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Application of Game Theory for Load Balancing in Long Term Evolution Networks

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Abstract –Game theory offers a set of effective tools to be applied in autonomous and distributed self-organizing networks. A typical use case is load balancing which aims at increasing the overall network capacity in case of unequal traffic distribution. The 3GPP Long Term Evolution (LTE) standard provides the means that enables the handover of users from highly loaded cells to the lower loaded neighbors. The method is based on exchanging load information between neighboring cells. However, the computation of the amount of load that a cell should either offload or accept is running autonomously in each cell and is most likely not generally specified, but rather vendor specific. In this case, a network-wide algorithm for load balancing may not be possible to use if eNodeBs from distinct vendors are deployed. In this game-theoretic analysis for load balancing, we consider each cell as a rational player that decides, in the worst-case, on the amount of load that maximizes its payoff in an uncooperative way. The simulation results for LTE network show that the resulting Nash equilibrium is able to achieve most of the gain expected from a strictly cooperative load balancing scheme. Though each cell acts independently, the Nash equilibrium almost provides the same performance of a network-wide algorithm for load balancing which would ease the players to decide on strategies that are more collaborative. The capacity gain of the Nash equilibrium is verified for the homogeneous network layout, different scenarios and parameter configurations. Moreover, to take real network effects, such as different cell sizes and number of neighbor cells into consideration, the Nash equilibrium is also tested in the heterogeneous network layout.

Index Terms – Game theory, Load balancing, Self optimizing network, Distributed systems.

1 Introduction

Future mobile systems will comprise self optimizing algorithms to reduce the operational expenditure while maintaining a high quality service. Due to the dynamic adaptation to the network behavior, the performance is expected to improve leading to an increase in the users' satisfaction level. Among the self optimizing network use cases defined in [1], load balancing copes with unequal traffic load distribution in the network. Though there is no unique way to approach the load balancing problem, adjusting the mobility parameters appears to be a practical solution as it can be carried out in a distributed manner on peer-to-peer level from the cell perspective.

In many circumstances, a cell may have a large number of connected User Equipments (UEs) and is not able to serve all of them due to its limited number of Physical Resource Blocks (PRBs). By modifying the cell-pair specific handover offsets, users from a highly loaded cell can be handed over to the lower loaded neighbors. As a result, the number of unserved users in the overloaded cell decreases as the other underloaded neighbors are accommodating, if possible, the excess traffic load.

The 3GPP LTE Release 9 provides the means to exchange the load information among the cells via the X2 interface, but does not specify the algorithm that computes the amount of load that an overloaded cell should offload and an underloaded cell should accept as it is implementation specific of the eNodeB and, therefore, vendor specific [1]. In [2], it is shown that the load balancing algorithm achieves a more efficient capacity usage in the network under the assumption that an overloaded cell and its underloaded neighbors are fully aware how the exchanged load values are determined which might not be the case if eNodeBs are from various vendors. To study the impact of the uncertainty in the values of the load to offload or to accept on the gains achieved by load balancing, a game-theoretic approach is followed where each cell is considered a rational player that decides, in the worst-case, autonomously on the load that maximizes its own utility in a non-cooperative manner. The game theoretic approach has been investigated in [3] for a homogeneous network layout. In this paper, the proposed approach is further tested in a heterogeneous network and the impact of different parameter configurations on the performance is analyzed for both network layouts.

The paper is organized as follows. The system model is described in section 2 and the algorithm used by an overloaded cell to generate the list of candidate users to be handed over to the underloaded neighbor cells is presented in section 3. The model of the load balancing game and the strategies of the players leading to the Nash equilibrium are defined in section 4. The overall performance of the network in LTE downlink for the Nash equilibrium, in addition to the performance of the network-wide algorithm, are evaluated in section 5 for heterogeneous and homogeneous network layouts and the work is concluded in section 6.

2 System model

In this section, we define the load metrics that are used in the sequel. In the network, each user u has a constant data rate denoted by D_u and a data rate per PRB given by $R(SINR_u)$ which depends on the Signal to Interference and Noise Ratio (SINR) of user u. The SINRs of the UEs are computed without taking fading into consideration. The number of required resources by user u can be written as

$$Q_u = \frac{D_u}{R(SINR_u)}. \tag{1}$$

We assume that all UEs have the same data rate requirement and each cell in the network has the same total number of PRBs per frame denoted by N_{tot}. We define the traffic load of user u as

$$\kappa_u = \frac{D_u}{R(SINR_u) \cdot N_{\text{tot}}}. \tag{2}$$

The load κ_u of user u is interpreted as the percentage of occupied PRBs per frame needed to make him satisfied [4],

i. e., meeting his data rate requirement D_u. Consequently, the load of a cell c having $U_c \geq 0$ connected users is computed as

$$\rho_c = \sum_{u \mid X(u)=c} \kappa_u \geq 0 \tag{3}$$

where $X(u) = c$ is the connection function that assigns user u to a single cell c. Assuming that the admission control of the cell arbitrarily selects the UEs to be served, irrespective of their radio conditions, the number of unsatisfied users in a network consisting of M cells can be expressed by

$$Z = \sum_{c=1}^{M} \max\left(0,\ U_c \cdot \left(1 - \frac{1}{\rho_c}\right)\right). \tag{4}$$

For instance, a cell c with a load $\rho_c = 2$ can only satisfy half of its users, whereas it can satisfy all of them if $\rho_c \leq 1$.

3 The load balancing algorithm

Having stated the necessary metrics, the load balancing algorithm described in [2] is reformulated to understand the rules of the game defined in section 4. Let us denote the load of the overloaded cell, having U_o connected users, by $\rho_o > 1$ and the load of each of its N underloaded neighbor cells, having U_i users, by $\rho_i \leq 1$ where $i = 1, \ldots, N$.

The overloaded cell gets from its connected UEs which are close to the cell borders periodic or event-driven measurement reports containing Reference Signal Received Power (RSRP) levels not only for the serving cell, but also for the neighboring cells having strong signals. The link imbalance value, defined as the difference in the RSRP levels of the overloaded cell and a neighbor underloaded cell i, is denoted by

$$\Delta RSRP_{u,i} = RSRP_{u,o} - RSRP_{u,i} \tag{5}$$

where $RSRP_{u,o}$ and $RSRP_{u,i}$ are the average reference signal measurements reported by user u for the overloaded cell o and the underloaded cell i, respectively. Assuming that the RSRP measurements are reliable, the overloaded cell can estimate the load that the user would produce if handed over to an underloaded cell. The load of user u having a load κ_u in the overloaded cell may increase/decrease if the signal to the connected cell is weaker/stronger. As a rough approximation, we assume, that in case of a positive link imbalance, a handover of user u to cell i decreases the $SINR_u$ by $\Delta RSRP_{u,i}$ dB, which in turn increases the load of user u. The load that user u would produce if handed over to an underloaded cell is denoted by $\tilde{\kappa}_u$. Thus, the best candidates to be handed over from the overloaded cell to the neighbor underloaded cells are the UEs that have small link imbalances as they would not require a dramatic increase in the number of PRBs if handed over. We denote by Ω the set of possible candidate UEs that are connected to the overloaded cell and have link imbalance values smaller than a certain threshold $\Delta RSRP_{\mathrm{thr}}$.

Prior to generating the list H of planned handover candidate UEs, the overloaded cell receives from each underloaded neighbor cell i the amount of available resources y_i, expressed as a percentage of N_{tot}, that it is willing to accommodate. Let us denote the number of handed over users from the overloaded cell to the underloaded cell i by $x_i \geq 0$. The new load of the accommodating cell i, having $U_i + x_i$ users after load balancing, is written as

$$\tilde{\rho}_i = \rho_i + \sum_{j=1}^{x_i} \tilde{\kappa}_j. \tag{6}$$

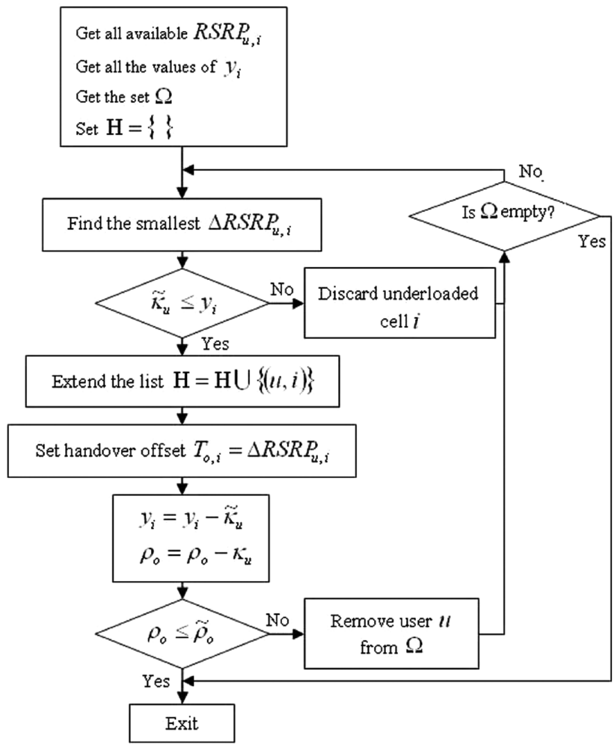

Fig. 1: The selection process of the candidate UEs that is followed by an overloaded cell.

In contrast to the underloaded cells, the overloaded cell executes the handover of $x_o = \sum_{i=1}^{N} x_i \geq 0$ users to all the neighboring cells. The overloaded cell can decide on the amount of load $\chi = \sum_{j=1}^{x_o} \kappa_j \geq 0$ to offload resulting in a new target load denoted by

$$\tilde{\rho}_o = \rho_o - \chi. \tag{7}$$

The selection process of the candidate users for handover, which is followed by the overloaded cell, is depicted in Fig. 1. First, the overloaded cell gathers all the available RSRPs from its connected UEs, the spare capacity y_i from each underloaded neighbor cell i, the set Ω of possible candidate UEs and initializes the list H of planned handover candidates to be empty. Secondly, the overloaded cell searches for the user u in the set Ω that has the smallest link imbalance value and checks whether the target underloaded cell i can accommodate its estimated load $\tilde{\kappa}_u$. If possible, the user u and its target cell i are added to the list H. To avoid the immediate back handover of the candidate user u to the overloaded cell, the handover offset between the overloaded cell and the underloaded cell i [5], denoted by $T_{o,i}$, is set to the link imbalance of the candidate user u. If the underloaded cell i is unable to accommodate the load $\tilde{\kappa}_u$ of the user u, it is not considered anymore as a target cell for handover. Finally, the selection process ends once the overloaded cell has reached its target load $\tilde{\rho}_o$ or there is no user left in the set Ω.

4 The load balancing game

After stating the necessary metrics and the approach used by the overloaded cell in selecting the candidate users, we model the load balancing game by defining the players, the utility function and the possible strategies. Moreover, we derive the strategies for the underloaded and overloaded cells that lead to the Nash equilibrium point and state the actions of the players which are recommended by a network wide-algorithm and can be achieved by modifying the utility function using the linear pricing technique.

4.1 Model of the game

The players of the game are on one side the overloaded cell having excess load and on the other side all its N underloaded neighbor cells. Each underloaded cell i should decide on an amount of resources $y_i \geq 0$ to accommodate from the overloaded cell. Having received all the accepted amount of resources from all the underloaded neighbor cells, the overloaded cell should decide on the load amount $\chi \geq 0$ to offload based on the selection process described in section 3.

A useful utility function for the game is the number of satisfied users in the cell. One may argue that each player has the incentive to maximize his number of satisfied users as he would have more capacity usage and income resulting from the data rate charging. The cell can satisfy all its users as long as its new target load is less than 1, e.g., $\tilde{\rho}_i \leq 1$ or $\tilde{\rho}_o \leq 1$, and can satisfy only a fraction of the users if its new target load exceeds 1. In the latter case, a floor operator is applied to the computed number of satisfied users as it might not be an integer.

The utility function of the underloaded cell i can now be expressed as

$$utility_i = \begin{cases} U_i + x_i & \text{if } 0 \leq \tilde{\rho}_i \leq 1 \\ \left\lfloor \dfrac{U_i + x_i}{\tilde{\rho}_i} \right\rfloor, & \text{otherwise} \end{cases} \tag{8}$$

Similarly, the utility function of the overloaded cell is written as

$$utility_o = \begin{cases} U_o - x_o & \text{if } 0 \leq \tilde{\rho}_o \leq 1 \\ \left\lfloor \dfrac{U_o - x_o}{\tilde{\rho}_o} \right\rfloor, & \text{otherwise} \end{cases} \tag{9}$$

4.2 Nash equilibrium

By definition, the Nash equilibrium point is achieved if each player is making the best decision, taking into consideration the decision of other players [6], [7]. For underloaded cell i, finding the optimal value of y_i that maximizes its utility is not trivial as it knows neither the number x_i of users that would be handed over by the overloaded cell nor their corresponding loads. However, the underloaded cell can still decide on an amount of available resources such that its utility is never decreased and maximized as much as possible. At first, the underloaded cell i will accept $y^* > 1 - \rho_i$ that leads in the worst case, i.e., only 1 user is handed over to the underloaded cell i, to the original utility value. The upper bound of y^* can be computed by using

$$\left\lfloor \frac{U_i + 1}{\rho_i + y^*} \right\rfloor = U_i \tag{10}$$

which yields

$$y^* \leq \frac{U_i + 1}{U_i} - \rho_i = y^*_{\max}. \tag{11}$$

If the cell decides to signal $y^*_{\max}$, it might end up with the same original value if the offered capacity has been fully consumed by a heavy overloaded cell. For this reason, the underloaded cell i signals $y^*_{\max}$ only if its load exceeds a certain threshold ρ_t and it signals $1 - \rho_i$ if $\rho_i < \rho_t$. The value of the threshold is strongly related to the load of the underloaded cell i. If it is highly occupied, it is most likely that no user is handed over to the cell i if it signals $y_i = 1 - \rho_i$ as the load of the user would probably not fit. In this case, the underloaded cell i is indifferent and signals $y^*_{\max}$ as it has a chance to increase its utility value.

In contrast to the underloaded cells, the overloaded cell can easily select the optimal load value of χ to offload to the neighboring cell. To this end, the overloaded cell sorts the users according to their link imbalances and keeps only those who fit in the target cells after calculating their estimated loads [see Fig .1]. The overloaded cell can now compute all the utility values corresponding to the handover of the first x_o users from the obtained list H, i.e., utility of executing the handover of the best candidate user, the second best candidate user and so on. The overloaded cell selects the number x_o of users that maximizes its payoff by comparing the utility values, without excluding the payoff if it does not offload at all, and sets χ to the sum of their respective loads.

In our context, the utility function of the players is based on the number of satisfied users which does not correspondingly consider the number of unsatisfied users in the network. In [3], the utility function is modified using the linear pricing technique to achieve the "natural" actions of the players, where the overloaded cell seeks to offload all its excess load and the underloaded cell i to accept users as long as its new target load $\tilde{\rho}_i$ does not exceed 1, i.e., it would signal $y_i = 1 - \rho_i$. Actually, these are the values (referred to Reference case) that would be recommended by a network-wide algorithm as they result in a better overall network performance.

5 Simulations

In this section, we evaluate the performance of the overall network for the Nash equilibrium in an LTE downlink system. The parameter values are set according to the reference settings for LTE simulations defined in [8].

5.1 Layout, parameters and user positions

For evaluation, we consider two different cellular layouts: a homogenous network composed of $M = 57$ hexagonal cells separated from each other by 500 m and a heterogeneous network consisting of $M = 36$ cells with different area sizes. Every cell is served by one of the three sectors of a single eNodeB and a wrap around is assumed.

In all the simulations, we will use the following default parameters defined in Table 1, unless stated otherwise.

Table 1: Simulation parameters

Parameter	Value
eNodeB transmission power	40 W
Path loss function	128.1+37.6log10(R [km]) dB
Penetration loss	20 dB
Thermal noise power	-114 dBm
Shadowing standard deviation	8 dB
De-correlation distance	50 m
Antenna beam width	70°
Antenna backward attenuation	20 dB
Handover hysteresis	3 dB
N_{tot}	50 PRBs
$\Delta RSRP_{thr}$	5 dB
D_u	512 kbps
ρ_t	0.9

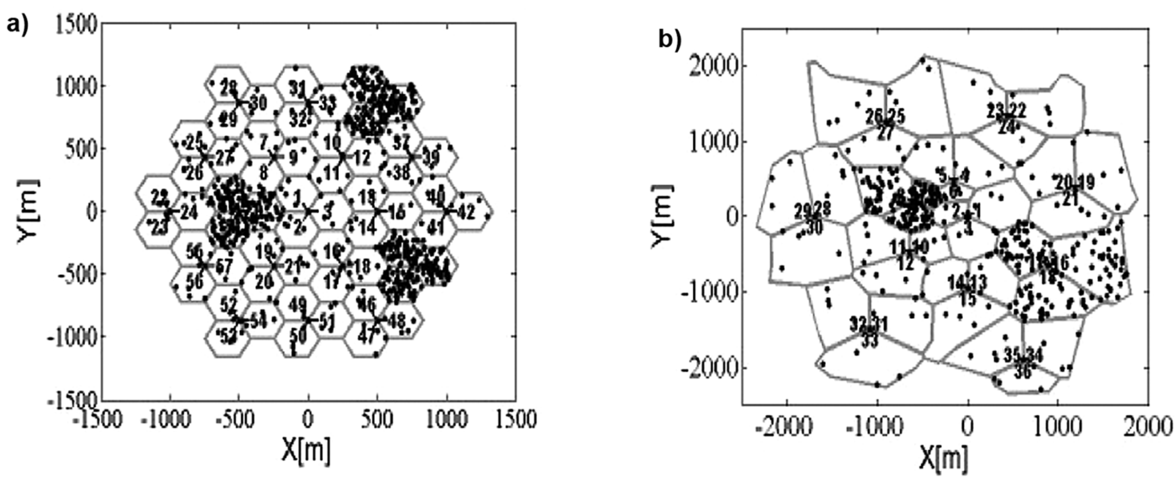

Fig. 2: (a) Homogeneous and (b) heterogeneous networks with nine and six generated hotspot cells respectively.

In order to have overloaded cells and other underloaded cells, we will generate heavy concentration of users in nine and six cells (hotspot cells) in the homogeneous and heterogeneous networks, respectively [see Fig. 2]. The number of UEs dropped in the hotspot cells is varied, whereas the default number of UEs dropped in each other cell is four, i. e., four users per cell in background. By following this distribution of the UEs, we guarantee that the load balancing game is played multiple times in the whole network. For every scenario, we average the number of unsatisfied users in the whole network over 20 different user drops.

5.2 Evaluation

The number of unsatisfied users is shown as a function of the number of UEs in the hotspot cells in Fig. 3 for the homogeneous and heterogeneous networks respectively.

In both networks, the Nash equilibrium succeeds in achieving a remarkable increase in the capacity when compared to a system without load balancing. The number of unsatisfied users decreases even if the cells behave in a selfish manner by deciding on the load values that maximize their own payoffs. However, the gain achieved from load

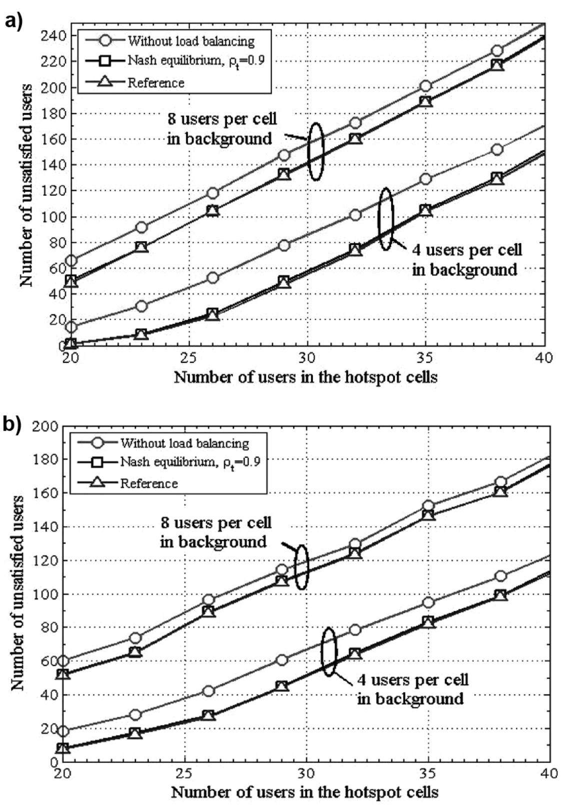

Fig. 3: Performance of the (a) homogeneous and (b) heterogeneous networks as a function of number of users in the hotspot cells with number of users per cell in background as parameter.

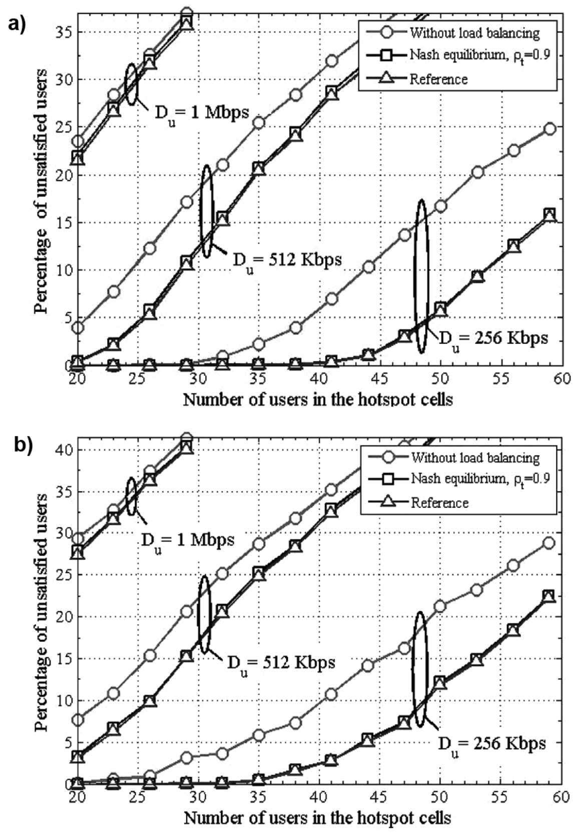

Fig. 4: Performance of the (a) homogeneous and (b) heterogeneous networks as a function of number of users in the hotspot cells with the data rate requirement D_u of the users as parameter.

Frequenz
64 (2010)
9–10

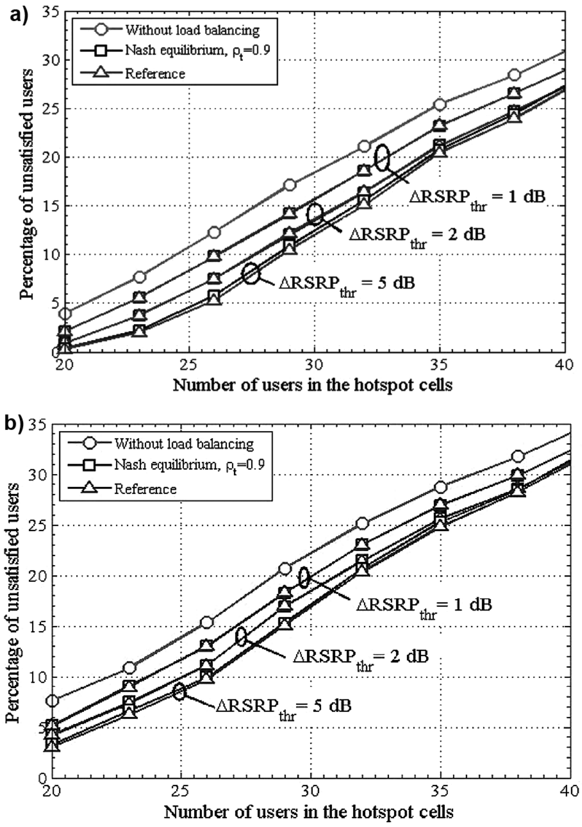

Fig. 5: Performance of the (a) homogeneous and (b) heterogeneous networks as a function of number of users in the hotspot cells with the link imbalance threshold $\Delta RSRP_{thr}$ as parameter.

balancing is lower when the number of users per cell in background increases, which reflects that the underloaded cells are not able to accommodate higher numbers of users when they are highly loaded. Moreover, the Nash equilibrium has a very slight degradation in performance when compared to the Reference case. The modified utility, which considers the number of unsatisfied users in the network, alters the actions of the players in the load balancing game, leading to some kind of collaboration and a minor improvement in performance when compared to the Nash equilibrium.

The percentage of unsatisfied users is shown in Fig. 4 as a function of the number of users in the hotspot cells for different data rate requirements.

According to the figures, a higher percentage of unsatisfied users is experienced in the network as the data rate requirement of each user increases. A higher D_u means that the user needs to occupy a higher number of PRBs to meet his data rate requirement, which limits the capability of the eNodeB to serve a large number of UEs. Moreover, the gain achieved by load balancing shrinks when the value of D_u increases. This is due to the fact that the overloaded cells are unable to execute the handover of users with very high data rate requirement, as they would produce a very high load that the neighbor underloaded cells can not handle. Once again, the Nash equilibrium provides results that are almost equal to the Reference case for various D_u values.

Fig. 5 shows the effect of the link imbalance threshold on the percentage of unsatisfied users. As the link imbalance threshold increases, the gain with respect to a system without load balancing also increases. A higher $\Delta RSRP_{thr}$ leads to a larger set Ω, and consequently to a larger number of candidate UEs. Thus, the overloaded cell can offload more UEs if the size of Ω gets larger, which in-turn decreases the percentage of unsatisfied users in the network.

6 Conclusion

The paper has shown that game theory provides valuable means for a distributed load balancing approach as proposed in 3GPP Release 9 for LTE where cells communicate, but probably act completely independent and autonomous as the executing entities (eNodeBs) might come from different vendors. The simulation results for the LTE network have shown that this autonomous approach of the cells, following a quite selfish utility function by maximizing the number of satisfied users, almost achieves the performance of the network-wide algorithm, which is reached by extending the utility using the linear pricing technique. The capacity gain, which is verified for various network layouts and scenarios, certainly paves the way for the mobile operators to consider the possibility of deploying different load balancing algorithms from various vendors as the loss in the network performance would be insignificant.

References

[1] 3GPP, "Self-configuring and self-optimizing network use cases and solutions," TR 36.902, Sophia-Antipolis, France, Tech. Rep., 2005.
[2] A. Lobinger, S. Stefanski, T. Jansen, and I. Balan, "Load balancing in downlink LTE self-optimizing networks," in IEEE Vehicular Technology Conference, Taipei, Taiwan, May 2010.
[3] A. Awada, B. Wegmann, I. Viering, and A. Klein, "A game-theoretic approach to load balancing in cellular radio networks," in IEEE International Symposium on Personal, Indoor and Mobile Radio Communications Conference, Istanbul, Turkey, September 2010.
[4] I.Viering, M. Döttling, and A. Lobinger, "A mathematical perspective of self-optimizing wireless networks," in IEEE International Conference on Communications, June 2009.
[5] 3GPP, "User equipment procedures in idle mode," TR 36.304, Sophia-Antipolis, France, Tech. Rep., 2009.
[6] A. MacKenzie and S. Wicker, "Game theory in communications: motivation, explanation, and application to power control," in Global Telecommunications Conference, vol. 2, 2001, pp. 821–826.
[7] A. MacKenzie and S. Wicker, "Selfish users in aloha: a game-theoretic approach," in IEEE Vehicular Technology Conference, vol. 3, 2001, pp. 1354–1357.
[8] 3GPP, "Physical layer aspects for evolved UTRA," TR 25.814, Sophia-Antipolis, France, Tech. Rep., 2005.

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