Optimal Energy-Efficiency under Power Allocation in Beyond 5G Networks

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Abstract —*Wireless communication systems have been experiencing a dramatic increase in data traffic volume due the introduction of new services and applications in every up-to-date generation of mobile wireless communication technology. In 5G and beyond communication systems, the emerging services and user cases (mission critical communication, Massive Internet of things Enhanced Mobile Broadband, and ultra-reliable communication) are envisaged to transform the digital society in the industrial sector. The heterogeneous cellular network (HCN) technology is suitable for handling the data traffic and fading, thus resulting in a high network coverage capacity and data rate of the system. However, deployment of numerous base stations in a cellular network presents crucial challenges owing to their significantly high-power consumption. To this end, this paper proposes a technique comprising a topology of distributed access points (APs) in the network coverage area for wireless communications to improve the energy efficiency by minimizing power consumption. The AP operations are controlled by a powerful central processing unit (CPU). The simulation results demonstrated that the proposed network topology significantly improves energy efficiency (approximately 60%) compared to the conventional heterogeneous cellular network, thus proving itself to be relatively environment friendly.*

***Index Terms*—Access point, beyond 5G, conventional cellular network, energy-efficiency, wireless communication technology.**

I. INTRODUCTION

Since the invention of smart devices, the data traffic has significantly increased due to the high demand of various services and applications utilizing wireless communication, such as, voice and video communication, connecting homes, massive to machine communication; as well as critical Internet of things, such as autonomous vehicle-to-augmented reality application. It is expected that the number of connected devices will surpass 20 billion by the end of 2020 and every user is expected to handle about 100GB of data yearly. This is considerably high when compared with 6 billion devices and 10GB of data in 2010 [1]. Wider spectrum and higher energy consumption are crucial metrics expected in future network systems to match with the exponential growth of data demand [2].

The 5^{th} generation mobile communication technology (5G) [3], [4] is considered as the ideal solution to revolutionize the behavior of the current environments to tackle the problem of massive device connectivity, thus resulting in a faster network connection, which would further lead to a potential internet transformation. Network developers predict that, it will a capacity hundreds of times that of the existing 4G, which indicates a dramatically improved internet speed. However, some constraints, such as throughput enhancement, increased bandwidth requirement, and spectral efficiency are encountered [5].

In a few technologies that rely on 5G, small cells are employed to bolster the network coverage area through ultra-densification in addition to the inherent macro cell to form a conventional heterogeneous cellular network (CHCN)[1] to provide higher data rate [6], [7]. Another important technology adapted by 5G—the milliliter waves ((30GHz–300GHz) —consists of the extension of the current radio frequency spectrum utilization (1GHz–6GHz), to overcome the congestion in this radio spectrum because it is clouded due its utilization by several technologies such as Wi-Fi, WiMAX, GPS, L-band satellite, S-band satellite, 3G, 4G, C-band satellite, etc. Herein, we propose the spectrum range: 24GHz to 100GHz for 5G communication. These millimeter waves are advantageous and are currently a less-utilized band. In addition, because they are higher-frequency waves, they can carry more data compared to the technologies adapted by previous generation wireless technologies (3G & 4G LTE) which utilize lower-frequency waves [8]. Moreover, millimeter wave enables massive MIMO technology, which enhances the spectrum efficacy [9].

Since a couple of decades, network densification became an increasingly popular technology in the revolution of wireless communication in the terms of connectivity and wider network coverage area. This is because it can handle an exponential data rate, and thus, provides a considerable spectral efficiency in 5G and beyond wireless systems. However, as the network densification consists of deploying a significant number of base stations with respect to a given coverage area [10], these base stations need to be powered to the power supply (power grid), and they subsequently use high amount of energy during transmission. In addition, since in a conventional HCN (also known as multitier network) both small cells and macrocell share the same radio frequency spectrum, and cross-tier as well as co-tier interference is generated, which makes its management a challenging task. More precisely, in downlink scenario, users linked to the small cells suffer additional interference from the macrocells. Idem to the macrocells[2]. Moreover, in an uplink transmission system, both small cells and macrocells suffer interference from each other [11].

References [12], [13] introduce non-coherent joint transmission to enhance the energy efficiency in cellular network with massive MIMO system, where small cell concept was implemented to ensure less power consumption compared to existing macrocells. However, in the case of a large coverage area, there is an increased number of small cell base stations that complement to the growth of emerging applications and services as well as serving the enormous number of connected devices in future communication systems [14]. It is expected that, the power consumption will clamber to thousands of Terawatts by next year. Specifically, the denser the network is, the higher the amount of energy needed to feed all the base stations within it[3], which may increase its carbon footprint, and which ultimately, proves it to be harmful to the environment [15], [16]. In order words, there exists a power-throughput trade-off. This power consumption is followed by a high deployment cost, increased complexity, as well as the inter-cell interference within the network [17], [18].

To reduce this high energy consumption caused by the increment of small cells, the concept of base station sleeping mechanism to improve the energy efficiency of the network system was conceived [19]. It consists of switching off some selected group of base stations in special time such as off-peak hours. Nevertheless, a drawback still exists because this typical ultra-dense HCN results in the transfer of a significant number of users from macrocell to small cell side, which becomes a serious issue in this switching off algorithm. Therefore, several metrics must be considered, especially the distance between macrocells and the small sleeping cells. Furthermore, efficient backhauls are required to provide connectivity between the macrocell base stations and small cell base stations as well as within the core network. In case of wired connections, either fiber or copper cables (backhaul) are used as the link to face high-rate heterogeneous cells. This is challenging because it requires an enormous expenditure for realizing this network connectivity, especially in the case of a large coverage area.

To overcome the aforementioned challenges and drawbacks, this paper proposes to enhance its energy efficiency and decrease its cost; this solution consists of revamping the network by replacing its base stations with randomly distributed access points (APs) in the coverage area. Briefly, the contribution of this study is summarized as follows:

- Instead of conventional cellular network topology with base station serving users allocated in a specific cell, we introduce a network topology comprising distributed APs, which are controlled by the centralized center processing unit, also known as Cloud Radio Access Network (Cloud RAN), which employs edge cloud computing cloud RAN (cell edge cloud computer).
- Unlike conventional cellular networks, in which the base stations are connected to the core network via powerful backhaul, in the proposed model the APs are connected to the limited fronthaul, which reduces the operational costs. In addition, the cells are no longer fixed; therefore, this new network suffers neither from the inter-cell interference, nor the handover mechanism. The latter among these two may degrade the quality of communication in conventional cellular network topology and is discussed further in section III.
- In the case of a downlink system, while the APs are controlled by the CPU via a server, the signal transmitted to the users has a significant amount of power downlink. However, in the uplink system, the signal is rotated appropriately to ensure a coherent communication between the network and its users. This is done using beam-formers.
- To make the network scalable, it is designed such that every user is served by all the access points — there is no signal abstraction to the users; consequently, they can arrive with a high signal-to-noise ratio. Moreover, as the number of users increases, the computational complexity and the fronthaul signaling at each access point remains finite. The proposed approach boasts the improvement of spectral efficiency, network reliability, and a larger network coverage area.

The rest of this paper is organized as follows. Section 2 elaborates the CHCN. Section 3 delineates the system model and topology of the proposed approach by thoroughly describing the optimization of energy consumption within the network. The performance evaluation is illustrated in Section 4. Finally, Section 5 concludes the work.

II. CONVENTIONAL HETEROGENEOUS CELLULAR NETWORK

The Fig. 1 depicts a two-tier downlink with macrocells and small cells, i.e.; an HCN, which is expected to be employed in 5G and beyond wireless communication systems. Each macrocell and small cell comprise a base station. This implies that there exist macro base stations and small cell base stations for macrocells and small cells, respectively, to serve users,

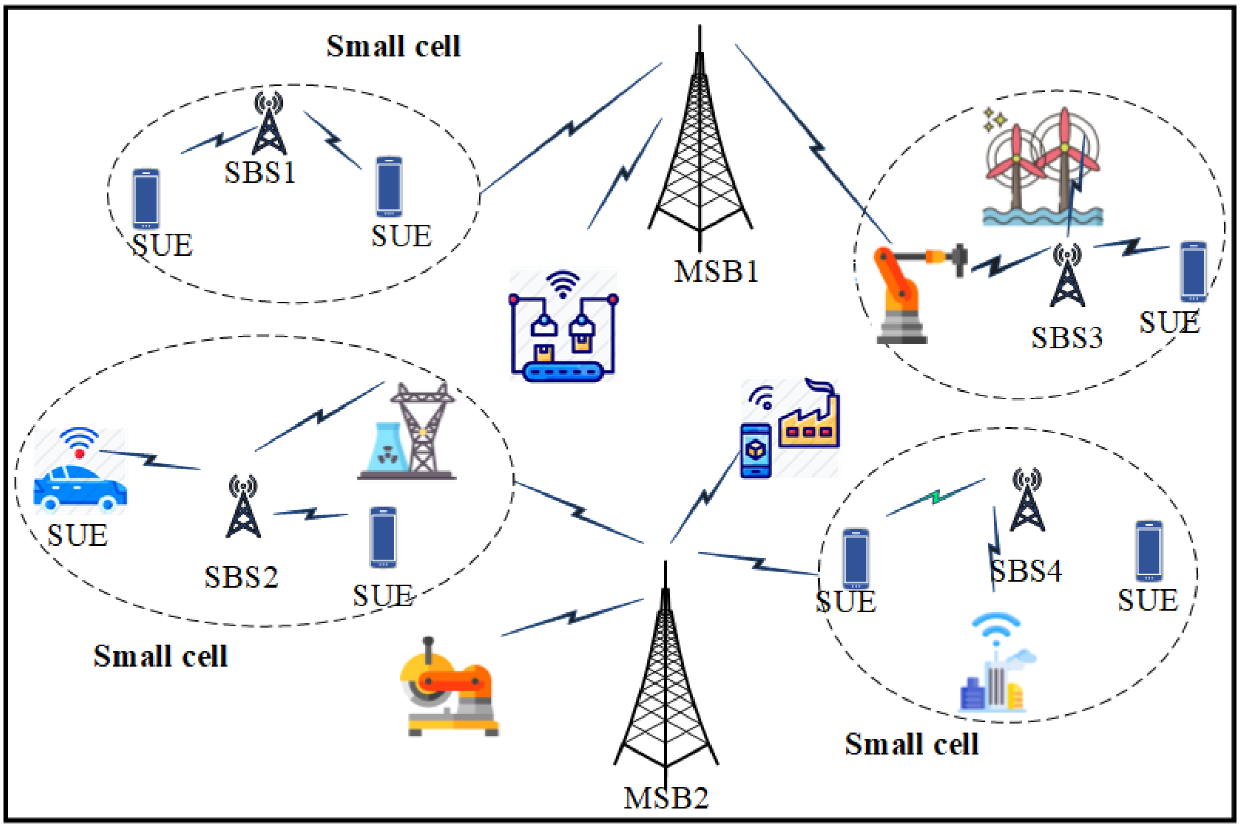


Fig. 1. Conventional cellular network based on densification to fit 5G data traffic: Heterogeneous cellular network with macrocells and small cells. The small cells assure the offloading of the traffic from the existing macrocells.

who are in their vicinity of the network. Every base station serves the users within a dedicated cell.

In a typical cellular network system, the primary aim is to enhance the network coverage and the data rate of the system. Moreover, the deployment of small cells with their small cell base stations significantly reduces the energy consumption of entire network as compared to the traditional power-hungry macrocell base stations. The users/devices are connected to the closest base station either mounted on a rooftop or on the big mast. Furthermore, because each user needs to fully communicate with the corresponding base station, smooth data offloading is required in order to tackle the heavy data traffic expected in 5G and beyond mobile communication systems.

A. Description

Let $N = 1, 2, 3..., N$represent the number of users—commonly known as the user equipment or mobile users in the cellular network; the number of base stations (both macrocells and small cells) and number of antennas for every base station are denoted as $M = 1, 2..., M$and $L = 1, 2, 3..., L$, respectively. For the sake of simplicity, we assume that, every user in the network has a single antenna; the channel response between user n in cell $j = k$ and its associated base stations operating in the same cell is assumed to be zero. However, signals from different cells, apart from the cells $j = k$ (i.e.; j 6= k), are considered as interfering signals. More relevant variables are defined in Table 1. The signal received at the user n can be expressed as follows:

$$y_{nk} = \underbrace{\sum_{m=1}^{M} h_{nm}^{T} v_{mk} S_k}_{Desired\ \ Signal} + \underbrace{\sum_{\substack{m=1 \\ j\neq k}}^{M} h_{nm}^{T} v_{mj} S_j}_{Interference\ \ Signal} + \underbrace{\eta_n}_{Additive\ \ Noise} ,$$

(1)

Here, the parameters h_{nm} and s_n denote channel vector and the symbol, respectively, while v_{mn} represents the vector of transmit beamforming from transmitter m to the user n. Note that, $E[|sk|] = 1$; and the transmitted signal from transmitter m is expressed as: $x_m = \sum_{k=1}^{K} v_{mk} s_k$

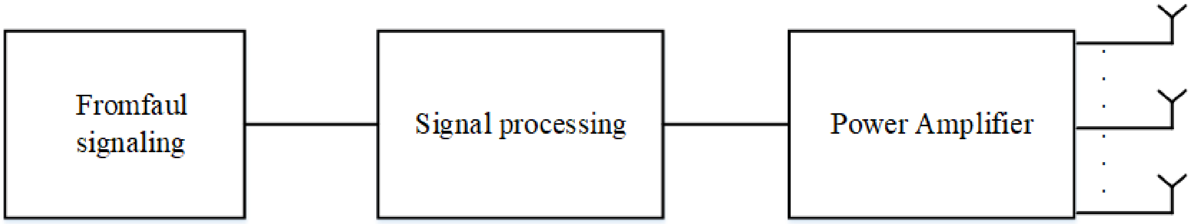


Fig. 2. Conceptual design of the base station illustrating power consumption

The Additive noise in (1) has 0 and δ_n^2 as mean and variance, respectively, i.e., $\eta_n \sim N(0, \sigma_n^2)$. Alternatively, the $h_n = h_{n1}^T, h_{n2}^T, h_{n3}^T, \ldots, h_{nM}^T$ and $v_k = v_{k1}^T, v_{k2}^T, v_{k3}^T, \ldots, v_{kN}^T$.
The interference is explained using the expression of signal-to-interference plus noise ratio (SINR) (the ratio of power of the useful signal to that of the harmful signals (noise and interference) as follows:

$$SINR = \frac{P_{signal}}{P_{interference} + P_{noise}},$$

$$\gamma_{nk} = \frac{\overbrace{v_K^T h_n h_n^T v_k}^{Signal\ Received\ Power}}{\underbrace{\sum_{j\neq k} v_K^T h_n h_n^T v_j}_{Interference\ Power} + \underbrace{\eta_n^2}_{Noise\ Power}}. \tag{2}$$

B. *Power and Data Throughput*

The power consumed within the network can be defined as the combination of the amount of power in macrocells and the active small cells within coverage area.

If the P_c and P_s indicate the power consumed by macrocells and small cells, respectively, the overall power consumption in the entire network can be represented as follows:

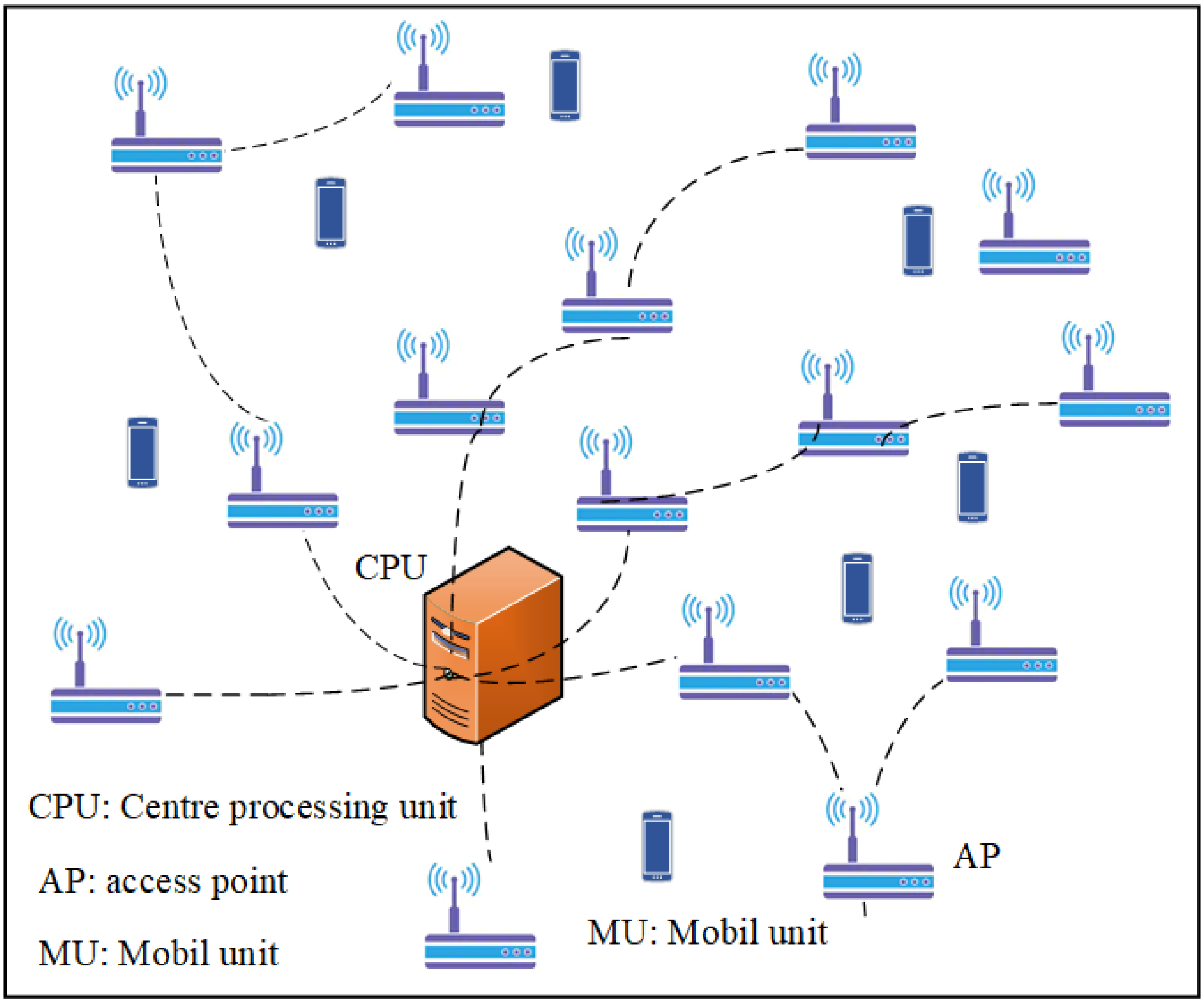
$$P_{overall} = P_c + P_m. \tag{3}$$

This power includes power consumption in the base stations and the backhaul, which connects both small and macrocell base stations to the main network (core network), as mentioned earlier. Additionally, both radiated power and cells' power consumption[4] exhibit a linear relationship, which can be represented form [20] as follows:

$$P_{cell} = \text{г}.P_{rd} + P_{fixed}, \tag{4}$$

where, P_{cell} and P_{rd} represent the average power consumed by each cell and the radiated power for each base station, respectively. The variable Γ that scales with P_{rd} denotes the power consumption due to the feeder losses, amplifier, and cooling base stations. P_{fixed} represents power consumed by the base stations, independent of P_{rd}, caused due to base station cooling, signal processing, etc. as depicted by the conceptual design of the base station in Fig. 2. Specifically, this is the power consumed irrespective the status of users or antenna (power consumed regardless of whether the users or base stations are active). The highest amount of power consumption in a cellular network system is concentrated in its base stations, which also includes following two parts: the transmit side which depends on the signal transmitted as well as dissipation side—due to the hardware technology implemented therein. Approximately, more than 60% of base station power is spent at the power amplifier side during amplification and radiation of energy. In other words, the higher the number of base stations[5], the more the amount of energy consumed. The aim of this study is to optimize the energy consumption of the entire network to meet the data demand of current 5G and future communication network systems to inhibit their environmental impact.

Accordingly, several approaches for improving the energy efficiency in 5G cellular network were proposed recently. One of these is the introduction of small cells in the existing macrocells. These small cells contain low powered small cell base stations to offload data to their corresponding users. In a network comprised of inherent macrocells and small cells with their corresponding base stations that are operating under MIMO system, some variables need to be optimized in the data throughput expression. Herein, we can select the number of optimal antennas at the base station and that of the simultaneously active users



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[5] HCN for covering a large-scale coverage area to efficiently accommodate the corresponding amount of smart equipment i.e.; the rise of the number of smart and connected devices corresponding to the number of base stations required for network connectivity. These base stations employ power amplifiersfor amplifying the transmission signal. A large amount of power is consumed by these numerousbase stations within the network.

Fig. 3. Proposed network typology for the energy efficient and environment friendly communication system.

per cell, assuming that there are numerous users that would prefer to be active, which can be selected as a certain number. The third optimization parameter is either the transmit power or some quantity that is proportional to it. The other variable is the space station density—a lower density indicates that the network has fewer cells in a certain area, whereas a network with higher density has more cells. Finally, the last optimization variable is the pilot reuse factor, which is required for real-time estimation of channel. The data throughput, under the assumption of Gaussian signaling, can be expressed as follows:

$$T_{th} = N. \underbrace{\left(1-\frac{\alpha N}{U}\right)}_{data\ fraction\ per\ frame} . \mathrm{B}log_2 \underbrace{\left(1+\frac{P_{tx}\gamma}{B\eta 0}\right)}_{data\ rate\ per\ user}, \quad (5)$$

where, B, P_{tx}, α, and $\gamma$are system bandwidth, transmit power, pilot reused factor used to estimate channels, and path loss, respectively. Furthermore, the η, U, and N are noise power spectral density, the number of frames (frame length), and number of active users per cell, respectively. As mentioned earlier, M and N are the number of base stations and number of users in the network, respectively; accordingly, the transmit power in (5) can be expressed as:

$$P_{tx} = \sum_{n=1}^{N} \left\|Q_{m,n}\right\|^2 E[|\eta(m)|^2] (6)$$

$$= \sum_{n=1}^{N} \emptyset_{m,n} \left\|Q_{m,n}\right\|^2,$$

where, $Q_e$and $\varphi_{m,n}$are the precoding vectors to be used for user n and the power allocated to a signal from the base station m to the user n,respectively; moreover, E is the expectation operator.

The energy consumption can also be calculated as follows:

$$E_c = \frac{P_{tx}}{\mu} + \beta, \quad (7)$$

where,⍰, ee_c,and β are the amplifier efficiency and circuit power respectively. Moreover, $P_{tx}$is the actual transmit power. However, it is divided by the amplifier efficiency because the power amplifiers can prove to be very inefficient. Specifically, if the signal is transmitted with a certain rate, the power consumption is multiplied by three to four times. Furthermore, the circuit power consumption in this expression considers all the analog and digital circuits employed in the network. In other words, this circuit power consumption is responsible for taking care of the analog and digital circuits that are being utilized for both radio as well as baseband processing.

C. Energy Efficiency and Cost-Benefit Analysis

References [21] and [22] define the energy efficiency using the idea of a benefit-cost analysis that can be made in economics for all kinds of systems. We can draw an analogy with our cellular network system by considering energy consumption as the cost and the data throughput as the benefit. Based on this analogy, the energy efficiency is conceptualized by determining the ratio between the data throughput and the overall energy consumption [23]. From the economic concept, this definition of energy efficiency can be diverted to the benefit-cost ratio whereby the cost denotes the input to the system, whereas the benefit indicates the result or the output. Therefore, applying (5) and (7), the energy efficiency can be expressed as follows:

$$EE = \frac{T_{th}}{E_c} = \frac{N.\left(1-\frac{\alpha.N}{U}\right).Blog_2\left(1+\frac{P_{tx}\gamma}{B\eta}\right)}{\frac{P_{tx}}{\mu}+\beta}. \quad (8)$$

The system metric for data throughput and energy consumption are bits per second and Joule per second, respectively; therefore, the system metric of energy efficiency is bits per joule. All other variables were defined earlier in this paper.

In a conventional cellular network system, there is no way of delivering a huge amount of data (thousands of times the current system) without consuming considerable amount of energy in the entire system, especially, in the transmission side (digital and analog processing, fronthaul signaling, power amplification, etc.), energy is required to run the circuit during transmission. Therefore, the most important task is to improve the energy efficiency by adjusting some parameters (transmit power in this case), provided that there will be some improvement in the overall system performance. Reference [12] proposed that the energy efficiency can be varied by controlling the transmit power which is equivalent to the following optimization problem:

$$\min_{\alpha_{m,\mathrm{nn}} \geq 0} \sum_{j=1}^{M} P_{tx,j} \text{ ,(9)}$$

$$s.t. R_k \geq r_k, \qquad \forall\, n = 1,2,\dots N,$$
$$P_{tx,m} \leq P_{max,m}, \qquad \forall\, m = 1,2,\dots,M,$$

where,P_{tx} and R_k are transmit power and fixed spectral efficiency required of user n, respectively. $P_{max,m}$ is the maximum transmitting power that can be supplied by the base station m. Equation (9) benefits the limitation of power budget at every base station through minimization of transmit power of all base stations, while ensuring a required spectral efficiency for each user.

The above optimization problem shows that the considered cellular technique is committed to improving its energy efficiency; despite this, it is not enough to withstand the power consumption in current 5G and future communication network because several base stations (small cell and macrocell bases stations) are involved. in the case of a large-scale coverage to
achieve an effective offloading of the data. Moreover, being a massive MIMO system, every base station is equipped with several antennas to serve an equivalent number of users. Accordingly, there will exist a significantly high power consumption in the entire network, especially through the active transmitters, including their dissipation portion, cooling system, as well as for running the circuit system such as mixers, filters, and converters. Nonetheless, the optimum energy efficiency is not sufficient to satisfy the requirement of 5G and the future network communication systems.
Briefly, the overall power consumption in each base station includes the power that is consumed in fronthaul, signal processing (both analog and digital), and the power amplifier. Therefore, the energy consumption of the entire cellular communication system consists of several fractions, which contain the following: transmit power with amplifier inefficiency, fixed circuit power (P_{fixed}) as expressed in (4), power per transceiver chain (assuming that every base station's antenna is turned on; additionally, that consumed by the user's antenna is considered),power required for signal processing, which usually depends on the number of antennas and users, and finally, the power consumed during coding/decoding and backhaul, which is proportional to the data throughput. This energy inefficiency has motivated us to propose the topology of mobile communication network, leading to the improvement of energy efficiency; it is discussed further in the following section.

III. SYSTEM MODEL AND PROPOSED NETWORK TOPOLOGY

A. *Description of Network Design*

Figure 3 is modification of Fig. 1, whereby the cellular network topology is replaced by a scalable model with distributed APs that are spread over the network coverage area. Additionally, all APs are controlled by a powerful central processing unit. In this study, we assumed that every user in the network had a single antenna; and that the number of APs is larger than the number of users. The system is considered as a time division duplex (TDD) mode with the signals that are transmitted in both uplink and downlink within the same coherence bandwidth and coherence time. Moreover, both channels are fixed, i.e., the same channel can be utilized in both uplink and downlink. The network scalability is based on the allocation of resources to pilots and the data. During the transmission of pilots in uplink, every AP measures the channel to any user from itself. This allows the APs to get all of the channel state information that is needed to transmit signals to their corresponding users. Let us assume that P is the number of channels assigned to the pilots, and C is the number of all channels used within one coherence block. Therefore, the number of channels saved for both uplink or downlink can be calculated as:

$$S = C - P \qquad (10)$$

In this scenario, each access point should serve at most P users i.e.; at most one user per pilot sequence. To decide which P users should be served by every AP, we use an approach similar to that employed for designing dynamic cooperative clusters [24], [25]. In our scenario, we call it dynamic operation clusters because the users can be served by any AP in the network regardless of its mobility or position. In other words, if the users are moving around within coverage area, the serving AP can be changed according to the region of accessibility of the user. When user attempts to access the network, it firstly turns on, and then, it sends a random-access request to be set by the network. Herein, an AP with only the strongest signal power is targeted. This user must be able to listen all the reference signals that are sent in downlink in order to figure out which AP should to be its master AP. Once this is identified, it is immediately responsible for serving the user. In this case, the master AP picks the pilot being to be used by the user being considered.

In this case, the master AP does so by monitoring all of the type of pilots to find the one that is being heard with the least power. This pilot would have the least amount of interference on this user. Accordingly, it is picked and assigned to the user. Furthermore, the AP contacts all the APs that are in its neighboring area and informs them that it has decided to serve a particular user with the abovementioned pilot. Subsequently, it suggests a different AP if they wish to participate. As pointed out earlier, at least one AP is required for every user. Based on the suggestion mentioned in [26], the overall spectral efficiency can be expressed as the sum of that corresponding to the n^{th} individual:

$$R = \sum_{n}^{N} r_n . \emptyset_{ln} ,(11)$$

where,$r_n$is thespectral efficiency corresponding to an individual n^{th} user, and$\varphi_{ln}$is the power coefficient from the l^{th}access point with respect to $e$symbol.

B. Power consumption in the network

Unlike cellular technique, the proposed network comprises of L access points serving N number of users. Therefore, this system's power consumption is a combination of all access points and that of the fronthaul, which quantifies the information between access points and users. The overall power consumption of entire network can be expressed as follows:

$$P_{overall} = \sum_{l=1}^{L} P_l + \sum_{l=1}^{L} P_{ca,l}, \qquad (12)$$

where, P_l is the power consumption at l^{th} access point due to two factors: circuits (employed for signal processing and transceiver chains) and amplifier. Moreover, $P_{ca,l}$is the power consumption for the fronthaul that connects cloud RAN to the l^{th}access point. By denoting P_{intern} as the internal power, which is necessary for running mixers, filters, and converters as the circuit components, P_{ca}can expressed as follows:

$$P_l = \frac{1}{\mu_l} . \psi_l . \eta_0 (D . \sum_{n}^{N} \emptyset_{ln} \psi_{ln}) + D . P_{intern\,,l}, \qquad (13)$$

where,η_0, ψ_l, and $\square_l$are noise power, maximal normalized transmit power, and efficiency of noise power, respectively; moreover,$\varphi_{ln}$and $\zeta_{\mathrm{ln}}$are power coefficient from the l^{th}access point with respect to n^{th}symbol.

Furthermore, the fronthaul assures the connection between the CPU APs for data transmission; consequently, the P_{ca} will depend on power consumed by each fronthaul P_{fixed} , as defined in (4), which can be computed as follows:

$$P_{ca,l}=P_{fixed} + B.R(\emptyset_{ln}).P_{tf,l} \text{ ,(14)}$$

where,B, R,and $P_{tf,l}$ are the system bandwidth, overall spectral efficiency (as defined and expressed in (11)), and power consumption, which depends on the data traffic. However, P_{fixed} may be dependent on the distance separating the CPU and the APs, but is independent of the data traffic.

C. *Optimal Energy Efficiency*

As discussed earlier in section II.A, energy efficiency is defined as the ratio of data throughput to the energy consumption of the system. Therefore, by substituting (11) and (12) after computing the data throughput (system bandwidth (Hz) ×spectral efficiency (bps/Hz)), the energy efficiency can be computed as follows:

$$E_e = \frac{B.R}{P_{overall}} = \frac{B.\sum_n^N r_n.\emptyset_{ln}}{\sum_{l=1}^L P_l + \sum_{l=1}^L Pa_{ca,l}}. \qquad (15)$$

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All variables mentioned herein are defined earlier in this article. This study aims to optimize the energy efficiency described through the modeling. This optimization is conducted by maximizing the energy efficiency, which is subjected to spectral efficiency, which further, is imitated as the following optimization problem:

$$\begin{aligned} \max_{\phi l,n} \quad & E_e, \\ \text{s.t} \quad & r_n \succeq r_{0n}, \quad \forall_n, \\ & \sum_{n=1}^{N} \phi_{ln}\zeta_{ln} \leqslant \frac{1}{D} \quad \forall_l, \\ & \phi_{ln} \succeq 0, \forall_n, \quad \forall_l. \end{aligned} \qquad (16)$$

Therefore, unlike the conventional approaches that are considered to provide meaningful but power-hungry base stations, which also are more complex (due to the ultra-densification), to satisfy the traffic demand, higher data rates and extend coverage (aimed at enriching the network capacity in cases where the signals are not able reach in inherent macrocells), the proposed approach is formulated with an efficient and reliable topology, which provide slow energy consumption and less complex, distributed, and CPU-controlled APs. The proposed network topology converges to the simplicity and meaningfulness, which is validated through performance evaluation discussed in the next section.

IV. PERFORMANCE EVALUATION

In this section, the performance of the proposed approach is evaluated with respect to the CHCN. The parameters to be evaluated are energy efficient in both scenarios.

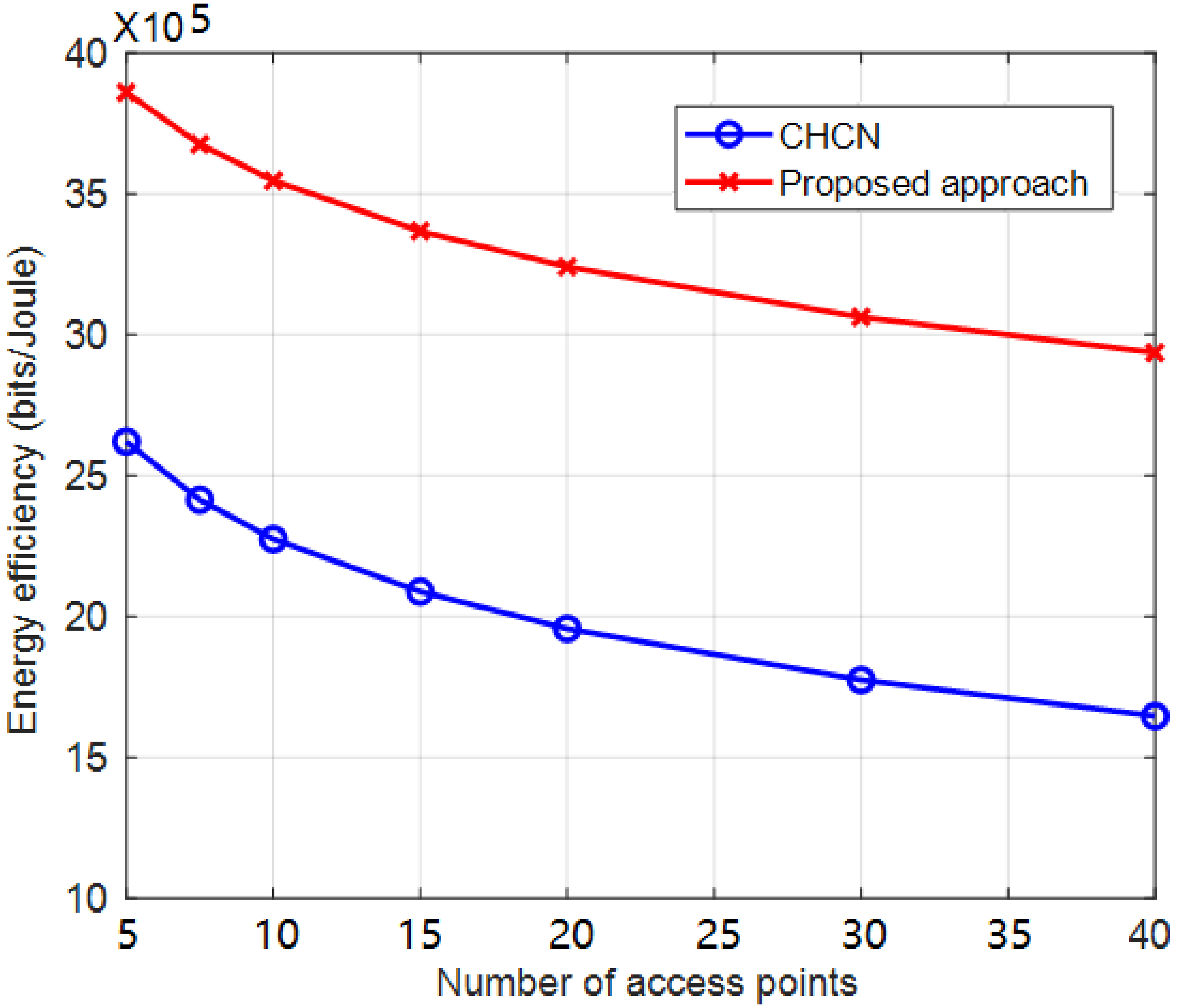

Fig. 4. Energy efficiency VS Number of APs. The new mobile communication topology was compared with conventional heterogeneous cellular network in which the number of small cells base station is the same as that of the APs in the proposed approach

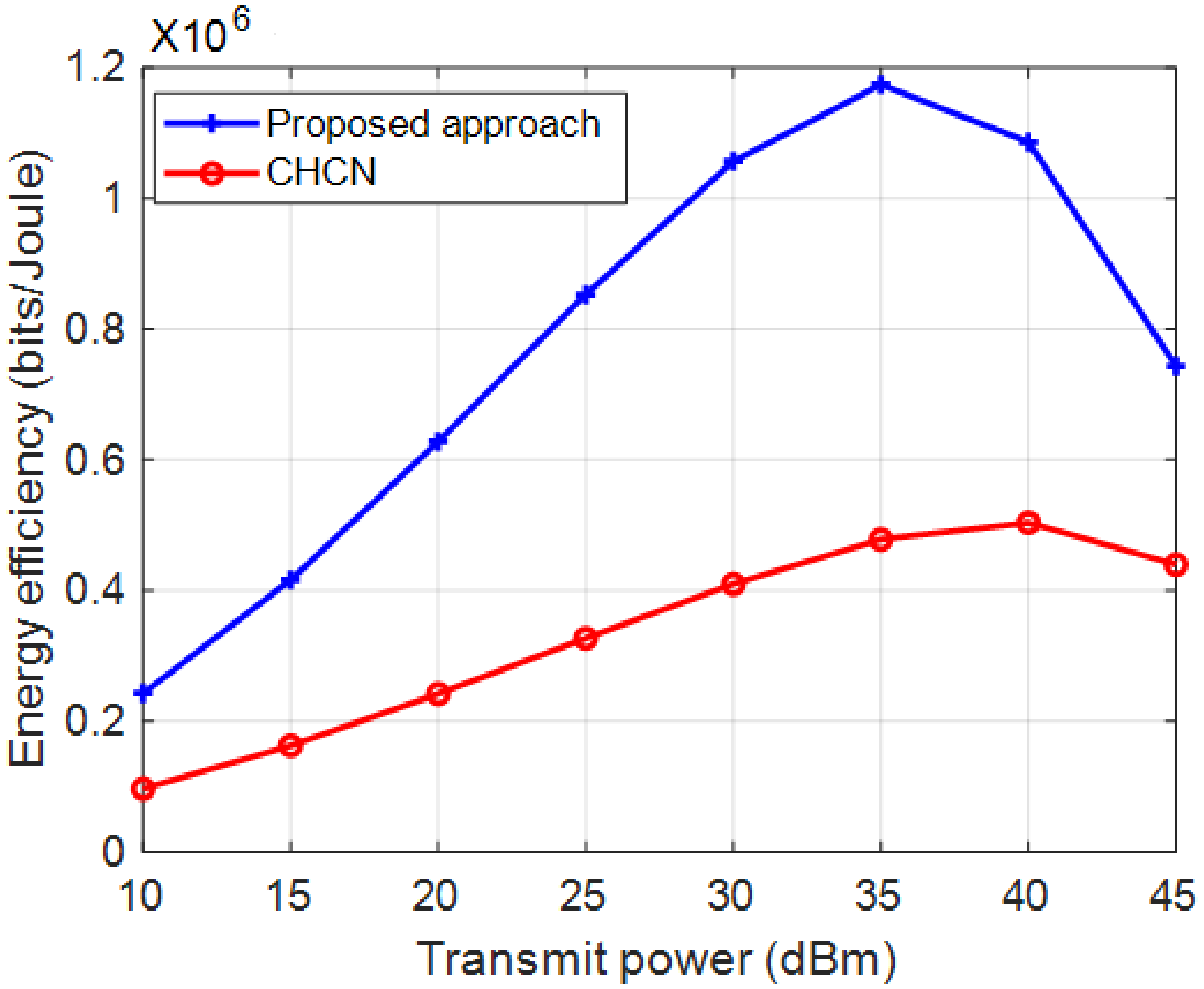

Fig. 5. Spectral Efficiency VS Transmit power

The number of APs experiencing massive MIMO system are randomly distributed in a150 $m \times 150\ m$ area, and send the signal to dedicated single antenna users in the same coverage area through APs. The number of APs and that of small cell base stationswas set accordingly. For the sake of simplicity, we assumed that, each small cell contained only one base station to serve its dedicated users. Power was equally allocated to small cells. The system bandwidth was chosen to be $B = 25$MHz. The simulation results were conducted under MATLAB R20186a environment, running on an Intel Core i3-7100 3.90 GHz CPU with RAM of 8GB.

Fig. 4 depicts the behavior of energy efficiency expressed in *bits/Joule* against the number of access points. For the sake of simplicity, we assumed that, each small cell contains only one base station to serve its dedicated users. Moreover, the results indicate that, the proposed approach exhibited better performance compared to the CHCN. This is due to the fact that in the conventional cellular network, the base stations require more power for communicating with their users.

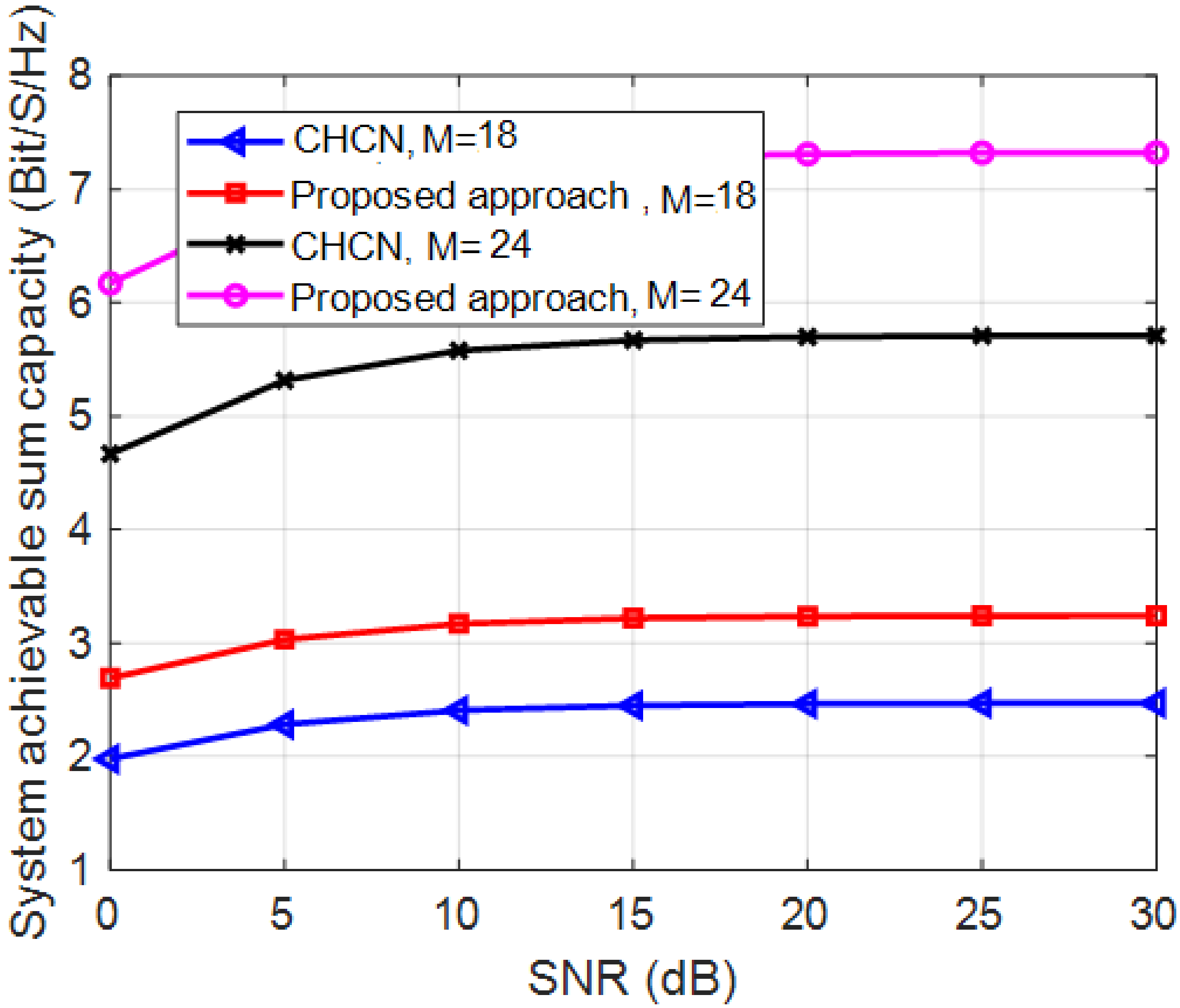

Fig. 6. Achievable sum-rate VS SNR.

The more the number of small cells is, the more backhauls are required to connect the base stations to the main network, which results in a higher energy consumption for these backhauls. As discussed earlier, in cellular network with every station dedicated to the corresponding cell, the base station alone consumes about 60% of the total power in the cellular network [27].

Moreover, increasing the number of access points (as well as small cells) consequently decreases the energy efficiency. This sounds logical because although there is energy efficiency improvement in our proposed approach, its implementation in an ultra-dense network is still challenging owing to the requirement of the considerable number of backhauls for connecting the main network/CPU to the base stations (macrocell and small cell base stations)/Aps, which will consume power according to the connectivity requirements. This decrease in the performance of CHCN is due to several factors mentioned throughout this article—the circuit power (amplifier, mixer, etc.). Fig. 5 depicted the energy efficiency with respect to the transmit power. As observed, in both curves, the energy efficiency increases with the transmit power up to a maximum point, after which, it begins to diminish i.e.; at 35dBm. The typical curves are known as unimodal[6]function [28].

Fig. 6 delineates the behaviors of both approaches by considering an achievable sum rate against the SNR. It is clearly shown that, the proposed approach can dominate through its cellular network topology even if

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[6] A function which is monotonically increasing in its lower boundary and monotonically decreasing in its upper boundary.

the number of APs is same as that of small cell base stations in the conventional cellular network. In this case, the number of small cells employed in macrocells system indicates an increase in the system achievable sum capacity. This is caused by a decreasing path-loss, which further, is a result of these small cells, which covered some empty space in macrocells network where the signals from macrocells base stations were unable to reach the users within the network previously i.e.; if there is a shorter distance between the transmitter and the receiver, the transmission is done with much less power; however, at the receiver, there is much larger fraction of what was transmitted. In other words, as long as the users are closer to base stations, the signal becomes stronger, thus resulting in the maximum data rate.

In Fig. 7, the power consumption of the entire system is evaluated with respect to the number of users. Moreover, it increases in both cases with the increase in the number of users. This increase in power consumption is due to the fact that every element in the network needs energy for its operation. This is apparent because there is no way of delivering a huge amount of data without consuming sufficient energy in any kind of system. This figure illustrates how the energy consumption can be handled while the data-hungry devices and applications keep utilizing the mobile data traffic. As it is shown in the curve of CHCN, when the load traffic (number of users) is increasing and when M=18, the energy consumption increases initially (beginning of the curve: when N=10, power consumption is 12×10^4); eventually, the consumption quickly increases as the number of users increase. Idem to the case when the number of small cell base stations was equal to 24, the energy consumption tremendously increased in the entire interval of the axis of the users. This is due to several factors in the heterogeneous cellular network, which have been previously mentioned in this paper (see energy required for operating the base stations, power circuits, and backhauls for connecting the main network to the base stations,...). It is clear that, this conventional approach consumes higher energy even when there is no significant traffic (at N=10), which subsequently becomes extremely high when the traffic load increases. On the other hand, in the curve of proposed approach when there is relatively low load, the energy consumption is lower in both scenarios (M=18 and M=24); later, this consumption steadily increases irrespective of the number of active users are connected in the network. The final evaluation of the performance of our system is shown in Fig. 8 whereby the energy efficiency was validated based on the total power required for the backhaul/fronthaul in the entire system; moreover, it is clearly shown that our proposed approach provides an improved energy efficiency.

V. CONCLUSION

In this work, the approach for optimal energy efficiency to endure operation of future wireless communication systems, which are required for satisfying the high demand of various services and applications, has been explored.

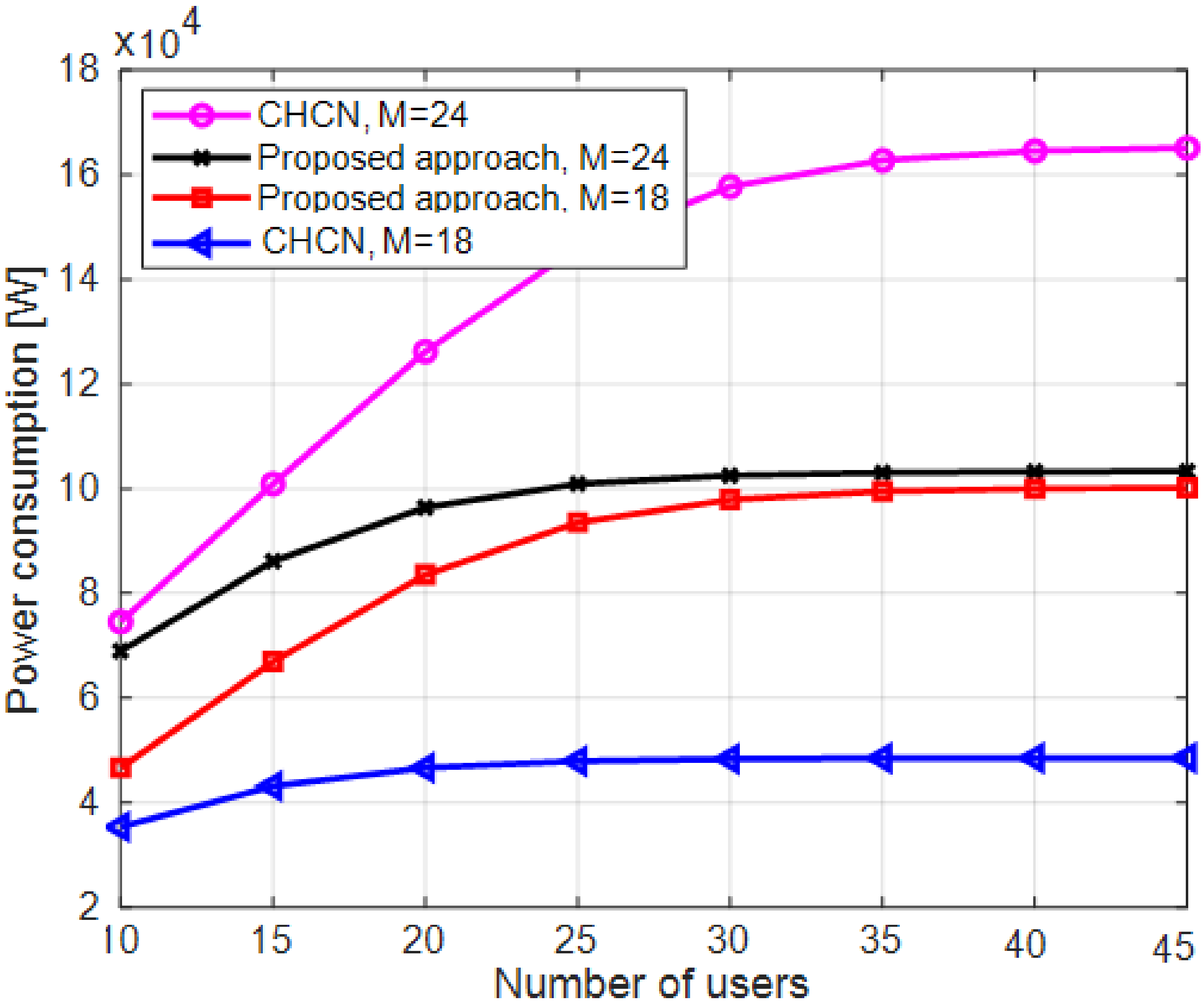

Fig. 7. Power consumption VS Number of users

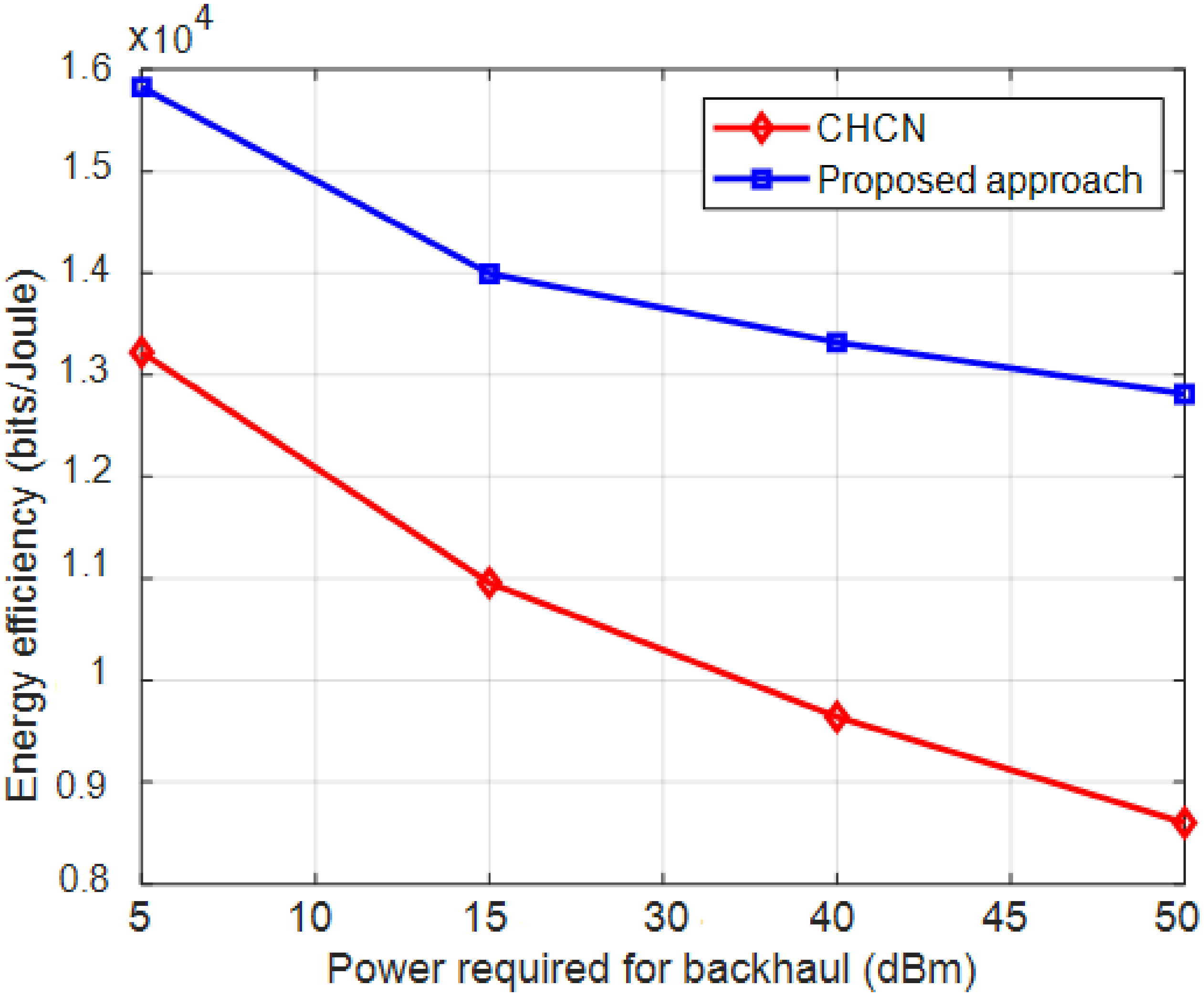

Fig. 8. Energy efficiency VS Power consumption required for backhaul required

It consists of randomly distributed APs controlled by a powerful CPU in a coverage area; therefore, the primary aim of this new network topology is to challenge the conventional heterogeneous cellular network (CHCN) in terms of energy efficiency of the entire network. Subsequently, assuming that the number of APs in the proposed topology is the same as that of the small cell base stations in CHCN, our proposed approach still outperforms the CHCN by evaluating the sum rate with respect to the SNR. These comparative results were validated through simulation using MATLAB environment. It was shown that, the proposed approach significantly improves the energy efficiency with respect to the power consumption as well as the transmission power. The performance evaluation was manifested through the improvement of energy efficiency by approximately 60% compared to that of the CHCN, which finally proves to be beneficial in terms of the costs as well as in handling the data traffic associated with the proliferation of the connected smart devices in the current and the future communication network systems, thus proving to be relatively more environment friendly.

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