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Evaluation of Energy-Efficiency Problem in Orthogonal Frequency Division Multiple Access Cellular Networks

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Abstract

In this study, the energy-efficiency (EE) problem is investigated for downlink Orthogonal Frequency Division Multiple Access (OFDMA) cellular networks. The EE maximization problem is defined under certain prescribed per-user quality-of-service (QoS) demands and maximum system power limit. EE metric that aims to maximize the system data rate and minimize the total power consumption at the same time is used as the objective function of the defined problem. In this form the optimization problem belongs to a broad class of problems called mixed-integer non-linear programming problem (MINLP), that is difficult to solve in its original form in such a multi-carrier, multi-user networks. Hence, we have decomposed the original problem into two parts and presented a solution that performs subchannel allocation and power allocation parts separately. Simulation results are obtained to confirm the performance of the presented scheme in terms of energy-efficiency and total data rate.

Keywords: Energy-Efficiency, OFDMA, Cellular Networks.

1. Introduction

The number of mobile users and mobile devices are increasing enormously and according to some researches, by the last quarter of 2017, total mobile subscriptions reached to 7.8 billion and they are growing around 4 percent year-on-year [1]. Not only the number of mobile broadband subscriptions is increasing but also the expectation of these users about ubiquitous access to the high-data rate wireless services such as video streaming, online gaming etc. is increasing. This case causes rapidly booming energy consumption which is a big problem for the next generation wireless networks. It is also reported that mobile operators are already among the top energy consumers that is about 3% of the worldwide energy consumption and contributed to about 2% of the global carbon dioxide emissions [2]. Thus, energy-efficient communication, also well-known as Green Communication has thereby been proposed as an effective solution and is becoming the mainstream for future wireless network design. To reach the targets of the Green Communication, two different and effective ways are used in the literature. The first way is harvesting energy from the surrounding environment including solar, wind and radio frequency (RF) signals [3,4]. The second way is designing energy-efficient communication systems to maximize the number of transmitted information bits per unit of energy [5]. The second way, in which system capacity should be enlarged and system energy consumption should be reduced at the same time has been adopted as one of the new obligatory evaluation metrics in 5th generation (5G) systems [6].

OFDMA is one of the key technologies used to meet the mobile users' increasing expectations for ubiquitous access to the high-data rate wireless services. The main advantages of the OFDMA can be listed as robustness against frequency-selective fading, high spectral efficiency and flexible resource allocation. In OFDMA, the frequency spectrum is divided into a number of subcarriers and then subsets of these subcarriers also called subchannels are allocated to different users by exploiting multiuser diversity. It is popularly used in 4th generation (4G) wireless systems of broadband communications such as 3rd Generation Partnership Project (3GPP) Long Term Evolution (LTE), LTE Advanced, Worldwide Interoperability for Microwave Access (WiMAX).

Radio resource management (RRM) schemes such as subchannel allocation and power allocation can be used to meet the certain demands of the users and service providers. Once the optimization problem has been established according to the different objective functions (rate maximization, power minimization, energy-efficiency maximization) and different optimization constraints, the problem can be solved optimally or in a heuristic manner. The RRM problem who aims rate maximization and power minimization in OFDMA based cellular networks is studied in many works [7-12]. However, these works disregarded the energy consumption of the system which is being a huge problem for the information and communication

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technology industries. Thus, recently, more attention has been paid to RRM problems whose target is maximizing the EE in OFDMA cellular networks [13-18]. Contrary to rate maximization and power minimization problems, EE maximization problems belong to a class of optimization problems called fractional programs which make them difficult to solve. In [13], energy-efficiency and spectral-efficiency trade-off is discussed for the downlink OFDMA networks. In [14], while the weighted EE maximization problem is explored for the downlink transmission, the minimum individual EE maximization problem is studied for the uplink transmission. In [15], the authors focused on system fairness issue in energy-efficient design for downlink OFDMA systems, and proposed energy-efficient downlink resource allocation by taking instantaneous fairness into account. Contrary to [13-15], in [16] a different EE metric that is defined as the ratio of total consumed power to the total data rate is used. In [17], instead of traditional energy-efficiency definition, a metric called effective energy efficiency (EEE) is defined. In this metric, effective capacity concept which characterizes the maximum throughput of a system subject to statistical delay-QoS requirements is used instead of Shannon's channel capacity. In [18], the authors investigated the EE resource allocation problem of the downlink transmission of OFDMA while considering discrete power levels. In the literature, the EE problem is examined in different forms under different assumptions. According to the definition of the problem, the solution approaches have also changed.

In this study, we have defined the EE maximization problem which considers not only energy-efficiency of the system but also QoS demands of the users for the downlink OFDMA cellular networks. Since the problem is a MINLP which is difficult to tackle, a solution that decomposes the original problem into two parts and perform disjoint subchannel and power allocation is presented in order to make the problem more tractable. Simulation results are obtained to reveal the advantages of the presented scheme.

The rest of the paper is organized as follows. System model is given in Section 2. In Section 3, problem definition and problem solution are presented. Performance evaluation and Conclusions are given in Section 4 and 5 respectively.

2. System Model

In this study, an OFDMA-based downlink cellular network model, which contains a BS in the middle of the cell and M mobile devices scattered around it, is used as shown in Figure 1. All mobile devices and the BS are running in the single antenna mode. The cellular area is thought to be partitioned into two areas in terms of proximity to the cell-center. The first area is bounded between the cell-center and half of the cell radius, R and the second area that is shown in grey shaded is far from the half of the cell radius R. The mobile device density in the first area is assumed higher than the second area since it is known that the BSs are placed to the regions where more users are. The BS communicates with the mobile devices through a direct link by using the allocated subchannels which composed of a set of adjacent Orthogonal Frequency Division Multiplexing (OFDM) subcarriers. There are N subchannels to be allocated in the BS as illustrated in Figure 1. It is assumed that one subchannel is exclusively allocated to maximum one user in order to avoid intra-cell interference. Each subchannel has a bandwidth Υ and total system bandwidth is $B = N \times \Upsilon$. The resource allocation such as subchannel allocation and power allocation is performed at the BS so all channel state information (CSI) between the BS and each mobile device is perfectly known at the BS.

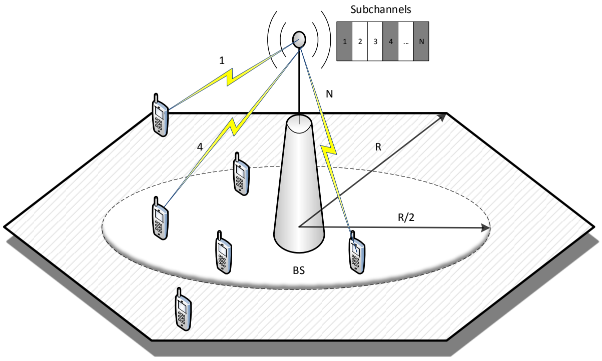

Figure 1. OFDMA Cellular Network Model.

3. Problem Definition and Solution

In this part, EE maximization problem for the OFDMA based downlink cellular networks will be defined and a solution methodology will be presented for the defined problem.

3.1. Problem Definition

The optimization problem considering the EE metric takes into account not only the maximization of the system capacity but also the minimization of the total consumed power. Thus, before giving the optimization problem, total system data rate and total consumed power can be formulated. Let $\mathbb{N} = \{1,2,\dots,n,\dots,N\}$ be set of subchannels and $\mathbb{M} = \{1,2,\dots,m,\dots,M\}$ be set of mobile devices, respectively. When, we assume that the distributed power of user m on subcarrier n is P_m^n and the bandwidth of each subchannel is Υ, the achievable data rate of user m on subchannel n is;

$$R_m^n = \Upsilon log_2(1 + P_m^n \Gamma_m^n) \qquad \mathbf{(3.1)}$$

where $\Gamma_m^n = \frac{|h_m^n|^2}{N_0 \Upsilon}$ is the channel-to-noise ratio. h_m^n is the channel coefficient between BS and any user m that includes path-loss and multipath fading and N_0 is the noise spectral density. Consequently, the overall system data rate and the total consumed transmit power can be formulated as follows;

$$R_T = \sum_{m=1}^{M} \sum_{n=1}^{N} \rho_m^n R_m^n \qquad \mathbf{(3.2)}$$

$$P_T = P_C + P_d \tag{3.3}$$

In these equations ρ_m^n is the binary subchannel allocation indicator that shows if subchannel n is allocated to any user m or not. As given in Equation (3.3), the total consumed power is defined as the summation of two different power values, as constant power P_C and dynamic power which is $P_d = \Omega(\sum_{m=1}^{M}\sum_{n=1}^{N}\rho_m^n P_m^n)$. The P_C is the power consumed by the electronic circuits such as mixers, filters and digital-to-analog converters. This value is ignored in some of the works but this is not realistic. The dynamic part of the power, P_d depends on the data transmission on the contrary to the constant term and it is the multiplication of the total transmit power with a constant parameter Ω that represents the reciprocal of drain efficiency of the power amplifier.

Hence, the EE maximization problem can be defined mathematically as follows;

$$\max_{\rho_m^n, P_m^n} \frac{R_T(\rho_m^n, P_m^n)}{P_T(\rho_m^n, P_m^n)} \tag{3.4}$$

subject to;

$$\rho_m^n \in \{0,1\}, \quad \forall m, \forall n \tag{3.5}$$

$$\sum_{m=1}^{M} \rho_m^n = 1, \quad \forall n \tag{3.6}$$

$$\sum_{m=1}^{M}\sum_{n=1}^{N} \rho_m^n P_m^n \le P_{max} \tag{3.7}$$

$$P_m^n \ge 0, \quad \forall m, \forall n \tag{3.8}$$

$$\sum_{n=1}^{N} \rho_m^n R_m^n \ge R_m^{min}, \quad \forall m \tag{3.9}$$

In (3.5), the constraint shows that the subchannel allocation indicators are binary variables. If the subchannel n is allocated to the user m then $\rho_m^n = 1$, otherwise $\rho_m^n = 0$. The constraint in (3.6) guarantees that each subchannel will be given to at most one user to eliminate the intra-cell interference. Constraint (3.7) limits the maximum transmit power at the source. Constraint in (3.8) is the non-negative power constraint. (3.9) is the QoS constraint and it ensures that each user is satisfied by getting their minimum required data rate.

3.1 Problem Solution

The defined problem in the previous subsection is very difficult to solve optimally because of the coupled integer and continuous variables with nonlinear functions. Moreover, the fractional form of the objective function makes the problem much more difficult to tackle. Hence, to make this challenging problem more tractable one, we have decomposed original problem into two parts and solved subchannel allocation and power allocation problems separately. The proposed solution for the defined optimization problem is given in detail in the following parts.

3.1.1 Subchannel Allocation

In this part, a two-step heuristic solution is presented to allocate the subchannels to the users by assuming the power is distributed equally among the subchannels. In the first step of the algorithm, QoS demands of the users are satisfied. First of all, the user whose minimum data rate requirement is maximum is selected and the achievable data rate of this user for all unallocated subchannels are calculated. Then, the absolute value of difference of the achievable data rate and required data rate for each unallocated subchannel is determined and minimum valued subchannel is assigned to the related user. After that, the data rate requirement of the user is updated and if it is zero or smaller than zero, this user is removed from the unsatisfied user set and added to the satisfied user set. Finally, the total data rate and total transmit power values are updated. This step is stopped when all users are satisfied or subchannel set is empty. In the second step of the algorithm, the remaining subchannels are allocated to the users according to the maximum EE metric. This step is terminated when the subchannel set is empty. The heuristic subchannel allocation algorithm is outlined below in detail.

Subchannel Allocation under equal power case

- Let $\mathbb{M}$ is the set of total users, $\mathbb{S}$ and $\mathbb{U}$ are the set of satisfied and unsatisfied users, respectively.
- $\mathbb{N} = \{1,2,\dots,N\}$, $R_T = 0, P_d = 0, \mathbb{S} = \emptyset$, $\mathbb{U} = \mathbb{M}$
- $p_{sub} = P_{max}/N$, $\tau_m = R_m^{min}$ $\forall m \in \mathbb{M}$.

Step1

while $\mathbb{U} \neq \emptyset$ and $\mathbb{N} \neq \emptyset$

- Find the user, $m^* = \arg\max_{m\in\mathbb{U}} (\tau_m)$
- Calculate $R_{m^*}^n$, $\forall n \in \mathbb{N}$ by using Equation (3.1).
- Find the subchannel n' that satisfies
  $$n' = \arg\min_{n\in\mathbb{N}} \left|R_{m^*}^n - \tau_{m^*}\right|$$
- Update $\tau_{m^*} = \tau_{m^*} - R_{m^*}^{n'}$ and if $\tau_{m^*} \le 0$ then, $\mathbb{S} \leftarrow \mathbb{S} \cup \{m^*\}$, $\mathbb{U} \leftarrow \mathbb{U} \setminus \{m^*\}$.
- Set $\rho_{m^*}^{n'} = 1$ and $\mathbb{N} \leftarrow \mathbb{N} \setminus \{n'\}$.
- Update $R_T = R_T + R_{m^*}^{n'}$, $P_d = P_d + \Omega p_{sub}$.

end while

Step2

while $\mathbb{N} \neq \emptyset$

- For $n \in \mathbb{N}$, calculate R_m^n and the EE metric $\omega_m = \frac{R_T + R_m^n}{P_C + P_d + \Omega p_{sub}}$, $\forall m \in \mathbb{M}$
- Determine the user, $m^+ = \arg\max_{m\in\mathbb{M}} (\omega_m)$.
- Set $\rho_{m^+}^n = 1$, $\mathbb{N} \leftarrow \mathbb{N} \setminus \{n\}$
- Update $R_T = R_T + R_{m^+}^n$, $P_d = P_d + \Omega p_{sub}$

end while

3.1.2 Power Allocation

The original problem given in Equation (3.4), is recovered from unknown integer variables after

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allocating subchannels to the users. From now on, the problem unknowns are only continuous power variables. Thus, the original optimization problem is reorganized and the new problem is defined as given below;

$$\max_{P_m^n} \frac{R'_T(P_m^n)}{P'_T(P_m^n)} \qquad \textbf{(3.10)}$$

subject to;

$$\sum_{m=1}^{M} \sum_{n\in S_m} P_m^n \le P_{max} \qquad \textbf{(3.11)}$$

$$P_m^n \ge 0, \qquad \forall m, \forall n, \qquad \textbf{(3.12)}$$

$$\sum_{n\in S_m} R_m^n \ge R_m^{min}, \quad \forall m \qquad \textbf{(3.13)}$$

where S_m represents the subchannel set allocated to the user m in the first part of the solution. Moreover, the new total data rate and total power values are $R'_T = \sum_{m=1}^{M} \sum_{n\in S_m} R_m^n$ and $P'_T = P_C + \Omega\left(\sum_{m=1}^{M} \sum_{n\in S_m} P_m^n\right)$.

The defined problem in Equation (3.10) is in a fractional form and non-convex. This problem can be solved by transforming it to an equivalent parametric form by using the theorem given below [19];

Theorem: *The maximum EE,* $\omega^* = \max_{P_m^n} \frac{R'_T(P_m^n)}{P'_T(P_m^n)}$ *is obtained if and only if;* $\max_{P_m^n}\left(R'_T(P_m^n) - \omega^* P'_T(P_m^n)\right) = R'_T(P_m^{n*}) - \omega^* P'_T(P_m^{n*}) = 0$ *where* P_m^{n*} *denotes the optimum power values.*

According to this theorem, an equivalent optimization problem exists with an objective function in the subtractive form for a fractional optimization problem, as $R'_T(P_m^n) - \omega^* P'_T(P_m^n)$. The parametric version of the problem given in (3.10) is mathematically represented as shown below;

$$\max_{P_m^n} \left(R'_T(P_m^n) - \omega P'_T(P_m^n)\right) \qquad \textbf{(3.14)}$$

subject to;

(3.11), (3.12) and (3.13).

The problem defined in (3.14) can be solved by using an iterative algorithm known as Dinkelbach method [19] which is outlined in the following algorithm.

Dinkelbach Algorithm

- Set $\varepsilon > 0$ and $i = 0$ where ε is the convergence tolerance and i is the iteration index.
- Initial value of EE metric, ω_0 is selected as 0.

while $|\omega_i - \omega_{i-1}| > \varepsilon$

- Obtain optimal power values P_m^{n*} by solving the optimization problem in (3.14)
- $i \leftarrow i + 1$
- $\omega_i = R'_T(P_m^{n*}) / P'_T(P_m^{n*})$.

end while

In this algorithm, an inner optimization problem is solved for the given EE metric, in each iteration. The algorithm is finished when ω_i converges. This algorithm converges to the optimal value at a super-linear convergence rate as proved in [19]. The inner optimization problem in the Dinkelbach method is convex so it can be solved by using convex optimization algorithms. Strong duality holds for this convex problem since the Slater's condition is satisfied. Hence, we can solve the dual problem to obtain the primal solution with zero duality gap. The Lagrange dual problem is defined as;

$$\min_{\lambda,\sigma} \max_{P_m^n} L \qquad \textbf{(3.15)}$$

where L is the Lagrange function given as $L = R'_T(P_m^n) - \omega P'_T(P_m^n) + \lambda\left[P_{max} - \sum_{m=1}^{M} \sum_{n\in S_m} P_m^n\right] + \sum_{m=1}^{M} \sigma_m\left[\sum_{n\in S_m} R_m^n - R_m^{min}\right]$. λ and $\boldsymbol{\sigma} = [\sigma_1, \sigma_2, \dots, \sigma_M]$ are nonnegative Lagrange multipliers.

The dual problem given in (3.15) can be solved iteratively by the dual decomposition technique. In each iteration several subproblems and a master problem are solved. Using the subproblems, optimal power values are obtained for each subchannel for given Lagrange multipliers. Then these power values are used as the input and Lagrange multipliers are updated by solving the master problem. The iteration lasts till the Lagrange multipliers converges to the desired value.

In each subproblem, optimal power values are obtained by solving $\max_{P_m^n} L$ with the given Lagrange multipliers. The closed-form optimal power allocation variables can be obtained according to the Karush-Kuhn-Tucker (KKT) conditions, in which state that the gradient is equal to zero at the optimal points,

$$\frac{\partial L}{\partial P_m^n} = 0 \qquad \textbf{(3.16)}$$

$$\frac{\Upsilon \Gamma_m^n}{(1 + P_m^n \Gamma_m^n)}\left(\frac{1+\sigma_m}{\ln 2}\right) - \omega\Omega - \lambda = 0 \qquad \textbf{(3.17)}$$

$$1 + P_m^n \Gamma_m^n = \frac{\Upsilon \Gamma_m^n (1+\sigma_m)}{(\omega\Omega + \lambda)\ln 2} \qquad \textbf{(3.18)}$$

$$P_m^{n*} = max\left(0, \frac{\Upsilon(1+\sigma_m)}{(\omega\Omega + \lambda)\ln 2} - \frac{1}{\Gamma_m^n}\right) \qquad \textbf{(3.19)}$$

After calculating the optimal power values for all subchannels, the Lagrange multipliers are updated by solving the master problem with subgradient algorithm. The updated variables are also presented below.

$$\lambda^{t+1} = max\left(0, \lambda^t - \alpha^t\left(P_{max} - \sum_{m=1}^{M} \sum_{n\in S_m} P_m^n\right)\right) \qquad \textbf{(3.20)}$$

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$$\sigma_m^{t+1} = max\left(0, \sigma_m^t - \beta^t\left(\sum_{n\in S_m} R_m^n - R_m^{min}\right)\right), \forall m \in M$$

(3.21)

where t represents the iteration index, α^t, and β^t are the positive constant step sizes.

4. Performance Evaluations

In this section, we will evaluate the performance of the EE maximization solution, which is performed in two parts, in terms of energy-efficiency and total data rate values. The EE maximization scheme that is presented for the OFDMA based cellular networks will also be compared with the existing rate maximization scheme by changing the parameters such as total system power, total number of users, cell-radius and the minimum data rate requirements of the users to observe the effects of these parameters. The downlink single cell network topology that we consider in this work is illustrated in Figure 1. The radius of the cell R is set to $800m$. As mentioned in Section 2, the cellular area is formed by using two areas and the user density in the first area is assumed higher than the second area. The percentage of the users are selected as 80% and 20% for the first and second areas respectively. If it is not stated elsewhere, one user from the first area and one user from the second area will have a minimum data rate requirement constraint which can be thought as the QoS constraint. A summary of the other simulation parameters are also listed in Table 1.

In Figures 2 and 3, the presented EE maximization scheme and the well-known rate maximization scheme are compared in terms of energy-efficiency and total data rate, respectively. In these figures, minimum data rate requirement value R^{min} is set to $0.5Mbps$ and total number of users, M is set to 20. Moreover, different maximum transmit power values, P_{max} are used to evaluate the EE and total data rate of the system. In Figures 2 and 3, it is observed that the EE and the total data rate values are almost the same for both compared schemes up to a threshold P_{max} value which is measured as $35dBm$ in this work. However, after this value the EE and total data rate trends of both schemes change completely. Although, the EE and total data rate values reach to their maximum values for the presented EE maximization scheme, the EE value for the rate maximization scheme is decreasing deeply and total data rate value is increasing linearly. It can be commented on that the rate maximization scheme continues to allocate more power in order to achieve a higher total data rate and this case causes the degradation of the energy- efficiency.

In Figures 4 and 5, the EE and total data rate values of both EE and rate maximization schemes are compared for different number of users in the cellular area. In these figures, R^{min} is set to $0.25Mbps$ and total transmit power P_{max} is set to $50dBm$. Both figures show us that not only EE but also total data rate for both schemes are increased by using more number of users because of the multi-user diversity increment of the system.

Table 1. Simulation Parameters.

Parameter	***Value***
Frequency	$2GHz$
Bandwidth	$5MHz$
Number of subchannels	25
Noise spectral density, N_0	-174dBm/Hz
Static power consumption,P_C	100W
Efficiency of the power amplifiers, Ω	2.6
UEs min. distance to BS	35m
Multipath Model	Extended Pedestrian A
Path-loss Model	$128.1 + 37.6\, log10\, d(km)$
Number of channel realizations	1000

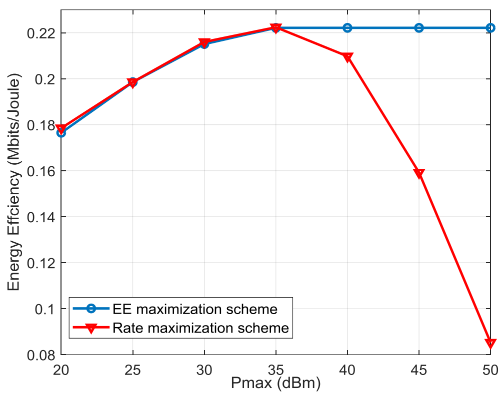

Figure 2. Energy Efficiency vs P_{max}.

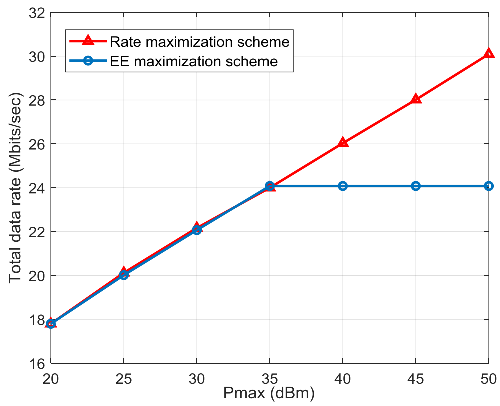

Figure 3. Total data rate vs P_{max}.

To see the QoS constraint effect on the problem, we have relaxed this constraint which means that $R^{min} = 0$.

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In Tables 2 and 3, the EE maximization and rate maximization schemes are compared in terms of EE and total data rate for $R^{min} = 0$ and $R^{min} = 0.5Mbps$. To form these tables, total number of users is selected as M=20. When the two tables are examined, it is seen that the EE and total data rate values are increased by relaxing the QoS constraint as expected. The EE and total data rate values are upper bounded with the results that are obtained for the relaxed QoS case for both schemes.

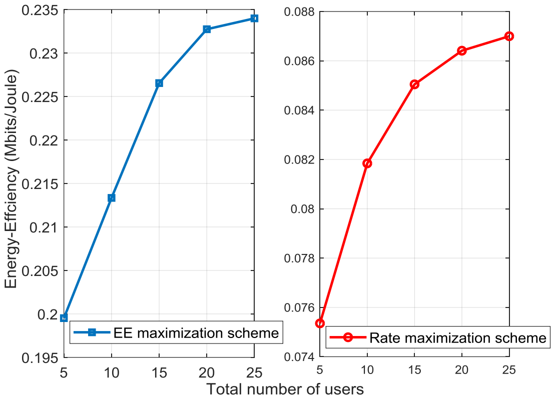

Figure 4. Energy Efficiency vs Total users.

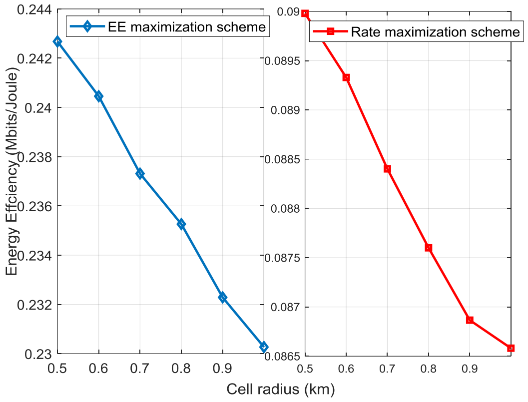

Figure 6. Energy Efficiency vs Cell radius (R).

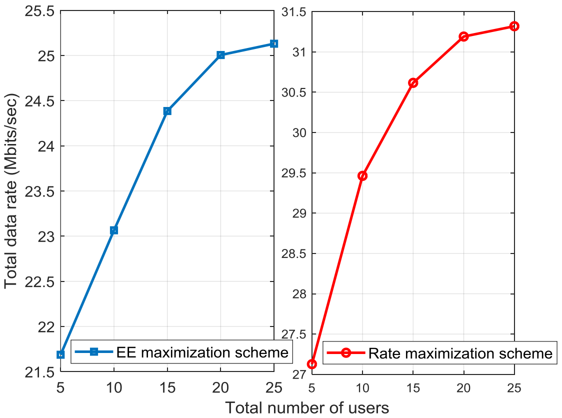

Figure 5. Total data rate vs Total users.

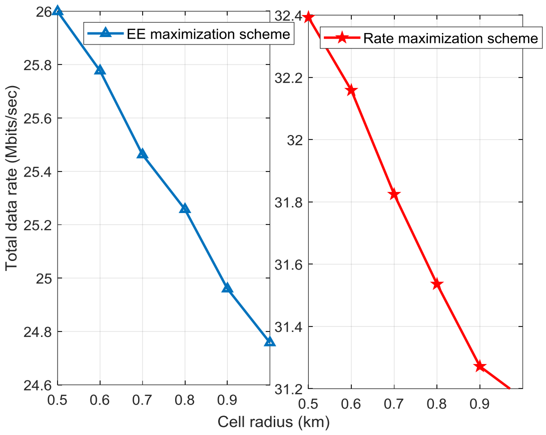

Figure 7. Total data rate vs Cell radius (R).

Table 2. Energy-Efficiency Values (Mbits/Joule).

	EE maximization Scheme		**Rate maximization Scheme**	
P_{max} ***(dBm)***	***Relaxed QoS***	$R^{min} = 0.5Mbps$	***Relaxed QoS***	$R^{min} = 0.5Mbps$
20	0.1979	0.17651	0.1956	0.1785
25	0.2135	0.19853	0.2135	0.1986
30	0.2295	0.21509	0.2315	0.2160
35	0.2353	0.22214	0.2360	0.2224
40	0.2353	0.22214	0.2180	0.2098
45	0.2353	0.22214	0.1622	0.1592
50	0.2353	0.22214	0.0876	0.0853

Table 3. Total Data Rate Values (Mbits/sec).

	EE maximization Scheme		**Rate maximization Scheme**	
P_{max} ***(dBm)***	***Relaxed QoS***	$R^{min} = 0.5Mbps$	***Relaxed QoS***	$R^{min} = 0.5Mbps$
20	19.641	17.797	19.606	17.798
25	21.527	20.016	21.526	20.122
30	23.429	22.068	23.548	22.165
35	25.26	24.08	25.28	24.0
40	25.26	24.08	27.467	26.032

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45	25.26	24.08	29.556	28.013
50	25.26	24.08	31.54	30.09

Finally, we have compared the EE and total data rate values of both schemes under the different cell-radius, *R* values by relaxing the QoS constraints and setting the total number of users to 20. The EE results are given in Figure 6 and total data rate results are illustrated in Figure 7. According to these figures, it is observed that the EE and total data rate values are decreasing when the cell-radius is increasing.

5. Conclusion

In this paper, we have focused on the energy-efficiency problem in OFDMA downlink cellular networks. The EE maximization problem is defined under the QoS and maximum transmit power constraints. Since, the defined optimization problem is MINLP which is very difficult to solve in its original form, we have presented a two-part solution to make it more tractable. The presented EE maximization solution is compared to the rate maximization scheme which aims to increase the data rate of the system and dominates the conventional cellular network design. The effect of different system parameters such total number of users, QoS parameters, cell radius and transmit power values on the energy-efficiency and system data rate are explored and the results are presented with the simulations.

Ethics

There are no ethical issues after the publication of this manuscript.

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