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Energy Efficiency Optimization and Interference Coordination in Next Generation Networks Using Game Theory

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Abstract The current trend of seamless and ubiquitous wireless communication in fifth generation (5G) ultra-dense networks (UDNs) has led to increased traffic intensity, extended capacity limits, while average energy demand has increased tremendously. In addition, as the demand for wireless data services increases, especially in the context of UDN, Inter-cell Interference (ICI) poses a lot of contention for access to the media. Hence, network utility theory has been extensively employed for resource management purposes. Power control proves to be an important scheme utilized to reduce interference and improve Quality of Service (QoS) requirements in wireless networks. This paper therefore presents power control solutions using Non-Cooperative Game (NCG) theoretic framework where players seek to maximize their utility, which represents degree of satisfaction. The solution to this game has inefficient Nash equilibrium outcome in power usage and convergence. Therefore, we introduce a novel Access-based Pricing Policy NCG (APPNCG) model to improve efficiency of the game and guarantee fairness. Performance analyses of the proposed scheme in comparison to existing schemes with and without pricing are illustrated. Simulation results showing robustness and performance enhancement with fast convergence of the scheme are also presented.

Keywords Game theory, intercell inter-cell interference, Nash equilibum, power control, utility function

1. Introduction

The current evolution and advancement in wireless communication system is enabled by the innovation and development of modern utilities for mobile devices [1]. One main target for this paradigm shift in communication system is the provision of considerably high data rate for end-users as against the achievable data rates available in previous standards. Recently, remarkable attention has been shifted to small cell technology due to the ability to offer enhanced capacity as well as providing seamless wireless coverage. This is in addition to their capability to improve spectral efficiency (SE), enhance capacity, offload traffic and optimize coverage in next generation wireless networks [2]. However, smart frequency reuse through densification of small cells has been acknowledged to provide considerable gains in network capacity. Consequently, future generation wireless networks are expected to be ultra-dense and heterogeneous, comprising various base stations (BSs) with different footprints and functionalities. Here, we succinctly refer to small cell as femtocells, picocells and remote radio heads (RRHs) with the range of coverage radius between 10 m and 300 m, being the adopted term by LTE [3]-[5].

Hence, to ensure a substantial Quality of Service (QoS) in the entire network, there is need to develop a cost-effective scheme for the purpose. Also, to attain higher channel utilization and improved system throughput in Ultra-Dense Network (UDN), it is important to deploy the available frequency spectrum in a co-channel manner [2]. Hence, there is need to increase wireless communication networks capacity for guaranteed user experience as well as to meet the demand for communication service expansion. In general, network's capacity can potentially be increased by enhancing the network architecture, modifying the physical layer air interface, and obtaining additional spectrum [3]. Among these, resource frequency reuse for spectral efficiency improvement will introduce severe interference (both inter and intra cell) between microcell and small cells. Although, the introduction of orthogonality feature in the Long-Term Evolution Advanced (LTE-A) system helps to mitigate the intra-cell interference.

However, the case is different for the inter-cell interference (ICI) scenario, as neighbouring users cause severe interference to the users who experience bad channel quality in a situation whereby the limited frequency spectrum is globally reused. This category of users is mostly located at the edge of the cell. One way to reduce the effect of ICI is efficient power control. Power control achieves this aim by reducing power levels of users at the center of the cell, thereby limiting the impact of interfering signals. Besides, power of resource blocks (RBs) suffering from bad channel quality can greatly be enhanced via power control techniques. Such conditions require each BS to make an informed decision on the optimal transmit power level on each RB at any instance, resulting to maximum satisfaction for its users.

The rest of this paper is organized as follows: Section II reviews the related literature. System model is first introduced in Section III and then description of the formulated noncooperative power control game follows. Thereafter, we present our proposed access-based pricing technique. Simulation results are reported in Section IV and Section V ends the paper.

2. Related Literature

Several works have proposed distributed power control as techniques used to mitigate interference in wireless data and cellular networks [6-9]. However, the majority of these approaches cannot guarantee optimal power and resource allocation in the traditional multiuser access scheme such as Orthogonal Frequency Division Multiple Access (OFDMA) networks, deployed for LTE/LTE-A and heterogeneous small cell technologies. Recently, Game theory is gaining popularity as it provides an insight into the utility function thus defining users' QoS and resolving the power allocation problems for cellular networks [10]. A game is a branch of mathematics that involves multiple players having conflicting and competitive interests such that each player's decision outcomes are influenced by the actions of others [11]. A detailed work on game theory approach in two-tier networks comprising of femtocells, exploiting local gains for efficient power control and interference coordination was provided in [6].

However, in [12], the authors developed a cooperative game model for cellular Het- Nets having three layers with optimized utility function for bandwidth allocation maximization. Also, a method that adapts the BSs transmit power using a noncooperative game-theory approach was developed in [13], to reduce co-channel interference and achieve required balance between macrocell and small cells. The works in [14] and [1] differ slightly as [14] addresses ICIC challenges in OFDMA downlink cellular systems, where the process of selecting RB power level is formulated as a sub-modular game. On the other hand, [1] combines game theory and the mechanism of virtual currency. The authors introduced incentive mechanism, which maximizes node returns through enhanced cooperative optimization model.

Recently, exponential growth of data-driven devices has made Energy Efficiency (EE) to become a topic of interest in research community. Hence, energy efficient communication design for UDN is important because the terminals are generally energy constrained. In [15], a convergent distributed power allocation based on pricing mechanism was proposed to reach the Karush-Kuhn-Tucker (KKT) of the EE algorithm. On the other hands, authors in [16] analysed and designed a unified framework for both network and user centric EE power allocation processes to maximize different EE metrics while satisfying minimum QoS requirements in a wireless network. To this end, most work on game theory application concentrate on cooperative game approach, which result to bargaining and coalition forming strategies. The need for bargaining process among the players is time consuming and ultimately renders the approach unsuitable for ultra-dense application. In this paper, we formulate a non-cooperative game theory technique to improve system performance, reduce signaling overhead and ultimately guarantee flexibility of radio resource management.

While we adopt a similar approach to [16], we succinctly distinguish our work in two ways. Firstly, we adopt weighted sum in our formulation for each power allocation link to manage EE individually. This approach helps to cater for the need of users for different power consumption levels, spectrum usage and QoS requirements.

The corresponding weights can enable more degree of freedom, prioritize specific links and provide useful information for system design purposes. Secondly, we seek to achieve efficient Nash Equilibrium (NE) in our game formulation by introducing a pricing function that incorporates various cost components for interference mitigation and provide fairness for all users in the network. To the best of our knowledge, this approach is the first to jointly consider weighted assignment and cost tuning parameters approach for EE and power control.

3. System Model

Our model considers a single cell downlink OFDMA system, where L information bits is transmitted by each BS frames of $M > L$ bits at a rate R b/s using power p in Watts. In previous work [17], R assumed a fixed rate which is not ideal in the downlink scenario due to varying transmit power of the BSs. In addition, we assume that each user is assigned to only one BS at a given time, i.e. no BS diversity. Let P_c denote the probability that a frame is correctly decoded at the receiver, termed frame success rate (FSR). However, in order to adequately predict the actual success rate of the signal and cancel out short term variations, successful reception of signal must be monitored over a certain period. Also, P_c represents the SINR function obtained by the user at its serving BS which depends on the system configurations such as receiver pattern, modulation and radio propagation model.

Thus, the generalized utility function, expressed as the number of information bits successfully received per Joule of energy expended is given as [17]

$$u = \frac{LRP_c}{Mp} \quad \text{bits/Joule} \tag{1}$$

In the absence of error correction, the FSR can be expressed as

$$P_c = (1 - P_e)^M \tag{2}$$

where P_e is the bit error rate (BER). Generally, the BER decreases monotonically with (SINR). Therefore, to accommodate some emerging technologies for 5G UDN, which were not considered by most previous related works, we assume that the SINR γ experienced by any user (UE) from its serving BS i on resource block k is given by [16]

$$\gamma_{i,k} = W \frac{\alpha_{i,k} p_{i,k}}{\sum_{i \neq j \in \mathrm{I}} \beta_{j,k} p_{j,k} + \mu_{i,k} p_{i,k} + \sigma^2} \tag{3}$$

where W denotes the available bandwidth in Hz, $p_{i,k}$ is the transmit power allocated by BS i on RB $k \in \mathrm{K}$, $\alpha_{i,k}$, $\mu_{i,k}$ and $\beta_{i,k}$ are positive quantities which are independent on the transmit power of the BS, but only on the system parameter and propagation channels, while σ^2 is the variance of the Gaussian noise. However, it is noteworthy that both $\alpha_{i,k}$ and $\mu_{i,k}$ are quantities assumed to depend only on the $i-\text{th}$ BS channel on RB k. Hence, the envisioned technologies for 5G are properly captured in the SINR expression by simply letting $\mu_{i,k} = 0$ for all i, k. To properly incorporate the tradeoff between saving transmit power and providing an acceptable throughput in the entire network, we adopt energy efficiency maximization approach for each BS. However, unlike the traditional average sum energy efficiency (ASEE), which accounts for the entire network's energy efficiency, this paper employs weighted sum energy efficiency (WSEE). This proves to be more efficient when utilized in ultra-dense setting where channels are differentiated by distinct quality levels and users have diverse QoS requirements [18].

The weighted sum EE $\eta_{i,k}$ of BS i which is the ratio of the achievable throughput on RBs and the power expenditure, measured in bit/Joule of energy consumed is expressed as [16]

$$\eta_i = \sum_{i=1}^{\mathrm{I}} \sum_{k=1}^{\mathrm{K}} \left(\omega_{i,k} . \frac{W \log_2(1+\gamma_{i,k})}{p_{c,i} + \mathbf{1}^T \mathbf{p}_i} \right) \tag{4}$$

where $\omega_{i,k} \geq 0$ is a constant, providing more degree of freedom for different EE priorities of the links, $\tau_{i,k} = \sum_{k=1}^{\mathrm{K}} W \log_2(1+\gamma_{i,k})$ is the achievable rate experienced by any UE attached to BS i on RB k, $p_{c,i}$ is the dissipated circuit power for the $i-\text{th}$ BS operation and its served UE, while $\mathbf{p}_i = [p_{i,1}, p_{i,2}, ..., p_{,K}]^T \in \mathrm{R}_+^K$ is the power allocation vector of $i-\text{th}$ BS on RB $k \in \mathrm{K}$. At any rate, the following average power constraint must be satisfied by $\mathbf{p}_i$

$$\mathbf{1}^T \mathbf{p}_i - \bar{p}_i \leq 0 \tag{5}$$

where our goal is to optimize $\bar{p}_i \in P_i @[0, P_i]$, which is the maximum power of the $i-\text{th}$ BS. To ensure that the minimum achievable rate is satisfied, we set $\tau_{i,k} - \underline{\delta}_i \geq 0$ so that

$$\tau_{i,k} \geq \underline{\delta}_i \tag{6}$$

where $\underline{\delta}_i$ denotes the target rates of $i-\text{th}$ BS in bit/s/Hz/cell. Thus, the feasibility set of $\mathbf{p}_i$ is expressed as

$$P_i @\{\mathbf{p}_i \in \mathrm{R}_+^K : \mathbf{1}^T \mathbf{p}_i \leq \bar{p}_i, \tau_{i,k} \geq \underline{\delta}_i\} \tag{7}$$

Consequently, the formulation of the noncooperative power control game can be mathematically described as follows:

$$G = [\mathrm{I}\ , \{\mathrm{P}_i\}_{i\in\mathrm{I}}\ , \{\mathrm{U}_i\}_{i\in\mathrm{I}}\ ] \tag{8}$$

where $\mathrm{I}\ = \{1, 2, ..., I\}$ is the set of players which are the base stations, $\{\mathrm{P}_i\}$ is the strategy set for each player i, given also as the subset of a finite dimensional Euclidean space and $\{\mathrm{U}_i(\mathbf{p})\}$ is the utility (payoff) associated to player i, for a combination of choices, $\mathbf{p} = [p_1, ..., p_I] = [p_i, \mathbf{p}_{-1}]$, where $\mathbf{p}_{-i} = [p_{1,...,} p_{i-I}, p_{i+I}, ..., p_K]$ denotes the strategies of all other players except player i. Each player i selects a transmit power level p_1 such that $p_i \in \mathrm{P}_i$. If P_i denotes the set of all power vectors, then power vector $\mathbf{p} = (p_1, ..., p_I) \in \mathrm{P}$ represents the game outcome in relation to all players selected power. This results to utility level $u_i(\mathbf{p})$ for the $i-\text{th}$ player. To demonstrate the strategic interdependence between players, each player gets a certain level of utility having close dependence on its own power level and also on the choice of other players' strategies. Hence, the strategy of each player $i \in \mathrm{I}$ is to select a power value $p_i \in \mathrm{P}_i$ so as to maximize its utility function given by

$$\arg\max_{p_i \in \mathrm{P}_i}\ u_i(p_i, \mathbf{p}_{-i}) \qquad \forall i \in \mathrm{I} \tag{9}$$

where $\mathbf{p}_{-i} = [p_{1,...,} p_{i-I}, p_{i+I}, ..., p_K]^T$ is the interference power vector of all players except $i-\text{th}$ player. The transmit powers of player i are selected from a convex and compact set with lower and upper bound power constraints $\underline{p}_i \leq p_i \leq \bar{p}_i,\ \forall i \in \mathrm{I}$. Hence, we let $p_i = 0,\ \forall i$ such that the strategy space $\mathrm{P}_i = [0, \bar{p}_i]$.

Generally in a non-cooperative game (NPG), it is often difficult to predict the interaction among players and the effect on the convergence to Nash equilibrium. Although, interference levels can prove effective in observing the outcome of other BSs' actions only, but explicit knowledge of their actions and payoffs may not be acquired in this way. In such a situation where information exchange is not possible among BSs, their transmission powers are chosen to maximize individual payoff functions. Thus, to attain NE in (9) and maximize player i 's choice, given other players' strategies, we employ the concept of best response dynamics (BRD), expressed by the following

$$b_i(\mathbf{p}_{-i}) \triangleq \arg\max_{p_i \in \mathrm{P}_i(\mathbf{p}_{-i})} u_i(p_i, \mathbf{p}_{-i}) \quad \forall i \in \mathrm{I} \tag{10}$$

More often, it is difficult for BRD to converge as well as find an optimal NE due to the tight coupling between the players strategy sets, which are solved with the following [16]:

$$\text{If } \ \bar{p} \geq \underline{\gamma}_i \frac{\sigma^2 + \sum_{i \neq j} \beta_j p_j}{\alpha_i - \mu_i \underline{\gamma}_i}, \ \forall i \tag{11}$$

Then $b_i(\mathbf{p}_{-i})$ follows from

$$b_i(\mathbf{p}_{-i}) = \min\left\{ \bar{p}_i, \max\{p_i^*, \underline{p}_i\} \right\} \tag{12}$$

so that

$$\underline{p}(\mathbf{p}_{-i}) \triangleq \frac{\underline{\gamma}_i}{\varepsilon_i}\left(1 - \frac{\underline{\gamma}_i}{\bar{\gamma}_i}\right)^{-1} = \underline{\gamma}_i \frac{\sigma^2 + \sum_{i \neq j} \beta_j p_j}{\alpha_i - \mu_i \underline{\gamma}_i} \tag{13}$$

and

$$p_i^* \triangleq \arg\max_{p_i \in \mathrm{R}_+} u_i(p_i, \mathbf{p}_{-i}) \tag{14}$$

At this point, we compute the best response of player i that yields a distributed solution for the NE. Hence, we define

$$\psi_i(z) \triangleq \bar{\gamma}_i \left[1 + \frac{z}{2W\varepsilon_i}(\bar{\gamma}_i - h_i(z)) \right]^+ \tag{15}$$

and

$$h_i(z) \triangleq \sqrt{\bar{\gamma}_i^2 + \frac{4W\varepsilon_i}{z}(1 + \bar{\gamma}_i)} \tag{16}$$

where $\varepsilon_i \triangleq \dfrac{\alpha_{i,k}}{\sum_{i \neq j \in \mathrm{I}} \beta_{j,k} p_{j,k} + \sigma^2}$ and $\bar{\gamma}_i \triangleq \dfrac{\alpha_{i,k}}{\tau_{i,k}}$.

Lemma 1: The solution to (14), considering $\mathbf{p}_{-i}$, is given by

$$p_i^* = \pi_i(\lambda_i^*) \triangleq \frac{\psi_i(\gamma_i^*)}{\epsilon_i}\left(1 - \frac{\psi_i(\lambda_i^*)}{\bar{\gamma}_i}\right)^{-1} \tag{17}$$

where λ_i^* follows from Dinkelbachs algorithm as the solution to

$$W \log_2(1 + \psi_i(\lambda_i^*)) - \lambda_i^*(p_{c,i} + \pi_i(\lambda_i^*)) = 0 \tag{18}$$

Consequently, the unique NE of game in (8) can be obtained by iteratively updating the initial feasible transmit power vector $\{p_i\}_{i=1}^{\mathrm{I}}$ according to (12). In this manner, it follows that an iterative algorithm of the form

$$p_i[t+1] = \min\left\{ \bar{p}_i, \max\{\pi_i(\lambda_i^*[t]), \underline{p}_i[t]\} \right\} \tag{19}$$

where the $i-\mathrm{th}$ player transmit power at iteration step t is given as $p_i[t]$, and $p_{-i}[t]$ computed using

$$\underline{p}_i[t] = \frac{\underline{\gamma}_i}{\varepsilon_i[t]}\left(1 - \frac{\underline{\gamma}_i}{\bar{\gamma}_i}\right)^{-1}, \tag{20}$$

will converge to the unique NE. Hence, $\varepsilon_i[t]$ corresponds to the channel gain at $t-\text{th}$ iteration step.

In a real environment, every BS requires specific information about the strategy of all other BSs on every used RB. Hence, Algorithm 1 is distributed as the downlink transmission signaling information is made available for convergence. Consequently, the computation of $p_i[t+1]$ basically requires knowledge of $\varepsilon_i[t]$, which can be obtained from

$$\varepsilon_i[t] = \frac{\gamma_i[t]}{p_i[t]}\left(1 - \frac{\gamma_i[t]}{\bar{\gamma}_i}\right)^{-1} \tag{21}$$

where $\gamma_i[t]$ denotes the SINR of $i-\text{th}$ player measured from its served UE at iteration t.

As with the base-station assignment case based on the maximum received signal strength [19], the Nash equilibrium can be inefficient, hence pricing strategies can be implemented to improve this efficiency. Hence, the optimal solution to the proposed pricing game follows Pareto optimality [20], which seeks to maximize the utility of individual players based on the price offered.

Algorithm 1 Power Allocation Algorithm

1: **initialize** $t=0$ and $\forall i \; p_i[0] \in \mathrm{R}_+$ in the feasible set
2: **repeat**
3: **for** $i=1$ to I **do**
4: **receive** $\gamma_i[t]$ from the serving BS
5: **compute** $\varepsilon_i[t]$ using (23)
6: **use** $\varepsilon_i[t]$ to update $\underline{p}_i[t]$ in (19)
7: **use** $\varepsilon_i[t]$ in (20) to run the Dinkelbach's algorithm
8: **set** $\lambda_i^*[t]$ equal to the Dinkelbach's output and update the power as (21)
9: **end** for
10: **update** $t=t+1$
11: **until** convergence

Proposed Access-based Pricing Policy NCG (APPNCG)

This APPNCG scheme proposes an improvement to the equilibrium utilities of NCG and aligns the users' goal with those of the network. Introduction of pricing into the game can effectively enhance system performance and efficiency by modifying the utility function while maintaining the game structure. An effective price should consider demand requirements for the services offered and also manifest accurately usage cost of all resources [17]. Such a pricing scheme ensures that players aim to improve their SINR as well as reduce their energy consumption, which eventually helps in minimizing the interference in the system. At this point, a cost function is introduced to capture the interference levels, as well as fairness for all users such that

$$\chi_i^c(p_i, \mathbf{p}_{-i}) = \vartheta p_i + \rho q_i \tag{22}$$

where ϑ and ρ denote assigned weight to each component of the cost function to indicate the price per transmitted power unit of player i and the unit price that each user is paid for not being served, respectively, while q_i is the fraction of UEs in the coverage of player i experiencing SINR below a certain threshold. Each player can estimate q_i depending on all available strategies with the knowledge of UE density in the network. Thus, the first part of (22) (i.e., ϑp_i) is targeted at penalizing players who choose high power strategies. On the other hand, the last term establishes fairness in the network by protecting UEs exposed to undue outages. Hence, the cost function is an increasing function of an increase in the transmit power level. In other words, low overhead cost will be incurred and some level of fairness is guaranteed for BSs serving users with bad channel condition.

Therefore, we express the payoff function as

$$u_i^c(p_i,\mathbf{p}_{-i}) = u_i(\mathbf{p}) - \chi_i^c(p_i,\mathbf{p}_{-i}) \tag{23}$$

Our objective is to find optimal payoff function that results in the best response approach, as stated in (14). This will allow a player to choose among its available strategies based on knowledge of other players' strategies. Therefore, the multi-objective optimization problem that the APPNCG attempts to solve can be expressed as

$$\max_{p_i \in \mathrm{P}_i} u_i^c(p_i,\mathbf{p}_{-i}) = u_i(\mathbf{p}) - \chi_i^c(p_i,\mathbf{p}_{-i}) \quad \forall i \in \mathrm{I} \tag{24}$$

The pricing equation in (24) is imposed on access-based policy and increases monotonically with respective players' transmission power. Importantly, the pricing factor must be adjusted appropriately in order to provide an improvement in the overall network performance, which is also an outcome of the users' interest. Therefore, the justification behind APPNCG is the need to reduce interference experienced by players and close the gap between equilibrium and optimal SINRs. This is achieved by imposing power taxation on each base station (player) as a way of discouraging them from transmitting at higher power level [20].

4. Simulation Results

In our simulation, we first consider two types of applications used in cellular systems to describe users' satisfaction, which are real-time and delay-tolerant applications, designated by sigmoid and logarithmic functions, respectively. The basis for this is to assess utility for data services and high transmission rate requirement in 5G UDN, which leads to high satisfaction levels. Hence, we use the sigmoidal function with the following mathematical representation [21-22]

$$U(r) = c\left(\frac{1}{1+e^{-a}(r-b)} - d\right) \tag{25}$$

where $c = \frac{1+e^{ab}}{e^{ab}}$ and $d = \frac{1}{1+e^{ab}}$. Similarly, the normalized logarithmic utility is represented by

$$U(r) = \frac{\log(1+kr)}{\log(1+kr^{\max})} \tag{26}$$

where r^{max} and k, respectively, correspond to 100% utilization of utility and increased utility function with increasing rate. It follows that $U(0)=0$ and $U(\infty)=1$ are satisfied for equation (25), much as $U(0)=0$ and $U(r^{max})=1$ are true for equation (26). In addition, the inflection point of the sigmoidal function is at $r^{inf} = b$. Table 1 shows different parameters corresponding to different applications (e.g VoIP, SD and HD video streaming).

Table 1: Application Utility Parameters [22]

Sigmoid1	a=5, b=10	log1	k=15, r^{max} = 100
Sigmoid2	a=3, b=20	log2	k=3, r^{max} = 100
Sigmoid3	a=1, b=30	log3	k=0.5 r^{max} = 100

Fig. 1 shows the utility functions of various applications plotted against their corresponding rates. It can be seen that the utility functions represent a strictly increasing continuous functions with zero value for zero rates. Hence, following from (2), the efficiency function given as $f(\gamma_i) = (1-2P_e)^M$ is a real-time application with inelastic traffic, which requires rate in order to arrive within a given delay bound irrespective of data arrival time. This shows minimum rate demand for real-time (sigmoidal) applications, and the upper limit of the inflection point to which the QoS is fully guaranteed. In the envisioned 5G UDN scenario, Fig. 1 reflects the trade-off between linear characteristic of the network throughput maximization and non-linear property of the users' QoS satisfaction.

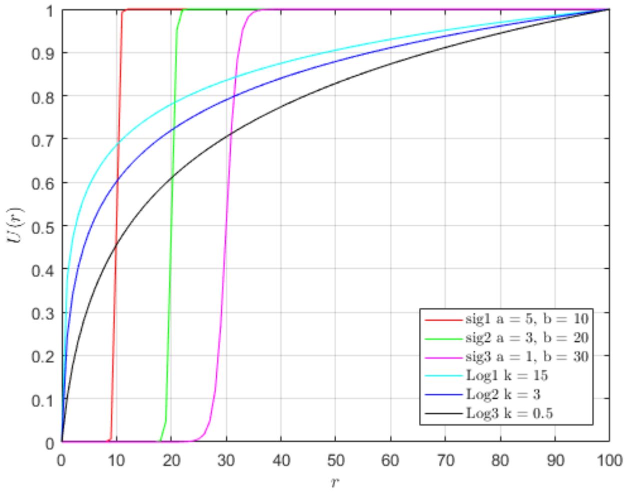

Figure 1: Application utility functions $U(r)$ plotted against rates r

In Fig. 2, we consider average throughput of the entire network over different values of SINR. It is observed that by maintaining the SINR below a tolerable threshold based on the price imposed to penalize the use of excessive power, there is considerable improvement in the throughput of the system. This is more noticeable at the point where the SINR value is at 0dB. Therefore, this demonstrates the fact that throughput is a monotonically increasing function of the SINR γ_i. Also, in Fig. 2, it can be seen that our proposed technique shows better performance than the popular scheme without assigned weights. Here, we clearly showed that adaptation of EE with different weights enables proper tuning and helps individual EEs spread to be controlled over the available bandwidth, as against classical EE which only takes into account the entire network [18].

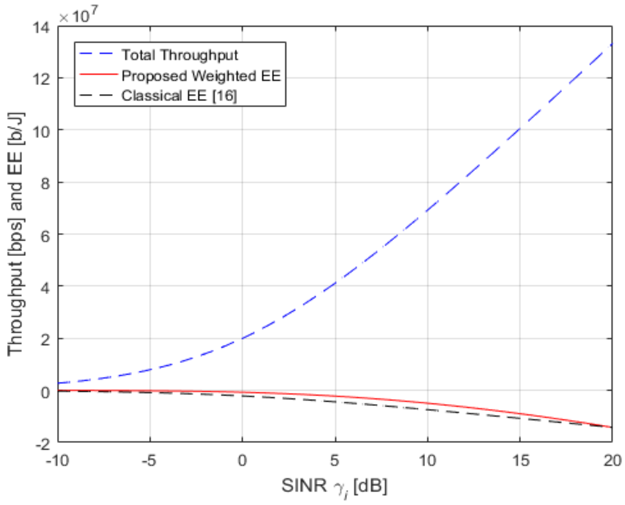

Figure 2: Improved Throughput and EE as functions of SINR

In Fig. 3, we show the relationship between the pricing factor and sum utility as an effective mechanism for improving the efficiency of the game, and evaluation of the NE p^* as a function of the pricing factor χ_i^c in (24). This value is chosen by each player and it is proportional to the traffic in the cell. As a result, the solution point $c^{optimal}$ of the pricing game offers a considerable improvement in sum utilities in relation to game without pricing. At this optimal point, it can be seen that further increase in the values of χ_i^c results in decrease of utility of at least one terminal. It is noteworthy, however, that users closer to the base stations experience higher SINRs at equilibrium with $c^{optimal}$, although the equilibrium SINRs of the game without pricing remain the same for all users.

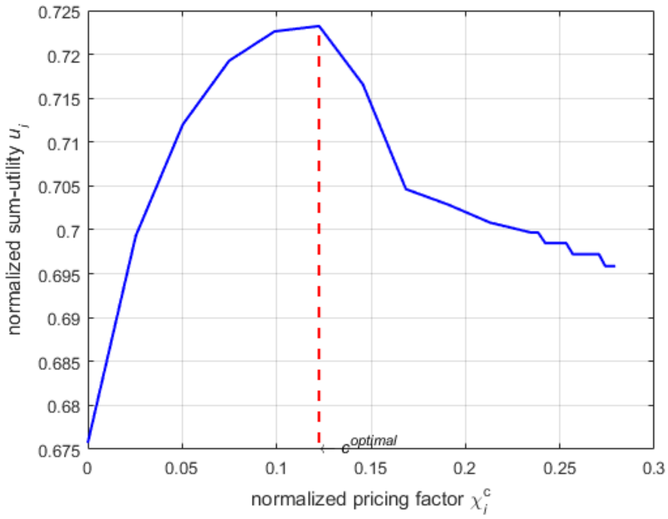

Figure 3: Normalized sum utility plotted against the pricing factor

5. Conclusion

In this paper, a Non-cooperative Power Control Game model is used to address the EE issue in the context of 5G UDN. Unlike previous works, our expression considered different rate constraints in order to capture emerging 5G technologies. In addition, we assigned weights to individual EEs so that each allocation link can be effectively managed, as opposed to traditional average sum EE. Thereafter, we discussed and analyzed the Nash Equilibrium's existence and uniqueness solutions of the formulated game. Subsequently, we introduced an access-based pricing scheme to improve the efficiency of the Nash equilibrium, mitigate interference and provide more degree of fairness for all users. Finally, effectiveness of the APPNCG model is validated through simulation results.

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