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ENERGY EFFICIENCY OPTIMIZATION IN MASSIVE MIMO USING A PRICING BASED APPROACH

Eze, Gerald C.
Department of Electronic/Electrical Engineering, Federal Polytechnic, Oko, Anambra State
Corresponding author: *eze.gerald@federalpolyoko.edu.ng*

ABSTRACT
Massive Multiple-Input Multiple-Output (mMIMO) is a promising technology for improving the energy efficiency (EE) of wireless communication networks. However, there are several conflicting objective problems that need to be addressed to achieve optimal EE in mMIMO network. In this paper, we present an optimization framework, which is based on multi-objective optimization (MOO) used to investigate a pricing cost based approach in mMIMO network. A network pricing cost is introduced to the energy consumption as a penalty for the achievable spectral efficiency (SE), and studies its impact on the tradeoff between the EE and the throughput. It is difficult to directly solve the problem as it is non-convex, and thus scalarization technique was used to transform the MOO problem into a single-objective optimization (SOO) instead of using iterative algorithms that relied on the dual decomposition for obtaining the pricing cost, optimal throughput and EE. Finally, numerical simulations are used to characterize the interaction between the EE and throughput for various network parameters such as power when the network is designed from the energy-efficient perspective.

Keywords—EE, mMIMO, MO, SOO, throughput.

INTRODUCTION
The future generation technology (5G/6G) is designed to give enhanced performance, providing gigabit data traffic, ultra reliable low latency and massive connectivity to internet of things [1], [2]. Due to their performance and enhanced hardware, 5G networks also result in improved energy efficiency (EE), in bits per Joule, with respect to the predecessor generations of technology like 4G and 3G. However, despite of this improved EE, the growth in data throughput and the use of massive MIMO (mMIMO) networks are presently leading to increase energy consumption [3].

The mMIMO network is one of the main key technologies for boosting energy performance as it allows antenna arrays to direct narrow beams towards the user equipments (UEs) thereby increasing the spectral efficiency (SE). 5G/6G together with mMIMO network is four to six times more spectrum efficient than 3G/4G deployed with conventional radio solution.

Furthermore, in the design and operation of mMIMO technology, different objective functions and requirements need to be considered, which calls for an efficient network optimization framework that is able to jointly take into account all the conflicting 5G/6G objectives.

Generally, the main challenges towards the efficient solution of multi-objective problems (MOPs) are the increased complexity and the selection of the best compromise solution.

However, a useful survey of multi-objective optimization (MOO) has been presented in [4-6], where its application on the design of 5G networks has been proposed. In [4], two different solving techniques have been discussed, namely scalarization and visualization, for example, weighted-sum metric (WSM), weighted product metric (WPM), weighted Chebyshev metric (WCM), etc. Also, a MO problem of three conflicting objective functions for designing mMIMO networks, that is the EE, average area rate, and user rate, have been considered as case study.

The authors in [5] considered the tradeoff between EE and spectral efficiency (SE) in the operation of downlink mMIMO networks utilizing MOP, where it is solved by transforming the MOP into a single-objective (SO) one with the help of a scalarization method and WSM.

The authors in [6] considered a complete framework for solving MOPs of conflicting objectives in 5G wireless networks with mMIMO, which is based on multi-objective evolutionary algorithms (MOEAs), namely, non-dominated sorting genetic algorithm-II (NSGA-II) and speed-constrained multi-objective particle swarm optimization (SMPSO). The authors compared two MOEAs (i.e., NSGA-II and SMPSO) and the numerical results generated shows that NSGA-II gives better Pareto Front quality, and SMPSO is faster.

Moreover, a pricing-based method in [7] and [8] is adopted for SE-EE tradeoff problem in many practical networks such as vehicular ad-hoc networks (VANETs) and relay-assisted multiuser networks. A network price is introduced to the total power consumption as the penalty for the achievable sum rates. A pricing-based utility was used to balance the power consumption and the sum rate. Since the utility function is non-convex and the probability constraints are intractable, the authors in [8] used Bernstein approximation and successive convex approximation (SCA) to tackle convex optimization problem. Besides, the EE maximization and q-price algorithms were only considered to solve a pricing-based method.

In this work, we use a MOO, which is a mathematical framework to solve design problems with pricing-based utility function.

METHODOLOGY

System Model

We consider a Zero forcing (ZF) precoding mMIMO network, assuming a cellular network of L wrap square cells of area $A = d^2$, where the UEs are uniformly distributed in each cell at a minimum distance d [3-6]. Here, K single-antenna UEs per BS are served by a BS having a uniform planar array (ULA) with $M = M_V \times M_H$ antennas and p_k is the allocated transmit power to kth UE in the L cells.

$$64 \leq M \leq M_{max} \tag{1}$$

$$8 \leq K \ll M \tag{2}$$

$$0 \leq \sum p_k \leq P_{max} \tag{3}$$

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For simplicity, perfect channel state information for each BS is assumed. The single-cell and multi-cell effective signal to interference and noise ratio (SINR) expressions using ZF as obtained in [9-10] are given below.

$$SINR_k^{ZF} = (M - K)\,\beta_k\, p_k \tag{4a}$$

Where β_k is the large-scale fading.

$$SINR_{mk}^{ZF} = \frac{(M_m - K)\,\beta_{mk}\, p_{mk}}{1 + \sum_{m\prime \neq m}^{M} (M_m - K)\,\beta_{m\prime k}\, p_{m\prime k}} \tag{4b}$$

Where M_m is the number of active antennas at the mth BS, β_{mk} is the large-scale fading of the kth UE at the mth BS and p_{mk} is the allocated transmit power to the kth UE at the mth BS and $(M_m - K)$ is the mth BS array gain. The summation $\mathbf{\Sigma}\{\}$ is used to determine interference. ZF precoding suppresses intra-cell interference [9] and we assume that each UE treats inter-cell interference as noise. Therefore, a SE maximizes the SINR in (4) for a given *M* and *K* as derived in [3]:

$$SE_{mk}^{ZF} = \frac{\tau_c - \tau_p}{\tau_c} \log_2(1 + SINR_{mk}^{ZF}) \tag{5}$$

Where τ_c is the total coherence block length and τ_p is the pilot coherence block length. The term $\frac{\tau_c - \tau_p}{\tau_c}$ is the prelog factor that represents the portion of samples per coherence interval that are used for downlink data transmission.

Throughput (bits/s) is obtained by the multiplication of operational Bandwidth (Hz) and SE (bits/s/Hz).

$$Throughput_k \left(\frac{bit}{s}\right) = Bandwidth\ (Hz) \times SE_{mk}^{ZF} \left(\frac{\frac{bit}{s}}{Hz}\right) \tag{6a}$$

$$Area\,Throughput \left(\frac{\frac{bit}{s}}{km^2}\right) = \frac{\sum_1^K Throughput_k \left(\frac{bit}{s}\right)}{Cell\ Area\ (km^2)} \tag{6b}$$

Accurate energy power consumption modeling is crucial for designing energy-efficient mMIMO networks. In a practical network, using more *M* has a cost in terms of increased circuit power [3]. Hence, more practical energy consumption as model during a time interval *T* may be expressed in (7) as obtained in [9] and [14].

$$Energy\ Consumption = T(\zeta_1 M + \zeta_2 \sum_{k=1}^{K} p_k + P_C) \tag{7}$$

where $\zeta_1 \geq 0$ and ζ_2 denote the energy consumption per antenna and the amplifier inefficiency factor which accounts for power dissipation in the amplifiers. The values depend on the hardware quality deployed at the BS. Circuit power consumption (P_C) is the total summation of the static hardware power, power per radio frequency transceiver chain, cooling system power, signal processing and coding/decoding/backhaul powers, etc.

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The EE of a cellular network is the throughput (number of bits transmitted successfully) per unit of energy. EE formulated below from the above definition as:

$$EE = \frac{\sum Throughput_k}{Energy\ Consumption}\left(\frac{bit}{Joule}\right) \tag{8}$$

Which is measured in bit/Joule and can be seen as a benefit-cost ratio, where the quality of service (throughput) is compared with the associated costs (energy consumption) [3]. Hence, it is a key performance indicator of the network's bit-delivery efficiency. In mMIMO networks, EE is dependent on many factors, i.e., network architecture, throughput, power consumption by the entire network, and transmission protocol [3–9].

Multi-Objective Optimization (MOO)

Instead of assuming that one of the objectives is the sole objective, the fundamental method is to recognize the existence of multiple objectives [4]:

$$f_1(x), f_2(x), \dots f_N(x) \tag{9a}$$

where N is the number of objectives. Single-objective optimization problems (SOOPs) are MOO problems with $N = 1$ and are thus trivial from the MOO perspective.

Solving a Multi Objective Optimization problems (MOOPs) by Scalarization

An alternative way to solve MOOPs in practice is the a priori method where the network designer articulates preferences before any computations take place. Consequently, the MOOP in (9a) is converted into the SOOP.

$$\max_{0 \le x \le \infty} f(f_1(x), f_2(x), \dots f_n(x)) \tag{9b}$$

This conversion is called scalarization and the solution is a weak, and usually also strong, Pareto boundary point. In contrast to the traditional method of having a sole performance objective and expressing other potential objectives as constraints, (9) combines the N objectives into a scalar goal function and has no additional constraints. It is indeed possible to impose constraints on the acceptable values for certain objectives also in the scalarization case, but it is not required. The goal function can take many forms and a variety of methods can be found in the literature; see [11–12].

Designing mMIMO by MOO Framework

MOOP is defined in (9). These objective functions ($N = 3$) are EE, area throughput, and UE throughput. The three objective functions are defined in (10).

$$f_{EE}(M, K, p_k) = EE \tag{10a}$$
$$f_{UE}(M, K, p_k) = Throughput_k \tag{10b}$$
$$f_A(M, K, p_k) = Area\ Throughput \tag{10c}$$

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Problem Formulation

The MOOP that aims at simultaneously maximizing the aforementioned three objective functions can be expressed as

$$f(M,K,p_k)=\begin{cases} f_{UE}(M,K,p_k), \\ f_{EE}(M,K,p_k), \\ f_A(M,K,p_k) \end{cases}$$

$$\max_{M,K,p_k} f\left(f_{UE}(M,K,p_k), f_A(M,K,p_k), f_{EE}(M,K,p_k)\right) \tag{10d}$$

$\textbf{subject to}$ *(1), (2), (3),*

Single-Objective Optimization (SOO)

The traditional method to physical-layer network optimization is that of selecting a scalar network utility function that is maximized under a set of constraints [7, 8]. A common problem formulation is that of maximizing the weighted sum of the UEs' data throughput under transmit power constraints. Alternatively, one can minimize the transmitted power under the constraint of guaranteeing certain data throughput to each UE. In recent years, the EE has also arisen as a utility function [13].

Pricing-based power Problem Formulation

A pricing-based power problem is formulated in this section. We first define a network pricing cost q ≥ 0 of consuming power resource and the associated network utility (U_{UE} or U_{Area}), which strikes a balance between the throughput (f_{UE} or f_A) in (11) and the utilizing power in the objective of (7) and expressed as

$$U_{UE}(p_k)=(1-q)f_{UE}(p_k)-q\left(\zeta_1 M+\zeta_2\sum_{k=1}^{K} p_k + P_C\right) \tag{11a}$$

$$U_{Area}(p_k)=(1-q)f_A(p_k)-q\left(\zeta_1 M+\zeta_2\sum_{k=1}^{K} p_k + P_C\right) \tag{11b}$$

Where U_{UE} and U_{Area} are the user network utility and area network utility functions of EE or throughput which depends on the network pricing cost q. When the network pricing cost, q, tends to zero, it implies that the cost to utilize power resource is negligible, and the problems (11) degenerate into a throughput maximization problem. With the growth of the cost, the network utility turns into an EE-like optimization function. For an extreme case where cost, q, tends to infinity, no transmission is the best strategy to maximize the network utility.

The SOOP that aims at maximizing the aforementioned area utility function can be expressed as

$$\max_{p_k} U_{Area}(p_k)=(1-q)f_A(p_k)-\boldsymbol{q}\left(\zeta_1 M+\zeta_2\sum_{k=1}^{K} p_k + P_C\right) \tag{12}$$

$\textbf{subject to}$ *(3)*

II. SIMULATION RESULTS AND DISCUSSION

A classic wrap-around was applied to avoid edge effects [3,4].The 16-cell setup is utilized, each cell has an area of 0.0625 km^2 and each consisting of a BS with *M* antennas and *K* single-antenna UEs. The antenna array used at the BS is uniform planar array (UPA) where *M* is 625 (25×25). The *K* UEs are uniformly distributed in the cell, with a minimum distance of 35 meters. For a randomly picked UE, let the channel variance and inter-cell interference power receive by all the base stations be represented as 1.72 $\times 10^9$ and 0.54.Using the same 3GPP pathloss model as in [13]. The optimization variables in this work are the number of BS antennas *M*, the number of

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users K, and the transmit power P per cell. The average user throughput and the total power consumption per cell are defined. For simplicity, we assume that each BS has obtained perfect CSI for its UEs and applies ZF precoding, which nulls out intra-cell interference by beamforming and adapts the power allocation to guarantee the same throughput to each UE. The throughput is shown in (6) to be under the assumption that each UE knows its useful channel. The prelog-factor in (5) accounts for the necessary overhead for channel acquisition. The EE, UE throughput, and Area throughput were computed by performing Monte-Carlo simulations to obtain the numerical results. The simulation parameters are listed in Table I.

Table 1: Simulation Parameters

Parameter	**Value**
Network layout	Square pattern (wrap-around)
Cell area	0.25km × 0.25km
Maximum Number of BS antennas (M_{max})	625
Communication Bandwidth (B)	20 MHz
Maximal radiated power per BS antenna (P_{max})	100W
Noise power	1×10^{-13}W
Coherence bandwidth	200×10^{3}Hz
Coherence time	5×10^{-3}s
Inter-site distance	0.25km
Average strength of inter-cell interference	0.5419
Hardware power consumed per transmit antenna, ζ_1	0.5W
Hardware power per UE	0.2W
Efficiency of the power amplifiers at the BS, ζ_2	0.31

We now depict how the MOO framework can be used to investigate tradeoffs between these f_{EE}, f_{UE}, and f_A with the purpose of deriving new insights and confirming old beliefs.

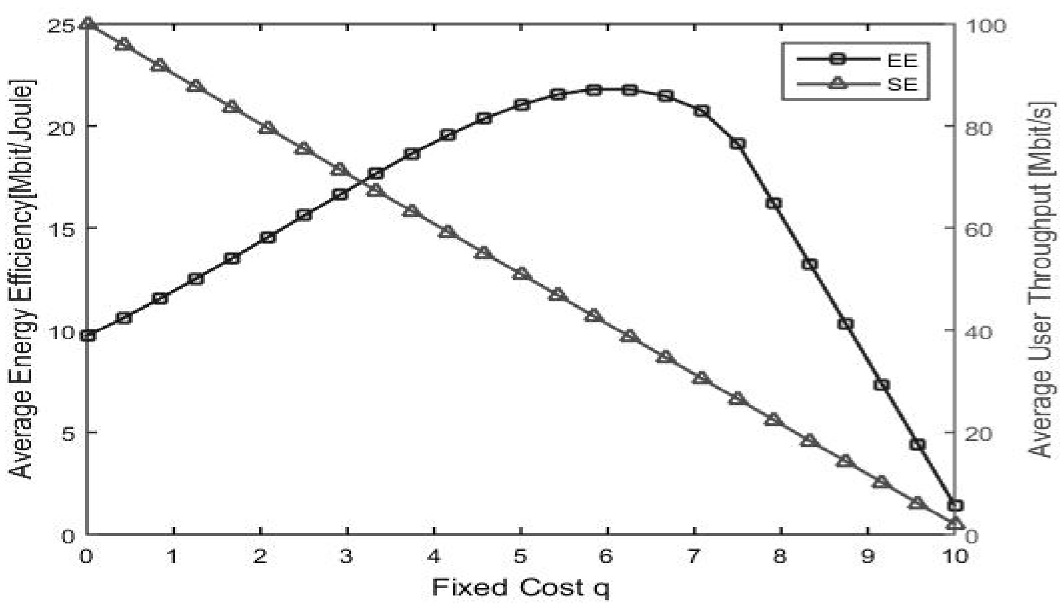

Fig. 1: Average EE and User throughput for different network Fixed Cost q.

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It is seen that the average User throughput performance decreases as the fixed cost q increases, while there exists an optimal cost in terms of the maximum average EE at q = 6.45. Therefore, the adjustment of the cost leads to a performance tradeoff between the average EE and User throughput.

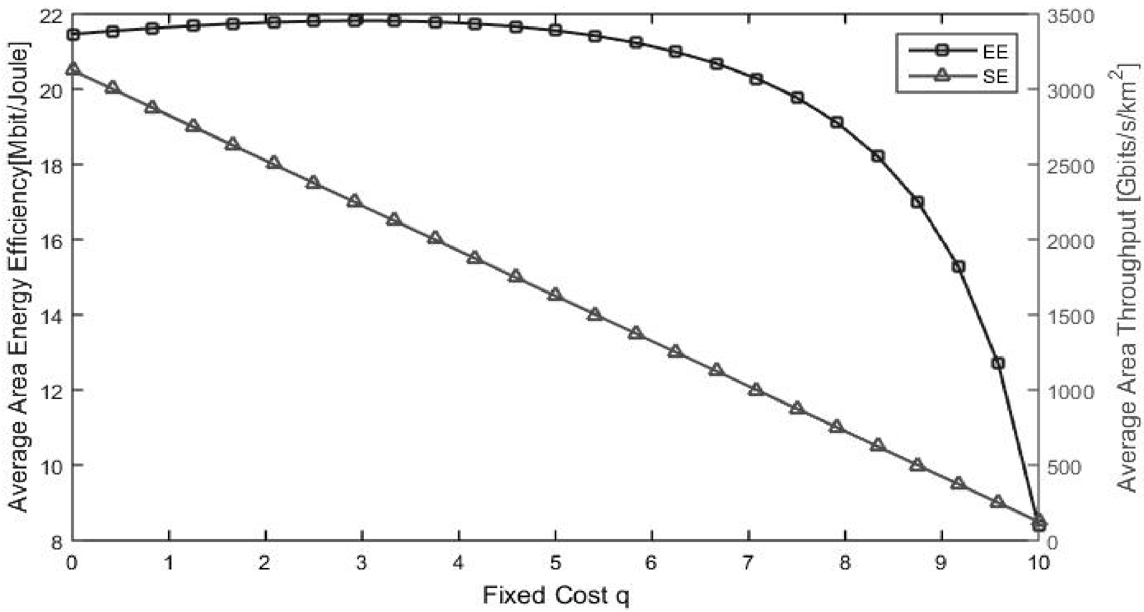

Fig. 2: Average Area EE and Area throughput for different network Fixed Cost q.

It is clear that the average Area throughput decreases with the growth of the Fixed Cost q, while there exists an optimal price in terms of the maximum average EE at q=3.7. The average EE at the cost q=2.21 or q=3.87 is not the maximum average EE since it is not equal to fixed cost q. Hence, in fig. 1 and fig. 2, the adjustment of the Fixed Cost q is vital when there is a tradeoff between the EE and throughput.

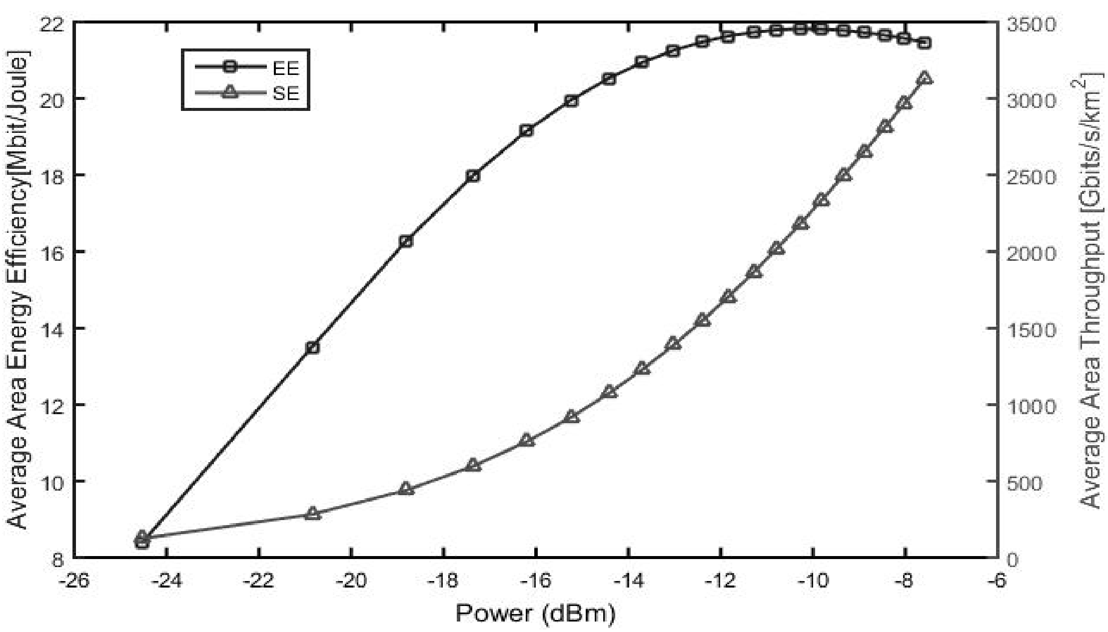

Fig. 3: Average Area EE and Area throughput versus BS transmitting power.

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There are exponential growth of average EE and area throughput from -24dBm to -14dBm and -16dBm to -8dBm respectively. There is a finite increase in area throughput from -24dBm to -14dBm while EE saturates at -11.84dBm and the average area EE is basically steady for most values of power ≥ -11.84dBm with small variations. In this case, the area EE saturates, which shows that the excess transmit power should not be used because it would degrade EE performance. The optimal area EE (Average Area EE = 21.89Mbit/J) can be achieved based on the optimal transmit power (-11.84dBm). However, one can increase the EE and area throughput by increasing the BS transmission power. Thus, the area throughput is improved by having a larger number of UEs transmitted to and not by increasing the user throughput. The EE is not monotone in the transmit power and this is a fundamental difference compared to conventional performance metrics, which instead are monotonically increasing in the transmit power and EE is maximized by a finite power level [14].

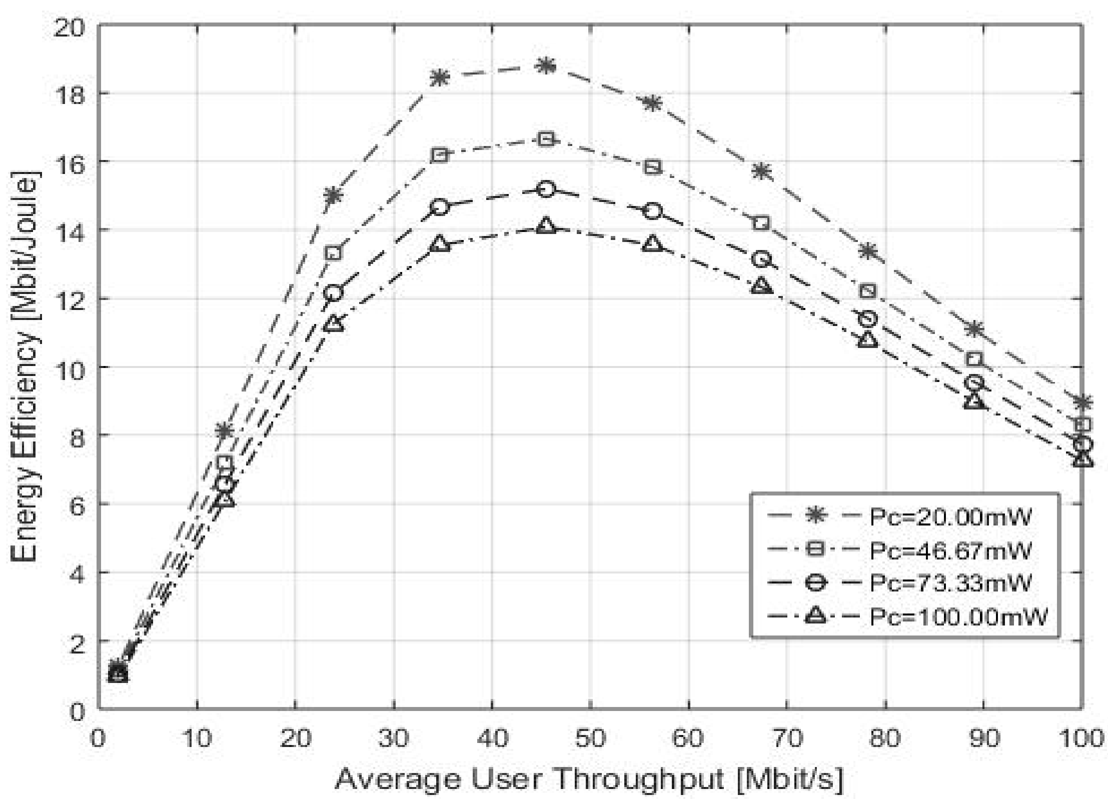

Fig. 4a: EE versus Area Throughput for different circuit power consumption (P_C)

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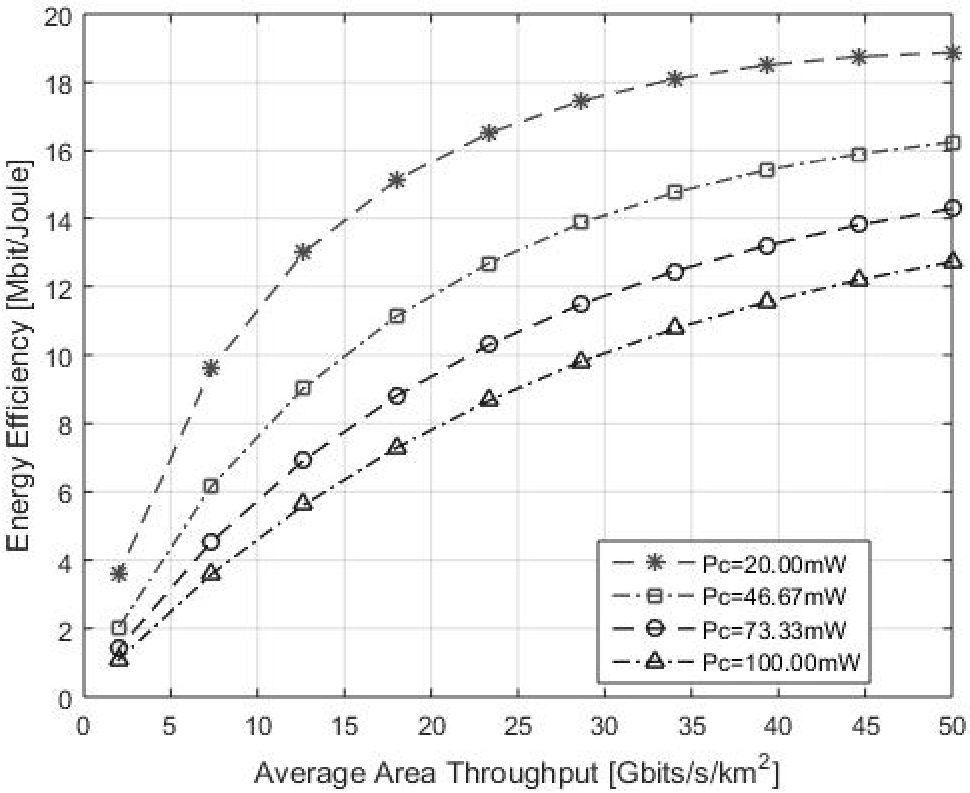

Fig. 4b: EE versus Area Throughput for different circuit power consumption (P_C).

In fig 4a and 4b, the optimal EE can be achieved based on the circuit power consumption (P_C). From fig. 4a, when the maximum EE = 18.86 Mbit/joule and the minimum EE = 14.00 Mbit/joule, the user throughput is 46.67Mbit/s with (M_{max}, P_C) = (625,20mW) and (M_{max}, P_C) = (625,100mW) respectively. While in fig 4b, the maximum EE = 18.87 Mbit/joule and the minimum EE = 12.67 Mbit/joule are achieved at area throughput of 50.00Mbit/s with (M_{max}, P_C) = (625, 20mW) and (M_{max}, P_C) = (625,100mW) respectively. If there is increased power consumption in radio frequency transceiver chain or any circuit components, the EE is drastically reduced. In this case, the EE saturates, which illustrates that the excess transmit power should not be used because it would decrease EE. The maximization of the numerator of (8) leads to growth in BS transmit power as illustrated in fig. 3 and maximizing the EE yields a P_C that has the lowest value in fig. 4. In (7), if $P_C >> p_k$, the denominator of (8) becomes approximately steady and EE maximization reduces to the maximization of the numerator of (8).

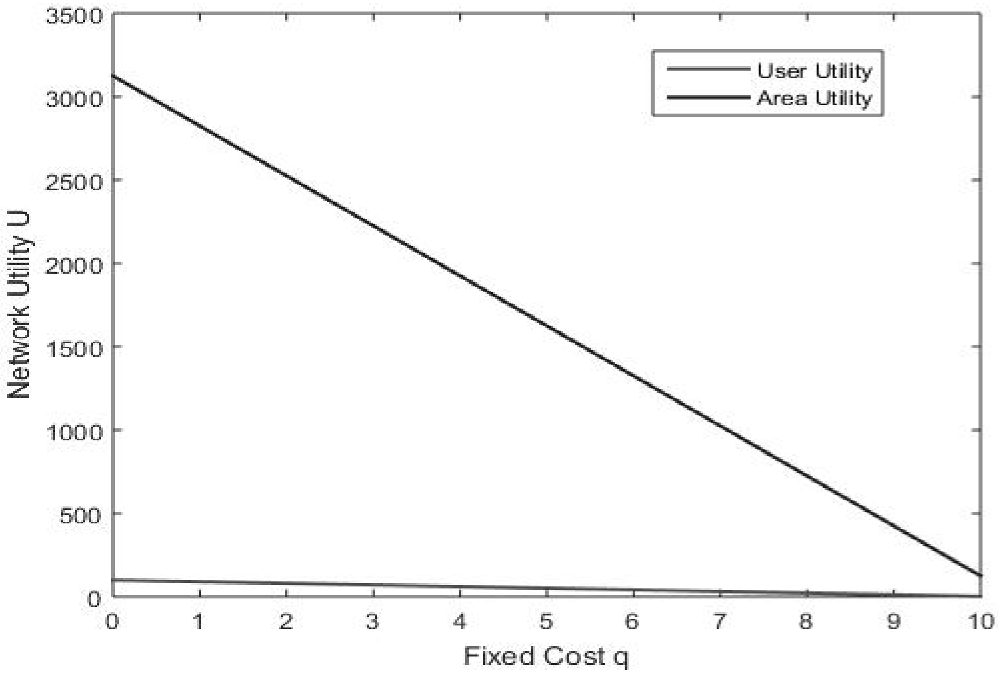

Fig. 5: Network Utility U versus Fixed Cost q

Fig.5 shows the comparison of the Network Utility between area throughput and user throughput. By noting that $f_A = \frac{K \times f_{UE}}{A}$ and comparing with the fig. 2, this obviously means that the area throughput is improved by transmitting to more UEs that is large K with small cell area and not by increasing user area throughput.

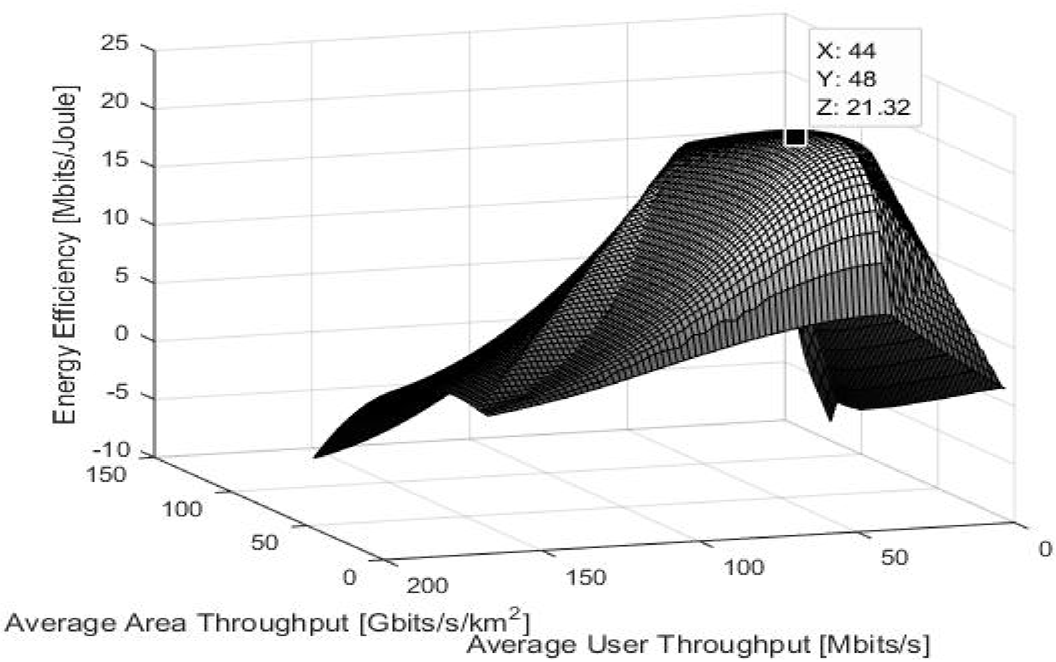

Fig. 6: Visualization of the tradeoff between average user throughput, average area throughput, and EE.

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Fig. 6 proves that high area throughput are only achievable when the user throughput is low, which shows that we serve many UEs in parallel. Contrarily, high user throughput is only achievable by having fewer active UEs. High EE is possible when user throughput is low. Thus, the optimal EE, the optimal area throughput and optimal user throughput values of the mMIMO network are obtained as shown in figure 6 are 21.32 Mbit/joule, 48.00 Gbits/s/km^2 and 44.00Mbit/s respectively with (M_{max}, P_{max}) = (625,100W). These different optimal values are achieved by different resource utilizations. Therefore, *M* and *K* are different and the signal processing related to precoding changes. This illustrates the otherwise heuristic belief that the network architecture must be dynamic (e.g., in terms of precoding adaptation and switching off antennas) if different optimal points should be attainable in different traffic cases.

CONCLUSION

In this paper, we have presented a MOO framework for solving conflicting objective function problem in mMIMO network using a pricing based method for improving the EE among UEs. A pricing based method was adopted to strike a balance between the throughput and energy consumption. While the considered objective function problem was intrinsically non-convex, a scalarization technique was used to transform the problem into a SOO instead of using iterative algorithms that relied on the dual decomposition for finding the q-pricing cost, power allocation, optimal throughput and EE. To further maximize the systematic EE and throughput in the perfect channel state information, ZF precoding was considered. We compared the performance of the MOO framework by monte-carlo simulations and quantified the effects of tradeoffs performance parameters on mMIMO network by obtaining the optimal EE and throughput.

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