployment of small cells incurs extra procurement overhead and energy cost in powering the base stations [60,72]. Another constraint in a network dominated by small cells is the higher vulnerability to radio interference as the distance between the co-channel cells may be closer. Heterogeneous networks-based approach can be improved to achieve energy efficiency by incorporating base station sleep-mode techniques, which will be covered in later sections.

On the other hand, heterogeneous networks play a potential role in enhancing the network performance by its multi-tier architecture for energy efficiency in the 6G networks perspective. 6G networks is expected to provide efficient and optimal power control capabilities with less complexity and high energy saving. By deploying the networks of MBS and SBS with MIMO and Non-orthogonal multiple access (NOMA) respectively, the energy efficiency is maximized for the heterogeneous networks [73–75]. Based on the channel state information (perfect or imperfect), energy efficiency is achieved with NOMA protocol deployed to SBS network in the heterogeneous networks. Power allocation allows increasing the energy saving in the heterogeneous networks even at Imperfect (I-CSI) [30].

[1] The short transmission distance of small cells saves energy as power consumption is a function of propagation distance

2.4. Renewable energy sources

Another base station energy conservation strategy is the usage of Renewable Energy Sources (RES) [76,77]. This approach is ecologically friendly as it is based on natural sources of energy including solar, wind, and geothermal heat, which relatively produce little or no hydrocarbon unlike the other widely used energy sources. Energy harvesting base stations have been used for off-grid base stations as the option for diesel generators where fuel transportation is not cost effective, particularly in developing countries. In [78–80], the authors proposed a framework that involves harnessing of both on-grid and renewable energy sources. The synergy of the two power sources with load balancing yields a considerable savings on-grid power. Although [53] suggested the preservation of data security and fault intolerance as drawbacks of energy harvesting base stations, the current major constraint is the cost of components replacement.

2.5. Massive MIMO

Multiple-Input Multiple-Output (MIMO) technology has been incorporated into wireless broadband technologies like LTE. It involves the use of multiple transmitters and receivers to increase capacity. As the number of antennas increases, the imperfect channel state information decreases [81]. The systems with large number of antennas, concurrently serving many tens of terminals, are called massive MIMO systems. With regards to the energy impact of massive MIMO, the transmit power for deliverable data rate is inversely proportional to the number of employed antennas [82]. Moreover, the power consumption expended by each transmitting antenna is relatively very low in the massive MIMO systems, thus, transmit power can be reduced at the base station by a factor of the number of antennas [83]. While analyzing the service of a user by non-coherent beamforming from multiple transmitters, the overall system power consumption can be significantly reduced by combining massive MIMO and small cells deployment [84]. Using multilevel beamforming allows balancing between the energy efficiency and the spectral efficiency by reducing the energy consumption at the transmission [85]. Adopting massive MIMO is challenging as the number of multiple antenna branches per base station may get to the point where further increasing antennas number will incur the increase in the base station circuit power consumption.

2.6. Comparison

The deployment of the 5G networks can break the high increase if the energy consumption with the help of several efficient and effective energy saving solutions and strategies with high sustainability achieved [86]. Energy saving mechanisms allow reducing the power consumption by the cellular network. The way in which these solutions are smartly developed and wisely adopted play a primordial rule in achieving the 5G promises. These mechanisms can be classified in different categories based on how they perform, including hardware/software based, alternative energy source based, and deployment based. Hardware based mechanisms perform by switching off the hardware components that consume energy when it is not in activity. Software based mechanisms allow deactivating a number of functionalities over the mobile networks. Energy saving hardware solutions are efficient in terms of saving up to 90% of energy consumption. However, they represent significant response delay, which requires more intelligent policies to balance the trade-off between the energy efficiency and the delay. They cannot perform well in delay sensitive scenarios where a microsecond of delay can do the difference. They also cannot be applied in dynamic environment with real traffic scenarios.

Through comparing the energy saving deployment-based solutions, HetNet and SON, one can conclude that they are effective solutions with some complexity, but they require extra implementation costs for designing and operating them. Alternative energy source-based solutions are efficient as they generate more sustainable energy with less consumption from free and available resources (solar, wind, and waterpower). They also help in protecting the environment emitting less emissions compared to the other source of energy. Moreover, most of these energy saving mechanisms aim at reducing the transmission energy and not the computation energy, which needs also to be saved.

On the other hand, the different energy saving solutions aim mainly at minimizing the power consumption by the different devices and components preforming for the well-functioning of the cellular network. These solutions can be applied in multiple wireless network scenarios according to how they operate including real time communication, multi-cell communication, device to device communication, wireless sensor networks, internet of things systems [87]. Selecting which solutions fits for a given scenario depends on several metrics including channel condition, transmit power, battery level, mobility, traffic type, graphical region, and available resources. Some of them can be applied to more realistic scenarios including fading channels, time varying scenarios.

Power amplifier improvement solution aims at boosting the power amplifier efficiency by enhancing the hardware design of the amplifier operating at the base stations to consume and waste less energy. Energy efficient amplifier solution can be applied in several scenarios including scenarios where operational conditions can be changed with high tolerance and easy adaptation to the hardware implementation [88]. For instance, energy efficient amplifier solutions have been used for scenarios requiring excessive energy consumption for wireless broadband [89]. Self-organizing networks solution aims at reducing the energy consumption at the base station by deactivating the base stations that are not active when the user equipment is no longer in its coverage. This solution can be applied in multiple scenarios including low load traffic condition. In [90], self-organizing networks solutions have been used for power saving by automatically powering on and powering off the base stations.

Heterogeneous networks deployment solution aims at maintaining a low power consumption of the overall network by operating small cells base stations. This solution can be applied in multiple scenarios including high-capacity networks, small distance communication, high coverage scenarios, and high throughout services. Best scenario is when high capacity is required by some network area to operate. For instance, heterogeneous networks deployment-based solutions have been considered for efficient mobile video on demand (VoD) services delivery in 5G networks and beyond [91]. They can ensure video delivery in ultra-dense network with high capacity, energy efficiency, high throughput, and low latency. Renewable energy sources solution aims at operating the base stations with energy from natural sources [92]. This solution can be applied in multiple scenarios including rural areas, low-income areas, area with limited grid supply, mountain regions, and areas with low population density [93]. For instance, renewable energy sources solutions have been used for some areas requiring expensive electricity grid connection [94].

Massive MIMO solution aims at reducing the transmit power at the base station by using multiple antennas at the transmission and at the reception. This solution can be used in multi-cell scenarios where pilot contamination may significantly impact the energy efficiency [95]. For instance, the authors investigated how massive MIMO and millimeter wave can significantly decrease the power consumption of the 5G radio frequency chains systems with high number of antennas and radio frequency chains [96]. To sum up, hardware-based solutions cannot perform well in delay sensitive scenarios and dynamic environment with real traffic scenarios. Alternative energy source-based solutions can be used for remote areas with limited grid supply resources and low density. Deployment based solutions can be used for specific scenarios with high capacity for different users and customized services. Moreover, investigating how much power can be saved in different scenarios using different energy efficiency solutions can tell about which solution to apply and in which scenario to achieve better results [97].

Table 1
Modeling factors for base station power consumption.

Modeling factor	Models	Remarks
Component-based	Eq. (1), (2), (3), (4), and (8)	base station unit level components are considered
Number of sectors	Eq. (1), (4), (7), and (12)	This accounts for number of base station sectors, active links or antenna
Load variation	Eq. (10), (12), (13), and (14)	Variation in traffic load profile is considered
Operation-based	Eq. (5), (6), (7), and (11)	Power evaluated and aggregated as dynamic and static parts
Active/Sleep mode	Eq. (12), (13), (14), and (15)	Model evaluated from power dissipation in active mode and the one in sleep mode
Scaling factor	Eq. (9), (11), (13), and (14)	Sub-units are scaled for peculiar characteristics

3. Power consumption models and energy metrics

A number of power consumption energy models and metrics have been proposed in the literature to define the base station sleep modes. The model selection depends on a number of modeling factors including number of sectors, load variation, and scaling factor. To measure how much power is reduced, energy saving measurements are used in addition to the evaluation metrics to assess the performance of the base stations sleep mode techniques.

3.1. Power consumption models

Modeling base station power consumption is usually the starting point in problem formulations towards designing sleep mode energy conservation strategies [98]. The derivations are operation-based and/or component-based of the base station. Numerous models of power consumption at cellular base station have been proposed and classified according to which modeling factor is applicable. Table 1 summarizes the power consumption models categorized as a function of the modeling factors, which are formulated from Eq. (1) to Eq. (15). These modeling factors are component-based model, size of the base station, traffic variation, operation of the base station, mode of the base station, and scaling factor.

First, component-based models are informed by the active power dissipating hardware component-level parts, which is considered as having direct impact on the base station power consumption. Examples of these models are formulated in Eqs. (1), (2), (3), (4), and (8).

Second, the size of the base station (macro, micro, pico, or femto) determines the inclusiveness of some hardware components in the model. For instance, pico and femto base stations contain more energy efficient dedicated hardware parts, whereas macro and micro base stations operations require less dedicated components and more reconfigurability in hardware such as more Field Programmable Gate Arrays (FPGAs). Moreover, the loose connection type interface between the amplifier and the antenna constitutes antenna feeder losses in macro base station, which is not included in small base station models due to more compact interfaces [99]. The number of antenna sectors in MBSs is accounted for in models such as in Eqs. (1), (4), (7), and (12).

Third, traffic variation is captured in some models. The representation of some base stations power consumption has been modeled as fixed load, such as the models presented in Eqs. (1), (3), (4), and (8). Variable load model, which is a more energy efficient model, is employed to consider possibility of achieving some energy savings from temporal traffic load fluctuation such as in Eqs. (12), (13), and (14).

The fourth modeling factor is based on the operation of the base station. It reflects the power dissipation of the hardware components in

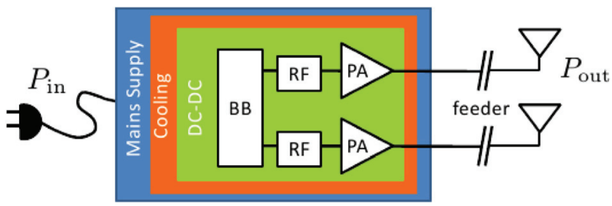

Fig. 2. Block diagram of a base station transceiver [100].

relation to the traffic load. This factor leads to two power model classifications: dynamic and static power consumption models. Dynamic power consumption model represents the power consumed when a component is operating to deliver its functions. This is the base station load-dependent part of the power consumption. Static power consumption model represents the power expended in powering a component regardless of the component functions. It is the power consumed when the base station is 'unloaded'. For example, the pair of (6) and (7) represent the static and dynamic power models, respectively.

The mode of the base station is another perspective of the power consumption modeling. The power dissipated when in active transmission and sleep mode are separately evaluated, and the resultant models are then derived. Examples are the models stated in (12), (13), (14) and (15).

The last factor is the scaling factor, which arises from the base station sub-unit split. The scaling of sub-units is due to different characteristic parameters along the hardware and architectural splits such as analog versus digital, active powering versus cooling, and functional split like frequency versus time-domain signal conditioning [99]. The unparalleled behavior to change in network parameters and sizes with relation to the power consumption is reflected in the scaling parameters in (9). The power factors and models slope in (13) and (14).

The representative of the previously discussed models and their equations are given from (1) to (14). Fig. 2 represents an example of a typical base station with different components to formulate the model's equations [56,100]. The base station power consumption is given by

$$P = N_{TRX} \frac{\frac{P_{out}}{\xi(1-\sigma_{feed})} + P_{RF} + P_{BB}}{(1-\sigma_{DC})(1-\sigma_{MS})(1-\sigma_{cool})} \tag{1}$$

where P_{out} denotes the base station power consumption at maximum load, ξ is the PA efficiency, P_{RF} is the RF power consumption, and P_{BB} is the power dissipated by the baseband unit. The power losses by antenna feeder, DC–DC power supply, main supply, and cooling are denoted by σ_{feed}, σ_{DC}, σ_{MS} and σ_{cool}, respectively.

Component based linear models for small base stations were proposed in [101,102]. In [101], all the base station hardware components are considered in the formulation. The active model is then represented as

$$\begin{aligned} P_{on} = P_{MP} + P_{AMI} + P_{BC} + P_{FPGA} + P_{AMII} \\ + P_{OHF} + P_{T} + P_{R} + P_{PA} \end{aligned} \tag{2}$$

where the power consumed by the microprocessor, associated memory I, backhaul circuitry, FPGA, associated memory II, other hardware functions, Radio Frequency (RF) transmitter, RF receiver, and RF power amplifier denoted by P_{MP}, P_{AMI}, P_{BC}, P_{FPGA}, P_{AMII}, P_{OHF}, P_T, P_R, and P_{PA}, respectively. A simplified hardware model was proposed in [102] as:

$$P = P_{\mu p} + P_{trans} + P_{PA} + P_{FPGA} \tag{3}$$

where $P_{\mu p}$, P_{trans}, P_{PA}, and P_{FPGA} represent the power consumption at the microprocessor, transmitter, power amplifier, and FPGA, respectively.

In [103,104], the authors proposed a distinct model for macro and micro base stations in which the power consumption models were formulated with focus on the network architecture in terms of the transmission parameters and the operational hardware. For the macro base station, the power consumption model, $P_{BS,Micro}$, is given as:

$$\begin{aligned} P_{BS,Macro} = N_{Sector} \cdot N_{PApSec} \cdot \left(\frac{P_{TX}}{\mu_{PA}} + P_{SP} \right) \times \\ \times (1 + C_C) \cdot (1 + C_{CPSBB}) \end{aligned} \tag{4}$$

where N_{Sector} is the number of base station sectors, N_{PApSec} is the power amplifier power consumption per sector, P_{TX} is the station transmission power, μ_{PA} is the power amplifier efficiency, P_{SP} is the signal processing overhead, C_C is the cooling power loss, and C_{CPSBB} is the battery backup and power supply loss. However, this macro base station model assumes that the power consumption is not dynamic while the base station can experience periods of low and high traffic in practice. This dynamic behavior is accommodated in the model of the micro base station, which is given as:

$$P_{BS,Micro} = P_{s,Micro} + P_{d,Micro} \tag{5}$$

where $P_{s,Micro}$ denotes the static power and it is derived from the formula

$$P_{s,Micro} = \left(\frac{P_{TX}}{\mu_{PA}} \cdot C_{TX,static} + P_{SP,static} \right) \cdot (1 + C_{PS}) \tag{6}$$

and the dynamic power form

$$\begin{aligned} P_{d,Micro} = \left(\frac{P_{TX}}{\mu_{PA}} (1 - C_{TX,static}) C_{TX,NL} + P_{SP,NL} \right) \times \\ \times N_L \cdot (1 + C_{PS}) \end{aligned} \tag{7}$$

where P_{TX}, N_L, $C_{TX,NL}$, $P_{SP,NL}$, μ_{PA}, $C_{TX,static}$, $P_{SP,static}$, and C_{PS} represent the maximum transmission power per PA, number of active links, dynamic mode signal processing per link, PA efficiency, static mode transmission power, static mode signal processing, and power supply loss, respectively.

In [105], the authors proposed a similar model to (4), which is based on the inclusion of power expended due to backhauling. The considered backhauling performs in cooperation between base stations in clusters, such as in Coordinated Multipoint (CoMP) [106]. For the base station in a cluster, its power consumption is derived by

$$P = \left(\frac{P_{TX}}{\mu_{PA}} + P_{SP} \right) \cdot (1 + C_C) \cdot (1 + C_{CPSBB}) + P_{bh} \tag{8}$$

where the additional term P_{bh} denotes the power due to backhauling. Furthermore, this model can be approximated as

$$P = aP_{TX} + bP_{SP} + cP_{bh} \tag{9}$$

where a, b, and c depict the scaling factors with the corresponding power [51,107]. There are other linear approximation of the model excluding backhauling and simplifying the formulas [108–114].

Traffic loads have been proposed for base station modeling [114–117]. A load-dependent formula that does not only entail the dynamic and static modes of the base station, but also includes the instantaneous weight of the traffic load is given as

$$E_i = (1 - q_i)\rho_i P_i + q_i P_i \tag{10}$$

where ρ_i is the load at the base station i, P_i represents the power of the base station i at maximum usage, and the static power of the base station is represented by the scaling $0 \le q_i \le 1$ [116]. For 3G networks, q_i ranges from 0.5 to 0.8 [116,118]. While this model encompasses the power consumption in the two distinct modes, it does not express the influence of the traffic load. Based on the physical layer model of the cellular networks, the power consumption takes into consideration the static and dynamic modes, and it is given as

$$P = \eta^{-1} P_t + P_c + LP_l \tag{11}$$

where $\eta^{-1} P_t$ is the static power consumption of the base station, η is the transmission power efficiency, P_t is the pilot signal maximum transmission power, P_c is the constant operational power [119], LP_l is the dynamic power consumption, L is the product of the number of network users, and P_l is the base station serving power. A simpler model with no dynamic power transmission is adopted in [120,121].

In [122–128], a *linear approximation model* has been proposed when representing small cell energy consumption, where the main operational modes—active and sleep—are approximated as

$$P = \begin{cases} N_v P_{active} + \Delta_v P_{trans,v} & 0 < P_{trans,v} \leq P_{v,max} \\ N_v P_{sleep,v} & 0 < P_{trans,v} = 0 \end{cases} \tag{12}$$

where N_v is the number of antennas in base station v, P_{active} is the power consumption of the hardware at the BS, $P_{sleep,v}$ is the base station power consumed at sleep mode, $\Delta_v \geq 1$ is the power amplifier inefficiency, $P_{trans,v}$ is the transmitted power, and $P_{v,max}$ is the maximum transmit power constraint of the base station. This model does not only account for traffic load but also load variation, as the Δ_v scales according to the load dependent power consumption. It does not take into consideration the variations at the MBS where only SBSs are put on sleep mode.

Conversely, the following model considers when the MBS is put on sleep mode and its load is transferred to SBSs. Let the index from 0 to S denotes the base stations in a cell such that 0 represents the MBSs, and SBSs if otherwise. q_j is the binary sleep indicator of the MBS mode (0 for sleeping and 1 for active) [129]. For a base station s in jth cell denoted by BS(j,s), the power consumption is given as:

$$P_{j,0} = \begin{cases} P_{M0} + \Delta_M W P_{tM} \rho_{j,0}, & \text{if } q_j = 1 \\ P_{Msleep}, & \text{if } q_j = 0 \end{cases} \tag{13}$$

$$P_{j,s\neq 0} = P_{S0} + \Delta_S W P_{tS} \rho_{j,s} \tag{14}$$

The MBS power consumption is depicted by (13) and the SBS power consumption model is presented by (14). P_{M0} is the fixed power factor, Δ_M is the power model slope, W is the total channel bandwidth, $\rho_{j,0}$ is the traffic load, P_{tM} is the transmit power spectrum density of MBS, P_{S0} is the SBS fixed power factor, Δ_S is the power slope, P_{tS} is the SBS transmit power spectrum density, and $\rho_{j,0}$ is the station associated traffic load. Although the models presented by (11)–(14) assume equal transmission power allocation to each resource block (RB) per base stations, they take into consideration the effect of the traffic load and the total channel bandwidth. The base station power consumption scales linearly with the bandwidth [100].

Energy saving model providing more spatially realistic model than the regular grid is formulated based on the stochastic geometry modeling [130]. The base station power consumption per unit area is given by:

$$E = \lambda_a P_a + (\lambda_B - \lambda_a) P_s = \lambda_B P_a(\rho + (1 - \rho)\theta) \tag{15}$$

where λ_a, P_a, P_s, ρ, and θ are the base station density in sleep mode, the active mode power, the sleep mode power, the traffic load, and the ratio between sleep mode and active mode power, respectively. The base station distribution is modeled with an ergodic Poisson Point Process (PPP) with density λ_B.

3.2. *Energy saving measurement*

How much energy is saved? In order to quantify a measure of energy efficiency of a cellular networks, different frameworks are used to evaluate the energy saving resulting from different schemes. In [131], energy measurement in wireless communication systems can be approached either by projecting energy to the system performance or by comparing the output power to the input. Energy measurement metrics can be classified into two categories: absolute and relative metrics. Absolute metrics are based on system performance while relative metrics relates the energy output to the input and depicts the improvement in energy efficiency of the system. Table 2 summarizes and classifies the different energy saving measurements metrics.

Absolute metrics

A number of absolute metrics have been proposed over the literature including bit per joule, energy efficiency, area green efficiency, power consumption, power consumption in rural areas, and power consumption in urban areas. *Bit-per-Joule* metric is one of the commonly used absolute metrics and it is given by

$$E_e = \frac{R}{E} = \frac{R}{PT} \tag{16}$$

where E denotes the energy in Joule, P denotes the power in Watt, which is the required power to deliver R bits over a period of T seconds [102,109,132–135]. *Bit-per-Joule* metric refers to the ratio of the network throughput and the power consumed by the base station. In [137–149], more complicated formulas of the Bit-per-Joule metric has been discussed, which indicates that the reciprocal of this metric is the *Energy Consumption Ratio* (ECR) and the *Energy per bit*. The former, in Joules/bits or Watts/bps, is the ratio of the energy consumption to the system capacity [64,136], and the latter is the ratio of the network consumption to the system throughput [100,137]. In [128], the authors proposed other formulas of the bit per joule metric in built upon its generic definition. The unit of Energy-per-bit is Joule/bits; thus, this metric is essentially equivalent to the ECR. Bit-per-Joule can be also defined as the ratio of data rate and the power consumed in $bit/s/Watt$ [133].

Energy Efficiency (EE) has also been evaluated from the perspective of area spectral density. In [138], in computing the energy saving in energy harvesting cooperative relay in cellular network, the Energy efficiency is expressed as

$$EE = \frac{\text{Area Spectral Efficiency}}{\text{Network Power consumption}} \tag{17}$$

Similarly, the ratio of the network spectral efficiency and the network power consumption is adopted in [145]. Another performance metric based on the spectral efficiency is proposed in [139], which is called Generalized Area Spectral Efficiency (GASE), η. It is defined as the ratio of the ergodic capacity of the link, denoted by C, and the coverage area of the transmission, denoted by A.

$$\eta = \frac{C}{A} \tag{18}$$

Area Green Efficiency (AGE) metric aims at quantifying energy savings at the macrocell area in an heterogeneous network with femtocells as the 2nd tier [140]. With the total power savings in macrocells and femtocells denoted by P_M and P_f, respectively, AGE is represented by

$$AGE = \frac{P_M + P_f}{\pi(R_M + R_f)^2} \tag{19}$$

where R_M is the radio of the macrocell and R_f is the radius of the femtocell.

Area Power Consumption (APC) metric is defined as the ratio of the total power consumed by the base stations and the area of the target coverage [104]. It is given as

$$APC = \frac{\text{Total power consumed by all base stations}}{\text{Area of coverage}} \tag{20}$$

Power consumption in rural areas metric has been proposed by the European Technical Standards Institute (ETSI), which focus on load conditions in the target coverage area. It aims at measuring the power consumed in rural areas where there is low density of mobile users [52]. It can be seen as the reciprocal of the APC metric, and it is given by

$$PI_{rural} = \frac{\text{Total coverage Area}}{\text{Power consumption}} \tag{21}$$

Power consumption in urban areas metric is used for areas with high density of users. It is characterized by the number of busy hours of the network with respect to the power consumption and it given as

$$PI_{urban} = \frac{\text{Number of users in peak hours}}{\text{Power consumption}} \tag{22}$$

Table 2
Energy savings measurement metrics.

Category	Performance parameter	Metric	Unit	References
Absolute metrics	Throughput/Capacity	Bit-per-Joule	*bits/Joule*	[102,109,132–135]
		Energy Consumption Ratio (ECR)	*Joules/bit, Watts/bps*	[64,136]
		Energy-per-bit	*Joules/bit*	[100,137]
	Area spectral efficiency	Energy efficiency	$(bps/(Hz \cdot m^2))/Watt$	[138]
		Generalized Area Spectral Efficiency (GASE)	$(bits/sec/Hz)/m^2$	[139]
	Coverage area	Area Power Consumption (APC)	W/m^2	[104]
		Area Green Efficiency(AGE)	$kWatt/km^2$	[140]
		Performance Indicator(PI)	$Km^2/Watt$	[52]
	Number of users		$users/Watt$	
Relative metrics	Energy gain	Energy Consumption Gain (ECG)	%	[64,141,142]
		Energy Reduction Gain (ERG)	%	[141,142]
		Network Power Gain (NPG)	%	[62]
		Energy savings	%	[62,143]

In either case, the higher the PI, the higher the overall energy efficiency.

Relative metrics

A number of relative metrics have been proposed including energy consumption gain, energy reduction gain, network power gain, and energy saving. In heterogeneous network involving deployment of macrocells and relays or femtocells, Energy Consumption Gain (ECG) and Energy Reduction Gain (ERG) are introduced to compute the overall energy consumption in such cellular networks [141]. With the macro-only network tagged baseline network and macro-relay or macro-femto network labeled joint network, the ECG is given in terms of percentage of the operational powers and the embodied energies as

$$ECG_{op} = \frac{(P_{op}^{tot})_{base}}{(P_{op}^{tot})_{joint}} \times 100\% \tag{23}$$

$$ECG_{em} = \frac{(P_{em}^{tot})_{base}}{(P_{em}^{tot})_{joint}} \times 100\% \tag{24}$$

where the total operational powers for baseline and joint networks, in Watt, are represented by $(P_{op}^{tot})_{base}$ and $(P_{op}^{tot})_{joint}$, respectively. $(P_{em}^{tot})_{base}$ and $(P_{em}^{tot})_{joint}$ are the total embodied energies in baseline and joint networks, measured in Joule (W/s). The ECG has been applied to legacy base station (macro-only) networks [64,142]. The ERG is derived by modifying the formulas of ECG.

$$ERG = \left(1 - \frac{(P_{op}^{tot} + E_{em}^{tot})_{joint}}{(P_{op}^{tot} + E_{em}^{tot})_{base}}\right) \times 100\% \tag{25}$$

In [62], the authors introduced an energy measure metric for base station sleep mode activation by self-organizing networks. This metric allows estimating the energy saved is termed of the *Network Power Gain* (NPG), which is given as

$$NPG = \left(\frac{\text{Power in the original network per area}}{\text{Power in the SON per area}} - 1\right) \times 100\% \tag{26}$$

There are some other forms of evaluating power conserved from base station sleep mode strategies in relation to the legacy network and are scheme specific [62,143]. For instance, energy saving can be expressed as

$$ES = \frac{EC - EC_s}{EC} \times 100\% \tag{27}$$

where EC is the energy consumption of the network when it is always active and EC_s is the energy consumption of the network when sleep mode strategy is applied.

3.3. Performance metrics

While the main objective of the base station sleep mode techniques is to improve the overall energy efficiency of cellular networks, there is a possibility to achieve the objective at the expense of other performance metrics. Therefore, the avoidance of conflict with core performance metrics is considered in devising, planning, and employing energy improving strategies. The performance metric considered in each sleep mode strategy depends on which approach is used to reduce the power consumption. For instance, invocation of N-policy in Mobile Users (MU) queue for network service as a power reduction strategy will necessitate a consideration of the delay as one of the metrics to qualify the QoS of the network.

Similarly, the coverage/outage probability will be a candidate metric to indicate the effect of energy savings when randomly switching off some base stations. Temporal disengaging some base stations into sleep mode instantaneously reduces the network density, which may necessitate the consideration of the network capacity and/or the spectral efficiency. Other options include using the coefficient of variation to capture the impact of the ping-pong effect of the base station mode changes, and the impact on SINR from path loss between MUs and the base stations due to switching. These performance metrics and where they have been applied are summarized below.

(1) Signal to Interference Plus Noise Ratio (SINR): The trade-off between the energy efficiency and the SINR implies improvement of the former and reduction of the latter. Low SINR hampers the quality of reception by the MUs. Therefore, the sleep mode strategies aimed at minimizing the energy consumption are subject to the SINR threshold. In determining the adequate QoS, the received SINR of MU is computed with, among others, the transmit power of the base station and the path loss between the base station and the MU [142,144].
(2) Coverage/outage probability: The coverage or success probability metric is related to SINR as it indicates the probability that the SINR at the MU is equal or larger than a QoS threshold. It can be utilized as the metric for sleep mode techniques, which considers segment of the area of interest to receive SINR greater than the QoS threshold. Outage probability, in contrast, is the probability that the area segment is below the QoS threshold [101,146].
(3) Throughput/network capacity: The increase in the density of the base station deployment to accommodate the rise in the number of MUs should increase the network throughput, but at the cost of increasing the power consumption [136,137]. The throughput is usually computed using Shannon formula. Sleep mode techniques are checked against the throughput for meeting QoS. In [147], a throughput-power consumption model is proposed as Achieved Capacity over Power Consumption Ratio (ACPCR) measured in bits/(s*Watts), which is the ratio of maximum

throughput to the power consumption. Higher ACPCR indicates better system performance. The Network Capacity Utilization Improvement (NCUI) is proposed to quantify the network in Erlang capacity utilization [62]. It indicates the network performance with SON activated base station sleep mode versus conventional base station network, and it captures the traffic and active MUs. It is expressed as:

$$NCUI = \left(\frac{\text{CUE of the proposed SON}}{\text{CUE of a legacy network}} - 1 \right) \times 100\% \tag{28}$$

where Capacity Utilization Efficiency (CUE) is the ratio between the network total traffic and the total active time of all the base stations. Network capacity with respect to cell size in sleep mode is used in [64]. It is termed capacity density, measured in $bits/sm^2$, which is the ratio of the average cell capacity to the cell area. Simulations show that for base stations without sleep mode, reducing the cell size only reduces the energy consumption and thus increases the capacity density. With sleep mode, reduction of the cell size decreases the energy consumption and increases the capacity density.

(4) Spectral efficiency: Switching off some base stations as well as variation of traffic load impacts the Network Spectral Efficiency (NSE). In [145], the selection criteria of sleep mode base stations are very crucial to NSE, as random base station selection for sleeping lowers the NSE while strategic base station selection yields higher NSE. Area Spectral Efficiency (ASE) is another performance metric used in evaluating energy efficiency in cellular network. It reflects the average data rates per unit bandwidth per unit area covered by a base station or equivalently, the number of active MUs per Hertz per unit area. In [104], it was shown that increasing SBSs deployment density increases both energy and ASE. Therefore, the base station sleep modes strategies are planned to reduce the energy consumption while taking the number of active users, reflected by ASE, into account. For instance, traffic load increase lowers the NSE while the average ASE increase provides an indication of traffic load variation [120].

(5) Coefficient of variation: The ping-pong effect can raise the energy consumption due to intermittent on-and-off switching of base stations [148]. Therefore, the coefficient of variation is used to capture the measure of base station modes variation to evaluate the stability of the base station sleep mode strategy and the impact on energy consumption. Lower coefficient of variation of the base stations number in sleep mode implies more stable modes and longer duration of the base stations in sleep mode, hence, more energy savings.

(6) Delay time: In [128], the authors investigated the trade-off between the delay and the energy consumption where they demonstrated how the energy consumption can be traded for delay in the base station sleep mode operation. The relationship between the trade-off and the base station control policies refers to multiple vacation policy and the N policy gives better energy efficiency than the single vacation policy.

4. Sleep mode enabling methods

A number of methods and strategies have been proposed to activate the base station sleep or idle modes to reduce the overall system power consumption. These methods are: specific cells switching, load adaptiveness, switching threshold, relay deployment, coordinated multi-point, cell discontinuous transmission, self-organizing networks based, delay tolerance, voting, network function virtualization, and Advanced Sleep Modes (ASMs). Switching specific cells method is easy to implement, but it does not guarantee an optimal choice of the cells to be switched off. Load adaptiveness method takes the network traffic profile into account and ensures that the least loaded cells are put into idle mode, however, it is prone to creating coverage holes. Switching threshold as one of the load dependent methods represents low complexity, but it is not applicable where the traffic profile is erratic.

Relays based methods have been deployed due to their low operating cost, but the proper network planning is required to ensure optimal placement. Coordinated Multi-Point (CoMP) schemes are helpful for minimizing coverage holes. Cell discontinuous transmission and self-organizing networks provide high energy savings; however, high cost is incurred in incorporating them in network planning. Applying some delays method to achieve lower base station power consumption is flexible and it does not require hardware cost. However, it is not applicable where or when non-delay tolerant users are served. Voting method ensures the best candidate base station is put to sleep, but if not combined with other algorithms, it is not immune to challenges like coverage holes. Network function virtualization provides relatively better energy control with high potential savings, but its application is still nascent. Fig. 3 summarizes and classifies these sleep mode strategies.

4.1. Specific cell(s) switching

Through the neighboring base stations taking over radio support to the MUs, only some specific base stations are powered off to conserve energy. Sleep mode is restricted only to these base stations while the rest always remain active. In [149], the authors proposed a specific cell switching technique where only the central cell is switched off. This technique is premised on cluster cells deployment with overlapping coverage. It is relatively simple and targets only the spatially center cell. It relies on the base station selection based on its spatial location instead of the traffic weight, which limits its efficiency in saving energy. As the most central cell does not necessarily imply the one with the least traffic, this method may not be optimal.

4.2. Load adaptiveness

One of the ideas behind the conceptualization of sleep mode is to disengage some base stations in a cluster when the traffic load is reduced. In [150], temporal variation of the traffic load and its relationship to the base station power consumption has been investigated by considering the load fluctuation at different hours in a certain location. In [100,150], the authors discussed the spatial variation of the traffic load in Europe as a case study where switching based on thresholds is applied. However, these two studies are dependable for energy reduction schemes only when one is fixed and the other fluctuates as regards to temporal and spatial traffic profile. In certain locations such as campus, the variation could be either way intermittently. Load aware adaptive schemes are devised to accommodate any form of load variation, such as in [101] where small cells in heterogeneous networks are put on sleep mode based on their load level. The base station switching according to traffic load profile is challenged by the coverage holes that may occur due to ineffective coverage support from the cells. consequently, Cell Overlap minimization with intersection covered (COMIC) load aware algorithm has been proposed to minimize the energy consumption and eliminate coverage holes [151]. While the simulation results show that the energy savings is improved with maintained network coverage, the complexity of the algorithm is high. Load balancing is also used to put the base stations to sleep mode and decrease energy consumption [123].

4.3. Switching threshold

Switching off the base stations based on certain thresholds techniques have been proposed by several studies including [109,152,153]. In [152], the authors proposed a network QoS based threshold technique for putting eNBs to sleep mode. A re-transmission tolerance

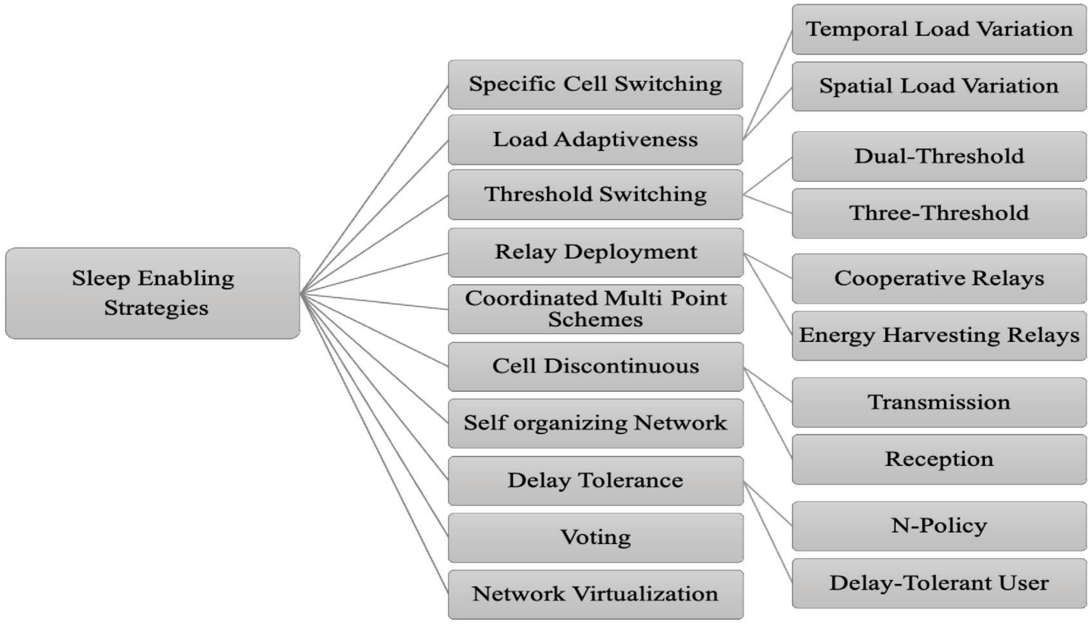

Fig. 3. Categories of sleep mode strategies.

range determined by QoS, such as delay and throughput, is used to select which nodes to put to sleep. This low complexity technique considers the load level of each base station in the sleep activation threshold. In [153], the authors proposed a sleep mode triggered by dual thresholds where the triggering thresholds for switching are the traffic load and the cell-edge QoS constraint.

Moreover, a switching threshold technique with three modes has been proposed where the base stations could be put on active, low power, or sleep mode according to the load threshold [109]. In low power mode, the base station operates at low capacity, hence at lower power than when active. While in sleep mode, neighboring base stations, each intermittently monitor their traffic usage, share this information among themselves in order to decide on reactivation of the base station to either low power or active modes corresponding to the new threshold reached. The introduction of low power mode saves more energy compared to the dual mode thresholds, which implies that the reduced power mode that would have been in active mode now contributes to the margin of the energy conservation. However, the proposed technique relied on a simplified model that assumes a co-location of MBS per SBS, and both cannot be active at the same time. The assumption does not represent the current deployment of heterogeneous networks.

4.4. Relay deployment

Leveraging on the base station energy consumption reduction using relay deployment, the combination of relays and base station switching has been proposed to improve the energy efficiency [154,155]. Sleep mode with optimal placement of relays in a network is considered in [156] where the Simulation results confirm that the power saving with optimized method of relay location when combined with base station switching off at low loads. In [157], a similar approach has been proposed with more sophisticated schemes to minimize the coverage and the power consumption, and optimally place relay stations for the uncovered users. Multi-hop, cooperative, and energy harvesting relays have been used with the base station sleep-mode [138,158]. Combining these schemes provides better results in terms of energy efficiency.

4.5. Coordinated multi-point (CoMP) schemes

In [76,159], coordinated multi-point with cell zooming or sleep mode has been proposed to improve the SINR. CoMP with sleep mode produces more energy savings than with cell zooming. In addition, at sleep mode, zooming out by active cells can improve performance at minimizing coverage holes. The performance is achieved with the co-operative characteristic of CoMP by allowing MUs situated in coverage holes and cell edges communicate with multiple base stations. CoMP with sleep mode gives 48% energy efficiency over Non-CoMP with all active base stations [159]. A form of CoMP with sleep mode, called Sleep Mode with Dynamical Clustering (SMDC), has been proposed to maximize the energy efficiency [132]. SLeep-WAke (SLAKE) algorithm has been proposed to put a base station to sleep mode with cooperation among cells in a cluster [160]. However, the decision to go to sleep depends on the acceptance of the base station, and the request to already sleeping base stations to bear its traffic load depends on the current traffic threshold. Multi-cell cooperation is required for acceptance of transferred traffic load so that the requesting base station can go to sleep.

4.6. Cell discontinuous transmission

Discontinuous Transmission (DTX) is the energy saving mode of a base station in which some components of the cells are left to remain active to ensure prompt response when needed. Some of the early work on DTX highlighted the energy saving capability of employing DTX in the network planning [161,162]. When included in the network planning, a 42% energy reduction is reported by [117] as compared to when the base stations are put to idle mode. Employing DTX in the network planning is unscalable and highly costly, which limits its efficiency. For the aforementioned increase in [117], the cost surges by 110%. In addition, this technique cannot be a retrofit as it comes with the network planning stage in which there is no room for direct adaption to existing networks. For the corresponding energy saving at MUs, the discontinuous reception (DRX) potentials are noted in [163,164].

4.7. Self-organizing networks

The abstraction of self-organizing network has been introduced in the 3GPP standard (3GPP TS 32.521). Since deployment of the SBSs is less planned compared to the MBSs deployment, self-organizing network-based algorithm is being harnessed to provide distributed control for the mobile networks. Its control algorithms can be used to put some base stations to sleep mode for energy savings. In [165], MUs access are categorized into registered and non-registered users. Priority access to the network is allowed only by registered users, and the base stations with no such users can be put to sleep mode. While in sleep mode, only registered users can activate the sleeping base station. In [166], SON utilization for energy savings by timed sleep mode has been proposed to coordinate and invoke the sleep mode at a pre-defined time interval while coverage demand is satisfied using the adjacent base stations.

4.8. Delay tolerance

In [167], the trade-off between the energy consumption and the delay in hyper-cellular networks has been explored as some resources could be saved by compromising on certain QoS performance. To formulate strategies hinging on delay tolerance, the base station is modeled as an M/G/1 vacation queue in [167], where the base station is put to sleep mode if there is no network access request from MUs and remains in this mode until N MUs queue builds up (N-Policy). This technique shows some limits where increasing the number of MUs results in mean power consumption decrease, and above the limit monotonic decrease of power is not achieved. Thus, there are delay bounds in which the base stations energy savings is increased.

In [168], the authors proposed two sleep mode strategies based on the cooperation of the MUs in accommodating some delays called Delay-Tolerant Users (DTU). Based on the assumption that DTUs are identifiable by the network, the cellular network with the strategy persistent DTU serves the Non-DTUs in its minimum-BSS on mode while the DTUs are left on queue until their number builds up to certain threshold where all the base stations are switched on. In Opportunistic DTU strategy, a minimum and maximum traffic loads are set. Below the minimum, all MUs are allowed to access at minimum-BSs on mode. Between the two thresholds, all users are allowed to access despite the possibility of insufficient network resource, hence delay-tolerance is expected. At greater than the maximum threshold, all the base stations are woken up. The energy saving increased when conducting a daily traffic pattern analysis. These two strategies are flexible and scalable as they do not involve the use or replacement of hardware and do not require to be integrated in the network planning stage. They are limited by the assumption of the DTUs availability versus Non-DTUs and their identification, which could pose constraints in real practice.

4.9. Voting

In [129], voting scheme has been explored to enable sleep mode of the base station. A cluster is assumed to be comprised of many MBS, each to a cell and multiple SBSs within a cell. Sleep mode mechanism is applied to the macro base station. When compared with the neighboring macro base station, the MBS with the lowest traffic load value is put to sleep. Each station votes for the base station with the lower load metric value. The vote is updated as the load information is shared among neighbors. To meet the network QoS requirement, the number of current users is taken into consideration. Therefore, the metric value, with which comparison is made, is determined as the ratio of the number of the current associated MUs to the number of votes. Though this technique includes the selection of active base stations at each cycle of pre-voting, the wake-up mechanism before the selection is not considered.

4.10. Network function virtualization

Despite the cellular network virtualization is still in its nascent stage, its potential in base station energy consumption reduction by sleep mode strategy has been investigated [148]. A virtualized network function of cell management architecture, called Software-Defined Energy Efficient Base STAtion (SieSTA), has been proposed to enable sleep modes of the base stations. It aims minimizing the power consumption while satisfying the coverage of all users. With a threshold of minimum and maximum traffic load determined for the base stations, Siesta matches the covered MUs for each base station with different statuses such as the power increased mode, active mode, and sleep mode. It improved the energy efficiency of the network and supported higher number of base stations in sleep mode with longer sleep duration.

5. Advanced sleep modes

Advanced sleep mode techniques perform by shutting down the base station progressively according to the activation and deactivation times of its components. When there is no traffic or users to serve, the base stations switch to the sleep mode or idle state. Advanced sleep modes are based on the lean carrier radio access offered by the 5G networks with configurable signaling periodicities. They enable the base station to alternate between active and sleep modes periodically [169]. They have been a promising solution for the 5G networks to enable energy efficiency. Several levels of the advanced sleep mode are defined based on the transition periods between the activation and the deactivation modes. Each network operator imposes how to manage these levels based on its policies and the traffic load in order to balance between the energy consumption and the response delay. Based on the transition time, advanced sleep modes can be classified into four levels, namely SM1, SM2, SM3, and SM4 [170]. SM1 refers to the shortest mode with short transition time while SM2 refers to the longest mode with long transition time. SM3 requires shutting down all the base station component at the sleeping window. SM4 corresponds to the deepest level [171].

A number of approaches and tools have been proposed to enhance the sleep mode management by the trade-off between the energy gain and the latency. For instance, the authors proposed a management strategy to enable advanced sleep modes when users requesting services while the base station is in the sleeping mode. The proposed technique performs by increasing the sleep mode duration of the base stations, which needs to wake up periodically for signaling. It can reduce the energy consumption up to 90% in low load traffic scenarios with significant latency [172]. However, this strategy does not take in consideration the delay sensitive scenarios such as 5G services with 1 ms as acceptable latency. In [169], the authors proposed a management strategy based on Q-learning for delay sensitive cases where very low load traffic scenarios were considered. However, this strategy does not analyze how the algorithm can perform at high load traffic scenarios. In [170], the authors extended their previous works by proposing a traffic aware management strategy based on the Q-learning algorithm for latency and energy sensitive scenarios in 5G networks. The proposed management strategy aims at finding the optimal combinations between the traffic load, latency, and energy gain. Several traffic loads levels (low, high, and moderate) are considered to find the optimal strategy to enhance the energy saving while respecting the latency constraint imposed by the operator.

In [173], the authors proposed a sleep window size selection algorithm in order to find the optimal sleep period considering the delay constraint. They analyzed the trade-off between the packet queuing delay and the energy efficiency of the terminal. In [174], the authors proposed a distributed reinforcement learning based algorithm for base station management and control. The proposed algorithm allows controlling the base station states according to the 5G requirement's defined by the periodicity of synchronization signaling bursts. It performs by analyzing different sleep mode levels to select the best level that by balances the trade-off between the saved energy and the response delay. Maximizing this trade-off allows saving up to 90% of energy in delay tolerance scenarios. In [175], reinforcement learning based Q-learning algorithm has been used also for energy efficiency to maximize the energy saving-delay trade-off in multilevel sleep modes environment. This location aware algorithm performs by controlling the base station states according to the geographical location of its neighbors' users and their mobile velocity. Maximizing this trade-off allows saving up to 92% of energy with respect to delay constraint.

In the context of 5G networks, there is always a trade-off between the saved energy and the response delay of the base station for waking up, which requires balancing between these two metrics to enable energy efficiency with time constraints [176,177]. A number of sleeping control strategies have been proposed enabling the advanced sleep modes for selecting the optimal sleeping policies and strategies [178–180]. Examples of these strategies are based on Markov decision process, qu, stochastic traffic models, and analytical derivation. Markov decision process-based strategy is based on the Markov decision process for scalable management of the base station states. It aims at finding the optimal advanced sleep mode policy that enables modeling the base station states and orchestrates the sleep mode levels.

In [178], the authors proposed a scalable management technique based on Markov decision process for base station optimal control. However, this approach is complex because of the high dimension required of the state space. In [179], the authors simplified their previous work by proposing a simplified model with less state space dimension. The simplified algorithm performs by finding the optimal sleep level based on the traffic load in order to maximize the trade-off between the saved power and the latency. It allows saving up to 91% of energy with delay tolerance. In [180], the authors proposed a data driven base station algorithm, called DeepNap, based on deep Q-network for dynamic sleeping control. DeepNap algorithm performs by learning the optimal way to save energy from system belief vectors or high dimensional raw of observations. It allows modeling the non-stationary of the real-world traffic for energy saving in such scenarios. Most of the sleeping control strategies enables designing optimal algorithms to balancing between the energy saving and the response delay. However, most of these algorithms cannot be applied in complex and the real scenarios and they do not take in consideration the real time network decisions.

6. Wake up schemes

A number of wake-up schemes have been proposed in the literature to wake up the sleeping base stations at the end of the idle mode to resume normal operations [181–183]. These schemes are: stand-alone self-activation, activation by macro base station, queuing based activation, and wake up by access reward. No technique is one-size-fits-all. Stand-alone self-activation is a simple and low overhead wake-up scheme, but it is prone to the energy inefficiency when more than necessary number of base stations are self-wake. Activation by Macro base station scheme provides the advantages of central coordination from the SBS, which precludes the downside of the self-activation. However, some form of its implementation may trigger all supported SBSs instead of the required number for the traffic. Queuing based activation scheme is not suitable for non-delay tolerant users, but it harnesses the Energy-Delay Trade-off (EDT), which guarantees the required level of users to be supported before switching the base stations. Wake-up by access rewards allows longer sleep duration and prompts wake-up due to the assigned rewards to the modes. It is prone to high complexity.

6.1. Stand-alone self activation

In [181], small cell self-activation scheme has been proposed for heterogeneous networks where macro base stations are always put on. The sleeping SBS has its uplink receiver turned on to intermittently measure the interference plus noise $(I+N)$. The detection of an increase in $(I+N)$ when a connection request is made from MU to the MBS will trigger the SBS to wake up and connect to the MU if it has higher $(I+N)$ than the macro base station.

6.2. Activation by macro base station

In [181], the macro base station is used to wake up the sleeping SBSs. When the number of MUs requesting connection with the MBS is greater than a pre-determined threshold, the MBS wakes up all the SBSs in the coverage area. However, this strategy does not select which SBS is woken up to assist and instead all are woken, which limits the efficiency of this method in terms of energy saving. An indicator, called Timing Advance (TA), is used to indicate how far the MU is from its serving base station. Each MU's uplink signal is transmitted with time TA ahead of the sub frame boundary. The TA of each SBS is also intermittently received. At the MUs connection request, the MBS is able to determine the distance with the TA and wake up the corresponding SBS closest to the MU. This method precludes unnecessary switching on of all the SBSs in the coverage area.

6.3. Queuing based activation

For a case where sleep mode is formulated as a queue model, the base station is put to sleep mode when the network is 'empty' and waits for some time. While waiting, the base station is woken up when a user arrives. The pattern of sleep is referred to a hysteresis sleep. In [182], the authors proposed and implemented three wake up schemes, namely single sleep, multiple sleep, and N-limited scheme, as illustrated in Fig. 4. In Single Sleep (SS) scheme, the base station wakes up from sleep mode after a certain pre-determined time. While it is easy to implement, it is insensitive to QoS degradation that may arise from 'blind' sleeping. In Multiple Sleep (MS) scheme, the sleeping base station wakes up when it discovers a waiting user, as it listens to the network status at a predefined time interval. When no waiting user is detected while listening, it continues sleeping. This approach solves the setback of the single sleep scheme, but it requires additional power for periodical listening to the network status. In the N-limited scheme, the base station wakes up when there are N users waiting in the network. While guaranteeing higher energy efficiency due to the energy-delay trade-off (EDT), additional network elements are required to keep the counts.

6.4. Wake-up by access reward

In [183], game theoretical approach has been applied where assessing to network by MUs is rewarded. A reward assignment is used to wake up an idle base station with higher reward assigned to the MUs requesting access. Conversely, the base station in sleep mode is given less revenue relative to the active ones. Thus, MUs requiring service are encouraged to wake up the idle base station, which is equally motivated.

7. Base station sleep-mode in ultra-dense mobile networks

Dense networks have been part of the current cellular network deployment under the category of heterogeneous network. However, they are only prevalent in fragmentary areas such as indoor and hotspot where they provide complementary support to the mobile network. To meet the ever-increasing demand traffic demand, which may amount

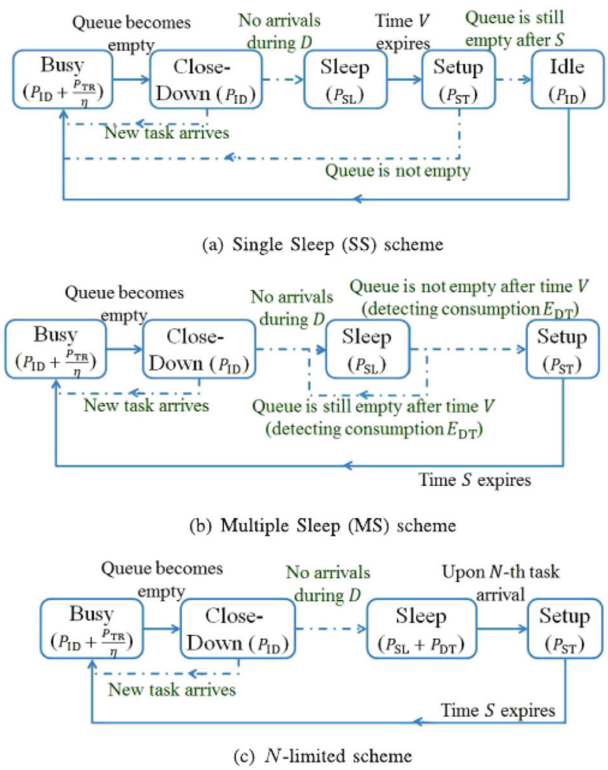

Fig. 4. The transition diagram of base station operation phases with different wake-up schemes [182]. P_{ID}, P_{TR}, η, P_{SL}, P_{ST} and D denotes the idle power, transmission power, load-dependent power efficiency, sleep power, setup power and close-down time, respectively.

to a 1000-fold demand surge over the coming decade, the focus is recently being geared towards ultra-dense base station deployment [184]. Ultra-dense networks refer to networks with more cells than active users [21]. With ultra-dense deployment, the network is comprised of large number of SBSs consuming high energy resources.

The evolution of different generation of cellular network technologies, with higher capacity delivery than its predecessor, is characterized by higher spatial base station density. In 3G cellular networks, dense deployment of MBS to support higher demand areas, such as urban areas, has a density of 4–5 base stations/km^2. LTE/LTE-A (4G) networks comprise of, as complement to the MBS, SBS deployment for high-capacity traffic need of specific areas (e.g. hotspot, heavy users' office complexes) leading to SBS density of 8—10 base stations/km^2. In the anticipated 5G networks where a base station will be equipped with hundreds of antennas (also referred to as massive MIMO antenna) for gigabit-level transmission and coupled with the option of millimeter-wave communication technology with attendant short distance propagation due to degradation in the atmosphere, the 5G base station density is expected to be 40–50 base stations /km^2 [185]. Therefore, the future base station deployment will be ultra-dense, better still, 5G ultra-dense networks.

As the ultra-dense cellular network differs from the conventional network, direct adaptation of sleep modes invocation and wake-up strategies of base stations in conventional networks to ultra-dense networks may be inefficient and inapt. Thus, this transition from a convectional network to an ultra-dense network is facing several challenges related to the network architecture, use of high frequency signals (such as millimeter-wave frequency band), higher spatial base station density, higher traffic load, and smaller cell size. There is a great need for potential solutions in adapting the aforementioned base station sleep mode and wake-up strategies to ultra-dense network.

7.0.1. Dichotomy of macro and small cells

MBSs have two distinct roles in the architecture of an ultra-dense network. In the conventional cellular networks, the base station manager coordinates the MBSs in the core network and all the backhaul traffic is conveyed by the designated gateway to the core network. In the heterogeneous networks, SBS manager manages the SBSs and the traffic from backhaul forwarded to the core network. An overlap is resulted between the MBS and the SBS and the Handover of the MUs is also possible. Though the development of architectures of ultra-dense networks is not completely closed yet, there is no overlap between MBS and SBS in 5G ultra-dense networks [185]. MBS allows transmitting management data while the SBS handles the user traffic. Therefore, sleep mode strategies based on the cooperation between MBS and SBS may not be feasible in ultra-dense networks. Since the architecture design for ultra-dense network is continually evolving, a cooperative layer of MBS and SBS to foster sleep mode activation and handover can be designed in ongoing research in transitioning over the ultra-dense network.

7.0.2. Smaller cell size

Spatial base station densification comes with a relatively smaller cell size. To achieve provision of data rates in the order of 10 Gb/s according to the Mobile and wireless communications Enablers for Twenty-twenty Information Society (METIS) project objective by 2020, ultra-dense networks are acknowledged to be promising in delivering high capacity and data rate to meet the growing connected devices base [186]. With the transmission bandwidth required to meet this demand, efforts are devoted in the direction of harnessing the millimeter-wave band. However, the millimeter-wave communications range would be about 100 m radius due to the degradation in the atmosphere, which results in high density of spatial deployed SBSs and smaller cell size [185]. With the coverage reduction, cell zooming range of each SBS in ultra-dense should be anticipated. Sleep mode strategies relying on certain extents of zooming range from MBS and/or SBS to support the sleeping base stations may not be directly transferable to ultra-dense networks. Using multiple relays is one of the potential solutions adaptable from the conventional base station deployment. Strategic deployment of relays can be utilized for coverage support when a set of SBSs are put on sleep mode, as well as incorporated in the wake-up algorithm. CoMP based sleep mode technique is potentially adaptable as denser networks will not forestall cluster cooperation.

7.0.3. Traffic fluctuation

Network densification increases the spatial and temporal load fluctuations. The probability that a base station is not supporting any traffic or only low traffic is sometimes possible [187]. Therefore, it is imperative to put some base stations to sleep at low or no traffic loads. However, the high fluctuations of localized user traffic as well as the nature and the margin of traffic load variation will be different in ultra-dense networks [186]. For most sleep mode strategies, traffic load threshold dependents on to trigger of the activation of idle mode as well as wake-up mode. Temporal and spatial load variation in ultra-dense networks may be unpredictable as there are more spatially localized high data users. Some of these users can be moving leading to inefficiency in applying load threshold used to put the base stations to sleep in conventional networks. For traffic load threshold-based base station methods in ultra-dense networks, there may not be one-fits-all algorithms. Optimization algorithms with consideration of local traffic peculiarity and fluidity will be required when applying saving energy methods to ultra-dense networks [188].

7.0.4. Complexity issues

Most of the algorithms proposed attempt to solve an optimization problem aiming at maximizing certain quality of service while minimizing the power consumption at the base station. As efficient as they may seem, the densification of the base stations will increase the complexity if these algorithms were replicated in an ultra-dense network, if assuming they are feasible. For instance, the polynomial time algorithm, Sleep Mode with Dynamic Clustering (SMDC), represented in [132] can get more compounded with higher complexity in an ultra-dense network. The complexity gets higher with high number of cells and users [189]. Harnessing Cloud Radio Access Networks (CRAN) in multi-cell cooperation algorithms have a potential of reducing the complexity, as CRAN efficiently centralizes the computational resources [187].

8. Open issues and future works

This section represents some of the learnt lessons from exploring the area of energy efficiency. It also discusses the open issues and challenges facing the existing energy efficiency solutions and how to address them through a number of future research direction.

8.1. Learnt lessons

A number of key lessons can be learnt from the investigation of the energy efficiency solutions in ultra-dense networks, including:

1- 5G emerging technologies are expected to enhance the next generation of wireless communication network through a number of improvements in terms of energy efficiency, data rate, number of connected devices, latency, and capacity. 5G networks combine several advanced solutions to meet these expectations in such heterogeneous ultra-dense networks by balancing the trade-off between the energy efficiency and the network performance. Switching some base stations from sleep mode to wake up mode based on the traffic load conditions allows ensuring the network performance while saving energy, especially at off-peak traffic conditions. It allows serving UEs with coverage areas ensured by the remaining active base stations. Thus, one of the lessons learned from the energy efficiency solutions is the ability to serve several UEs with full coverage over the network area by only few active base stations with lower energy costs.

2- Although some energy efficiency solutions represent good results with high performance, they can also impact the network in terms of security, architecture, and cost. Thus, there is a need for adaptive and flexible solutions that can fit the right scenario in an energy-aware environment.

3- Multiple solutions can be combined to decrease the power consumption while achieving network performance.

4- Moreover, power consumption can be negligible as the expense of the gain resulted from the point of view of some deployment architectures or versus other metrics. An example refers to reducing the spectrum efficiency when enhancing the energy efficiency. Moreover, energy efficiency can be ensured when operating with low frequencies at the network backhaul.

5- Moreover, energy efficiency solutions allow measuring how greener is the network, which enables green communications over the 5G networks.

6- We can conclude that there is no one solution that can fit all 5G scenarios. We can also conclude that there is no unique set to achieve energy efficiency while meeting the other requirements for the 5G networks. Therefore, in addition to designing new and efficient customized solutions to ensure the next generation of wireless communication expectations, getting the best from the existing solutions already deployed in the network can be also considered while exploring new technologies.

8.2. Challenges

Some energy efficiency solutions are complex to implement, sensitive to interferences, and security concerns. Energy efficiency can be considered as the priority target for some wireless communication applications, and it is still facing several challenges to meet the 5G networks expectations. For instance, latency and throughput are priorities for video conferencing applications while energy efficiency is crucial for smart metering application as low-cost devices with long battery life. For massive MIMO based solution, pilot contamination impacts the energy efficiency as adjacent cells reuse the same pilot. The pilot resource contamination prevents saving energy in multi-cell scenarios, which requires finding a solution to balance the utilization of the time–frequency resource for uplink and downlink transmission. As future work, designing efficient pilot mitigation strategies with less complexity can be investigated to achieve high energy efficiency with massive MIMO based solutions.

For the heterogeneous network deployment-based solutions, the increase of the base station density is one of the challenges limiting the energy efficiency of the SBSs, which impacts the energy saving over the heterogeneous network. As a small cell network, heterogeneous network uses the coordinated multi-point to enhance the spectrum efficiency while reducing the inter site interferences. Thus, massive traffic is generated to ensure data sharing and coordination among small cells, which consumes more energy and bandwidth leading to network congestion and handover issues. Moreover, sharing the heterogeneous resources and the network infrastructure leads to severe vulnerabilities opening the door to security concerns. For SON based solutions, deploying SON to allow self-optimization of the network resources to save energy consumption. It can rapidly adapt to dynamic network and update its parameters. However, it is still facing some challenges related to its design, computational complexity, and cost. Designing and deploying efficient SON algorithms requires network element to operate, which results in increase in energy consumption. The implementation of most of the energy saving solutions is challenged by the compatibility and reference signaling requirements.

8.3. Future directions

Towards green communication networks, device to device communication can also be considered as one of the research opportunities to enhance the energy efficiency [190]. It allows measuring the devices capabilities to communicate while conserving energy by offloading the data traffic coming from the base stations [191]. With the green expectation of the 5G networks and beyond, energy harvesting is deserving more investigation to explore its capabilities at achieving high energy efficiency under the future scenarios of the wireless networks [192]. Towards energy transfer over the network, efficient energy harvesting techniques are required to recycle the energy by extracting and transferring renewable energies, thus, the energy can be harvested forever. Designing new hardware devices compatible with the energy requirement by the future wireless networks where devices can have extended battery life from alternative energy sources from the wireless communication. Elaborating research in cooperative small cell groups may help solving some of the issues facing the heterogeneous networks with small cell base stations for energy saving purposes. Examples of these issues include handover in small cell networks. Thus, designing and deploying energy efficient transmission strategies is required to ensure low energy consumption in the 5G networks.

Moreover, developing new network protocols to minimize the energy consumption is also an open research area to enhance the sleep mode solutions. For instance decreasing the network traffic volume allows increasing the sleep mode periods based on new protocols able to eliminate the control packets. Multiple solutions can be combined to decrease the power consumption while achieving network performance. Combining all the energy efficient solutions in one holistic solution can be also considered as an open research direction to be investigated. More research in this direction is required to investigate how a holistic solution can achieve high benefits to the network.

Artificial intelligence is one of the nominated solutions to solve the energy efficiency challenges by developing new and advanced learning models able to predict how much energy resources are required to operate a given task or service. It allows the devices to learn from past experiments and respond intelligently and deal with the randomness in the network. More research in this direction is required to investigate how artificial intelligence-based approaches can be applied for energy efficiency purposes. These approaches include deep learning, and reinforcement learning. Moreover, the artificial intelligence can be used to design and optimize the future architecture by considering varying traffic pattern for cost-efficient network. Dynamic energy resource allocation is also an interesting topic for researchers when applying artificial intelligence for prediction purposes at the edge devices. Edge artificial intelligence can be accomplished through federated learning models.

9. Conclusion

In this paper, we presented and categorized the different techniques for enabling sleep mode of the base stations in the 5G heterogeneous cellular networks with the ultimate goal of reducing the power consumption. We discussed the cost consequence of the increase of power consumption at cell sites as well as the effect on global carbon footprint. We reviewed the power consumption models, energy saving measurements, and performance evaluation metrics. We discussed and classified the different sleep mode techniques into different classes according to the nature of hardware, algorithms, or applications peculiar to each grouping of a varied number of techniques. The admission of the fact that the activation of a mode is as important as the deactivation from that mode informed the survey of wake-up schemes in putting a sleeping base station into active mode whenever its service is required. We also discussed the different wake-up schemes for energy efficiency purposes.

The ever-increasing demand for high data rates and densification of base stations necessitate the need to prepare towards the soonest ubiquity of ultra-dense networks. Thus, we discussed the possibilities of adapting the presented sleep mode enabling methods to ultra-dense networks. Energy saving is one of the primordial objectives of the future mobile networks, which still require more research efforts to design and develop effective solutions for energy saving while serving the increasing demand in energy utilization. As future directions, artificial intelligence is the future of the next generation of mobile networks, and it can be also an effective solution for energy saving. When the artificial intelligence meets the 6G networks, advanced and efficient solutions will be provided for energy efficiency.

CRediT authorship contribution statement

Fatima Salahdine: Conception and design of study, Acquisition of data, Analysis and/or interpretation of data, Writing – original draft, Writing – review & editing. **Johnson Opadere:** Conception and design of study, Acquisition of data, Analysis and/or interpretation of data, Writing – original draft, Writing – review & editing. **Qiang Liu:** Conception and design of study, Acquisition of data, Analysis and/or interpretation of data, Writing – original draft, Writing – review & editing. **Tao Han:** Conception and design of study, Acquisition of data, Analysis and/or interpretation of data, Writing – original draft, Writing – review & editing. **Ning Zhang:** Conception and design of study, Acquisition of data, Analysis and/or interpretation of data, Writing – original draft, Writing – review & editing. **Shaohua Wu:** Conception and design of study, Acquisition of data, Analysis and/or interpretation of data, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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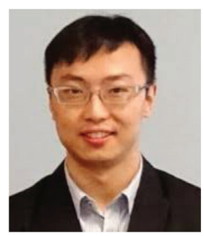

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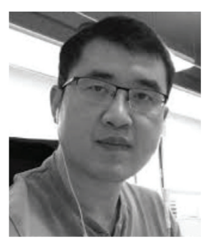

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