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Energy efficiency techniques in ultra-dense wireless heterogeneous networks: An overview and outlook

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ABSTRACT

In wireless heterogeneous networks (HetNets), the spatial densification through small cells and the application of massive MIMO antenna arrays are key enablers for high data throughput, wider coverage, and improved energy efficiency (EE). However, ultra-dense deployment of small cells is envisioned to exacerbate network management and increase energy consumption in HetNets. To this end, this paper first identifies the peculiarities that make energy consumption one of the challenging problems in wireless communication networks. Further to this, we categorize the EE techniques used in wireless HetNets and discuss various enabling strategies under each technique. Based on these categories, an overview of past works carried out on EE techniques in HetNets is provided with reference to their major contributions and key findings. This work also presents EE metrics used to gauge energy consumption rate and performance trade-off. Finally, the paper concludes by discussing promising future research directions in the area of EE in Ultra-dense HetNets.

Contents

1. Introduction

The recent surge in data intensive applications coupled with the proliferation of mobile smart devices have been identified as the prime contributors to the rapid growth of data traffic in wireless mobile networks. In order to satisfy the coverage and capacity

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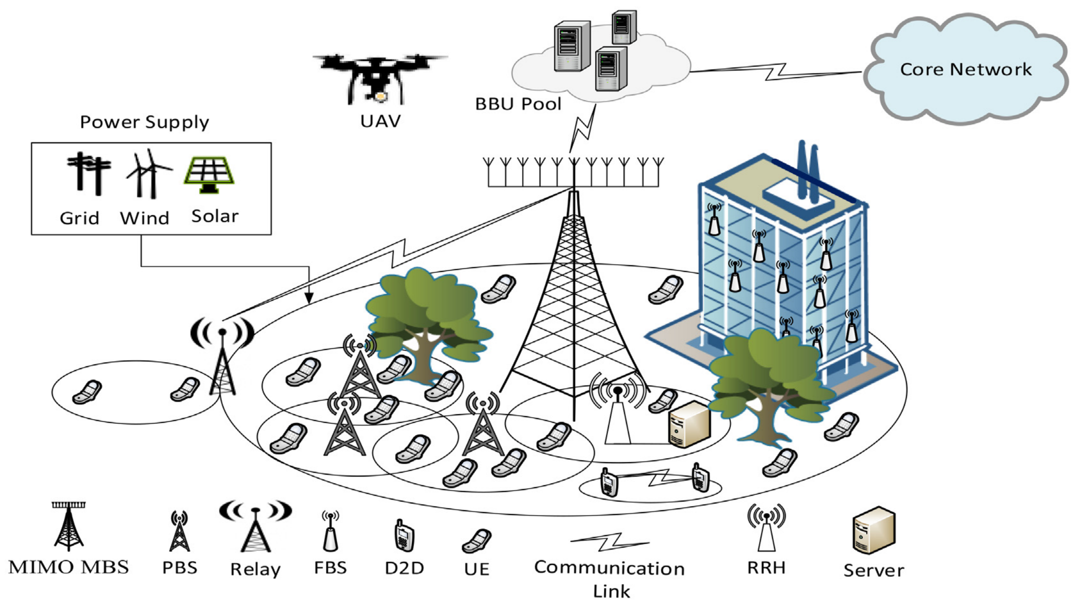

Fig. 1. Typical Next Generation Wireless Mobile Heterogeneous Networks.

demands from the ever-increasing growth of mobile network subscribers combined with the densification of macro base stations (MBS) approaching its theoretical limit, network operators are compelled to opt for varying degree of deployment of small cells [1–3]. Small cells comprise of microcell, picocell, femtocell and MBS remote access points such as remote radio heads (RRHs) and relays [4,5]. The network emerging from the mix of small cells overlaid by MBS is referred to as HetNets [6]. A typical illustration of HetNets is shown in Fig. 1. With the benefits of small cells such as low cost deployment, traffic offloading from MBS, improved indoor throughput, and low power consumption [7,8], also comes the drawbacks in terms of increased energy consumption and difficulties in network management. Though small cells consume low power but an ultra-dense deployment of them will increase energy consumption [9,10]. According to a report in [11], the estimated energy consumption bill incurred by mobile network operators constitute about 30% of OPEX. Also, the electrical national power grid being the most reliable energy source for powering BSs are being energized by methods that produce CO_2 emissions [12]. Hence, maintaining a viable business environment and healthy ecosystem has become a growing economic and ecological concern in wireless mobile networks [13]. Table 1 presents the list of Acronyms used throughout this review.

From economic standpoint, the spatial densification of small cell BSs (SBSs) in HetNets brings about complexities in network management since the SBSs are expected to be deployed in adhoc manner [14,15]. In ultra-dense networks, unplanned deployment of small cells increases network interference level and energy consumption, hence degrading the EE of the network [16,17]. Thus, the cost incurred on energy consumption bills and difficulty in managing small cells coupled with the use of centralized network controllers are the major causes of skyrocketing CAPEX and OPEX in HetNets [18].

From ecological perspective, the greenhouse gas (GHG) emissions in which CO_2 contribute the largest share has been identified as the cause of global warming [19,20]. The ICT industry contributes 2% to global CO_2 emission and it is anticipated to rise to 4% by the year 2020 [21] and it could reach up to 14% by the year 2040 [22]. In the ICT industry, the contribution of CO_2 by wireless mobile network sector ranges from 15% – 20% [23], and the

Table 1
List of Acronyms.

Abbreviation	Full Meaning
5G	Fifth Generation Cellular Networks
ABS	Absolute Blank Sub-frame
BBU	Base Band Unit
BS	Base Station
CAPEX	Capital Expenditure
CO_2	Carbon dioxide
CRAN	Cloud Radio Access Network
CRE	Cell Range Expansion
CSI	Channel State Information
EE	Energy Efficiency
GHG	Greenhouse Gas
HetNet	Heterogeneous Network
LoS	Line of Sight
MEC	Mobile Edge Computing
MRC	Maximum Ratio Combining
MRT	Maximum Ratio Transmission
MBS	Macro Base Station
MIMO	Multiple Input Multiple Output
mMIMO	massive MIMO
MMSE	Minimum Mean Square Error
mmWave	Millimeter Waves
MUE	Macrocell User Equipment
NLoS	Non-Line of Sight
NOMA	Non-Orthogonal Multiple Access
OFDMA	Orthogonal Frequency Division Multiple Access
OMA	Orthogonal Multiple Access
OPEX	Operational Expenditure
PCP	Poisson Cluster Process
PD-NOMA	Power Domain NOMA
PPP	Poisson Point Process
QoS	Quality of Service
RAN	Radio Access Network
RF	Radio Frequency
SBS	Small Cell Base Station
SD-CRAN	Software Defined Cloud Radio Access Network
SE	Spectral Efficiency
SIC	Successive Interference Cancellation
SINR	Signal to Interference Plus Noise Ratio
SON	Self-Organizing networks
SUE	Small Cell User Equipment
TDMA	Time Division Multiple Access
UAV	Unmanned Aerial Vehicle
UD-HetNet	Ultra-Dense HetNet
UE	User Equipment
ZF	Zeroforcing

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contribution is expected to rise to 51% by year 2020 [24]. This emission is anticipated to further increase every year if preventive measures are not established [25]. The current policies to checkmate the rising earth's temperature due to GHG emission has been able to slightly achieve an average reduction from approximately 65 $GtCO_2e$ to 58 $GtCO_2e$ and it is expected to further reduce to 26 $GtCO_2e$ by year 2030 [26].

Motivated by these challenges, EE has become a major factor considered in the cellular design phase of next generation wireless communication systems [27]. Therefore, from wireless mobile network perspective, researchers both in academia and industry would strive to achieve sustainable market growth with affordable and high quality of service (QoS) and ecofriendly environment.

The rest of this paper is organized as follows: Overview of EE techniques and various optimization tools for energy-efficient design are presented in section 2. Section 3 describes the energy consumption model of a communication link. Research directions are delineated in section 4. Finally, conclusions are drawn in section 5. Table 1 presents the list of acronyms used throughout this review.

2. Overview of energy efficiency techniques

In recent years, EE has become a hot topic in the field of wireless mobile networks due to huge energy consumption bill and large contribution of CO_2 to global carbon footprint from the BSs [28,29]. Various techniques for energy-efficient network design have been proposed in the literature for wireless mobile network operations. Most of these techniques focus on EE of BS since the BS is responsible for 60% to 80% of the total energy consumption in the wireless mobile network [30–32]. The authors in [33] classified the EE techniques under five categories most of which overlap with the classifications identified in [34] and [35]. These techniques are summarized under the following five categories;

1. Network Planning and Deployment
2. Optimization of Radio Transmission Process
3. Base Station Sleeping Strategy
4. Hardware Solution
5. Energy Harvesting and Transfer

It is noteworthy that each technique has its own benefits and drawbacks. While some methods have been solely considered, several hybrid methods have been proposed where the features of two or more techniques are merged to further optimize the EE of the network. The layout of these techniques are presented in Fig. 2. In this work, it is assumed that Base station (BS) represents both the MBS and SBS. Also, small cell and small cell base station (SBS) are used interchangeably.

2.1. Network planning and deployment

Energy-efficient planning and deployment of cellular networks could be described from the viewpoint of planning of BS deployment and well known techniques used in HetNets. These approaches are discussed under the following headings;

Optimization of BS Density: A critical factor considered in the planning phase of mobile cellular networks is the mapping out of network coverage area of interest [36]. Once the coverage area is ascertained, the number of BSs required to deliver certain level of QoS can be estimated [37,38]. Compared to the planning and estimation process inhomogeneous networks [39,40], the case in dense HetNet could be more complex owing to the unplanned manner of SBS deployment [41,42]. Towards developing simplified and realistic frameworks for planning and derivation of optimal BSs density in HetNets, different solution methods such as metaheuristic approach [43], greedy based algorithm [44] and stochastic geometry [32,45] have been explored and found to be useful.

The metaheuristic approach presented in [43] focuses on the application of particle swarm optimization (PSO) and grey wolf optimization (GWO) methods. Utilities based on data rate and coverage constraints are formulated and incorporated in the proposed PSO and GWO algorithms in order to generate optimal global population. The population representing the number of BSs is further reduced by shutting down redundant BSs while an additional energy saving scheme based on day-night traffic profile is introduced to enhance the process. However, the application of the proposed solutions may not be applicable in UD-HetNet due to uniform distribution of SBSs considered. For the greedy based algorithm proposed in [44], the SBSs under different topologies are added to the set of BSs until the condition for average spectral efficiency is fulfilled. A Lagrangian-based distributed algorithm is later proposed to deactivate redundant BSs during off-peak traffic period. Though the BS distribution topology is extended to random topology which is more preferable in UD-HetNet, the analytical basis for the topology is not explicit. Motivated by the limitations experienced in designing a practical and detailed analysis of adhoc BS planning and deployment led to introduction of stochastic geometry. Zhou et al. [45] applied Poisson distribution process for modeling UE distribution in order to generate different traffic patterns. From these patterns, statistical traffic models are developed. Based on these models, a heuristic algorithm is developed to verify the state of BS and its associated UEs. Depending on the type of traffic distribution selected whether uniform, random or cluster, the total active BSs for different patterns are estimated and reported via a central controller which is taken as the optimal number of BS to be deployed. But the use of centralized processing scheme as highlighted in [44] may affect the network scalability of the proposed design due to high signaling overhead. In another related design, Alkan [46], propose that the planning of SBS deployment should be in line with the reported signal strength of MUE pilot channels. The areas where signal strength from pilot channels of MBSs are below certain threshold are considered for SBS deployment following Poisson point distribution process. Although, details on pilot channel information processing is not discussed which is key due to challenges of false information as a result of pilot contamination.

Table 2 provides additional features to characterize the performance of different approaches of the identified contributions. Hence, it can be inferred that a practical BS optimization approach for planning energy-efficient UD-HetNet must consider certain critical requirements such as minimum required QoS, appropriate analytical model for various topologies, the traffic dynamics and algorithm implementation.

HetNet Deployment: In HetNet, network EE is improved due to short transmission distance between the SBSs and UEs. Fortunately, mmWaves support this attribute, thus enhancing spatial densification of SBSs and spectrum densification through massive MIMO (mMIMO) [47–49]. Furthermore, reducing the distance between the core network and edge devices by migrating signal processing and content delivery from cloud to edge devices otherwise known as edge computing, could also yield significant energy saving [50]. These approaches are discussed under the following headings:

a) Ultra-Dense (UD) BSs: In UD-HetNet, EE and spectrum efficiency (SE) are expected to increase to a certain limit, but further increase in BS density beyond a maximum number will degrade the network EE and SE [51,52].The fundamental question here is; to what extent should a network be densified to improve EE without violating the SE? And how can the EE and SE be jointly optimized? To answer these questions, analytical tools such as

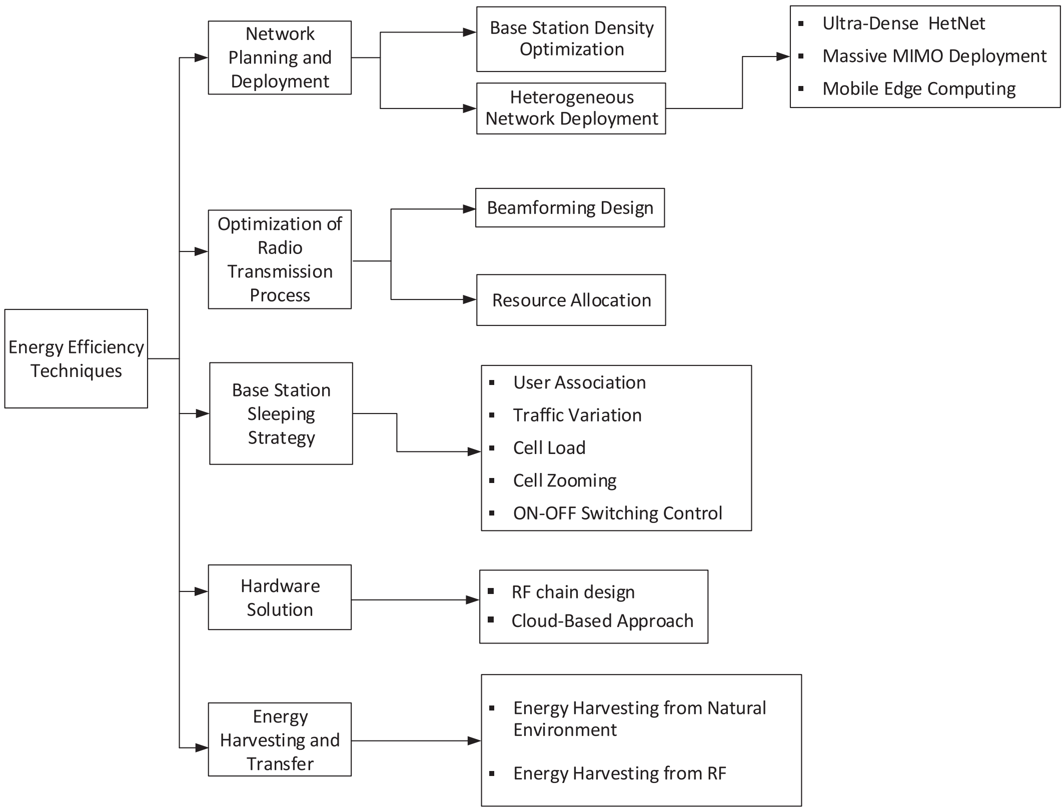

Fig. 2. Energy Efficiency Techniques in Wireless Mobile Networks.

Table 2
Comparative Summary of BS Optimization Techniques.

Ref.	HetNet	Topology	Analytical Model	QoS Provision	Algorithm Implementation	Traffic Profile	Performance Metrics
[39]	–	Manhattan, Hexagonal and Poisson	Combinatorial Geometry andStochastic Geometry	✓	–	Mixed	Load level, Power consumption, and Energy saving
[40]	–	Hexagonal	Stochastic	–	Centralized	Dynamic	EE
[43]	✓	Hexagonal	Metaheuristic	✓	Centralized	Dynamic	Coverage probability
[44]	✓	Hexagonal and Poisson	Greedy based method and Lagrangian constrained algorithm	✓	Centralized and Distributed	Fixed	Average spectral efficiency and Energy consumption
[45]	✓	Poisson	Stochastic and Heuristic	✓	Centralized	Mixed	Number of served UEs and EE
[46]	✓	Hexagonal and Poisson	Combinatorial Geometry andStochastic Geometry	–	Centralized	Fixed	EE and Area spectral efficiency.

Poison Point Process (PPP) have been used to formulate parameters needed to develop frameworks for characterizing the network EE and SE [53–55]. These parameters can be summarized under coverage probability and association probability. According to the authors in [53], the traffic load of each network tier can be estimated from coverage and user association probability in order to calculate the minimum achievable throughput. Based on this idea, the authors develop a closed-form expression needed to establish global EE model but the aspect of SE is not addressed. In [54], both EE and SE are addressed but only the effect of SBS density on EE is captured in their results. The SE is rather measured against SINR which does not give the clear picture of the effect of SBS density on SE. On the other hand, their findings validate the fact that EE is bound at certain density of SBSs due to interference caused by adjacent cells. In another similar work [55], the authors propose a joint optimization of SE and EE. Also, the performance of EE and SE is not evaluated based on SBS density. These limitations are addressed in the work presented in [56], where a heuristic procedure is developed based on firefly algorithm to jointly optimize area SE and EE. Results obtained indicate that at a certain number of SBS the EE starts to decrease due to cumulative effect of circuit power consumption while the SE continues to increase. However, SE also start to diminish at certain point mainly because of interference. The limitations caused by interference in deriving optimal EE and SE is investigated in [51] using cooperative game approach. Though the effect of SBS density on optimal trade-off between EE and SE is presented, the analytical model to derive SBS distribution is not carried out. Rather, a simulation based approach is used. It is noteworthy that the use of PPP may not accurately give a clear picture of BS distributions in UD-HetNet since SBS clustering is expected hence, making Poisson Cluster Process (PCP) a preferable approach [57–59]. The PCP approach for energy-efficient network design is yet to receive significant attention in literature. Nevertheless, the concept has been introduced in [60] where a variant of PCP known as Matern cluster process is used to develop the expressions for spectrum efficiency and power consumption minimization problem. The power consumption problem is solved by minimizing the cooperative radius of the cluster. With the PCP model, result obtained shows that the received interference by UEs in a cluster is larger than that of PPP model due to close proximity of BSs.

The general observations from these investigations indicate that EE limit in HetNet is as a result of rise in inter-tier and intra-tier interference due to increase in BSs density. Since both EE and SE are tightly coupled, it is important that when considering the EE objective in dense network, the SE of such network must be constrained within a tolerable value.

b) Massive MIMO Deployment: Even though EE achieved via BS densification is limited due to interference from adjacent BSs, this limit can be exceeded via mMIMO deployment [61]. In mMIMO systems, interference, fading, and noise power diminish with increasing array of antennas, thus, enabling both BSs and UEs to transmit at lower power without compromising QoS [62–64]. Therefore, mMIMO is a promising technique for improving both the EE and SE in wireless communication systems [65]. For a practical energy-efficient mMIMO design, it is very crucial to consider the power consumption in the RF unit and the computation power which scales with increasing number of antenna arrays [66,67]. The quest to reduce energy consumption in the RF unit, its hardware complexities, beamforming accuracy and financial cost constitute the basis for replacing digital and analog precoders with hybrid precoders [68–70]. An illustration of digital and analog precoders is depicted in Fig. 3a and 3b, respectively. Major types of hybrid precoder structures used in mMIMO systems can be classified under fully-connected hybrid precoder or partially-connected Hybrid Precoder as shown in of Fig. 3c and 3d, respectively [71]. Generally, hybrid precoders operate with lesser number of RF units, which are connected to each antenna via simple phase shifters [72,73]. Moreover, due to the growing number of phase shifters in large-scale mMIMO networks, the problem of hardware complexities and increased energy consumption resurface in fully-connected hybrid structures. Hence, the rationale for preferring partially-connected structure for energy-efficient design [74,75]. With focus on EE design of partially-connected structure, Gao et al., [74] propose a low-complexity algorithm for successive interference cancellation (SIC) based on premise of complexities associated with singular value decomposition (SVD) and matrix inversion approach. The optimal precoding vectors used as input into the algorithm are derived by maximizing the sub-rate of each sub-antenna array. Similar to the work presented in [74], the authors in [75] establish that low-complexity SIC algorithm can be achieved via partial SVD using Givens transformation, a method used to ease the derivation of orthogonal matrix. The EE performance of these precoding schemes are presented in [76] for comparison and it is observed that EE of partially-connected hybrid precoder outperforms its fully-connected hybrid counterpart. Nonetheless, the SE of fully-connected hybrid precoder is higher than that of the partially-connected structure due to higher beamforming gain which also agrees with the findings reported in [74,75]. Contributions from [77] shows that EE of hybrid precoders can be improved by replacing phase shifters in the analog unit with phase over-samplers (POS) and switches. Depending on the number of information streams from digital precoder unit, a POS unit produces multiple parallel streams of signal with different phases from a single input while network of switches is required to feed the antennas with the proper phase. Performance evaluation shows that the proposed design outperforms both the digital precoding and phase shifting-based hybrid precoder in terms of EE due to reduced hardware complexities of POS and switching network. But it is observed that the SE of the proposed design is slightly lower than in digital precoding and phase shifting-based hybrid precoders. Special contributions from [78] and [79] indicate that dynamic and adaptive operation of hybrid precoders can further improve EE due to optimal configuration of the precoding components. For instance, authors in [78] propose the inclusion of an adaptive circuit between the RF unit and phase shifters of a

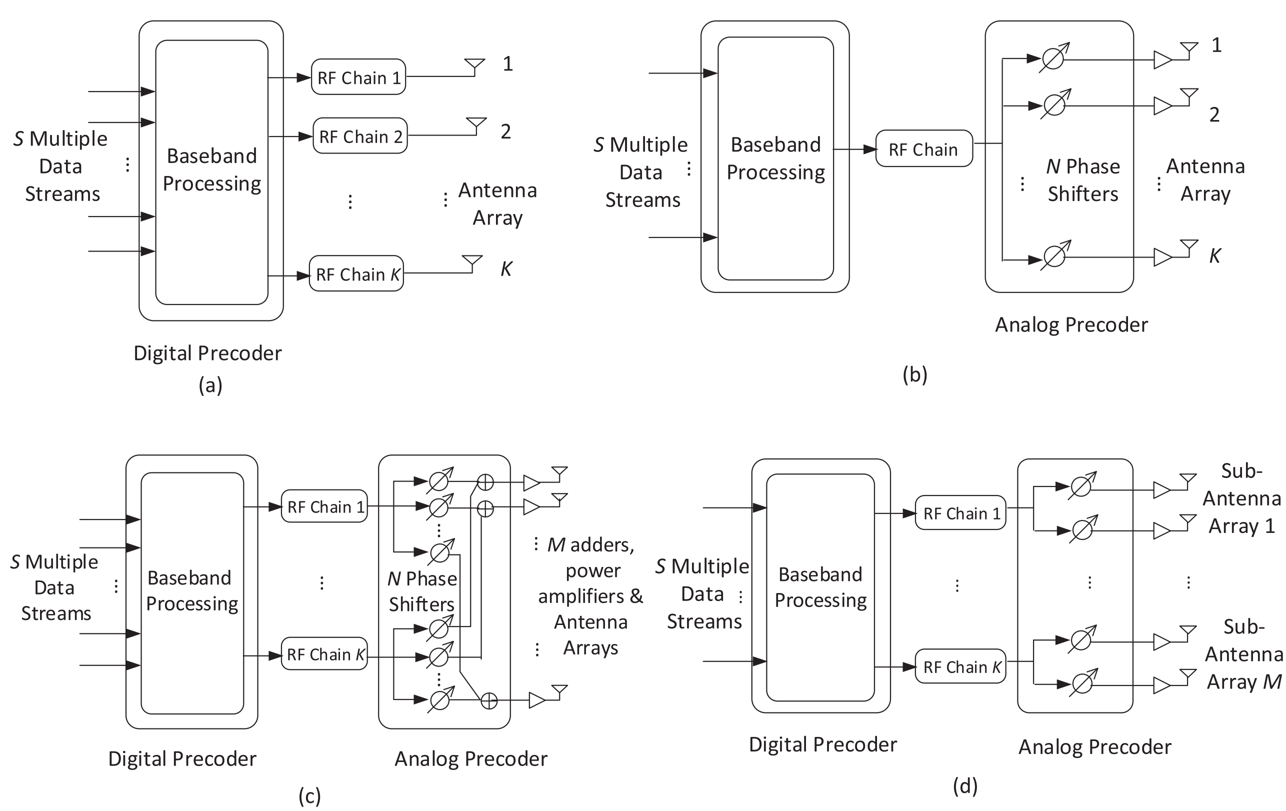

Fig. 3. Precoders for mMIMO Systems (a) Digital precoder with dedicated RF unit per antenna (b) Analog precoder with single RF unit connected to multiple antennas via phase shifters (c) Fully-connected hybrid precoder (d) Partially-connected hybrid precoder.

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fully-connected hybrid structure thereby eliminating the need for independent adder unit in the precoder structure. The adaptive unit dynamically matches the phase shifters of each antenna to a single RF unit. Surprisingly, the EE performance of the structure is not discussed. Zheng et al. [79] propose the adaptive activation of RF chains for a given MIMO configuration and channel condition. For a large-scale antenna system, they observe via a closed-form expression that at high SNR region, the number of RF unit that will maximize EE of the proposed structure can be estimated in order to indicate the EE limit.

From these contributions, it can be deduced that in designing energy-efficient hybrid precoders, the hardware complexities especially the RF chains configuration and the component of analog unit, and SE are critical factors that must be considered since the energy consumption rate and data throughput of a BS largely depend on them.

c) Mobile Edge Computing (MEC): MEC technology enables cloud computing to be performed locally at the edge network [80], that is, among the BSs and UEs, thus, eliminating the need for centralized processing in the core network. Bringing network contents closer to the UEs reduces latency in service delivery and offers low computational complexity by efficiently offloading the computational processes from the core network [81]. These features supports the internet of things (IoT) networks and augmented application deployment due to limited battery life of mobile smart devices [82,83]. In conventional MEC system, EE is usually addressed from the perspective of computation offloading [84–87], but with the introduction of caching in MEC technology, significant gain in EE can be further achieved [88]. In [84], a multi-user computation offloading game is proposed where UEs can decide whether to select local or cloud computing option depending on the interference level in the network. The expression for computation overhead is formulated as a function of energy consumption and processing time. Their findings show that at high interference level, UEs consume more energy under cloud computation offloading strategy and also experience high latency in processing time. Hence, UEs prefer to select the local computation offloading under severe interference which amounts to low energy consumption and short processing time. In another similar contribution [85], the authors propose energy-efficient offloading strategies that would minimize the energy consumption problem. To achieve this, they group UEs into three classes based on the type of selected computation strategies. The first group of UEs choose MEC server to carry out the computation task when local computing time is higher than maximum time required to perform a computation task. The second group carry out their computation task on local devices when local computation time is less than the maximum time required to perform a computation task and with energy consumed during the process is less than minimum energy consumption required. The third group dynamically choose between MEC server or local computation depending on wireless channel states. Afterwards, iterative algorithms to perform the grouping function, optimal resource allocation and offloading strategies are developed. Though the results obtained in [84] and [85] validate the fact that energy consumption can be reduced through optimal computation offloading strategies, but the EE quantification problem is not explicitly addressed in their works. This limitation is addressed in [87] where a joint optimization problem for energy-efficient computation offloading is formulated. To solve the problem, they develop an iterative technique based on gradient descent method. According to the trade-off study between local computing and data offloading to the server, their findings reveal that local computation is more effective to use when data size is small; otherwise offloading to server is preferable.

The impact of caching on energy-efficient MEC architecture can be found in [89] and [90]. In [89], the efficiency of joint combination of cooperative caching and coded caching for minimizing energy consumption is investigated. While the coded caching addresses the encoding and placement of cached files in SBSs, the cooperative caching, achieved from SBS clustering ensures effective and fast delivery of the cached files to UEs by selecting the shortest route for data transfer. The energy consumption minimization problem is solved by Greedy based algorithm. In [90], the application of task caching and task offloading to enhance the performance of virtual reality application is proposed. The main objective of their investigation is to reduce energy consumption of mobile devices while satisfying the minimum time required to accomplish a task. They develop a linear iterative algorithm which decides whether the task caching or offloading is to be performed locally on UE or at the edge cloud. The decision variable is expressed as a binary variable but the physical parameters that constitute the decision variable are not defined.

2.2. Optimization of radio transmission processes

Optimizing radio transmission parameters to improve signal transmission pattern, resource allocation, network coverage, and interference reduction has proven to be cost effective in energy-efficient network design, since hardware replacement may not be necessarily required. These schemes are discussed in the following:

Beamforming Design: In MIMO HetNet, steering and detection of transmitted signals in the direction of the desired users otherwise known as beamforming is an effective method to suppress both the cross-tier and co-tier interference [91,92]. Since interference in wireless networks have a degrading effect on the EE of a network [93,94], beamforming strategy is a potential technique for improving the EE of a network. Beamforming process largely depends on the type of RF precoding units. Intuitively, precoding and beamforming are synonymous. But in beamforming context, emphasis is more directed towards signal processing schemes rather than the RF hardware architecture. These schemes include linear and non-linear beamforming techniques. Well known linear beamforming techniques are; maximum ratio combining or transmission (MRC/MRT), zeroforcing (ZF) and minimum mean square error (MMSE) while non-linear beamforming comprise of dirty paper coding (DPC), vector perturbation and lattice-aided techniques [95,96]. However, linear beamforming schemes are preferred due to their low computational complexities compared to the non-linear schemes. Application of ZF and DPC for energy-efficient design in multi-user MIMO system is discussed in [97] where centralized and decentralized solutions for cooperative beamforming are proposed. The decentralized solution is proposed in order to enhance the scalability of the system. DPC is adopted as the transmission strategy in the downlink while ZF is employed in the uplink but the EE performance of DPC is not discussed. Rather than focusing on MIMO system, the application of ZF in downlink of mMIMO system for signal processing is presented in [98]. Their work further suggests that the complexities associated with centralized signal processing can be reduced by the application of the firefly algorithm. The limitation observed in the studies presented in [97] and [98] is that the performance application of other beamforming schemes are not presented for comparison. This drawback is addressed in [66] where the EE performance of MRC, ZF and MMSE schemes under mMIMO design is presented. The findings of the work show that EE in ZF scheme outperforms MRC and MMSE due to its interference suppression feature, and low computational complexities. Though MRC offers lower computational complexities than ZF, the EE under MRC scheme is poor because it does not account for interference and noise factor. In MMSE, both interference and noise are suppressed enabling it to outperform ZF. However, the EE of MMSE is poor due to high signaling overhead. These factors may justify the reason why ZF is widely used in energy-efficient beamforming design.

Resource Allocation: Effective allocation of network resources such as subcarrier and transmission power are fundamental determinants for network performance. Since EE has become a critical metric for gauging the performance of wireless communication system, researchers' interests have been drawn to the area of energy-efficient resource allocation. For any resource allocation strategy, it is important to accentuate the issue of fairness. As reported in [31], the authors stressed that unfair resource allocation will further degrade the EE of UEs with poor channel conditions. This may be more pronounced in overlay spectrum access scenario where the bandwidth portion allocated to SBSs may be insufficient. For instance, the studies presented in [99], which focuses on EE of HetNet with overlay and underlay access scheme is prone to such limitations. Details on overlay and underlay spectrum access are discussed in [100]. Towards achieving energy-efficient fair resource allocation, the concept of boundary allocation is introduced in [31] where UEs with similar channel condition are grouped with the purpose of identifying and compensating worst group. In [101], upper and lower bound EE maximization problem is formulated under absolute blank subframe (ABS) scheme. The lower bound guarantees minimum achievable QoS for worst served UEs.

Another enabling technique used to enhance energy-efficient resource allocation in HetNet is the soft frequency reuse (SFR). The SFR is proposed to suppress inter-cell interference at the cell edge region in order to improve the SINR of UEs at the edge region [102]. In SFR scheme, each cell is divided into two regions; the cell edge region and cell center region. These regions are assigned an exclusive portion of the total cell bandwidth and different levels of transmit power in order to satisfy minimum data rate requirement [103]. The SFR operates in such a way that the sub-band of the edge region of a cell is orthogonal to any adjacent cell in order to avoid severe interference [104]. The energy saving potentials of SFR emanates from the BSs being able to reduce their transmission power due to optimal power allocation according to traffic condition in each region coupled with interference reduction at the cell edge region [105]. Contributions on energy-efficient network design using SFR scheme can be found in [106] and [107]. In [106], the global network EE optimization problem is investigated. To achieve this, the authors formulate a joint expression for optimal transmission power and sub-carrier allocation using Lagrangian multipliers with Karush-Kuhn-Tucker (KKT) condition. They further propose heuristic algorithm based on simulated annealing in order to reduce the latency and computational complexities of the expressions derived from Lagrangian functions. In [107], successive convex approximation approach is used to develop the algorithm for optimal power and subcarrier allocation. The Lagrangian multipliers with KKT condition is later introduced in the inner loop of the algorithm to further relax the power allocation function. However, they did not consider the joint optimization of power allocation and subcarrier allocation as demonstrated in [106].

A major setback identified in the SFR scheme is the limited reuse of spectrum [108]. This challenge led to the modification of SFR scheme where each cell is divided into regions more than two. This modified SFR scheme is known as the multi-layer frequency reuse (MSFR) and it has the capacity to enhance the SINR of UEs of the intermediate regions while maintaining suitable channel conditions for UEs at the edge regions [109]. Unfortunately, energy-efficient network design using this scheme is still lacking in the literature.

Nevertheless, in this study on energy-efficient resource allocation, more emphasis will be placed on transmission power allocation being a major parameter that determines the dynamic power consumption of BSs. Transmission power could be allocated optimally to different transmit streams such that channels with large gain are allocated higher power while UEs with poor channels are allocated lesser power. In this situation, UEs with worst channel condition suffers poor QoS. From another perspective, minimum throughput constraint can be set for all UEs in order to achieve fairness. A lot of work on power allocation strategies for energy-efficient network design have been report under Orthogonal multiple access (OMA) technology [99,110,119,111–118] and Non-Orthogonal multiple access (NOMA) technology [120–126]. Unfortunately, due to the exponential growth of UEs, OMA has limitation to numbers of UEs that can be scheduled simultaneously on different orthogonal resources [127]. For this reason, NOMA is gaining considerable research attention owing to its massive connectivity support, high spectral efficiency, improved cell edge throughput and low latency [128,129]. With NOMA schemes which is broadly categorized under power domain (PD-NOMA) and code domain (CD-NOMA), it is possible to concurrently serve multiple users within the same cell using the same time and frequency resources [130,131]. Fig. 4 shows an illustration of resource allocation technique in OMA and NOMA systems. Nonetheless, the power domain NOMA is more relevant in EE network design since UEs are multiplexed based on different power level and with their receiver capable of eliminating inter-user interference using SIC

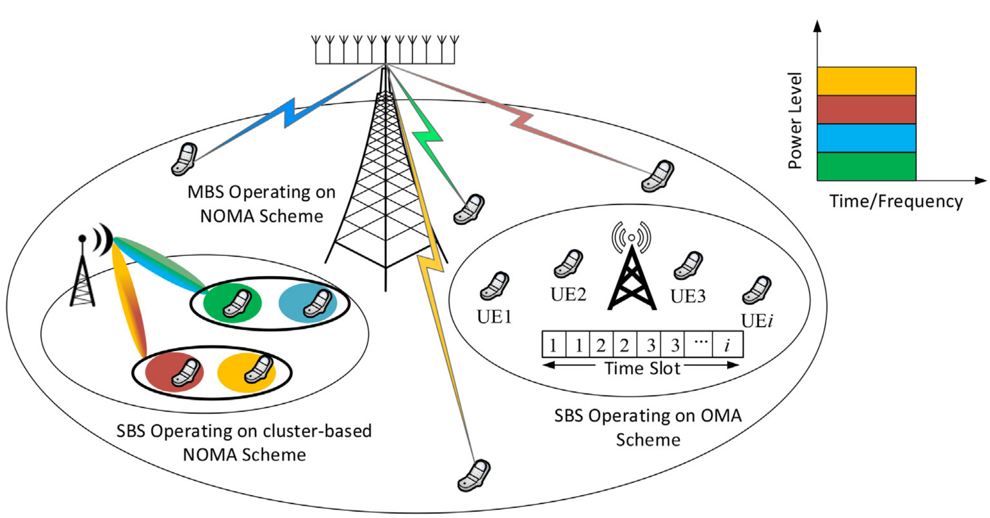

Fig. 4. Resource Allocation in OMA and NOMA Networks.

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Table 3
Comparative analysis of energy-efficient power allocation techniques.

Ref.	Objective	Cell Scenario	SBS Distribution	Channel Direction	Access Domain	CSI	UE Clustering	Problem Type	Solution Method
[110]	Joint EE and SE maximization	MC-MU	Random	Uplink	OFDMA	Perfect	–	Multi-Objective Optimization problem	Weighted sum method for transforming multi-objective problem into single objective problem, then solved iteratively using combination of Dinkelbach method and Lagrangian dual decomposition.
[111]	EE maximization	MC-MU	Random	Uplink	OFDMA	Perfect	–	Debreu game approach in which UEs are the players	Obtaining Debreu equilibrium point by incorporating water-filling and Dinkelbach iterative technique.
[112]	EE maximization	MC-MU	Uniform	Downlink	OFDMA	–	–	Mixed combinatorial and non– convex optimization problem	Gradient iterative technique
[113]	Co-channel interference mitigation and EE maximization	MC-MU	Uniform	Downlink	OFDMA	–	–	Non-cooperative game in which BSs are the players	No-regret learning algorithm
[114]	Interference mitigation and EE maximization	MC-MU	Random	Downlink	–	–	–	Stackelberg game in which BSs are the players	Obtaining Nash equilibrium point by incorporating Dinkelbach iterative technique with KKT conditions
[99]	Comparative study of EE maximization of underlay and overlay spectrum access	MC-MU	Uniform	Downlink	OFDMA	–	–	Mixed combinatorial and nonconvex optimization problem	Successive convex approximation and gradient search method
[115]	EE maximization in the backhaul network	MC-MU	Uniform	Downlink	OFDMA	Perfect	–	Non-convex nonlinear programming problem	Gradient assisted binary search approach
[116]	Average EE and Average SINR maximization	MC-MU	Uniform	Downlink	–	–	–	Transmission power optimization problem	Gradient iterative technique
[117]	EE maximization	MC-MU	Uniform	Downlink	TDMA	Perfect	–	Non-convex optimization problem	Bisection algorithm
[118]	Interference Coordination and EE maximization	MC-MU	–	Downlink	OFDMA	–	–	Stackelberg game in which BSs are the players	Obtaining Nash equilibrium point by incorporating Lagrangian iterative technique with KKT conditions
[119]	Comparative study between power consumption minimization and EE maximization	MC-MU	Random	Downlink	TDMA	–	–	Multi objective problem	Lagrangian multipliers and Sub-gradient method
[120]	EE maximization	MC-MU	Uniform	Downlink	PD-NOMA	Perfect	–	Mixed integer nonconvex optimization problem	Lagrangian dual decomposition for deriving closed-form expression
[121]	EE maximization	MC-MU	–	Downlink	PD-NOMA	–	–	Stackelberg game in which BSs are the players	Obtaining Nash equilibrium point by incorporating Lagrangian multipliers with KKT conditions
[122]	EE maximization and UE admission maximization	SC-MU	–	Downlink	PD-NOMA	–	Multiple UE per Cluster	Non-convex optimization problem	Water filling algorithm
[123]	Analysis of trade-off between data rate and energy consumption	MC-MU	Random	Downlink	PD-NOMA	Perfect and Imperfect	–	Non-convex combinatorial optimization problem	Fractional transmit power allocation
[124]	EE maximization and analysis of trade-off between throughput and energy saving	MC-MU	Random	Downlink	PD-NOMA	Perfect	–	Mixed integer nonconvex optimization problem	Lagrangian dual decomposition for deriving closed-form expression
[125]	EE maximization and derivation of trade-off between power consumption and sum rate	MC-MU	Random	Downlink	PD-NOMA	Imperfect	–	Probabilistic non-convex problem	Gradient-based bisection search algorithm and Lagrangian multipliers
[126]	EE maximization	SC-MU	–	Uplink	PD-NOMA	Perfect	Multiple UE per Cluster	Non-convex optimization problem	Gradient search method

MC-MU - Multi-Cell Multi UE **SC-MU** - Single-Cell Multi-UE **CSI –** Channel State Information.

[132]. Table 3 presents a comparative analysis of various works identified on energy-efficient power allocation.

2.3. Sleep mode/ON-OFF techniques

Techniques based on switching off BSs during low traffic period have received a lot of attention in recent works since much energy can be saved by completely turning off a BS. Depicted in Fig. 5 is a typical network scenario where base station sleeping technique is adopted. The MBS can as well reduce its transmission power and be eventually turned off when all small cells are inactive. Some of the notable approaches for enabling BS sleeping operations are discussed in the following paragraphs with other performance indicators presented in Table 4.

User Association: Associating UEs with a particular BS enhances the BS sleep mode technique in HetNet because with effective UE-BS association, lightly loaded BSs can be identified and turned off. A typical UE will connect to a BS with strongest Reference Signal Received Power (RSRP). For effective UE association in HetNet, cell range expansion (CRE) feature of SBSs also known as biasing is one of the commonly used technique to achieve this purpose [133–135]. Furthermore, in ultra-dense HetNet, investigations on CRE has shown that it can be used to minimize frequent and unnecessary handovers experienced by fast moving users thus enhancing the UE association process [136,137]. However, due to the higher transmission power of MBS, UEs may still prefer to connect to MBS if the CRE process is uncoordinated. To address this challenge, a dedicated sub-frame in the ABS scheme could be assigned for SBS operation [138], or the MBS transmission power on a sub-frame can be constrained to a lower value in order to lessen its interference effect [139]. To improve on these solutions, further contributions in this direction have considered factors such as random distribution of BSs and UEs [140], effect of LoS and NLoS propagation [141], traffic awareness [142], mobility of UEs and handover [143], throughput latency [144], and fair resource allocation [145].

Traffic Variation: Traffic pattern of UEs can be modeled in order to predict the best period to deactivate BSs during certain hours of the day. But periodic on–off triggering action may not be desirable in case of sudden outage of BSs during peak period. Hence, the use dynamic traffic strategy which takes into account the fluctuating activities of UEs such as UE velocity is more relevant for practical network design [146]. Applications of dynamic traffic model for energy-efficient design is demonstrated in [147] using queuing theoretic model, in [116] using Markov decision process, and in [148] based on principle of genetic algorithm.

Cell zooming: In a ultra-dense HetNets, deactivation of BSs using dynamic traffic profile may increase energy consumption in the network due to higher interference level as a result of over-provisioning from neighboring BSs [149]. But with cell zooming approach, a BS in HetNet can adaptively adjust its transmission power and consequently vary its cell size according to traffic fluctuations [150,151]. Depending on the design objective, the transmission power can be increased for effective UE association in order to shut down lightly loaded cells while maintaining coverage [152]. Alternatively, the transmission power may be reduced in order to lower the interference level in the network [153]. Another instance is when the transmission power is reduced according to the mobility pattern of UEs in order to reduce energy consumption [154].

Cell Load: Before switching off a BS, it is necessary to consider the load level of its neighboring cells otherwise UEs transferred from sleeping cell to active neighbors may experience poor QoS and may be eventually dropped. Contributions on this issue is presented in [155–157]. In [155], the authors propose an algorithm to identify potential cells to be switched off using packet-based traffic model for load estimation. After the identification stage, the impact factor on neighboring cells are estimated and the BS with minimum impact factor on neighboring cells is selected as a preferred BS to be switched off. Instead of using packet-based approach, algorithm developed in [156] is designed to turn off SBS experiencing highest level of interference and at the same time, avoiding to

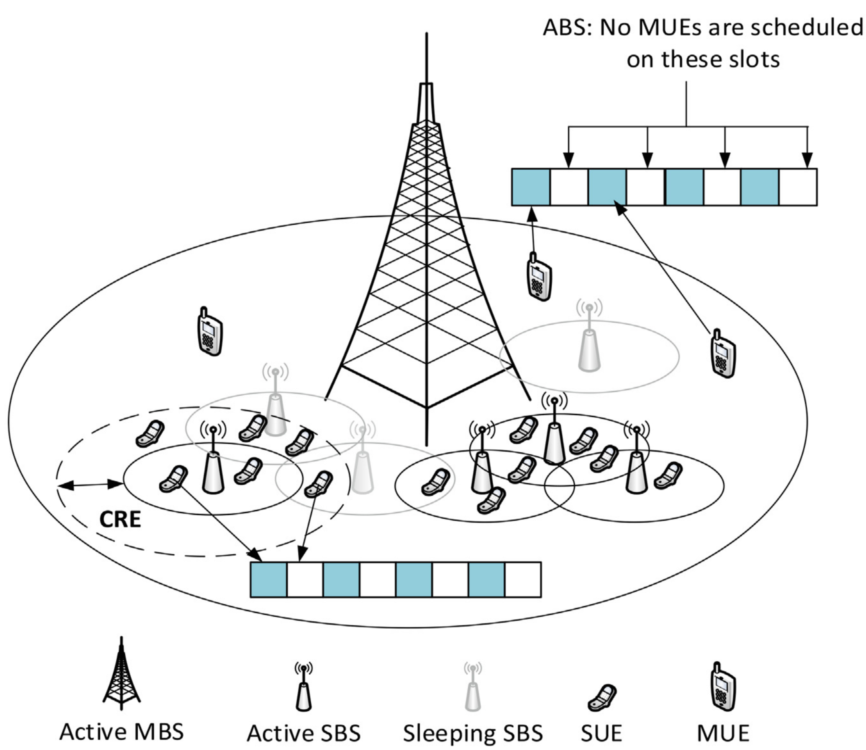

Fig. 5. Sleep Mode Scenario in HetNets.

Table 4
Comparison of Different BS Sleeping Enabling Schemes.

Scheme	Ref	Modelling Technique	Parameter Considered	AlgorithmImplementation	Performance Metrics
User Association	[138]	Stochastic Geometry	Maximum biased received power	Centralized	Coverage Probability and Power Consumption
	[139]	Heuristic	Utility function	Decentralized	Average EE
	[140]	Stochastic Geometry	Maximum biased received power	Centralized	SINR Coverage, Rate Coverage and EE Coverage
	[141]	Stochastic Geometry	Average biased received power	Centralized	Coverage Probability, Throughput and EE
	[142]	Stochastic Geometry	Reference signal received power	Centralized	Coverage Probability and EE
	[143]	Combinatorial Geometry	Utility function	Centralized	EE and Network throughput
	[144]	Stochastic Geometry	Average biased receivedsignal strength	Centralized	Local Delay and EE
	[145]	Simulation-Based	Utility function	Centralized	Sum Rate, Average percent of served users, EE and Computation time
Traffic Dynamics	[147]	Queuing Theory	Arrival Intensity	Centralized	EE and Throughput
	[116]	Markov Decision Process	Vehicular mobility pattern	Centralized	Average SINR, Average EE
	[148]	Genetic Algorithm	Traffic load	Centralized	Network Power Saving
Cell Zooming	[152]	Game Theory	Transmission power	Centralized	Throughput, SINR and Power saved
	[154]	Heuristic	Transmission power	centralized	Energy consumption, Area SE and EE
	[153]	Heuristic	Transmission power	Hybrid	Throughput, Spectral Efficiency, and Power consumption
Cell Load	[155]	Queuing Theory	Arrival rate, Average packet size and data rate	Centralized	Capacity, Number of switching of BSs
	[156]	Simulation-based	Interference Magnitude	Centralized	EE
	[157]	Markov Decision Process	Arrival rate, mean packet size and data rate	Centralized and Decentralized	Total traffic load and Energy consumption
BS ON-OFF Switching Control	[32]	Queuing Theory	Data rate	Centralized	Average power saved and Mean delay
	[158]	Queuing Theory	Data rate	Centralized	Average power saved and Mean delay
	[159]	Markov Decision Process	Traffic load	Centralized	Throughput, Energy consumption and EE
	[160]	Fuzzy Logic	Packet size and Data rate	Centralized	Average QoS, Power Consumption and User latency
	[161]	Game Theory	Transmission power	Decentralized	Change in power levels and Average number of ON/OFF switching
	[162]	Markov Decision Process	Transmission power	Centralized	Cumulative Energy Consumption

turn off a cell with highest number of serving users. Further contribution in this aspect is presented in [157], where discrete-time Markov process is used to develop optimal traffic offloading strategy with a minimum energy consumption.

BS ON-OFF Switching Control: ON-OFF switching strategy can be classified into two parts; the fractional ON-OFF approach where fraction of radio resources are activated or deactivated, or fully ON-OFF approach where BS is completely ON or OFF [163]. However, for practical design of ON-OFF switching strategy, it is necessary to consider its effect on service delay and energy consumption [164,165]. The impact of service delay experienced by UEs associated with BS in sleep mode and its EE trade-off is investigated in [158] and [32]. The authors formulate different types of wake-up strategies based on vacation queuing model. On the switching effect on energy consumption, recent contributions in this aspect is presented in [159–162]. Authors in [159] propose an enhanced Markov procedure for traffic prediction to minimize frequent switching at locations with fluctuating traffic. A fuzzy logic central controller for SBS coordination is proposed in [160] to prevent simultaneous activation of small cell with discontinuous transmission (DTX) features and also to avoid sudden surge in interference level. However, it is possible to avoid the use of central controller by developing a distributed scheme as demonstrated in [161], where a non-cooperative regret-based satisfaction game approach is proposed. In [162], the cumulative effect of start-up energy consumption cost due to frequent switching of SBSs is investigated. Energy minimization problem is formulated and analyzed considering the transmission power of UEs and BS, density and mobility pattern of UEs.

2.4. Hardware solution

Low circuit power consumption of BSs and UEs can be achieved by reducing their hardware complexities. A comprehensive study on UE hardware design for applications in 5G networks is presented in [166]. However, energy savings at the BSs is of greater concern in wireless mobile networks. Notable studies in this area are dedicated towards RF hardware design and the cloud-based network implementation.

On the RF hardware design, several connection configurations of RF chains with the antenna unit have been proposed as discussed under mMIMO deployment in section 2.1. Another important contribution in this direction is the aspect of power efficiency of power amplifier (PA). High power efficiency of PA will significantly improve the EE of a network. But due to high peak-to-average power ratio (PAPR) usually associated with MIMO-OFDMA networks, the PA output signals shifts from dynamic linear range to non-linear range causing the PA saturation [167]. PA operating in non-linear saturation region causes signal distortion, adjacent channel interference and high power consumption [168,169]. Studies on PA efficiency solutions for improving EE of a network are presented in [170] and [171]. In [170], the replacement of digital pre-distorter (DPD) with inference-aware clipping and filtering circuit is proposed. This is based on the premise that the application of DPD in mMIMO systems may be expensive and difficult to implement. An adaptive expression for the clipping level is developed based on inter-user interference information while the distortion introduced by the clipping process is suppressed via optimal choice of clipping ratio. In [171], the memoryless polynomial approach is used to model the non-linear behavior of PA based on which a closed-form expression for stochastic model of distorted signal is derived. Beamforming filter is developed in order to reconstruct the distorted signals. Based on these parameters, the expression for EE maximization problem is derived. Results obtained confirm that PA operating in non-linear region suffers signal distortion which in turn degrades both the SE and EE of a network. However, the impact of beamforming filter on the distorted signals is not discussed.

The cloud-based approach otherwise known as cloud radio access network (CRAN) also has the capability of reducing the hardware complexities of BSs by migrating many computation tasks carried out at the BS to remote central location [172]. The CRAN separates the baseband signal processing and the RF unit into the base band unit (BBU) and RRH, respectively [173]. The BBU are implemented in the cloud network and are connected through backhaul links to the BS located remotely in area of coverage interest. In HetNets, the radio access technology developed based on this approach is known as heterogeneous cloud radio access networks (H-CRAN). The studies presented in [174] and [175] are parts of several efforts dedicated towards improving the EE of CRAN. In [174], a comparative study of EE in the downlink of CRAN using data sharing and data compression transmission strategies is presented. In the data sharing transmission, the message for a particular UE from the central processor is distributed among multiple BSs in the network where a joint beamforming is performed in order to deliver the message to the intended user. In the compressed strategy, the beamforming operation is implemented at the central processor. For these strategies, transmission power minimization problem is formulated which is constrained by user target rate. The findings of the work show that the EE of data sharing strategy at low user target rate performs better than the compressed approach due to lower backhaul power consumption. But at higher data rate, the backhaul power consumption increases making the compression strategy preferable. In [175], the authors propose the integration of software defined network in CRAN (SD-CRAN). Based on this, a comprehensive power consumption model for SD-CRAN transceiver is presented. The power model is developed based on power consumption evaluation of individual component of SD-CRAN. From the outcome of the studies, it is observed that the power consumption in the SD-CRAN is higher than that of CRAN. However, the benefit of SD-CRAN in terms of network scalability makes it more suitable for implementation in ultra-dense network.

It is noteworthy that as the network scales, the computational complexity in the CRAN and SD-CRAN is bound to increase. Also, throughput latency is another challenge due to distance from BSs to the core network. On the aspect of through latency, the MEC technology discussed in section 2.1 has proven as an effective solution to the problem. Nonetheless, since these cloud technologies have their pros and cons in terms of network scalability, computation power consumption and data service latency, it is necessary to consider these factors before deciding the suitability of SD-CRAN, CRAN or MEC for deployment.

2.5. Energy harvesting and transfer

The quest to reduce CO_2 emission and to avoid frequent recharging of UEs has given rise to a new exciting energy-efficient technique dubbed energy harvesting and transfer. Works reported on this technique can be grouped under energy harvesting from natural and radio environment. An illustration of this scenario is shown in Fig. 6.

Energy Harvesting from Natural Environment: Recent investigations on economic and ecological performances of renewable energy sources in wireless cellular networks are presented in [30,176,178]. These energy sources may not be sustainable since they largely depend on climate condition, which varies over space and time. To overcome this challenge, these renewable energy sources are merged with the conventional grid energy source with their operations controlled by smart grid technology. The CO_2 reduction in smart grid setup can be discussed from the standpoint of energy procurement cost minimization since lower procurement

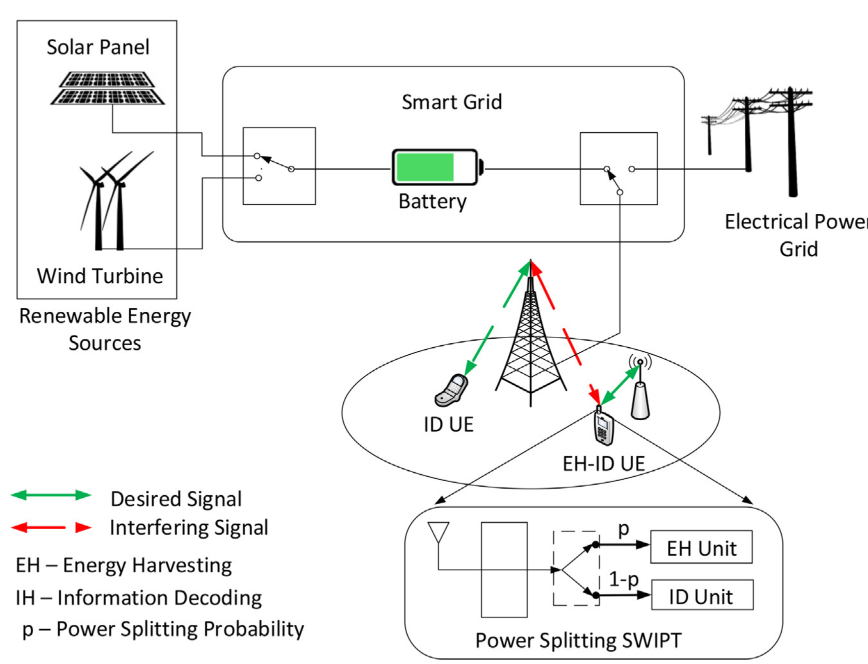

Fig. 6. HetNet with Energy Harvesting and Transfer Features.

cost translate to low energy consumption [176,177]. In [176], the authors investigate the performance of genetic algorithm (GA) and particle swarm optimization (PSO) in deactivating redundant BSs so as to enable mobile operators to optimally procure energy from smart grid. In the problem formulated which is constrained by target profit and CO_2 emission level, the mobile operator is able to decide the energy retailer to patronize and amount of energy to purchase. Though the PSO approach outperforms the GA technique, but the results obtained indicate that purchasing energy from renewable energy retailer reduces the network operators profit and CO_2 emission level while purchase from conventional energy retailers increases operators profit and CO_2 level. Though the cause of operator's lower profit as a result of purchase from renewable energy retailer is not stated but this may be attributed to the expensive nature of renewable energy [178]. In [177], the idea of BS cooperation to minimize energy procurement cost from smart grid is introduced. They propose three cooperation schemes viz; energy cooperation, communication cooperation and hybrid cooperation. The energy cooperation scheme allows BSs with excess harvested renewable energy to trade with BSs deficient of harvested energy. In communication cooperation, BSs adjust their propagation parameters in a way to lessen the load of BSs with insufficient renewable energy. The hybrid scheme developed from energy and communication cooperation scheme outperforms the other two schemes in terms of energy saving cost. However, the performance of the schemes in terms of CO_2 emission is not discussed. Further to these methods, some approaches rely on integration of radio optimization techniques in reducing energy consumption rate from renewable energy sources. Recent contributions using this approach include the optimization of transmission power and sub-carrier allocation technique [178], and the application of joint coordinated multipoint technique for interference avoidance [30].

Energy Harvesting from Radio Frequency: Ultra-high data rate has been a major target objective to be achieved in the next generation wireless cellular networks. However, the power consumption of mobile devices increases in order to satisfy the higher data delivery rate [179]. Due to limited battery lifetime of mobile devices, Simultaneous Wireless Information and Power Transfer (SWIPT) has been proposed as a solution to serve as a perpetual energy source for mobile terminals, hence improving the quality of user experience. In SWIPT networks, UEs are able to scavenge energy from radio frequencies which are used to charge their inbuilt batteries. Further details on SWIPT is presented in [180]. In conventional HetNet, PPP is commonly adopted to formulate the expressions for association probability, coverage probability and ergodic rate expression. But in energy-efficient SWIPT HetNet design, it is necessary to include the expressions for the amount and rate of energy harvested. This issue is addressed in [181] where a tractable model for performance evaluation in the uplink and downlink of K-tier SWIPT HetNet are formulated. Further to this, the EE performance evaluation of SWIPT networks is investigated in [182–184]. In [182], the authors propose mixed beamforming technique based on ZF method to cancel interference in the direction of information-decoding Femto-UEs (ID-FUEs) and retain the interference towards energy harvesting (EH)-FUEs. This is to enable the EH-FUEs to harvest more energy from the interfering signals. Results obtained show that information transmission and EE is higher under mixed beamforming scheme compared to ordinary ZF scheme. However, the feasibility of realizing the UEs that will achieve this purpose is not discussed. Efforts to address this limitation is initiated in [183] where two separate UE device architecture for information decoding and energy harvesting is proposed. Unfortunately, this approach does not support the main objective of SWIPT networks because the expected purpose of SWIPT UEs is to be able to merge both ID and EH functions on a single device. Though, similar to the beamforming approach adopted in [182], their findings also confirm that apart from energy harvested from desired signals, additional energy can be scavenged from interfering signals with the use of partial ZF technique. In a bid to merge the ID-UE and EH-UE functions on a single device, authors in [185] propose a power splitting ZF receiver that will simultaneously receive information and scavenge energy rather than having dedicated device for each function. They formulate the expression for power splitting ratio using a closed-form approach. Unfortunately, the EH and ID efficiency of the system is not addressed. Furthermore, another important factor to consider in SWIPT network design is the type of power consumption model adopted and computational complexities of the solution algorithms. This factor form the basis of the study presented in [184] where linear and non-linear power consumption model are proposed for EH efficiency maximization. Moreover, due to the high signaling overhead associated with the centralized scheme, they present a distributed beamforming which relies on local channel state information obtained at the BSs. In terms of computational complexities, result obtained verifies that the proposed decentralized scheme converges with few iterations which translates to low signaling overhead. The reported findings also show that the EH efficiency using non-linear power consumption model is bounded at certain limit as the transmission power and circuit power increase unlike the linear model where EH efficiency continues to increase. The main drawback in their report is that the ID efficiency is not addressed. It is worth mentioning that the use of linear power model is not suitable for practical EE related design due to non-linear characteristics of PA at high frequencies.

3. Energy efficiency problem formulation in HetNets

A critical parameter used to formulate the expression for EE of a communication link in wireless networks is the cost-benefit ratio of data rate to its associated energy consumption. The widely used EE expression in wireless networks is given in (1) [186].

$$\mathrm{EnergyEfficiency}(\eta_{EE}) = \frac{\mathrm{DataRate}}{\mathrm{PowerConsumption}}(\mathrm{bit/Joule}) \tag{1}$$

In a communication network comprising of L mutually interfering links, the expression for data rate transmission over a link l between a transmitter (BS) and the intended receiver (UE), can be formulated by considering the downlink of a K-tier HetNet comprising of a MBS and SBSs. If the spatial distribution of BSs in i^{th} tier are modeled according to homogeneous PPP Φ_i with density λ_i and UEs location also modeled as independent PPP Φ_u with density λ_u [146], the SINR of a link l connecting a BS of i^{th} tier $(l_i)$to a UE is given as (2).

$$\gamma_{l_i} = \frac{P_{l_i} h_{l_i} \|x_{l_i}\|^{-\propto}}{\sum_{j=1}^{K} \sum_{l\in\Phi_j\{l} i P_l h_l \|x_l\|^{-\propto} + \sigma^2} \tag{2}$$

P_{l_i} denotes the transmit power level of the link, h_{l_i} is the channel gain and $\|x_{l_i}\|^{-\propto}$ is the pathloss exponent which can vary depending on the nature of radio environment (indoor or outdoor).$P_l h_l \|x_l\|^{-\propto}$ represents interference power from other tiers. σ is the additive white Gaussian noise power level in the communication link. From (2), the expression for the achievable data rate using Shannon's capacity formula is given in (3) where R_{l_i} and B are the achievable rate of the link and assigned downlink channel bandwidth, respectively.

$$R_{l_i} = Blog_2\left(1 + \gamma_{l_i}\right) \tag{3}$$

Table 5
Power Consumption of Hardware Unit of HetNet BSs [190].

BS Type	Main Supply	DC-DC	Base-band	RF	Power Amplifier	Cooling
Macro	8%	6%	13%	6%	57%	10%
Pico	11%	8%	41%	14%	26%	0%
Femto	11%	8%	47%	12%	27%	0%

3.1. Power consumption model

The power consumption model of a BS required to operate a link l is usually developed as a function of its transceiver architecture and the power consumed by their various components and it varies for different types of BSs [24]. A BS comprises of multiple transceivers (TRXs), which are connected to the transmit antenna elements [187]. The antenna connection configuration to the TRXs depends on the preferred signal processing scheme as illustrated in Fig. 3. Basically, a TRX consists of main supply (AC-DC) unit for connection to electrical power grid, the cooling unit, DC to DC power supply, base-band (BB) signal processing unit, RF and power amplifier (PA) unit [188].

Under the assumption that BS power consumption grows proportionally with number of transceiver chain N_{TRX}, a comprehensive expression for a linear power consumption model of a BS in i^{th} tier operating a link l under maximum load condition can be given as (4) [189]. $P_{BB}, P_{RF} and P_{PA}$ represent the power consumed in the baseband unit, RF unit, and the power amplifier unit, respectively. The parameters λ_{DC}, $\lambda_{MS}, \lambda_{Cool} and \lambda_{feed}$ signify the losses incurred in the DC–DC power supply, main supply, cooling unit (usually neglected for small cell power model) and feeder cables, respectively [161]. The percentage of power consumed by these units is presented in Table 5. The expression for P_{PA} is given in (5) where P_{TX}, η^{PA} and λ_{feed} denotes the transmission power, and power amplifier efficiency.

$$P^B_{l_i} = N_{TRX} \cdot \frac{P_{BB} + P_{RF} + P_{PA}}{(1-\lambda_{DC})(1-\lambda_{MS})(1-\lambda_{Cool})} (\mathrm{Watt}) \quad (4)$$

$$P_{PA} = \frac{P_{TX}}{\eta^{PA}.(1-\lambda_{feed})} (\mathrm{Watt}) \quad (5)$$

However, since the power dissipation of BS largely depends on traffic load which varies over space and time [30], using the power consumption model under maximum load condition will amount to waste of energy. Hence, for energy-efficient power consumption model, it is more appropriate to use the power consumption model that takes into account the varying load condition of a cellular network. Hence, the power model given in (4) can be further approximated by a linear model given in (6) [191].

$$P^B_{l_i} = \begin{cases} N_{TRX}.(P_O + \propto P_{out}), 0 < P_{out} \le P_{max} \\ N_{TRX}.P_{sleep}, P_{Out} = 0 \end{cases} \quad (6)$$

P_O is the BS power consumption at minimum non-zero output power, $\propto$ is the slope of the load dependent power consumption curve, P_{out} is the load-dependent part of the RF output power and P_{max} is the value of P_{out} at maximum load. In the model (6), two distinct components can be identified which comprises of the static power consumption P_O, and load dependent power consumption P_{out}. P_{sleep} is the expected power consumption at no-load traffic condition, that is, when the value of P_{out} is zero. At this point, major components of BS are expected to be deactivated for energy saving. Table 6 presents the power consumption of different types of BS under variable load condition.

Therefore, the EE of the of a link$l$ connecting a BS of i^{th} tier(l_i)to a UE can be expressed by substituting (3) and (6) in (1)

$$\eta_{EE} = \frac{R_{l_i}}{P^B_{l_i}} \quad (6)$$

Hence, a typical EE optimization problem is expressed in (7) - (9)

$$\max \eta_{EE} \quad (7)$$

$$s.t. C1 : P_{out} \le P_{max} \quad (8)$$

$$C2 : R_{l_i} \ge R_{th} \quad (9)$$

The first constraint ensures that the power allocated to a link l does not exceed the total BS transmission power budget. The second constraint guarantee a minimum achievable data rate for any UE in the network connected via the link.

It is noteworthy that linear power consumption model is analytically tractable and commonly adopted based on the assumption that circuit power remains fixed and the dynamic power scales linearly [196]. Usually, the circuit power consumption, is taken as the fixed power consumed in the cooling, BB unit, and RF unit. However, this may not be valid under practical scenario especially for BSs with mMIMO antenna system. Notable works in [186] and [197] introduced new parameters in the existing model in order to formulate a refined circuit power consumption model. In the model presented in [186], load-dependent backhaul power consumption, channel estimation and channel coding power consumption are included in order to validate the fact that total power consumption of BSs and UEs depends on number of antennas, number of active users and gross rate. A similar model is also adopted in [197], where the effect of non-linear characteristics of power amplifiers are investigated. In addition to the model presented in [186], the oscillator power consumption is included as the additional parameter to the circuit power model.

It is also worth mentioning that some remarkable research initiatives have been proposed to towards optimizing the EE of BS hardware components indicated in Table 5. From the viewpoint of power supply, presently, the renewable energy sources have been introduced as means of powering BSs most especially in remote areas that are not accessible to electrical power grid. Some of the contributions in this direction have been discussed in section 2.5 under energy harvesting from natural environment. On the aspect of BB signal processing, ZF technique discussed in section 2.2 under beamforming design is considered as the most effective in terms of energy-efficient BB signal processing strategy. Discussions on energy-efficient RF and PA design have been reviewed in section 2.4 under hardware solutions. Towards improving EE of BS cooling unit, free or natural air cooling system have been proposed for the replacement of compressor-based cooling system due to their

Table 6
BS Power consumption parameters at variable load [191]

BS Type	P_{max}(W)	P_o(W)	P_{sleep}(W)	α
Macro	40	130	75	4.7
Pico	0.13	6.8	4.3	4
Femto	0.05	4.8	2.9	8

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Table 7
Energy Efficiency Metrics of some selected references.

References	EE Metrics	Level of Measurement
[38,61,76,140,142,147,159]	bit/Joule	Network, Node
[98,115,119,122,126]	bit/Joule/Hertz	Network
[192,39,193]	Area Power Consumption (W/m^2)	Node
[194,195]	Energy Consumption Index (ECI)	Node
[194]	Energy Reduction Gain (ERG)	Node

higher energy saving potentials [198]. According to the studies presented in [199], the authors demonstrate that the natural cooling unit of a BS can be further enhanced by carefully designing the cooling unit structure for natural air circulation to take place through the principle of stack effect. Some other techniques such as evaporative direct and indirect air cooling have also been identified in [200], though the schemes are proposed for data center cooling unit but the technique can also be adopted for BS cooling system.

3.2. Energy efficiency metrics

EE metrics are used to measure the energy consumption rate or performance trade-off of energy-efficient design. The metrics can be grouped under three major classes, which are the component level, equipment or node level and system or network work level [201]. The component level metrics is concerned about the performance of individual component of a wireless communication elements such as the power supply, power amplifier, antenna and so on [202]. While the equipment level metrics are used to measure the performance of network access node such as UEs and BSs, the network level metrics measure the performance on network access nodes with respect to the coverage area and expected QoS [203]. Commonly used EE metrics are presented in Table 7.

4. Research directions

Although various investigations on energy-efficient solutions for HetNets design have been carried out, there are still some areas yet to be sufficiently discussed. These areas are presented in Table 8.

Table 8
Future Research Directions.

S/N	Key Areas for Future Research	Possible Research Focus
1	Analytical Model	**Tractable Models for Energy-Efficient UD-HetNets:** With the massive growth of UEs, future generation networks are expected to experience ultra-dense deployment of BSs in order to cope with the capacity and coverage demands. The use of PPP for modeling the BSs and UEs distribution in order to develop a realistic network model have been widely adopted. The application of PPP in UD-HetNets may not accurately represent the expected interactions between network element since BS and UE clustering is anticipated in UD-HetNet. For this purpose, developing tractable models using cluster process such as PCP rather than PPP to characterize network performance is more appropriate for a realistic UD-HetNets design. Surprisingly, the application of cluster process for energy-efficient network design is yet to receive major attention. The only notable contribution in this regard is reported by Jiang et al., [60]. However, only BS clustering is investigated in the study; UE clustering is not considered.
2	Radio Transmission Optimization	**Beamforming Design in MIMO-NOMA Networks:** MIMO-NOMA technique addresses the limitations encountered in ultra-dense HetNets such as massive connectivity, SINR and EE [204]. To achieve energy-efficient MIMO-NOMA network design, effective beamforming design is very crucial. A lot of investigations have been carried out on hybrid beamforming design being the most effective in terms of EE, cost and beamforming accuracy. However, most of these beamforming techniques utilize fully-connected phase shifters and the beams are usually dedicated towards a specific UE. The aspect of cluster-based beamforming with partially-connected structure, where individual beam is steered towards a specific UE cluster is yet to fully develop. Furthermore, single-cell multiple user scenarios under MIMO-NOMA scheme are considered in recent works as indicated in Table 3. The single-cell multiple user scenario indicates that the problem of interfering signals form adjacent cells is not applicable in the design. This scenario is not likely to be valid in practical HetNet where various cells of different sizes exist. In addition, due to channel feedback error, quantization error, and estimation error, the assumption of perfect CSI at the BSs may not be realistic [125]. Therefore, another practical area that needs to be investigated is the EE of multi-cell multi-UE MIMO-NOMA networks with imperfect CSI.
3	Hardware Solution	**Hardware Efficiency:** In a recent contribution, the perception that digital precoder is not suitable for EE design in the context of mMIMO has been discredited [205]. Though some research initiatives have been proposed in order to optimize the EE performance of digital precoders such as antenna selection technique [206], but research contributions in this area is still lacking. To further enhance the antenna selection algorithm, the RF chain deactivation approach can be incorporated in the selection process in order to turn off inactive antennas. This is another area that is worth exploring. On SWIPT receiver design, it is noteworthy that other techniques apart from power splitting method exist. These techniques include time switching, integrated receiver and antenna switching method [191]. However, the EH and ID efficiency of these techniques are yet to receive the desired attention in the literature.
4	Hybrid Techniques	**BS Deployment and Planning with MSFR:** Some techniques such as BS deactivation and cell traffic have been merged with BS density optimization technique to further maximize its EE capacity. Since there has not been any major contribution on energy-efficient network design with MSFR, planning BS deployment with this approach could substantially offer additional energy savings. As such, the EE performance of BS deployment optimization technique with MSFR scheme is worth investigating. **Hybrid Cloudified Networks:** Spurred by limitations of CRAN, SD-CRAN and MEC in terms of data service latency, network scalability, and computation power consumption led to the development of new hybrid technology known as fully Cloudified Networks [207]. The fully cloudified network combines the CRAN and MEC technology to optimize the performance of cloud computing. Also, the EE solutions for this technology is yet to receive major attention in the literature. **Energy Harvesting and Transfer with Computation Offloading strategies:** In recent contributions, it is shown that the performance of energy harvesting and transfer technique can be further improved by complementing them with other EE techniques such as sleeping strategy [176] and some approaches under radio transmission optimization technique, such as beamforming optimization. However, much attention has not been devoted to improving the performance of energy harvesting and transfer with MEC and CRAN technologies. Hence, this is another area worth investigating
5	Algorithm Implementation	**Self-Organizing Networks:** The management of small cells by the operators in ultra-dense scenario constitute high CAPEX and OPEX. Hence, the rationale for integrating Self-Organizing techniques in HetNets [208]. Self-organising solutions introduce intelligence to the operations of SBSs in HetNet such that each SBS can autonomously operate in a decentralized fashion [209]. These solutions are basically characterized by scalability, agility and stability [210]. In ultra-dense scenario, the use of centralized controllers and manual configuration of beam steering process, activating and deactivating BSs will be relatively difficult especially under rapid varying traffic conditions [211]. Furthermore, the use of centralized processing will increase signaling overhead which may increase energy consumption in the network and limit the scalability. Hence, the introduction of self-organising solutions for energy-efficient HetNet design is another interesting research direction.

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4.1. Lessons learned

Lesson One: In summary, energy-efficient design of wireless mobile HetNets can be investigated from various perspectives which include optimal BSs deployment, radio transmission optimization, hardware solution, BS sleeping, and energy harvesting from natural and radio environment. For a realistic design of energy-efficient HetNets with each technique, there exist certain critical factors that should be considered. Some of these factors are expected to take the following form; random SBSs distribution, digital or partially connected precoder design constrained by preferred level of SE, ZF for beamforming signal processing, biased UE association, adaptive resource allocation and dynamic traffic profile.

Lesson Two: To further enhance the performance of any of the outlined techniques, it has been demonstrated that two or more techniques can be merged together in order to develop a hybrid technique. For instance, sleep mode, SFR and MEC approach can be combined with BS planning and deployment approach for additional energy saving. Also, several techniques under radio transmission and optimization processes are applicable in most of the techniques. For example, optimal transmission power allocation is a fundamental parameter used in formulating the energy consumption minimization problem when using techniques such as sleep mode, MEC, CRAN and SWIPT.

Lesson Three: When formulating EE maximization problem, the problem is usually constrained by desired level of resource utilization. These resources basically comprise of transmission power and subcarriers. Nonetheless, the issue of fairness especially for UEs with poor channel condition must not be ignored. Example of schemes used to achieve fair resource allocation include the MSFR and NOMA. Also, in a situation where two conflicting objectives exist in a problem, it is more appropriate to consider the joint optimization approach. The advantage of joint optimization lies in the fact that the trade-off point of the conflicting objectives can easily be determined. With this, the set constraints can be adjusted in order to achieve an optimal trade-off level.

Lesson Four: From the perspective of hardware solution, the EE of a BSs can be enhanced by selecting a suitable precoding structure. The type of structure selected largely depends on the solution objective. Even though the digital precoder for energy efficient design is the way forward, but so far, the partially-connected hybrid structure is still known to be adopted for energy-efficient design with tolerable level of SE. Furthermore, the CRAN and SD-CRAN have the potentials of reducing energy consumed by the BSs by offloading the computation processes from the BS to the cloud. Though a major drawback in the SD-CRAN is associated to its higher computation power compared with CRAN but it outperforms the CRAN in terms of network scalability support.

Lesson Five: On renewable energy, it is known that these energy sources are not reliable due to variation in weather conditions over space and time. Hence mobile operators still largely depend on the national electrical power grid for smooth running of their operations. However, the consumption rate from the renewable energy storage batteries can be reduced by introducing other EE techniques capable of minimizing BS power consumption. Such techniques include sleep mode, interference management, introduction of cloud services and so on.

Lesson Six: Implementing control algorithms in a distributed manner eliminates reliance on single central controlling unit because if the central unit is compromised, the whole network may experience failure. With the decentralized EE solutions, the BSs can operate based on local information exchange and take decisions independent of other BSs in the network. These autonomous features can reduce the signaling overhead and enhance network scalability.

5. Conclusion

Ultra-dense small cells, mMIMO, and NOMA are some of the recent technologies incorporated in present wireless mobile communication networks to meet the unprecedented data traffic demands. The deployment of ultra-dense HetNets introduces certain challenges including high energy demands within the networks and complexities in network management. A lot of efforts to tackle these challenges have been presented in literature with a focus on the different phases of network deployment and operations. However, these solution approaches may become less optimal at some point due to complexities that accompany emerging technologies in wireless mobile networks.

In this review, recent works on EE techniques in wireless mobiles networks have been presented. Various enabling approaches for each technique have also been discussed. Furthermore, critical contributions under each technique have be identified in order to provide guidelines for a robust and optimal system design of emerging wireless technologies. Also presented is power consumption and data rate expression in order to illustrate the fundamental EE maximization problem. We also discussed and outlined fundamental metrics used to characterize EE performance in HetNet. Finally, potential research directions in the field of green communications are outlined. It is anticipated that this survey will serve as an effective guideline for energy-efficient design of 5G networks, emerging 6G wireless communication networks and beyond.

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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