

See discussions, stats, and author profiles for this publication at: <https://www.researchgate.net/publication/341635404>

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

Article · May 2020

DOI: 10.1016/j.jestch.2020.05.001

CITATIONS

0

READS

22

5 authors, including:



[Agbotiname Lucky Imoize](#)

University of Lagos

31 PUBLICATIONS 100 CITATIONS

SEE PROFILE

Some of the authors of this publication are also working on these related projects:



Wireless networks [View project](#)



Efficient Load Balancing Techniques in Heterogeneous LTE Advanced Wireless Networks [View project](#)

HOSTED BY



ELSEVIER

Contents lists available at ScienceDirect

Engineering Science and Technology, an International Journal

journal homepage: www.elsevier.com/locate/jestch

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

Olumide Alamu^{a,*}, Abiodun Gbenga-Ilori^a, Michael Adelabu^a, Agbotiname Imoize^a, Oluwabusayo Ladipo^b

^a Department of Electrical and Electronics Engineering, University of Lagos, Akoka, Lagos, Nigeria

^b Department of Electrical and Electronics Engineering, Yaba College of Technology, Yaba, Lagos, Nigeria

ARTICLE INFO

Article history:

Received 23 December 2019

Revised 31 March 2020

Accepted 7 May 2020

Available online xxxx

Keywords:

Heterogeneous Networks

Ultra-Dense Small Cells

Massive MIMO

Energy Efficiency

Optimization Techniques

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.

© 2020 Karabuk University. Publishing services by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

Contents

1. Introduction	00
2. Overview of energy efficiency techniques	00
2.1. Network planning and deployment	00
2.2. Optimization of radio transmission processes	00
2.3. Sleep mode/ON-OFF techniques	00
2.4. Hardware solution	00
2.5. Energy harvesting and transfer	00
3. Energy efficiency problem formulation in HetNets	00
3.1. Power consumption model	00
3.2. Energy efficiency metrics	00
4. Research directions	00
4.1. Lessons learned	00
5. Conclusion	00
Declaration of Competing Interest	00
Acknowledgement	00
References	00

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

* Corresponding author.

E-mail address: oaalamu@unilag.edu.ng (O. Alamu).

Peer review under responsibility of Karabuk University.

<https://doi.org/10.1016/j.jestch.2020.05.001>

2215-0986/© 2020 Karabuk University. Publishing services by Elsevier B.V.

This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

Please cite this article as: O. Alamu, A. Gbenga-Ilori, M. Adelabu et al., Energy efficiency techniques in ultra-dense wireless heterogeneous networks: An overview and outlook, Engineering Science and Technology, an International Journal, <https://doi.org/10.1016/j.jestch.2020.05.001>

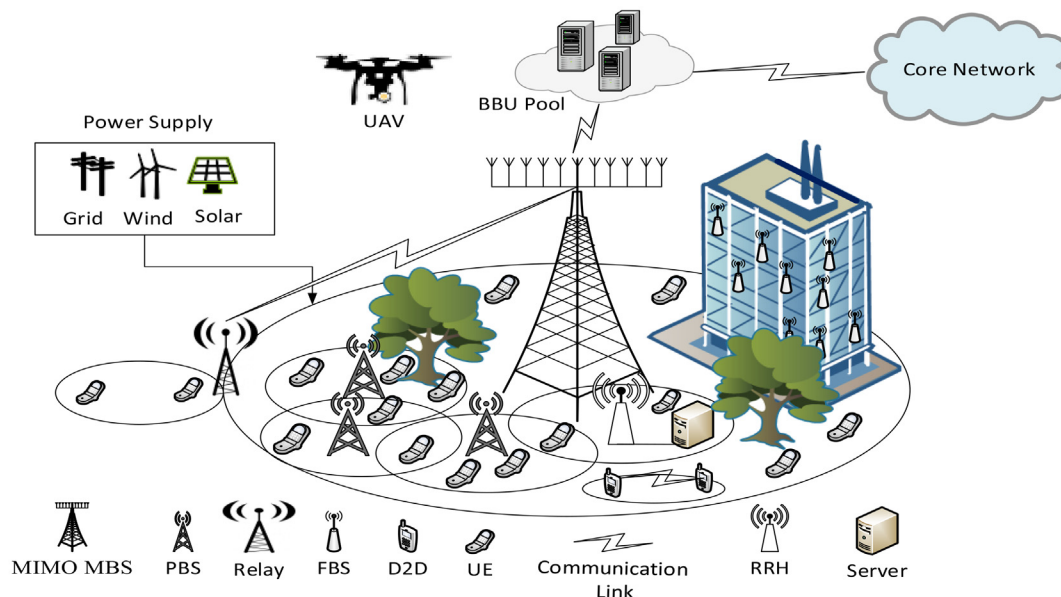


Fig. 1. Typical Next Generation Wireless Mobile Heterogeneous Networks.

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 CO₂ 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 CO₂ contribute the largest share has been identified as the cause of global warming [19,20]. The ICT industry contributes 2% to global CO₂ 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 CO₂ 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

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 GtCO₂e to 58 GtCO₂e and it is expected to further reduce to 26 GtCO₂e 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 CO₂ 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

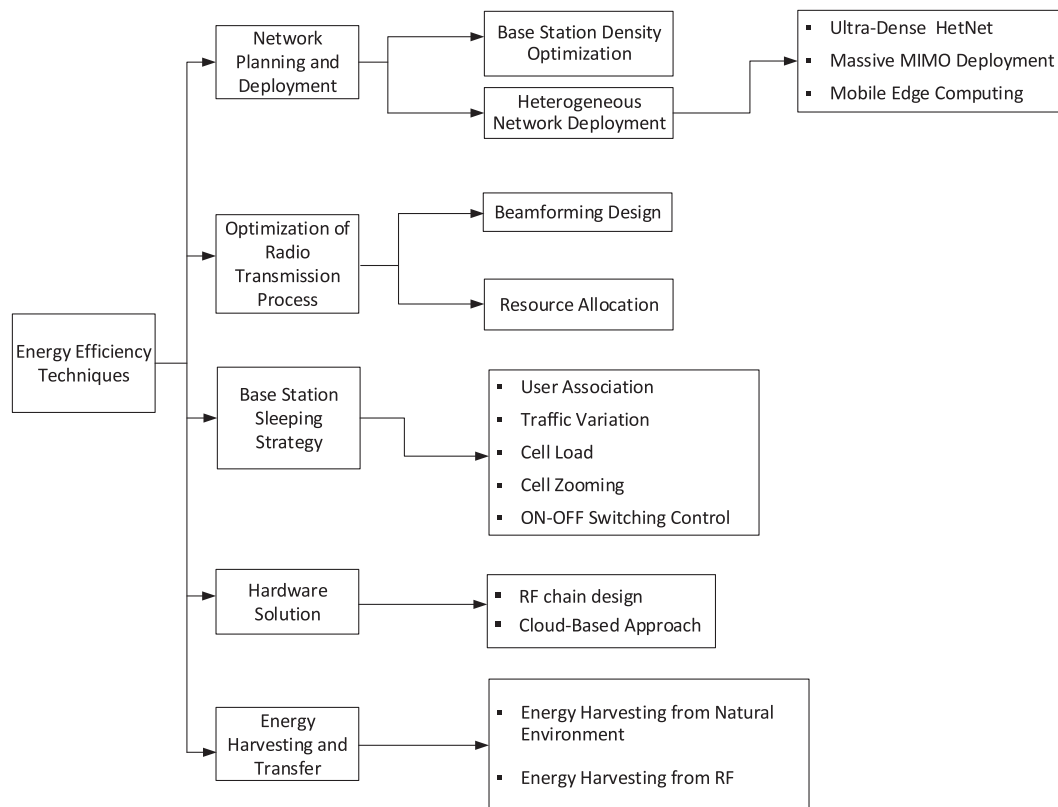


Fig. 2. Energy Efficiency Techniques in Wireless Mobile Networks.

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 and Stochastic 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 and Stochastic Geometry	-	Centralized	Fixed	EE and Area spectral efficiency.

Poisson 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 prefer-

ring 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

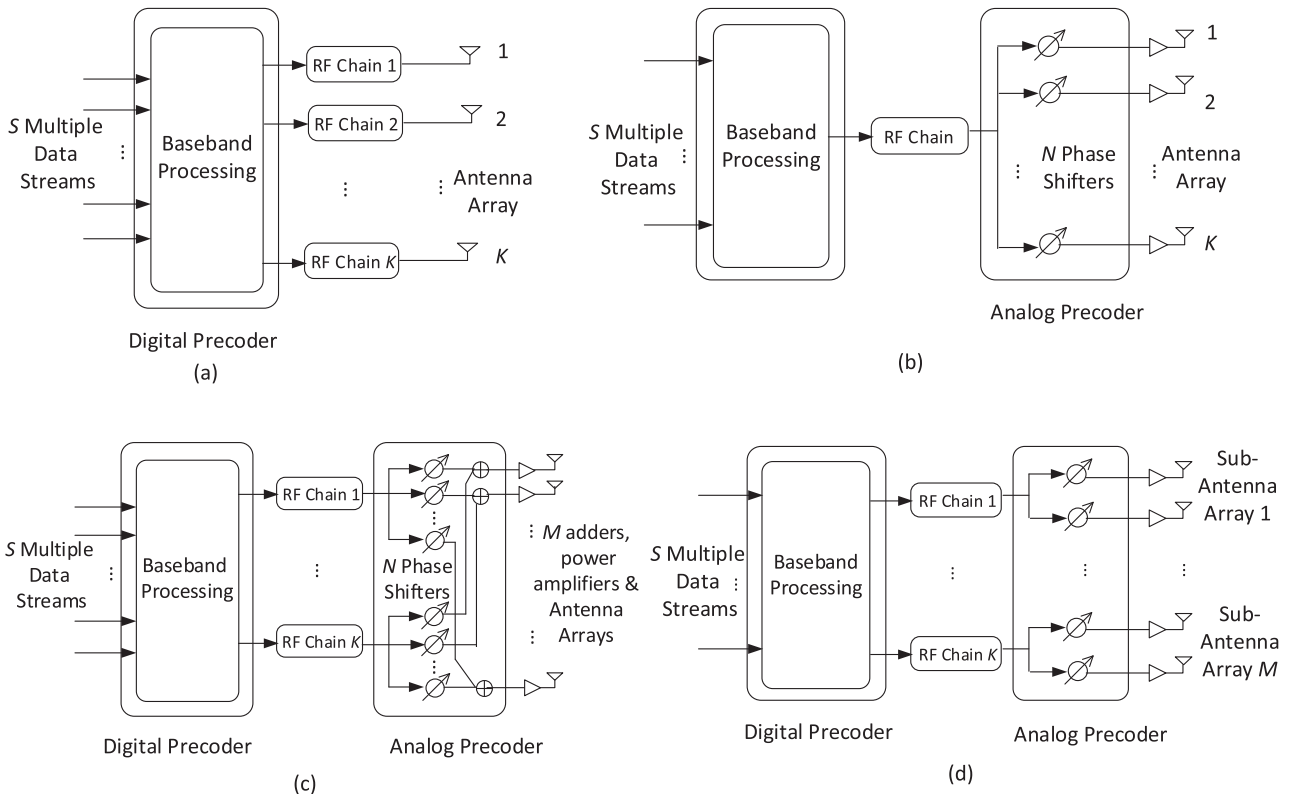


Fig. 3. Precoders for mMIMO Systems (a) Digital precoder with dedicated RF unit per antenna (b) Analog precoder with single RF unit connected to multiple antennas via phase shifters (c) Fully-connected hybrid precoder (d) Partially-connected hybrid precoder.

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 support 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 combina-

tion 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 sig-

naling 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

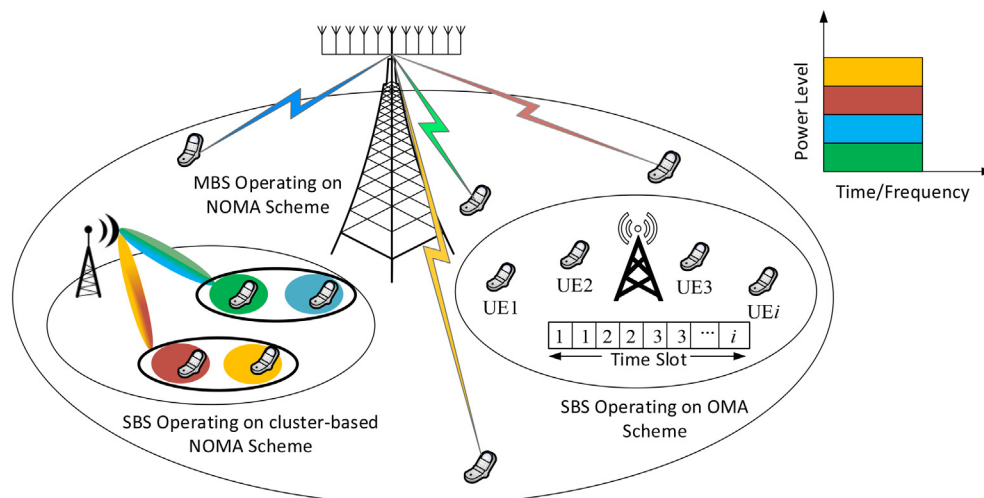


Fig. 4. Resource Allocation in OMA and NOMA Networks.

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

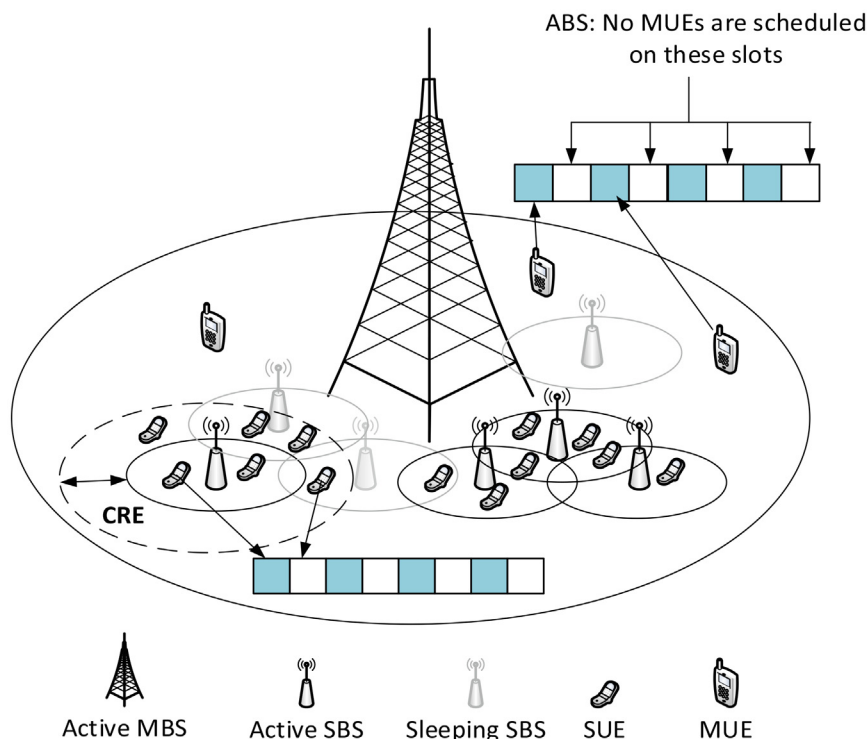


Fig. 5. Sleep Mode Scenario in HetNets.

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 received signal 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]	Queueing 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]	Queueing 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]	Queueing Theory	Data rate	Centralized	Average power saved and Mean delay
	[158]	Queueing 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 queueing 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 applica-

tion 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 CO₂ 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 CO₂ reduction in smart grid setup can be discussed from the standpoint of energy procurement cost minimization since lower procurement

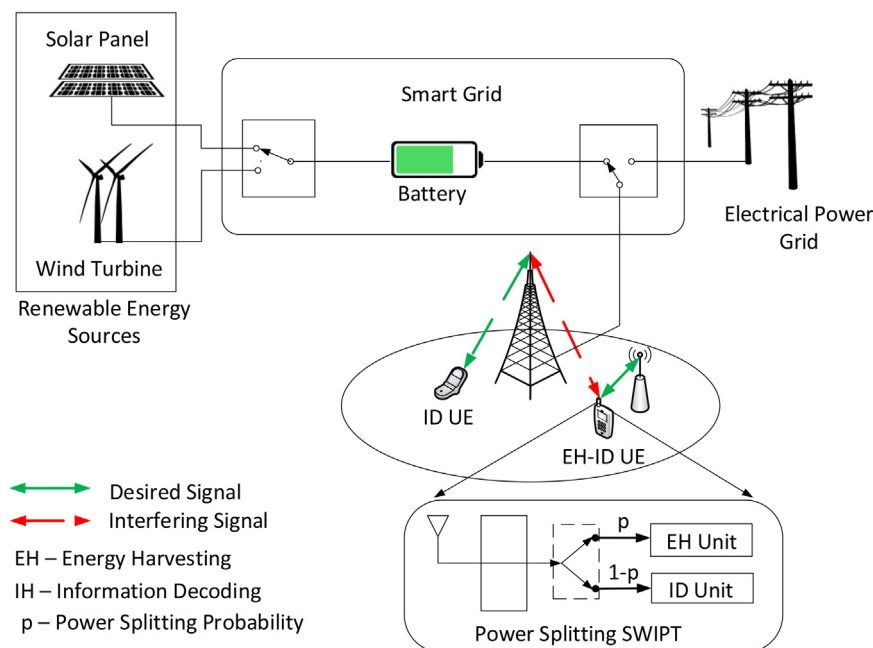


Fig. 6. HetNet with Energy Harvesting and Transfer Features.

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 CO₂ 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 CO₂ emission level while purchase from conventional energy retailers increases operators profit and CO₂ 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 CO₂ 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].

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

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).

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

P_{l_i} denotes the transmit power level of the link, h_{l_i} is the channel gain and $\|x_{l_i}\|^{-\alpha}$ is the pathloss exponent which can vary depending on the nature of radio environment (indoor or outdoor). $P_l h_l \|x_l\|^{-\alpha}$ 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.

$$R_{l_i} = B \log_2 \left(1 + \gamma_{l_i} \right) \quad (3)$$

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} , λ_{MS} , λ_{Cool} and λ_{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.

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

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

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].

$$P_{l_i}^B = \begin{cases} N_{TRX} \cdot (P_O + \alpha P_{out}), & 0 < P_{out} \leq P_{max} \\ N_{TRX} \cdot P_{sleep}, & P_{out} = 0 \end{cases} \quad (6)$$

P_O is the BS power consumption at minimum non-zero output power, α 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 $P_{out} \cdot P_{sleep}$ 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)

$$\eta_{EE} = \frac{R_{l_i}}{P_{l_i}^B} \quad (6)$$

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

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

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

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

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

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.

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 from 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.

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.

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 been 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.

Acknowledgement

The authors would like to thank the anonymous reviewers and the editor for their valuable comments and constructive suggestions to improve the quality of the paper.

References

- [1] M. Kamel, W. Hamouda, A. Youssef, Ultra-Dense Networks: A Survey, *IEEE Commun. Surv. Tutorials* 18 (4) (2016) 2522–2545.
- [2] G. Chopra, R.K. Jha, S. Jain, A survey on ultra-dense network and emerging technologies: Security challenges and possible solutions, *J. Netw. Comput. Appl.* 95 (2017) 54–78.
- [3] Y. Teng, M. Liu, F.R. Yu, V.C.M. Leung, M. Song, Y. Zhang, Resource Allocation for Ultra-Dense Networks: A Survey, *Some Research Issues and Challenges*, *IEEE Commun. Surv. Tutorials* 21 (3) (2018) 2134–2168.
- [4] M.M. Mowla, I. Ahmad, D. Habibi, Q.V. Phung, A Green Communication Model for 5G Systems, *IEEE Trans. Green Commun. Netw.* 1 (3) (2017) 264–280.
- [5] B. Kazi, G. Wainer, Next Generation Wireless Cellular Networks : Ultra-Dense Multi-Tier and Next generation wireless cellular networks : ultra-dense multi-tier and multi-cell cooperation perspective, *Wirel. Networks* 25 (4) (2019) 2041–2064.
- [6] L. F. Ibrahim, "A survey on heterogeneous mobile networks planning in indoor dense areas," Springer Pers. Ubiquitous Comput., pp. 1–12, 2019.
- [7] P. Hoadley, J. Maveddat, Enabling Small Cell Deployment with HetNet, *IEEE Wirel. Commun.* 19 (2) (2012) 4–5.
- [8] N. Slamnik, A. Okic, and J. Musovic, "Conceptual radio resource management approach in LTE heterogeneous networks using small cells number variation," 2016 11th Int. Symp. Telecommun. BIHTEL, 2016.
- [9] Y. Li, Y. Zhang, K. Luo, T. Jiang, Z. Li, W. Peng, Ultra-Dense HetNets Meet Big Data: Green Frameworks, Techniques, and Approaches, *IEEE Commun. Mag.* 56 (6) (2018) 56–63.
- [10] Y. Wu, L.P. Qian, J. Zheng, H. Zhou, X.S. Shen, Green-Oriented Traffic Offloading through Dual Connectivity in Future Heterogeneous Small Cell Networks, *IEEE Commun. Mag.* 56 (5) (2018) 140–147.
- [11] P. Gandotra, R.K. Jha, S. Jain, Green Communication in Next Generation Cellular Networks: A Survey, *IEEE Access* 5 (2017) 11727–11758.

- [12] W. Mwashita, M.O. Odhiambo, Base Station Energy Efficiency Improvement for Next Generation Mobile Networks, *Int. J. Electron. Telecommun.* 63 (2) (2017) 187–194.
- [13] J. Wu, E.W.M. Wong, J. Guo, M. Zukerman, Performance analysis of green cellular networks with selective base-station sleeping, *Perform. Eval.* 111 (2017) 17–36.
- [14] S. Sun, M. Kadoch, T. Ran, Adaptive SON and Cognitive Smart LPN for 5G Heterogeneous Networks, *Mob. Networks Appl.* 20 (6) (2015) 745–755.
- [15] R. Balakrishnan, I. Akyildiz, Local Anchor Schemes for Seamless and Low-Cost Handover in Coordinated Small Cells, *IEEE Trans. Mob. Comput.* 15 (5) (2016) 1182–1196.
- [16] Yanzan Sun, Han Xu, Shunqing Zhang, Yating Wu, Tao Wang, Yong Fang, Shugong Xu, Joint Optimization of Interference Coordination Parameters and Base-Station Density for Energy-Efficient Heterogeneous Networks, *MDPI Sensors* (2019) 1–24.
- [17] J. Park, H. Byun, Autonomous Transmission Power Decision Strategy for Energy Efficient Operation of a Dense Small Cell Network, *Wirel. Commun. Mob. Comput.* 2018 (2018).
- [18] C. Yang, J. Li, M. Guizani, Cooperation for spectral and energy efficiency in ultra-dense small cell networks, *IEEE Wirel. Commun.* 23 (1) (2016) 64–71.
- [19] T.R. Anderson, E. Hawkins, P.D. Jones, CO₂, the greenhouse effect and global warming: from the pioneering work of Arrhenius and Callendar to today's Earth System Models, *Endeavour* 40 (3) (2016) 178–187.
- [20] "The Causes of Climate Change," 2019. [Online]. Available: <https://climate.nasa.gov/causes/>. [Accessed: 07-Jun-2019].
- [21] M. Ismail, W. Zhuang, E. Serpedin, K. Qaraqe, A survey on green mobile networking: From the perspectives of network operators and mobile users, *IEEE Commun. Surv. Tutorials* 17 (3) (2015) 1535–1556.
- [22] L. Belkhir, A. Elmelig, Assessing ICT global emissions footprint: Trends to 2040 & recommendations, *J. Clean. Prod.* 177 (2018) 448–463.
- [23] F. Han, S. Zhao, L. Zhang, J. Wu, Survey of Strategies for Switching Off Base Stations in Heterogeneous Networks for Greener 5G Systems, *IEEE Access* 4 (2016) 4959–4973.
- [24] M. H. Alsharif, J. Kim, and J. H. Kim, "Green and sustainable cellular base stations: An overview and future research directions," *Energies*, vol. 10, no. 5, 2017.
- [25] B. Wang, Q. Yang, L.T. Yang, C. Zhu, On minimizing energy consumption cost in green heterogeneous wireless networks, *Comput. Networks* 129 (2017) 522–535.
- [26] A. Olhoff, "Emissions Gap Report 2018," 2018. [Online]. Available: http://wedocs.unep.org/bitstream/handle/20.500.11822/26896/EGR-KEYMESSAGES_2018.pdf?sequence=1&isAllowed=y. [Accessed: 09-Jun-2019].
- [27] Y. Zhang, Y. Xu, Y. Sun, Q. Wu, K. Yao, Energy Efficiency of Small Cell Networks: Metrics, Methods and Market, *IEEE Access* 5 (2017) 5965–5971.
- [28] K. Davaslioglu, E. Ayanoglu, Quantifying potential energy efficiency gain in green cellular wireless networks, *IEEE Commun. Surv. Tutorials* 16 (4) (2014) 2065–2089.
- [29] H. Lu, B. Hu, Z. Ma, S. Wen, Reinforcement learning optimization for energy-efficient cellular networks with coordinated multipoint communications, *Math. Probl. Eng.* 2014 (2014).
- [30] A. Jahid, M.S. Islam, M.S. Hossain, M.E. Hossain, M.K.H. Monju, M.F. Hossain, Toward Energy Efficiency Aware Renewable Energy Management in Green Cellular Networks with Joint Coordination, *IEEE Access* 7 (2019) 75782–75797.
- [31] T. Yang, F. Heliot, C.H. Foh, Energy-Efficient Boundary-Enabled Scheduling in the Downlink of Multi-Carrier Multi-Access Heterogeneous Network, *IEEE Trans. Green Commun. Netw.* 3 (1) (2019) 79–92.
- [32] X. Guo, Z. Niu, S. Zhou, P.R. Kumar, Delay-Constrained Energy-Optimal Base Station Sleeping Control, *IEEE J. Sel. Areas Commun.* 34 (5) (2016) 1073–1085.
- [33] J. Wu, Y. Zhang, M. Zukerman, E.K.N. Yung, Energy-efficient base-stations sleep-mode techniques in green cellular networks: A survey, *IEEE Commun. Surv. Tutorials* 17 (2) (2015) 803–826.
- [34] S. Buzzi, I. Chih-Lin, T.E. Klein, H.V. Poor, C. Yang, A. Zappone, A survey of energy-efficient techniques for 5G networks and challenges ahead, *IEEE J. Sel. Areas Commun.* 34 (4) (2016) 697–709.
- [35] S. Kahveci, Evaluation of energy efficiency of fifth generation mobile systems, *J. Commun. Technol. Electron.* 62 (10) (2017) 1130–1135.
- [36] A. Taufique, M. Jaber, A. Imran, Z. Dawy, E. Yacoub, Planning Wireless Cellular Networks of Future: Outlook, Challenges and Opportunities, *IEEE Access* 5 (2017) 4821–4845.
- [37] F. Richter, A.J. Fehske, G.P. Fettweis, Energy efficiency aspects of base station deployment strategies for cellular networks, *IEEE Veh. Technol. Conf.* (2009) 1–5.
- [38] L. An, T. Zhang, C. Feng, "Stochastic geometry based energy-efficient base station density optimization in cellular networks", *2015 IEEE Wirel. Commun. Netw. Conf. WCNC 2015* (4144079) (2015) 1614–1619.
- [39] B. Rengarajan, G. Rizzo, and M. Ajmone Marsan, "Energy-optimal base station density in cellular access networks with sleep modes," *Comput. Networks*, vol. 78, no. December, pp. 152–163, 2015.
- [40] R. Di, Z. Marco, L. Thanh Alessio, D. Mérouane, System-Level Modeling and Optimization of the Energy Efficiency in Cellular Networks – A Stochastic Geometry Framework, *IEEE Trans. Commun.* 17 (4) (2018) 2539–2556.
- [41] S. Wang, R. Chen, Rethinking Cellular Network Planning and Optimization, *IEEE Wirel. Commun.* (2016) 118–125.
- [42] D.G. González, E. Mutafungwa, B. Haile, J. Hämäläinen, H. Poveda, A Planning and Optimization Framework for Ultra Dense Cellular Deployments, *Mob. Inf. Syst.* 2017 (2017) 7–9.
- [43] H. Ghazzai et al., Optimized LTE Cell Planning with Varying Spatial and Temporal User Densities, *IEEE Trans. Veh. Technol.* 65 (3) (2015) 1575–1589.
- [44] K. Son, E. Oh, B. Krishnamachari, Energy-efficient design of heterogeneous cellular networks from deployment to operation, *Comput. Networks* 78 (2015) 95–106.
- [45] L. Zhou et al., Green cell planning and deployment for small cell networks in smart cities, *Ad Hoc Networks* 43 (2016) 30–42.
- [46] M. Demirta, A. Soysal, Nonoverlay Heterogeneous Network Planning for Energy Efficiency, *Wirel. Commun. Mob. Comput.* (2017).
- [47] J. Xu, J. Yao, L. Wang, K. Wu, L. Chen, W. Lou, Revolution of Self-Organizing Network for 5G mmWave Small Cell Management : From Reactive to Proactive, *IEEE Wirel. Commun. Mag.* 25 (August) (2018) 66–73.
- [48] Z. Lin, X. Du, H. Chen, B. Ai, Z. Chen, D. Wu, Millimeter-Wave Propagation Modeling and Measurements for 5G Mobile Networks, *IEEE Wirel. Commun.* 26 (1) (2019) 72–77.
- [49] R.I. Ansari, H. Pervaiz, C. Chrysostomou, S.A. Hassan, A. Mahmood, M. Gidlund, Control-Data Separation Architecture for Dual-Band mmWave Networks: A New Dimension to Spectrum Management, *IEEE Access* 7 (2019) 34925–34937.
- [50] J. Xu, K. Ota, M. Dong, Saving Energy on the Edge : In-Memory Caching for Multi-Tier Heterogeneous Networks, *IEEE Commun. Mag.* 56 (5) (2018) 102–107.
- [51] C. Yang, J. Li, Q. Ni, A. Anpalagan, M. Guizani, Interference-Aware Energy Efficiency Maximization in 5G Ultra-Dense Networks, *IEEE Trans. Commun.* 6778 (2016) 1–12.
- [52] Y. Chen, X. Wen, Z. Lu, H. Shao, W. Jing, Cooperation-enabled energy efficient base station management for dense small cell networks, *Wirel. Networks* 23 (5) (2017) 1611–1628.
- [53] T. Zhang, L. An, Energy Efficiency of Base Station Deployment in Ultra Dense HetNets: A Stochastic Geometry Analysis, *IEEE Wirel. Commun. Lett.* 5 (2) (2016) 184–187.
- [54] J. Lei, H. Chen, F. Zhao, Stochastic Geometry Analysis of Downlink Spectral and Energy Efficiency in Ultradense Heterogeneous Cellular Networks, *Mob. Inf. Syst.* (2018).
- [55] X. Chen, X. Wu, S. Han, and Z. Xie, "Joint Optimization of EE and SE Considering Interference Threshold in Ultra-Dense Networks," 2019 15th Int. Wirel. Commun. Mob. Comput. Conf., pp. 1305–1310, 2019.
- [56] Y. Luo, Z. Shi, F. Bu, J. Xiong, Joint optimization of area spectral efficiency and energy efficiency for two-tier heterogeneous ultra-dense networks, *IEEE Access* 7 (2019) 12073–12086.
- [57] M. Afshang, H.S. Dhillon, Poisson Cluster Process Based Analysis of HetNets with Correlated User and Base Station Locations, *IEEE Trans. Wirel. Commun.* 17 (4) (2018) 2417–2431.
- [58] J.D.R. Member, M. Tummala, S. Member, J.C.M. Member, Fundamental Implications for Location Accuracy in Ultra-Dense 5G Cellular Networks, *IEEE Trans. Veh. Technol.* 68 (2) (2018) 1784–1795.
- [59] X. Jia, P. Ji, Y. Chen, Modeling and Analysis of Multi-Tier Clustered Millimeter-Wave Cellular Networks With User Classification for Large-Scale Hotspot Area, *IEEE Access* 7 (2019) 140278–140299.
- [60] X. Jiang and F. C. Zheng, "User Rate and Energy Efficiency of HetNets Based on Poisson Cluster Process," *IEEE Veh. Technol. Conf.*, vol. 2018-June, pp. 1–5, 2018.
- [61] E. Björnson, L. Sanguinetti, M. Kountouris, Deploying Dense Networks for Maximal Energy Efficiency: Small Cells Meet Massive MIMO, *IEEE J. Sel. Areas Commun.* 34 (4) (2016) 832–847.
- [62] A. Lee Swindlehurst, Ender Ayanoglu, Payam Heydari, Filippo Capolino, Millimeter-Wave Massive MIMO: The Next Wireless Revolution?, *IEEE Commun. Mag.* 52 (9) (2014) 56–62.
- [63] S. Prasad, H. Ekram, K. Vijay, Energy Efficiency in Massive MIMO-Based 5G Networks: Opportunities and Challenges, *IEEE Wirel. Commun.* 24 (3) (2017) 86–94.
- [64] M.A. Abuibaid, S.A. Çolak, International Journal of Electronics and Communications (AEÜ) Energy-efficient massive MIMO system : Exploiting user location distribution variation, *AEUE - Int. J. Electron. Commun.* 72 (2017) 17–25.
- [65] S. Rajoria, A. Trivedi, W.W. Godfrey, A comprehensive survey: Small cell meets massive MIMO, *Phys. Commun.* 26 (2018) 40–49.
- [66] E. Björnson, L. Sanguinetti, J. Hoydis, M. Debbah, Optimal design of energy-efficient multi-user MIMO systems: Is massive MIMO the answer?, *IEEE Trans. Wirel. Commun.* 14 (6) (2015) 3059–3075.
- [67] X. Ge, J. Yang, H. Gharavi, Y. Sun, Energy Efficiency Challenges of 5G Small Cell Networks, *IEEE Commun. Mag.* 55 (5) (2017) 184–191.
- [68] S. Gimenez et al., "Performance evaluation of analog beamforming with hardware impairments for mmW massive MIMO communication in an urban scenario," *Sensors (Switzerland)*, vol. 16, no. 10, 2016.
- [69] W. Tan, D. Xie, L. Fan, S.H.I. Jin, W. Tan, Spectral and Energy Efficiency of Massive MIMO for Hybrid Architectures Based on Phase Shifters, *IEEE Access* 6 (2018) 11751–11759.
- [70] K. Satyanarayana, S. Member, M. El-hajjar, S. Member, P. Kuo, Hybrid Beamforming Design for Full-Duplex Millimeter Wave Communication, *IEEE Trans. Veh. Technol.* 68 (2) (2018) 1394–1404.
- [71] I. Ahmed et al., A survey on hybrid beamforming techniques in 5G: Architecture and system model perspectives, *IEEE Commun. Surv. Tutorials* 20 (4) (2018) 3060–3097.

- [72] F. Sohrabi, W. Yu, Hybrid Analog and Digital Beamforming for mmWave OFDM Large-Scale Antenna Arrays, *IEEE J. Sel. Areas Commun.* 35 (7) (2017) 1432–1443.
- [73] K.B. Dsouza, S. Member, K.N.R.S.V. Prasad, S. Member, K. Vijay, Hybrid Precoding with Partially Connected Structure for mmWave Massive MIMO OFDM : A Parallel Framework and Feasibility Analysis, *IEEE Trans. Wirel. Commun.* 17 (12) (2018) 8108–8122.
- [74] X. Gao et al., Energy-Efficient Hybrid Analog and Digital Precoding for MmWave MIMO Systems with Large Antenna Arrays, *IEEE J. Sel. Areas Commun.* 34 (4) (2016) 998–1009.
- [75] Y. Liu, Q. Feng, Q. Wu, Y. Zhang, M. Jin, T. Qiu, Energy-Efficient Hybrid Precoding With Low Complexity for mmWave Massive MIMO Systems, *IEEE Access* 7 (2019) 95021–95032.
- [76] L.N. Ribeiro, S. Schwarz, M. Rupp, A.L.F. De Almeida, Energy Efficiency of mmWave Massive MIMO Precoding with Low-Resolution DACs, *IEEE J. Sel. Top. Signal Process.* 12 (2) (2018) 298–313.
- [77] M. Li, Z. Wang, H. Li, Q. Liu, L. Zhou, A hardware-efficient hybrid beamforming solution for mmWave MIMO systems, *IEEE Wirel. Commun.* 26 (1) (2019) 137–143.
- [78] X. Zhu, Z. Wang, L. Dai, Q. Wang, Adaptive Hybrid Precoding for Multiuser Massive MIMO, *IEEE Commun. Lett.* 20 (4) (2016) 776–779.
- [79] Z. Zheng, H. Gharavi, L. Fellow, Spectral and Energy Efficiencies of Millimeter Wave MIMO with Configurable Hybrid Precoding, *IEEE Trans. Veh. Technol.* 68 (6) (2019) 5732–5746.
- [80] E. Ahmed, I. Mubashir, H. Rehmani, S. Member, Mobile Edge Computing : Opportunities, Solutions, and Challenges, *Futur. Gener. Comput. Syst.* (2016).
- [81] H. Tan, Z. Feng, Power Optimization in Self-Organizing MEC Based Heterogeneous Small Cell Networks, *IEEE Access* 6 (2018) 59109–59117.
- [82] C. You, K. Huang, H. Chae, B. Kim, Energy-Efficient Resource Allocation for Mobile-Edge Computation Offloading, *IEEE Trans. Wirel. Commun.* 16 (3) (2017) 1397–1411.
- [83] A. Al-shuwaili, O. Simeone, Energy-Efficient Resource Allocation for Mobile Edge Computing-Based Augmented Reality Applications, *IEEE Wirel. Commun. Lett.* 6 (3) (2017) 398–401.
- [84] X. Chen, L. Jiao, and W. Li, “Efficient Multi-User Computation Offloading for Efficient Multi-User Computation Offloading for Mobile-Edge Cloud Computing,” *IEEE/ACM Trans. Netw.*, pp. 1–14, 2015.
- [85] K.E. Zhang, Y. Mao, S. Leng, Energy-Efficient Offloading for Mobile Edge Computing in 5G Heterogeneous Networks, *IEEE Access* 4 (2016) 5896–5907.
- [86] J. Zheng et al., Joint Downlink and Uplink Edge Computing Offloading in Ultra-Dense HetNets, *Mob. Networks Appl.* 24 (5) (2019) 1452–1460.
- [87] H. Sun, S. Member, F. Zhou, Joint Offloading and Computation Energy Efficiency Maximization in a Mobile Edge Computing System, *IEEE Trans. Veh. Technol.* 68 (3) (2019) 3052–3056.
- [88] L. Li, G. Zhao, R.S. Blum, A survey of caching techniques in cellular networks: Research issues and challenges in content placement and delivery strategies, *IEEE Commun. Surv. Tutorials* 20 (3) (2018) 1710–1732.
- [89] Q. Jia, R. Xie, T. Huang, J. Liu, and L. Yunjie, “Energy-efficient Cooperative Coded Caching for Heterogeneous Small Cell Networks,” 2017 IEEE Conf. Comput. Commun. Work. (INFOCOM WKSHPS), pp. 468–473, 2017.
- [90] Y. Hao et al., Energy Efficient Task Caching and Offloading for Mobile Edge Computing, *IEEE Access* 6 (2018) 11365–11373.
- [91] B. Giulio et al., Beamforming for small cell deployment in LTE-advanced and beyond, *IEEE Wirel. Commun.* 21 (2) (2014) 50–56.
- [92] D. Marabissi, G. Bartoli, R. Fantacci, and L. Micciullo, “Energy efficient cooperative multicast beamforming in ultra dense networks,” *IET Commun.*, pp. 573–578, 2018.
- [93] S. Bhattacharjee, S. Bandyopadhyay, An Interference Aware Minimum Energy Routing Protocol for Wireless Networks Considering Transmission and Reception Power of Nodes, *Procedia Technol.* 4 (2012) 1–8.
- [94] Y. Qiu, H. Zhang, K. Long, Y. Huang, X. Song, V.C.M. Leung, Energy-Efficient Power Allocation with Interference Mitigation in MmWave-Based Fog Radio Access Networks, *IEEE Wirel. Commun.* 25 (4) (2018) 25–31.
- [95] E. Ali, M. Ismail, R. Nordin, N.F. Abdulah, Beamforming techniques for massive MIMO systems in 5G: overview, classification, and trends for future research, *Front. Inf. Technol. Electron. Eng.* 18 (6) (2017) 753–772.
- [96] S.A. Busari et al., Millimeter-Wave Massive MIMO Communication for Future Wireless Systems : A Survey, *IEEE Commun. Surv. Tutorials* 20 (2) (2018) 836–869.
- [97] Q. Vu, L. Tran, R. Farrell, Energy-Efficient Zero-Forcing Precoding Design for Small-Cell Networks, *IEEE Trans. Commun.* 64 (2) (2016) 790–804.
- [98] L.D. Nguyen, H.D. Tuan, T.Q. Duong, O.A. Dobre, H.V. Poor, Downlink Beamforming for Energy-Efficient Heterogeneous Networks with Massive MIMO and Small Cells, *IEEE Trans. Wirel. Commun.* 17 (5) (2018) 3386–3400.
- [99] J. Tang, D.K.C. So, E. Alsusa, K.A. Hamdi, A. Shojafard, K.K. Wong, Energy-Efficient Heterogeneous Cellular Networks with Spectrum Underlay and Overlay Access, *IEEE Trans. Veh. Technol.* 67 (3) (2018) 2439–2453.
- [100] S.M. Baby, M. James, A Comparative Study on Various Spectrum Sharing Techniques, *Procedia Technol.* 25 (2016) 613–620.
- [101] J. Zheng et al., Joint Energy Management and Interference Coordination with Max-Min Fairness in Ultra-Dense HetNets, *IEEE Access* 6 (2018) 32588–32600.
- [102] A. Adejo, S. Boussakta, J. Neasham, Interference modelling for soft frequency reuse in irregular heterogeneous cellular networks, *Int. Conf. Ubiquitous Futur. Networks, ICUFN*, 2017, pp. 381–386.
- [103] M. Qian, W. Hardjawana, Y. Li, B. Vucetic, X. Yang, J. Shi, Adaptive Soft Frequency Reuse Scheme for Wireless Cellular Networks, *IEEE Trans. Veh. Technol.* 64 (1) (2015) 118–131.
- [104] X. Yang, S. Member, A Multi-level Soft Frequency Reuse Technique for Wireless Communication Systems, *IEEE Commun. Lett.* 7798 (2014) 8–11.
- [105] B. Rong, C. Canada, M. Kadoch, “Traffic Aware Power Allocation and Frequency Reuse for Green LTE-A Heterogeneous Networks, *IEEE Int. Conf. Commun.* (2015) 3167–3172.
- [106] L. Huo, D. Jiang, Z. Lv, Soft frequency reuse-based optimization algorithm for energy efficiency of multi-cell networks, *Comput. Electr. Eng.* 66 (2018) 316–331.
- [107] H. Zhou, S. Zhao, R. Jiang, H. Huang, X. Jiang, L. Wang, “Energy Efficiency Optimization in SFR-Based Power Telecommunication Networks”, *Springer Nat.* 848 (2018) 52–59.
- [108] S. Hossain, F. Tariq, and G. A. Safdar, “Multi-Layer Soft Frequency Reuse Scheme for 5G Heterogeneous Cellular Networks,” 2017 IEEE Globecom Work., pp. 1–6, 2018.
- [109] G. Giambene, S. Member, V.A. Le, S. Member, T. Bourgeois, H. Chaouchi, Iterative Multi-Level Soft Frequency Reuse With Load Balancing for Heterogeneous LTE-A Systems, *IEEE Trans. Wirel. Commun.* 16 (2) (2017) 924–938.
- [110] H. Pervaiz, L. Musavian, Q. Ni, Z. Ding, Energy and Spectrum Efficient Transmission Techniques Under QoS Constraints Toward Green Heterogeneous Networks, *IEEE Access* 3 (2015) 1655–1671.
- [111] G. Bacci, E.V. Belmega, P. Mertikopoulos, L. Sanguinetti, Energy-Aware Competitive Power Allocation for Heterogeneous Networks under QoS Constraints, *IEEE Trans. Wirel. Commun.* 14 (9) (2015) 4728–4742.
- [112] J. Tang, D.K.C. So, E. Alsusa, K.A. Hamdi, A. Shojafard, Resource Allocation for Energy Efficiency Optimization in Heterogeneous Networks, *IEEE J. Sel. Areas Commun.* 33 (10) (2015) 2104–2117.
- [113] A.H. Arani, A. Mehbodniya, M.J. Omid, F. Adachi, W. Saad, I. Guvenc, Distributed Learning for Energy-Efficient Resource Management in Self-Organizing Heterogeneous Networks, *IEEE Trans. Veh. Technol.* 66 (10) (2017) 9287–9303.
- [114] M. Lashgari, B. Maham, H. Kebriaei, “Energy Efficient Price Based Power Allocation in a Small Cell Network by Using a Stackelberg Game”, 2018 *IEEE Int. Black Sea Conf. Commun. Networking, BlackSeaCom* (2018, 2018.), 1–5.
- [115] H. Zhang, H. Liu, J. Cheng, V.C.M. Leung, Downlink Energy Efficiency of Power Allocation and Wireless Backhaul Bandwidth Allocation in Heterogeneous Small Cell Networks, *IEEE Trans. Commun.* 66 (4) (2018) 1705–1716.
- [116] H. Park and Y. Lim, “Energy-effective power control algorithm with mobility prediction for 5G heterogeneous cloud radio access network,” *Sensors (Switzerland)*, vol. 18, no. 9, 2018.
- [117] M. Koolivand, M.H. Bahonar, M.S. Fazel, Improving Energy Efficiency of Massive MIMO Relay Systems using Power Bisection Allocation for Cell-Edge Users, *ICEE* 2019 (2019) 1470–1475.
- [118] L. Huo, D. Jiang, Stackelberg game-based energy-efficient resource allocation for 5G cellular networks, *Telecommun. Syst.* 72 (3) (2019) 377–378.
- [119] J. Chakareski, S. Naqvi, N. Mastronarde, J. Xu, F. Afghah, A. Razi, An Energy Efficient Framework for UAV-Assisted Millimeter Wave 5G Heterogeneous Cellular Networks, *IEEE Trans. Green Commun. Netw.* 3 (1) (2019) 37–44.
- [120] F. Fang, J. Cheng, Z. Ding, and H. V. Poor, “Energy Efficient resource optimization for a downlink noma heterogeneous small-cell network,” *Proc. IEEE Sens. Array Multichannel Signal Process. Work.*, vol. 2018-July, pp. 51–55, 2018.
- [121] D. Gao, Z. Liang, H. Zhang, O.A. Dobre, and G.K. Karagiannis, “Stackelberg Game-Based Energy Efficient Power Allocation for Heterogeneous NOMA Networks,” 2018 *IEEE Glob. Commun. Conf. GLOBECOM* 2018 - Proc., pp. 1–5, 2018.
- [122] M. Zeng, A. Yadav, O.A. Dobre, H.V. Poor, Energy-Efficient Power Allocation for MIMO-NOMA With Multiple Users in a Cluster, *IEEE Access* 6 (2018) 5170–5181.
- [123] H. Zhang, K. Long, F. Fang, J. Cheng, V.C.M. Leung, W. Wang, Energy-Efficient Resource Allocation in NOMA Heterogeneous Networks, *IEEE Wirel. Commun.* 25 (2) (2018) 48–53.
- [124] F. Fang, J. Cheng, Z. Ding, Joint energy efficient subchannel and power optimization for a downlink NOMA heterogeneous network, *IEEE Trans. Veh. Technol.* 68 (2) (2019) 1351–1364.
- [125] X. Song, L. Dong, J. Wang, L. Qin, X. Han, Energy Efficient Power Allocation for Downlink NOMA Heterogeneous Networks with Imperfect CSI, *IEEE Access* 7 (2019) 39329–39340.
- [126] M. Zeng, W. Hao, O.A. Dobre, H.V. Poor, Energy-Efficient Power Allocation in Uplink mmWave Massive MIMO With NOMA, *IEEE Trans. Veh. Technol.* 68 (3) (2019) 3000–3004.
- [127] J.M.T. Cai, Z. Qin, F. Cui, G.Y. Li, “Modulation and Multiple Access for 5G Networks”, *IEEE Commun. Surv. Tutorials* 20 (1) (2018) 629–646.
- [128] W. Shin, M. Vaezi, B. Lee, D.J. Love, J. Lee, H.V. Poor, Non-orthogonal multiple access in multi-cell networks: Theory, performance, and practical challenges, *IEEE Commun. Mag.* 55 (10) (2017) 176–183.
- [129] S.M.R. Islam, M. Zeng, O.A. Dobre, NOMA in 5G Systems: Exciting Possibilities for Enhancing Spectral Efficiency, *IEEE* 1 (2) (2017) 1–6.
- [130] S.M.R. Islam, N. Avazov, O.A. Dobre, K.S. Kwak, Power-Domain Non-Orthogonal Multiple Access (NOMA) in 5G Systems: Potentials and Challenges, *IEEE Commun. Surv. Tutorials* 19 (2) (2017) 721–742.
- [131] M. Aldababsa, M. Toka, S. Gökçeli, G.K. Kurt, O. Kucur, A Tutorial on Nonorthogonal Multiple Access for 5G and Beyond, *Wirel. Commun. Mob. Comput.* (2018).

- [132] A. Nasser, O. Muta, M. Elsabrouty, H. Gacanin, Interference Mitigation and Power Allocation Scheme for Downlink MIMO-NOMA HetNet, *IEEE Trans. Veh. Technol.* 68 (7) (2019) 6805–6816.
- [133] Q. Ye, B. Rong, Y. Chen, M. Al-Shalash, C. Caramanis, J.G. Andrews, User association for load balancing in heterogeneous cellular networks, *IEEE Trans. Wirel. Commun.* 12 (6) (2013) 2706–2716.
- [134] Y. Lin, W. Bao, W. Yu, B. Liang, Optimizing user association and spectrum allocation in HetNets: A utility perspective, *IEEE J. Sel. Areas Commun.* 33 (6) (2015) 1025–1039.
- [135] S. Fan, H. Tian, W. Wang, Joint effect of user activity sensing and biased cell association in energy efficient hetnets, *IEEE Commun. Lett.* 20 (10) (2016) 1999–2002.
- [136] F. Tariq, L. S. Dooley, and A. S. Poulton, "Analysis of coverage range expansion in closed access cognitive femtocell networks," *Int. Symp. Wirel. Pers. Multimed. Commun. WPMC*, no. June 2013, 2013.
- [137] F. Tariq, L. Dooley, B. Allen, A. Poulton, E. Liu, A Cell Range Expansion Framework for Closed Access Femtocell Networks, *Wirel. Pers. Commun.* 93 (3) (2017) 601–614.
- [138] R. Tao, W. Liu, X. Chu, J. Zhang, An Energy Saving Small Cell Sleeping Mechanism with Cell Range Expansion in Heterogeneous Networks, *IEEE Trans. Wirel. Commun.* 18 (5) (2019) 2451–2463.
- [139] H. Ding, H. Zhang, J. Tian, S. Xu, D. Yuan, "Energy Efficient User Association and Power Control for Dense Heterogeneous Networks", *2018 Int. Conf. Comput. Netw. Commun. ICNC 2018* (2018) 741–746.
- [140] Y. Zhang et al., Energy Efficiency Analysis of Heterogeneous Cellular Networks with Extra Cell Range Expansion, *IEEE Access* 5 (2017) 11003–11014.
- [141] B. Yang, G. Mao, X. Ge, M. Ding, X. Yang, On the Energy-Efficient Deployment for Ultra-Dense Heterogeneous Networks with NLoS and LoS Transmissions, *IEEE Trans. Green Commun. Netw.* 2 (2) (2018) 369–384.
- [142] L. Li, M. Peng, C. Yang, Y. Wu, Optimization of base-station density for high energy-efficient cellular networks with sleeping strategies, *IEEE Trans. Veh. Technol.* 65 (9) (2016) 7501–7514.
- [143] J. Gao, Q. Ren, P.S. Gu, X. Song, User association and small-cell base station on/off strategies for energy efficiency of ultradense networks, *Mob. Inf. Syst.* (2019).
- [144] X. Dong, F.C. Zheng, X. Zhu, J. Luo, HetNets with Range Expansion: Local Delay and Energy Efficiency Optimization, *IEEE Trans. Veh. Technol.* 68 (6) (2019) 6147–6150.
- [145] W.S. Lai, T.H. Chang, T.S. Lee, Joint power and admission control for spectral and energy efficiency maximization in heterogeneous OFDMA networks, *IEEE Trans. Wirel. Commun.* 15 (5) (2016) 3531–3547.
- [146] C. Liu, B. Natarajan, H. Xia, Small Cell Base Station Sleep Strategies for Energy Efficiency, *IEEE Trans. Veh. Technol.* 65 (3) (2016) 1652–1661.
- [147] H. Klessig et al., From immune cells to self-organizing ultra-dense small cell network, *IEEE J. Sel. Areas Commun.* 34 (4) (2016) 800–811.
- [148] Y. El Morabit, F. Mrabti, and E. H. Abarban, "Small cell switch off using genetic algorithm," *Proc. - 3rd Int. Conf. Adv. Technol. Signal Image Process. ATSIP 2017*, pp. 1–4, 2017.
- [149] Z. Li, P. Yu, W. Li, X. Qiu, "Modeling and optimization of self-organizing energy-saving mechanism for HetNets", *Proc. NOMS 2016–2016, IEEE/IFIP Netw. Oper. Manag. Symp.* 2014 (2016) 146–152.
- [150] Z. Niu, Y. Wu, J. Gong, Z. Yang, Cell zooming for cost-efficient green cellular networks, *IEEE Commun. Mag.* 48 (11) (2010) 74–79.
- [151] Z. Zhang, F. Liu, and Z. Zeng, "The cell zooming algorithm for energy efficiency optimization in heterogeneous cellular network," *2017 9th Int. Conf. Wirel. Commun. Signal Process. WCSP 2017 - Proc.*, vol. 2017-Janua, pp. 1–5, 2017.
- [152] X. Xu, C. Yuan, W. Chen, X. Tao, Y. Sun, Adaptive Cell Zooming and Sleeping for Green Heterogeneous Ultradense Networks, *IEEE Trans. Veh. Technol.* 67 (2) (2018) 1612–1621.
- [153] S. Mollahasani, S. Member, E. Onur, Density-Aware, Energy- and Spectrum-Efficient, *IEEE Access* 7 (2019) 65852–65869.
- [154] J. Sheng, Y. You, D. Ma, C. Zhu, and F. Xu, Continuous cell zooming algorithm towards energy efficient in random heterogeneous cellular networks, vol. 236. Springer International Publishing, 2018.
- [155] F.R. Arvaje and B.S. Ghahfarokhi, "A spectrum efficient base station switching-off mechanism for green cellular networks," *2017 7th Int. Conf. Comput. Knowl. Eng. ICCKE 2017*, vol. 2017-Janua, no. Iccke, pp. 433–438, 2017.
- [156] L. P. Tung, L. C. Wang, and K. S. Chen, "An interference-aware small cell on/off mechanism in hyper dense small cell networks," *2017 Int. Conf. Comput. Netw. Commun. ICNC 2017*, pp. 767–771, 2017.
- [157] X. Chen, J. Wu, Y. Cai, H. Zhang, T. Chen, Energy-efficiency oriented traffic offloading in wireless networks: A brief survey and a learning approach for heterogeneous cellular networks, *IEEE J. Sel. Areas Commun.* 33 (4) (2015) 627–640.
- [158] Z. Niu, X. Guo, S. Zhou, P.R. Kumar, Characterizing energy-delay tradeoff in hyper-cellular networks with base station sleeping control, *IEEE J. Sel. Areas Commun.* 33 (4) (2015) 641–650.
- [159] X. Huang, S. Tang, Q. Zheng, D. Zhang, and Q. Chen, "Dynamic Femtocell gNB On/Off Strategies and Seamless Dual Connectivity in 5G Heterogeneous Cellular Networks," *IEEE Access*, vol. 6, no. c, pp. 21359–21368, 2018.
- [160] A. De Domenico and D. Ktenas, "Reinforcement learning for interference-aware cell DTX in heterogeneous networks," *IEEE Wirel. Commun. Netw. Conf. WCNC*, vol. 2018-April, pp. 1–6, 2018.
- [161] A. Hajijamali Arani, M.J. Omid, A. Mehbodniya, F. Adachi, "Minimizing Base Stations' ON/OFF Switchings in Self-Organizing Heterogeneous Networks: A Distributed Satisfactory Framework", *IEEE Access* 5 (2017) 26267–26278.
- [162] X. Gan et al., Energy efficient switch policy for small cells, *China Commun.* 12 (1) (2015) 78–88.
- [163] T. Zhou, N. Jiang, Z. Liu, C. Li, Joint Cell Activation and Selection for Green Communications in Ultra-Dense Heterogeneous Networks, *IEEE Access* 6 (2017) 1894–1904.
- [164] M. Feng, S. Member, S. Mao, S. Member, T. Jiang, S. Member, BOOST : Base Station ON-OFF Switching Strategy for Green Massive MIMO HetNets, *IEEE Trans. Wirel. Commun.* (2017).
- [165] A. Gbenga-Ilori, O. Ladipo, O. Alamu, Queueing decision model for throughput maximization in green communications networks, *Int. J. Eng. Bus. Manag.* vol (2019) 11.
- [166] Y. Huo, X. Dong, W. Xu, 5G cellular user equipment: From theory to practical hardware design, *IEEE Access* 5 (2017) 13992–14010.
- [167] S. P. Yadav and S. M. Ieee, "Linearity Improvement of Microwave Power Amplifiers," *IEEE Annu. India Conf.*, pp. 1–6, 2016.
- [168] R.V.S. Devi, D.G. Kurup, "Behavioral Modeling of RF Power Amplifiers for Designing Energy Efficient Wireless Systems", *IEEE WiSPNET Conf.* (2017) 1994–1998.
- [169] P. D. Pamungkasari, I. Shubhi, F. H. Juwono, P. D. Mariyam, and D. Gunawan, "Time Domain Cyclic Selective Mapping for PAPR Reduction in MIMO-OFDM Systems," *2018 IEEE Int. Conf. Innov. Res. Dev.*, no. May, pp. 1–4, 2018.
- [170] B. Lee, Y. Kim, Interference-Aware PAPR Reduction Scheme to Increase the Energy Efficiency of Large-Scale, *Energies* 11 (2017) 1–16.
- [171] N.N. Moghadam, G. Fodor, S. Member, On the Energy Efficiency of MIMO Hybrid Beamforming for Millimeter Wave Systems with Nonlinear Power Amplifiers, *IEEE Trans. Wirel. Commun.* 17 (11) (2018) 7208–7221.
- [172] D. Pompili, A. Hajasami, T.X. Tran, Elastic Resource Utilization Framework for High Capacity and Energy Efficiency in Cloud RAN, *IEEE Commun. Mag.* 54 (1) (2016) 26–32.
- [173] Q. Liu, T. Han, N. Ansari, G. Wu, On Designing Energy-Efficient Heterogeneous Cloud Radio Access Networks, *IEEE Trans. Green Commun. Netw.* 2 (3) (2018) 721–734.
- [174] B. Dai, S. Member, W. Yu, Energy Efficiency of Downlink Transmission Strategies for Cloud Radio Access Networks, *IEEE J. Sel. Areas Commun.* 34 (4) (2016) 1037–1050.
- [175] R. S. Alhumaima and H. S. Al-raweshidy, "Evaluating the energy efficiency of software defined-based cloud radio access networks," *IET Commun.*, pp. 987–994, 2016.
- [176] H. Ghazzai, E. Yaacoub, M.S. Alouini, A. Abu-Dayya, Optimized smart grid energy procurement for LTE networks using evolutionary algorithms, *IEEE Trans. Veh. Technol.* 63 (9) (2014) 4508–4519.
- [177] J. Xu, L. Duan, R. Zhang, Cost-aware green cellular networks with energy and communication cooperation, *IEEE Commun. Mag.* 53 (5) (2015) 257–263.
- [178] Q. Wang, F. Zhao, T. Chen, A Base Station DTX Scheme for OFDMA Cellular Networks Powered by the Smart Grid, *IEEE Access* 6 (2018) 63442–63451.
- [179] D. Zhai, R. Zhang, J. Du, Z. Ding, F.R. Yu, Simultaneous wireless information and power transfer at 5G new frequencies: Channel measurement and network design, *IEEE J. Sel. Areas Commun.* 37 (1) (2019) 171–186.
- [180] T.D. Ponnimbaduge Perera, D.N.K. Jayakody, S.K. Sharma, S. Chatzinotas, J. Li, "Simultaneous Wireless Information and Power Transfer (SWIPT) Recent Advances and Future Challenges", *IEEE Commun. Surv. Tutorials* 20 (1) (2018) 264–302.
- [181] S. Akbar, Y. Deng, A. Nallanathan, M. ElKashlan, A.H. Aghvami, Simultaneous wireless information and power transfer in K-tier heterogeneous cellular networks, *IEEE Trans. Wirel. Commun.* 15 (8) (2016) 5804–5818.
- [182] M. Sheng, L. Wang, X. Wang, Y. Zhang, C. Xu, J. Li, Energy Efficient Beamforming in MISO Heterogeneous Cellular Networks with Wireless Information and Power Transfer, *IEEE J. Sel. Areas Commun.* 34 (4) (2016) 954–968.
- [183] J. Tang, A. Shojaeifard, D.K.C. So, K.K. Wong, N. Zhao, Energy efficiency optimization for CoMP-SWIPT heterogeneous networks, *IEEE Trans. Commun.* 66 (12) (2018) 6368–6383.
- [184] S. Jang, H. Lee, S. Kang, T. Oh, I. Lee, Energy Efficient SWIPT Systems in Multi-Cell MISO Networks, *IEEE Trans. Wirel. Commun.* 17 (12) (2018) 8180–8194.
- [185] Z. Fang, Y. Wu, Y. Lu, J. Hu, T. Peng, J. Ye, Simultaneous Wireless Information and Power Transfer in Cellular Two-Way Relay Networks with Massive MIMO, *IEEE Access* 6 (2018) 29262–29270.
- [186] A. Zappone, E. Björnson, L. Sanguinetti, E. Jorswieck, Globally Optimal Energy-Efficient Power Control and Receiver Design in Wireless Networks, *IEEE Trans. Signal Process.* 65 (11) (2017) 2844–2859.
- [187] G. Auer et al., How Much Energy is Needed to Run a Wireless Network?, *IEEE Wirel. Commun.* 18 (5) (2011) 40–49.
- [188] K. Kanwal and G. A. Safdar, "Growing green with improved profit through reduced power consumption in LTE networks," *ACM Int. Conf. Proceeding Ser.*, pp. 3–8, 2017.
- [189] R.S. Alhumaima, M. Khan, H.S. Al-Raweshidy, Component and parameterised power model for cloud radio access network, *IET Commun.* 10 (7) (2016) 745–752.
- [190] M.H. Alsharif, R. Nordin, M. Ismail, Survey of green radio communications networks: Techniques and recent advances, *J. Comput. Networks Commun.* vol (2013, 2013.).
- [191] N. Piovesan, A. Fernandez Gambin, M. Miozzo, M. Rossi, P. Dini, Energy sustainable paradigms and methods for future mobile networks: A survey, *Comput. Commun.* 119 (2018) 101–117.
- [192] Y. Ramamoorthi, A. Kumar, Resource allocation for energy efficient next generation cellular networks, *CSI Trans. ICT* 5 (2) (2017) 179–187.

- [193] B. Perabathini, E. Bastug, M. Kountouris, M. Debbah, A. Conte, "Caching at the edge: A green perspective for 5G networks", *2015 IEEE Int. Conf. Commun. Work. ICCW 2015* (2015) 2830–2835.
- [194] A. Jahid, A. Bin Shams, M.F. Hossain, Green energy driven cellular networks with JT CoMP technique, *Phys. Commun.* 28 (2018) 58–68.
- [195] A. Jahid, A. Bin Shams, M.F. Hossain, PV-powered CoMP-based green cellular networks with a standby grid supply, *Int. J. Photoenergy* (2017).
- [196] D. Sabella et al., Energy efficiency benefits of RAN-as-a-service concept for a cloud-based 5G mobile network infrastructure, *IEEE Access* 2 (2014) 1586–1597.
- [197] A. A. Khan, P. Uthansakul, P. Duangmanee, and M. Uthansakul, "Energy efficient design of Massive MIMO by considering the effects of nonlinear amplifiers," *Energies*, vol. 11, no. 5, 2018.
- [198] E.B. Haghighi, "Displacement free cooling for telecommunication base stations", *INTELEC. Int. Telecommun. Energy Conf.* (2017) 54–58.
- [199] G. Wu, F. Zeng, G. Zhu, Research on ventilation cooling system of communication base stations for energy saving and emission reduction, *Energy Build.* 147 (2017) 67–76.
- [200] W. Tschudi, *Guide to Minimizing Compressor-based Cooling in Data Centers*, Washington D.C. (2013).
- [201] R. Mahapatra, Y. Nijsure, Energy Efficiency Tradeoff Mechanism Towards Wireless Green Communication : A Survey, *IEEE Commun. Surv. Tutorials*, 2015.
- [202] M.H. Alsharif, R. Nordin, M. Ismail, Classification, recent advances and research challenges in energy efficient cellular networks, *Wirel. Pers. Commun.* 77 (2014) 1249–1269.
- [203] E.F. Orumwense, T.J. Afullo, V.M. Srivastava, Energy efficiency metrics in cognitive radio networks: A holistic overview, *Int. J. Commun. Networks Inf. Secur.* 8 (2016) 75–85.
- [204] Y. Chi, L. Liu, G. Song, C. Yuen, Y.L. Guan, Y. Li, Practical MIMO-NOMA: Low Complexity and Capacity-Approaching Solution, *IEEE Trans. Wirel. Commun.* 17 (9) (2018) 6251–6264.
- [205] E. Björnson, L. Sanguinetti, H. Wymeersch, J. Hoydis, T.L. Marzetta, Massive MIMO is a reality — What is next ? Five promising research directions for antenna arrays, *Digit. Signal Process.* 94 (2019) 3–20.
- [206] M. Olyae, M. Eslami, J. Haghighat, An energy-efficient joint antenna and user selection algorithm for multi-user massive MIMO downlink, *IET Commun.* 12 (3) (2018) 255–260.
- [207] A. Alnoman, G.H.S. Carvalho, A. Anpalagan, I. Woungang, Energy Efficiency on Fully Cloudified Mobile Networks : Survey, Challenges, and Open Issues, *IEEE Commun. Surv. Tutorials* 20 (2) (2017) 1271–1291.
- [208] T. Zhang, K. Zhu, D. Niyato, A Generative Adversarial Learning Based Approach for Cell Outage Detection in Self-organizing Cellular Networks, *IEEE Wirel. Commun. Lett.* 9 (2) (2019) 171–174.
- [209] P.V. Klaine et al., A Survey of Machine Learning Techniques Applied to Self Organizing Cellular Networks, *IEEE Commun. Surv. Tutorials* 19 (4) (2017) 2392–2431.
- [210] O.G. Aliu, A. Imran, M.A. Imran, B. Evans, A Survey of Self Organisation in Wireless Cellular Communication Networks, *IEEE Commun. Surv. Tutorials* 15 (1) (2013) 336–361.
- [211] A. Mohamed, O. Onireti, M.A. Imran, A. Imran, R. Tafazolli, Control-data separation architecture for cellular radio access networks: A survey and outlook, *IEEE Commun. Surv. Tutorials* 18 (1) (2016) 446–465.