SpiderNet: Spectrally Efficient and Energy Efficient Data Aided Demand Driven Elastic Architecture for 6G

Muhammad Nabeel, Umair Sajid Hashmi, Sabit Ekin, Hazem Refai, Adnan Abu-Dayya, and Ali Imran

Abstract

Legacy base station (BS) centric cellular architecture is marked by tight interlock between spectral efficiency (SE) and energy efficiency (EE). That means, unless new degrees of freedom and intelligent dynamic adaptability is added, any significant gain in SE must come at the cost of EE. Even the most predominant approaches for capacity enhancement such as network densification yield gains in SE at the cost of increased energy consumption. Moreover, in future mobile networks, the key challenge is not only the rampantly growing volume of traffic, but also the spatiotemporal variability of the traffic. These observations call for a paradigm shift in the way cellular networks are designed and operated. Therefore, in this work, we propose a new cellular architecture called SpiderNet: Spectrally Efficient and Energy Efficient Data Aided Demand Driven Elastic Architecture for 6G Wireless Networks. The key idea behind SpiderNet is to introduce additional degrees of freedom to relax the tight coupling between the SE and EE and database-aided intelligence to enable dynamic adaptive operation for simultaneous enhancement of both SE and EE. This goal is achieved by shifting the pivot of operation from the rigid always ON BS centric cells to user centric (UC) on demand cells. The SpiderNet architecture consists of a layer of low-density large footprint and database aided control BS underlayed by high-density switchable data BS. This database enables artificial intelligence (AI) powered proactive dynamic orchestration of UC cells to maximize not only SE and EE, but quality of experience (QoE) as well. We also identify the challenges that arise in the practical realization of SpiderNet and propose solutions. Finally, we present a case study that compares SpiderNet performance with legacy HetNets. The results show that compared to current BS centric cellular architecture, SpiderNet can substantially enhance both SE and EE without compromising QoE.

Introduction

The cellular industry undergoes a generational transition almost after every decade due to the growing number of new applications and their advanced requirements. With the recent rollout of Fifth Generation (5G), the research community has already turned its attention toward Sixth Generation (6G) and its targeted applications. Unlike 5G which focused on tradeoffs to provide enhanced Mobile Broadband (eMBB), Ultra Reliable Low Latency Communications (URLLC), and massive Machine Type Communications (mMTC), 6G is envisioned to jointly meet strict network demands (e.g., high energy- and spectral-efficiency, high throughput, ultra-high reliability, and ultra-low latency) [1]. Both user-centric network architecture and ultra-dense deployment of small base stations (BSs) are considered as key enablers for 6G.

In ultra-dense deployment, the density of BSs plays a crucial role in achieving the best performance. Recent studies, for example, [2], show that there exists an optimal BS density that maximizes network energy efficiency (EE) defined as area spectral efficiency (ASE) divided by BS power consumption per unit area. However, a different, often much higher cell density is needed to maximize spectral efficiency (SE) or ASE. This is illustrated in Fig. 1. Similarly, findings from the EARTH project [3] show that for a given BS density, traffic and BS type (and hence BS power consumption model), there exists an optimal set of BS transmission powers that maximizes SE, but a different set of optimal transmission powers is needed to maximize network EE. This is because depending on BS type, the EE of BS varies differently with traffic load. Measured data in [3] also show that BS overall power consumption can be a linear or non-linear function of load depending on the type of the BS that in turn dictates load dependency of component level power consumption. Another dimension is added to the problem of jointly maximizing SE and overall EE (including that of network and user equipment (UE)) when we take into account the fact that though increasing BS density increases the network energy consumption, it decreases energy consumption of UE for uplink (UL) transmission by bringing the BSs closer to the UE on average. Yet another SE-EE interplay dimension is analyzed in [4], which shows that though increased BS density decreases UE battery consumption for data transmission, it increases the UE battery consumption for cell discovery, signaling and handovers. The analysis in [4] also proves that there exists an optimal cell discovery periodicity that optimizes UE EE and it is non-linearly related to a number of factors including cell density, UE mobility pattern and cell loads.

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These observations clearly suggest that existing cellular architecture's rigid cell-centric always ON modus operandi simply does not have the degrees of freedom and adaptability to simultaneously maximize both SE and EE. Therefore, a new elastic architecture with higher degrees of freedom is needed to enable a simultaneous increase in SE and EE.

Building on these findings, in this article we propose a novel architecture called SpiderNet, that is, Spectrally Efficient and Energy Efficient Data Aided Demand Driven Elastic Architecture for 6G Wireless Networks. Instead of just trading SE with EE and vice versa as is the case with BS switch ON/OFF schemes in legacy architecture, the SpiderNet architecture exploits user centric elastic cells in conjunction with historic databases at control base stations (CBSs) to intelligently maximize both SE and EE while taking into account spatiotemporally varying demand. The introduction of user centric elastic cell is a new degree of freedom which breaks the tight SE-EE interplay, and hence makes it possible to maximize both SE and EE at the same time by controlling and dynamically changing the radius of this user centric cell. Thus, this architecture can be a possible candidate for 6G. The goal of this article is to explicate, analyze and evaluate SpiderNet architecture.

The article's main contributions can be summarized as follows. We propose the SpiderNet architecture to intelligently maximize both SE and EE in future cellular networks. We identify key challenges that can arise when realizing SpiderNet in practice and present potential solutions. We present a comparative study that shows the performance improvement achieved with the proposed SpiderNet architecture compared to legacy HetNets.

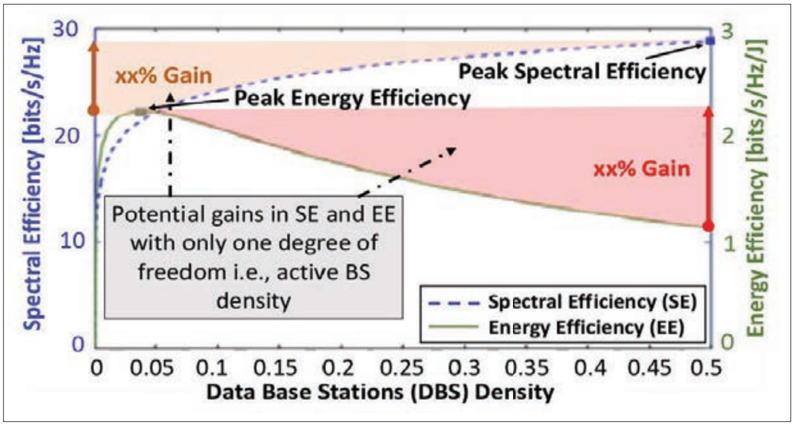

FIGURE 1. Spectral efficiency and energy efficiency vs. base stations density.

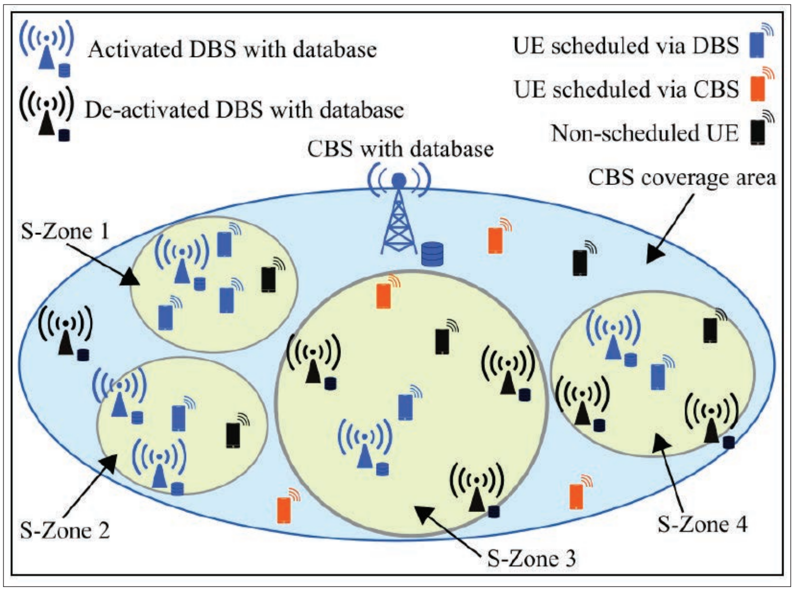

FIGURE 2. SpiderNet architecture with four different S-Zones, that is, S-Zone 1 created by a cluster of scheduled UEs to be served by a single DBS, S-Zone 2 created around a scheduled UE to be served by two DBSs simultaneously using cooperation, S-Zone 3 is a larger S-Zone created around a scheduled UE for higher EE in the network, and S-Zone 4 is a smaller S-Zone created around a UE for better ASE.

SpiderNet Overview

In this section, we explain the SpiderNet architecture as well as the unique features it offers. Figure 2 illustrates the proposed SpiderNet architecture. It consists of a minimum two layers of BS deployments with at least two distinct bands. The top layer consists of low-density macro BSs hereafter called CBSs, while a lower layer consists of low energy consumption ultra-dense small remote radio heads hereafter called data base stations (DBSs). This two-layer coverage allows orchestration between different active DBS densities by switching DBSs ON/OFF as needed without creating coverage holes.

The idea of switching ON/OFF for saving energy is not new; however, switching ON/OFF schemes suffer from two key problems: discovering OFF DBSs is a challenge, and it exploits only one degree of freedom in the multidimensional SE-EE interplay explained in the last section, that is, BS density λ. Therefore, current BS ON/OFF schemes can only increase EE at the cost of SE and quality of experience (QoE) and vice versa. The SpiderNet architecture is designed to solve the latter problem through the introduction of a new degree of freedom, that among other benefits, relaxes the tight SE-EE tradeoff relationship, thereby allowing enhancement of both SE and EE substantially beyond what current architecture can offer. This new degree of freedom called service zone (S-Zone) is defined as follows. During every transmission time interval (TTI), each scheduled UE or a set of UEs (referred to as a UE cluster (UEC)) acts as a center of a virtual cell and this cell constitutes the S-Zone. The most suitable DBS within that S-Zone is then activated to serve the UE/UEC in that TTI. The rest of DBSs inside the S-Zone remain OFF. UEs/UECs are scheduled each TTI based on their QoE requirements.

The S-Zone concept ensures no interfering DBSs within the distance dictated by the size of the S-Zone is activated. However, this idea can be extended to activate multiple DBSs within an S-Zone by exploiting coordinated multi-point transmission (CoMP) [5], thus retaining the key benefit of the S-Zone, that is, UEs within the S-Zone do not face interference from any other DBS within its S-Zone. The UEs with no DBS within their S-Zones are served by a CBS. Larger S-Zones enables better link-level SE due to lower interference, better DBS selection, or enhanced cooperation diversity, and higher EE in network but lower system level spectrum reuse efficiency and higher energy consumption in the UE. In contrast, smaller S-Zones result in decreased network level EE due to larger number of active DBSs in given TTI, but increased UE battery life by selecting the serving DBS closer to the UE.

The rationale for the S-Zone centric, instead of classic BS centric, architecture stems from the insights gained from our earlier work [2]. Joint SE-EE analysis in [2] shows that S-Zone controls SE and EE in a way oppositive of that of active DBS density λ. While SE increases monotonically with λ and EE has a highly gainful optimal point in λ, with S-Zone size, SE has a highly gainful optimal point and EE increases monotonially. The size of the S-Zone is thus a new degree of freedom that offers unprecedented leverage in SE-EE tradeoff that is distinct from that attainable by simply switching ON/OFF base stations to change λ in legacy BS centric architecture. When optimized in conjunction with other design parameters in SpiderNet such as λ, S-Zone based orchestration in SpiderNet has the potential to achieve higher gains in SE and EE simultaneously (as shown later). The resultant gains are not possible in current architecture where typically BSs are switched ON/OFF to adapt λ only and thus always trade SE with EE along a unidirectional pareto optimal front. It is important to highlight that S-Zone also introduces new challenges including an increase in optimization complexity in the case of dynamic S-Zone selection, scheduling delay with non-overlapping S-Zones, and fronthaul control load increase due to continuous control information exchange between CBS and DBSs. These challenges can be addressed by intelligently choosing the S-Zone size and that also from a carefully designed finite sample space.

To address the former problem, that is, discovering an OFF BS, the SpiderNet architecture incorporates a database of selected measurements that includes reference signal received power (RSRP), physical resource block (PRB) usage, and mobility traces among others for proactively orchestrating S-Zones leveraging Artificial Intelligence (AI). Exploiting a database and AI not only addresses the OFF DBS discovery challenge, but can also address several issues in the practical deployment of SpiderNet: dynamically defining optimal S-Zones, DBs activation/deactivation delay, spectrum as well as energy resource allocation in DBSs and UEs for jointly optimizing SE and EE. Moreover, AI based models may be employed to enable real-time adjustments to operating parameters and yield optimal SE-EE tradeoffs. For instance, a deep neural network (DNN) may be trained with an aggregated network generated and simulation generated dataset to learn the mapping between operating parameters (such as S-Zone size, λ), network counters (such as user distribution density, EE-SE tradeoff factor, traffic distribution, propagation terrain) and the SE-EE tradeoff optimization utility function. A well trained DNN would take the real-time network counters as input and yield near-optimal operating parameters for an operator desired SE-EE tradeoff. The utility obtained from AI-based network wide automation can then be compared against simulator-based measurements and passed through ensemble classifiers for continuous updating of DNN weights.

Key Challenges and Solutions

In order to successfully realize SpiderNet architecture in practical networks, the first step would be to derive analytical models to characterize the SE and EE of SpiderNet and determine the key design parameters that can be used to optimize its performance such as S-Zone size, DBS density, and other system parameters. Moreover, simulation-based models need to be developed to test the performance empirically against legacy HetNet architecture. In the following, we identify the key challenges that must be addressed before the SpiderNet can be transformed from an idea into a functional network and hint on potential ways to tackle these challenges.

Exploiting First Degree of Freedom for Optimally Trading SE and EE

Challenge: Earlier studies show that the SE and EE are the tractable functions of BS density λ [2]. The expression for ASE (i.e., SE averaged over an area) as a function of λ is derived using stochastic geometry tools, if DBS deployment is approximated as a Poisson point process (PPP) with λ, whereas EE is defined as the ASE over power consumption per unit area. The power consumption per unit area is usually calculated from a very simple model that depends on fixed power consumption of an active DBS, expressed as a constant that sums together frequency dependent power amplification, active UE density load dependent DBS transmit power, and several other factors. To overcome the limitation of this simple model, there is a need for a method to accurately capture power consumption at DBS as well as CBS in the SpiderNet. A key challenge is to model the power as function of load, bandwidth, and frequency of operation. Additionally, it is also important to consider the user device perspective in this EE analysis. Moreover, the PPP assumption considered for ASE calculation does not accurately model the repulsion that exists in the actual deployment of BSs.

Potential Solutions: To analyze the SpiderNet architecture accurately, the load dependent power consumption can be modeled at the component level for more accurate representation. This is possible with the help of component datasheets that constitute different types of DBS and CBS as well as with the help of literature such as [3]. The obtained values can then be fed into regression or deep neural network (DNN) based models for overall power consumption estimation.

By changing λ, in addition to changing SE and network EE, the EE of an UE is affected in two ways: it changes the average distance to the serving DBS, and it changes the UE energy consumption in the cell discovery process. Therefore, the analytical model for energy consumption during cell discovery derived in [4] can be extended for SpiderNet by including the user-centric cells instead of BS-centric cells. Hence, resulting in developing a new metric for evaluating the EE of UE to be considered in the overall EE estimation.

Finally, β-Ginibre point process (GPP) that captures repulsion in practical BSs deployments can be considered instead of PPP. However, once a repulsion-based point process and non-linear power consumption model are used to characterize ASE and overall EE (including that of UE), unlike the results shown in Fig. 1, the resultant EE-ASE optimization problem is not likely to be convex. In this case, the problem can be solved by leveraging the fact that the feasible range of λ is small enough to allow the use of many non-convex optimization tools suitable for small scale non-convex optimization problems. One such tool is sequential quadratic programming that has already been used successfully in the literature for other similar small-scale non-convex problems [6].

Exploiting Higher Degrees of Freedom for Jointly Maximizing SE and EE

Challenge: As can be seen from Fig. 1, the DBS density λ that yields optimal SE is not the same that yields optimal EE. Therefore, it is impossible to enhance both SE and EE beyond a limit without compromising one of them. This reinforces the need for the proposed introduction of a second degree of freedom for maximizing both ASE and EE. The previous section introduced S-Zone as a new degree of freedom to tackle this challenge. However, finding optimal user-centric S-Zone size especially under Spatio-temporally varying QoE constraints is significant. Moreover, it is challenging to group multiple UEs as a single point to create S-Zones. Finally, modeling network power consumption in the S-Zone based operation is another challenge.

Potential Solutions: In the scope of SpiderNet, the ASE and EE can be characterized as the function of S-Zone that involves QoE measure and, hence, makes it possible to find optimal S-Zone size by solving it as an optimization problem. The optimization here considers the operator's priority between SE and EE, and quality of service (QoS) outage criteria. Previously in [2], we have shown that for each UEC (or UE) density as well as DBS density λ, there exists an optimal S-Zone size that maximizes the ASE under fixed network parameters. Similarly, the investigation of EE in SpiderNet showed that i) EE has a monotonically increasing trend with S-Zone size; ii) higher path loss exponents result in lower mean interference and consequently a more energy efficient network. These findings demonstrate that optimization of S-Zone size when performed in conjunction with λ (and other design parameters including DBS transmission power and scheduling schemes) has the potential to substantially enhance both SE and EE.

In the literature, clustering based algorithms are used for combining users to act as a single point to simplify the antenna parameter optimization solution [5]. In a similar way, UEs can be merged here to be served by CoMP for creating S-Zone. Since multiple UEs are clustered into a single UEC, they can be approximated with a tractable point process.

Finally, the active DBS density λ can be modeled as a stationary process that stays constant throughout the network. With service centric elasticity introduced by S-Zone based operation, the number of active DBSs can change every TTI, depending on the size of the S-Zone, that in turn depends on spatiotemporally changing service requirements. The average number of activated DBSs within each S-Zone can then be derived considering only a single DBS activated per cluster for downlink (DL) transmission. Furthermore, to enable spatial elasticity to further maximize SE-EE while ensuring UE/UEC specific QoE, distributed solution approaches, for example, game theory, can be targeted.

Designing the Database

Challenge: For a successful operation of SpiderNet to optimally orchestrate λ and S-Zone size for maximum SE and EE, switching DBS ON/OFF without compromising QoE is crucial. However, cell switching is difficult to implement as OFF cells do not transmit pilot signals, making them impossible to be discovered by incoming UEs. In the literature, proposed solutions to this problem fall into two categories: i) a UL signaling based approach in which an RF receiver module of small cell is kept active even when in sleep mode and only starts transmitting pilot signals after receiving a wake-up signal from incoming UEs [7]; ii) a DL signaling based approach is an alternative approach in which small cells in sleep mode send pilots to remain discoverable by the UEs, but at a much-reduced rate compared to when in the ON state [8]. Even if the cell discovery problem is solved by any of the approaches, the delay in switching cells ON and OFF increases service latency. Such connection establishment latency may be acceptable for legacy services but is not acceptable for emerging ultra-low latency use cases.

Potential Solution: SpiderNet can address the aforementioned challenges by equipping each DBS/CBS with a database that stores maps of various channel quality measurements and other training data within its coverage. For example, the database can also include call detailed records (CDR) that can be easily harnessed to predict traffic patterns and user mobility traces that in turn can be leveraged to predict traffic in space and time. The key idea is to exploit these databases to proactively switch ON DBSs anticipating incoming traffic load and user mobility, thereby eliminating the DBS switching ON/OFF delay. The SpiderNet performance can then be analyzed with the assumption of unlimited (and infinite) database storage capacities and perfect data quality which can provide the upper bound on the performance of SpiderNet.

However, as in practice the storage and processing cannot be infinite particularly at low cost DBS, it is important to identify the exact data that should be stored at DBS/CBS. Moreover, even when some data is available, it is often not enough to train an AI engine adequately. Finally, data inaccuracies can impact the overall performance, therefore, it is important to devise methods to deal with imperfect data. Thus, realizable performance gains of SpiderNet hinge on the type, quantity, and quality of the data to be stored and mined. Candidate data streams include RSRP, reference signal received quality (RSRQ), signal-to-noise ratio (SNR), signal-to-interference-plus-noise ratio (SINR), channel quality indicator (CQI), PRB usage, CDR index, radio link failure (RLF), and handover (HO) reports. For data such as RSRP, recent work [9] shows that there exists an optimal spatial resolution that minimizes the impact of reporting UE positioning error and quantization error. Therefore, realizing the optimal spatial reso-

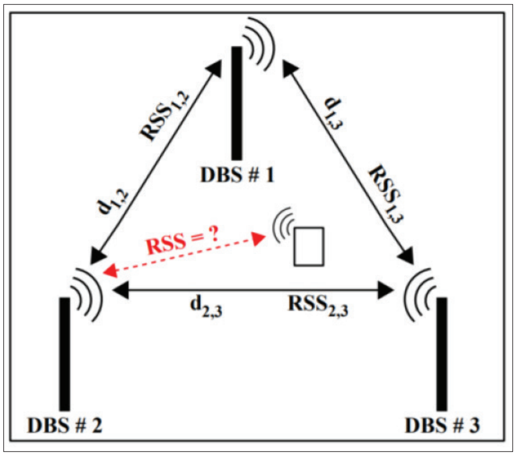

FIGURE 3. Approach to enrich the database.

lution and temporal update frequency associated with each of the data streams is important. It is also worth noting that out of the aforementioned data, measuring and storing actual SINR might not be practically feasible as it changes rapidly with traffic load variations. To circumvent this issue, the SNR (which can be estimated via RSRP) can be logged and then translated into SINR using approximations of total number of active cells and devices.

The database for SpiderNet can be designed by extending the principle recently adopted by the Third Generation Partnership Project (3GPP) for minimization of drive test (MDT) reports. This certainly means that UE reported measurements along with their location coordinates can be used to create a map/database of coverage/service quality without performing extensive drive tests. To reduce the complexity of this database, the coverage area can be divided into virtual data bins. Ideally, we want measurements from each spatial bin for each temporal interval to have an entry. However, in practice, it is highly likely that most of the bins would be empty due to the absence of users in those bins. To address this problem, a tri-pronged approach can be leveraged.

Intelligent Interpolation: By analyzing the underlying features of particular data streams, for example, spatiotemporal auto-correlation and stationarity, suitable interpolation methods such as moving average, nearest neighbor, spline method, inverse distance weighted, natural neighbor, Kriging, and matrix completion (MC) (e.g., fixed point continuation (FPC) and singular value thresholding (SVT)) can be used to address the sparsity challenge. Complex approaches such as Kriging yields better accuracy compared to simple approaches such as moving average. Therefore, a suitable approach can be selected based on the accuracy vs. complexity tradeoff.

Interpolation using DBSs: DBSs in SpiderNet are very densely deployed (by virtue of switching OFF DBSs to keep energy consumption and interference at a minimum), measurements for bins with no UE reports can be estimated using the geometry shown in Fig. 3. These additional measurements, after appropriate transformation, can be used to increase the accuracy of intelligent interpolation methods proposed previously. However, this approach can complement only simple measurements such as received signal strength (RSS). Therefore, a different approach, such as identified next, are needed for measurements that feature UE specific idiosyncrasies such as RLF, mobility traces, and traffic pattern.

Parameter	Value
Simulation area dimensions ($\|A\|$)	100 m × 100 m
CBS, DBS frequency bandwidth	800 MHz
Mean PPP density: $\lambda_{UE}\|A\|$; $\lambda_{DBS}\|A\|$; $\lambda_{CBS}\|A\|$	400;400;16
p_{UE}	[0.25 0.5 0.75 1]
CBS separation R_0	50 m
Pathloss exponent: α	3
Tx Power: $P_{CBS,Tx}$; $P_{DBS,Tx}$	10 W; 1 W
CBS Power consumption (always ON)	64.17 W
DBS activated state power consumption	25.15 W
DBS OFF state power consumption	1.932 W
No. of Monte Carlo realizations	100000

TABLE 1. Simulation parameters.

Addressing the Sparsity Challenge through Generative Adversarial Networks (GAN): The power of using GANs to generate synthetic yet realistic new data has been demonstrated recently in many fields. A recent study [10] has shown that GANs can also be used successfully for different types of data generation to improve training of an AI model, for example, autonomous wireless channel model, in advanced wireless networks. Building on this finding, GANs and other generator methods can be used to overcome the aforementioned challenges of sparsity and scarcity of training.

The resultant SpiderNet database can then have two types of data, that is, perfect and imperfect. Perfect data represents the data which is 100 percent accurate. Analysis using perfect data can provide upper bounds on SpiderNet performance, while the imperfect data reflects estimated data obtained by training or interpolation which can have some degree of uncertainty. In the case of perfect database aided SpiderNet, many interference modeling approaches available in the literature such as stochastic geometry [11] or geometric probability [12] can be extended to characterize ASE and ultimately EE. However, for imperfect database aided SpiderNet, these approaches lack the capability to capture the impact of uncertainty in the data. A feasible methodology toward this end can be the fluid model-based approach, as shown in our earlier work [13]. Finally, the database can be used to train ML based models to determine an optimal configuration for SpiderNet to achieve maximum SE and EE for a given state.

Case Study: SpiderNet Architecture Comparison with a Dense HetNet Deployment

In this section, we target user-centric Stienen cell based SpiderNet architecture for joint performance analysis in terms of ASE, EE and scheduling latency for comparison with a traditional HetNet deployment. We evaluate the performance measures at different values of network design variables and discuss the QoE enhancement as well as inherent tradeoffs for a network operator.

We consider the downlink of a two-tier ultradense network consisting of sparse CBS deployment and dense small cell DBSs, both operating at distinct frequency bands. The spatial distributions for CBSs, DBSs and UEs are modelled using three independent homogeneous Poisson point processes with intensities λ_{CBS}, λ_{DBS} and λ_{UE}, respectively. To model realistic CBS deployment, we distribute it according to a type II Matern hardcore process [14], which induces repulsion between the points in the CBS tier. Downlink resources are granted to requesting UEs on a priority-based mechanism. This means that high priority UEs demanding connectivity through DBSs will be first assigned a S-Zone around its geographical location. The S-Zone around each scheduled UE is formed by constructing a circular disk around each UE with a flexible radius which is less than or equal to half of the distance between the UE and its closest neighbor. This Stienen cell geometry not only ensures non-overlapping S-Zones but also guarantees a larger spatial separation between an arbitrary UE and an interfering DBS as compared to the UE-serving DBS link [15]. While the Stienen based SpiderNet architecture activates a single DBS within a UE's S-Zone as explained in preceding sections, the benchmark HetNet deployment considers a non-UE-centric always ON DBS network. For both network scenarios, we assume perfect channel state information (perfect CSI database) at the CBSs and small cell DBSs. In the case of SpiderNet, the channel measurement database, as elaborated previously, is assumed to be available at the CBS. The CBS calculates a moving time average of recent channel quality measurements between a UE and all DBSs within its S-Zone, and activates a single DBS that provides the highest SINR. Rayleigh fading is assumed for both the UE-CBS and UE-DBS links. The small-scale Rayleigh fading is complemented by a large-scale path loss modeled by power-law function. The fading channel gains are assumed to be mutually independent and identically distributed (i.i.d.). Finally, omni directional transmission is assumed at both CBSs and DBSs to provide uniform antenna gain pattern in all directions.

Simulation Scenario

In this article, our emphasis is on network wide efficiency analysis for an ultra-dense deployment of DBSs having same order of deployment density as UE population. The analysis is performed for variation in three key design parameters, namely: the active UE population (p_{UE}), Stienen cell size factor (ζ), and DBS deployment density (λ_{DBS}). The active UE population denotes the percentage of UEs that participate in the downlink scheduling process, hence determining the average geometry of the SpiderNet network. If this percentage of participating UEs is low, the average separation between UEs is increased, thereby also increasing the mean of Stienen cell sizes (or S-Zones) around UEs. Another consequence is the increase in probability for an arbitrary UE to be scheduled via DBSs in a fixed DBS deployment. The Stienen cell size factor is simply a parameter that varies between 0 and 1. A factor of 1 indicates that the S-Zones are at the largest allowable size and touching (but not overlapping) the closest neighboring S-Zones. Variations in this parameter affect the UE load distribution between the CBS and DBS tiers, and consequentially impact the ASE and EE. Finally, a higher DBS deployment density also causes a larger number of UEs to be connected to the DBSs, which increases the SE but reduces EE owing to increased DBS power consumption. Unless otherwise specified, the key simulation parameters are summarized in Table 1.

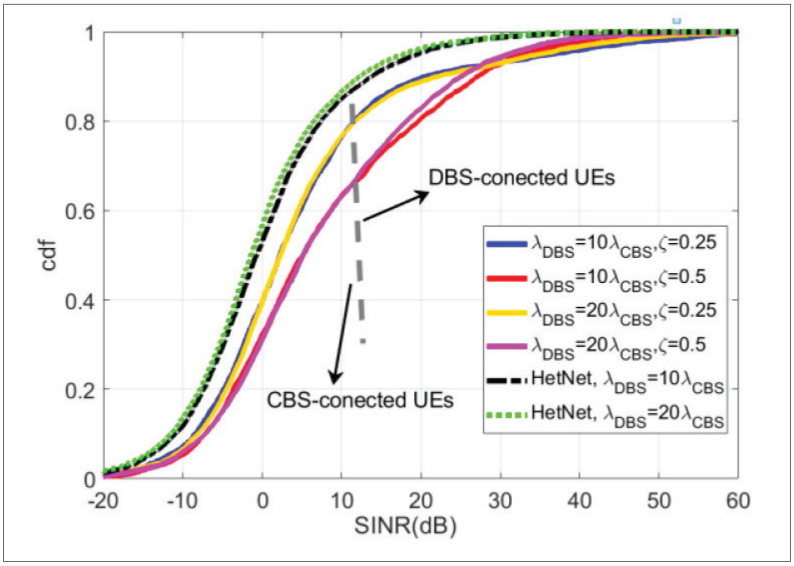

FIGURE 4. User quality of experience (QoE) comparison between SpiderNet and traditional HetNet deployment.

Results and Discussion

We first analyze the performance in terms of SINR cumulative distribution function (cdf) between UEs that are connected at different tiers in the network in Fig. 4. SINR is chosen as the first metric of comparison because it dictates several KPIs of interest such as coverage quality, link SE, ASE, QoS and QoE. We observe a clear distinction between the SINR of the UEs connected to the CBS and DBS tiers. More specifically, two distinct regions can be identified from the multi-tier SINR distribution plot in Fig. 4:

- The majority of UEs are served via CBS tier having SINR less than 15 dB SINR for all the simulation cases.
- About 20 percent of UEs connected with the DBS tier have SINR over 20 dB for ζ = 0.25. Doubling the DBS density has marginal impact on the SINR distribution. Doubling the S-Zone size increases the SINR by about 5 dB for 60 percent of UEs.

The proposed architecture clearly outperforms the traditional non-user-centric HetNet deployment. Another insight from the figure is the ability of the network operator to tune the design parameters, in particular the S-Zone size, and vary the load sharing between the CBS and DBS tiers. Consequentially, through efficient self-organization, the network operator may fluctuate the percentage of UEs that avail extremely high user QoE at the cost of higher power consumption of the DBS-tier.

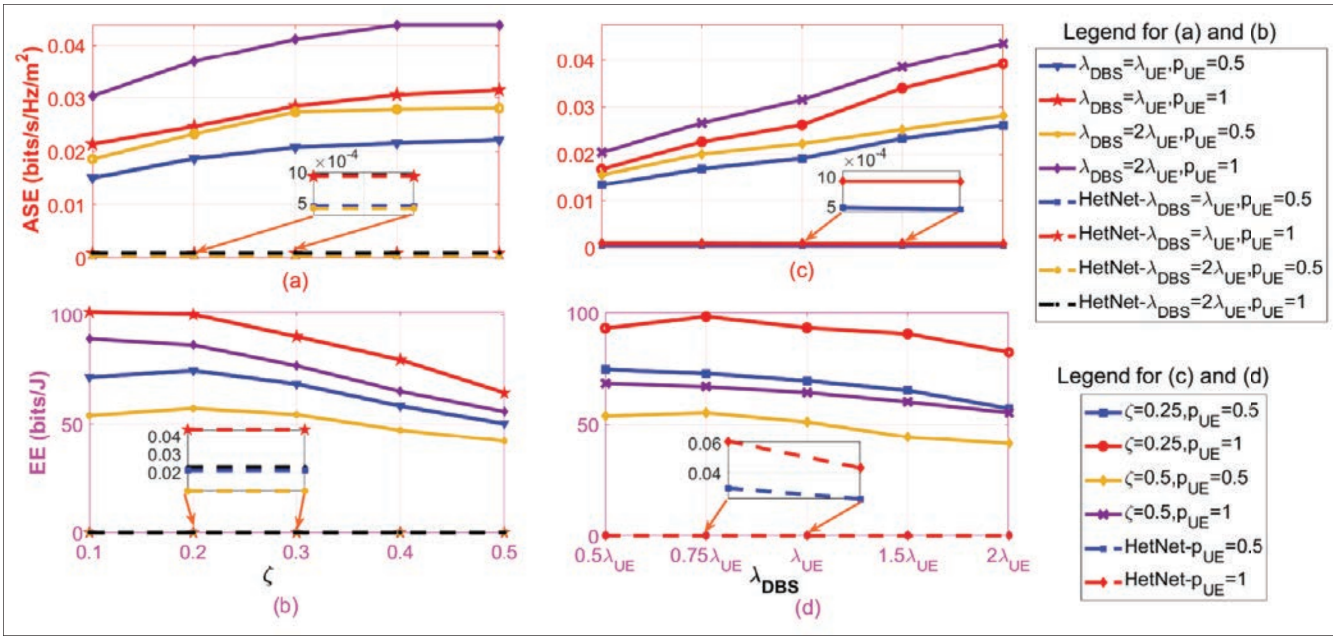

FIGURE 5. Area spectral efficiency (ASE) and energy efficiency (EE) analysis.

Next, in Fig. 5, we plot network wide ASE and EE with variations in the design parameters ζ, p_{UE}, and λ_{DBS}. We observe greater than 10x increase in network-wide ASE and greater than 1000x enhancement in network wide EE when compared to the benchmark non-user-centric HetNet. In Fig. 5a, we observe a monotonic increase in ASE with an increase in the S-Zone size. This is because a higher S-Zone size corresponds to more activated DBSs which enhances the network sum throughput. However, when analyzing the network wide EE in Fig. 5b, we observe that peak EE for p_{UE} =1/2 scenarios is at ζ =0.2, while for p_{UE} = 1, there is a marginal decrease in EE from ζ = 0.1 to ζ = 0.2, followed by a rapid decline to ζ = 0.5. While the ASE maximizes for largest DBS deployment density and UE density, the EE maximizes for largest UE population but lower DBS deployment density. Similar trends are observed in Figs. 5c and 5d where the ASE increases monotonically with DBS deployment density. On the other hand, EE increases with an initial increase in λ_{DBS} due to an increase in sum throughput, but with a further increase in λ_{DBS}, the additional power consumption due to both active and inactive (due to signaling) DBSs kicks in causing a decline in EE (Fig. 5d). The network operator therefore has the option of dynamically adjusting the network parameters ζ, p_{UE} and λ_{DBS} to balance between a high ASE or EE depending upon its spatiotemporal business model.

Conclusion

In this article, motivated by the fundamental limitation of the legacy cellular architecture in terms of simultaneously yielding gain in SE and EE, we present a novel SpiderNet architecture for future cellular networks vis-a-vis 6G. SpiderNet exploits the concept of user centric elastic and on demand cells and databases at the base stations to intelligently maximize both SE and EE in response to spatiotemporally varying demands. We have also identified key challenges that need to be addressed in realizing the SpiderNet architecture in practice and discussed potential solutions. Preliminary results show that the SpiderNet architecture can significantly improve SE as well as EE compared to legacy HetNets and thus has the potential to be further investigated and adapted as an alternative architecture for future cellular technology and standardization.

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