Femtocells Sharing Management using Mobility Prediction Model

Dominique Barth
Université de Versailles
45, Av. des Etats-Unis
78000 Versailles, France
Email: barth@prism.uvsq.fr

Amira Choutri
Université de Versailles
45, Av. des Etats-Unis
78000 Versailles, France
Email: amira.choutri@prism.uvsq.fr

Leïla Kloul
Université de Versailles
45, Av. des Etats-Unis
78000 Versailles, France
Email: kle@prism.uvsq.fr

Olivier Marcé
Alcatel-Lucent
France
Email: Olivier.Marce@alcatel-lucent.com

***Abstract*—With the unexpected increase of mobile data requests which overload the traffic control infrastructure of the network, operators are faced with a serious capacity management problem. In femtocell networks, bandwidth sharing paradigm constitutes an incentive solution for femtocells owners to offer a QoS guaranteed network access to mobile users in their femtocell coverage. In this paper, we consider a techno-economic bandwidth sharing model inspired from FON system and based on a reinforcement learning algorithm. Such a model does not allow the convergence of the learning algorithm because of the small size of the femtocells, the mobile users velocity and, more importantly, the randomness of their arrivals. In order to overcome the real-time constraints faced by this bandwidth sharing model, we propose to use a mobility prediction approach based on the analysis of movements history of the mobile users. Knowing the next visited cell in advance provides more time to mobile user to negotiate with the access provider and to generate synchronized resource reservation requests that maximize the gain of the access provider.**

I. Introduction

The topology and the architecture of cellular networks requires a major paradigm change from central voice, central switching and optimization of circuit, up to coverage data centralization, switching and deployment packages. Indeed, with the explosion of smart-phone market and the emergence of new services (VOD, TV mobile, ...), the number of registered mobile operators has significantly increased. This has led to an unexpected increase in the mobile data requests, overloading the network infrastructure and the traffic control equipments.

Thus, today operators are faced with a capacity management problem. They must find a compromise between, on the one hand, the QoS that must be offered to the users, and on the other hand, the cost that allows providing more capacity to their final mobile customers [2, 10]. Allowing mobile users the access to 4G applications, that is, data communications with high quality of service constraints (delay, bandwidth guarantee and continuity of service) is a key issue for the operators, for which a macrocell coverage cannot meet high population density of urban areas. Moreover, in order to boost the network capacity, mobile operators have to determine the good compromise between the size of the cells and the population density in these covered area.

In these urban areas, many users have contracted a wireless access point for private use, developing indoor and outdoor coverages by small cells (femtocells [5, 2]), and consequently offering an alternative to 4G mobile deployment [20]. Exploiting this alternative, a techno-economic mechanism, partially inspired from the FON system, was proposed to encourage the access point owners to share their femtocell radio resources with nomadic or mobile users [13]. This mechanism is primarily based on the use of a reinforcement learning algorithm distributed among the mobile users who are happy to use the offered radio resources for sharing in a given cell.

However, the reinforcement learning process used in the resources sharing algorithm assumes an unrealistic synchronization between competitive mobile users. This assumption is far from reality as mobile users arrive randomly to a cell. This algorithm also requires potentially long computation time and important message exchanges with the base station to converge. This cannot be compatible with the velocity of the mobile users movements in the femtocell coverage.

In order to overcome the real-time constraints faced by the bandwidth sharing model, we propose, in this paper, to use a mobility prediction approach which allows anticipating the next movements of the mobile users. Knowing the next visited cell in advance provides more time to mobile users to negotiate with the access provider and to generate synchronized resource reservation requests that maximize the gain of this provider. We consider the mobility prediction model developed in [6, 7] and which exploits the mobility trace of the mobile user to determine the next femtocell he/she will cross, allowing thus the network to anticipate the handover procedure.

The aim of this paper is to define a complete architecture for users mobility management in a femtocell coverage allowing a realistic use of the resources sharing mechanism studied in [13].

Structure of the paper: Section II is dedicated to related work. In Section III, we provide a background to both the resources sharing mechanism and the mobility prediction model we consider. Section IV presents our mechanism of femtocell sharing management based on mobility prediction. Its performances are analysed in Section V, using simulations. Section VI concludes the paper.

II. Related Work

The model proposed in this paper combines two mechanisms that have been studied through Celtic European projects AWARE and HOMESNET: the first one consists of a techno-economic model and a reinforcement learning algorithm for sharing femto radio resources [13] and the second one provides the combination of a local and centralised algorithms for mobility prediction [6].

The problem of sharing bandwidth and pricing has been already addressed in [16], then modelled as a game. The challenging problem in this context is that bandwidth sharing requires a stable coexistence of both primary and secondary users. In game theory, this peaceful coexistence represents a stable state and is denoted by Nash Equilibrium (NE). Using potential games properties is a classical method to prove the existence of a NE and that every improvement path is finite and leads to such a NE which is also a local optimum to a potential function. This property has been used in [15] for congestion game with resource reuse in a wireless context, in [22] for a real-time spectrum sharing problem with QoS provisioning and in [1] for spectrum sharing problem considered as a congestion game. The approach [13] we consider in this paper is based on a decentralized learning algorithm defined in [19].

Concerning prediction mobility, many studies were carried out on the mobile user behaviour. Based on six months tracking of $100,000$ mobile phone users, Gonz$\acute{a}$lez et al. have proved in [12] that humans follow simple reproducible patterns. The human trajectories show a high degree of temporal and spatial regularity, each individual being characterised by a time-independent characteristic travel distance and a significant probability to return to a few highly frequented locations. To detect mobile user patterns trajectories, clustering was proposed in [18]. Rinzivillo et al. suppose that each cluster corresponds to one typical trip, like going from home to work. Similarity is also defined between a cluster and routes, like the peripherals, the inwards or the outwards routes. Various models have been proposed to predict the complete itinerary [11, 14, 8] but requires a centralised and offline treatment. In [9] and [21], the authors propose prediction models which are based on the first order of Markov chains and the second order of Markov chains, respectively. Their results show that the second order based model performs better predictions than the first order based one. In [3], Markov chains were combined with a notion of local profiles to predict the next cell of a user.

III. The Models

As our femtocells sharing management solution is based on the bandwidth sharing model in [13] and the mobility prediction model proposed in [7, 6], before developing our solution, we present both models.

A. The Bandwidth Sharing Model

In the context of femtocells sharing management, a techno-economic model for sharing femtocell access has been proposed in [13]. This model is based on the idea that femtocells owners are offered by their access provider to share their bandwidth against some remuneration. By accepting sharing their femtocells access, partially or completely, a femtocell owner will join the club of the network bandwidth sharing owners.

Sharing the femtocell access is then considered as a game where the players are the access requesters and the shared bandwidth capacity is fixed. Using potential game characteristics, the authors [13] have proved that a pure Nash equilibrium is reached when many service providers share the access. In the following, we describe the actors involved in the model and present the paradigm behind.

1) The Actors of the Model: the different actors interacting in this model are the service provider customers SPC and the service requester customers SRC.

The SPCs are the owners of the femtocells who allow other customers of the network the access to their resources. The SRCs are the mobile users in need of a connection to the network. Note that a network customer can be a SRC and a SPC, at the same time.

- **Service Provider Customer:** this is an operator's mobile client who owns the access to its femtocell with possibly a good outdoor coverage. He proposes to share his bandwidth with SRCs against an award. This one depends on the SPC itself as it can be of two types, either a Bill or a Linus:
  - A Bill shares his femtocell access for economic reasons. Usually, his access point is well situated (next to a restaurant, bar or gas-station, ...) and his signal has a good outdoor accessibility. Thus, Bill will receive gains, he will have to share with his mobile operator.
  - A Linus shares his bandwidth for free or to be able to use an outdoor bandwidth of other SPCs (Bill or Linus) when needed. Usually, a Linus buys a femtocell for his own needs.

  Thus an SPC can be characterized using two parameters: gain sensitivity and connection sensitivity. The former, noted $\mu \in [0, 1]$, indicates sensitivity degree to the price of a shared connection. In [13], the authors assume that the closer to 1 is μ, the more the SPC is sensitive to the gain. Otherwise, he is considered as sensitive to his access QoS. The latter parameter, noted $\gamma \in [0, 1]$, refers to the tolerance degree of the preemption risk.
- **SRC:** he is a mobile operator's client who needs a good QoS for a reasonable price when moving. Two types of requester customers are defined [13] :
  - Bill and Linus requester customers: they are SRCs and, at the same time, registered as SPCs who receive a free roaming.
  - Alien requester customers: they are mobile users who do not have femto access at home, and need an outdoor QoS at a reasonable price. Aliens have to pay to have roaming. The mobile operator receives all the benefit if the SPC is a Linus, whereas he will have to share it, if the SPC is a Bill.

  Two parameters characterize a SRC: a Qos sensitivity and a price sensitivity. The former, noted $\alpha \in [0, 1]$, refers to the tolerance degree to the QoS degradation of the SRC. The closer to 1 α is, the more sensitive to QoS this customer is. Otherwise, he is considered as sensitive to the price. The latter, noted $\beta \in [0, 1]$, refers to the tolerance degree of the SRC to the connection cost.

The femtocells sharing management solution in [13] is a distributed mechanism managed by the club members and a countability system using tokens. This solution guarantees:

- Eco-system sharing: the model guarantees that no profit can happen between the club members.
- Fairness: a justice is established between SRCs (billing, access, . . .)
- Quality of service: the bandwidth sharing management guarantees a fixed access speed and a data transmission speed according to

the type of the SRC.

2) The Bandwidth Sharing Model : this model consists of a learning and a negotiation phase [13]. The learning phase allows the mobile user to collect data about the access provider customer and the concurrent mobile users before starting the negotiations with the SPC to get the targeted amount of bandwidth.

The solution for the access guarantee problem is based on a distributed learning. Consider a network where P is the total number of SPC. Let p, $p \in [1, P]$, be one of these SPCs and $B(p)$ the shared bandwidth of p, such that:

$$B(p) = B_g(p) + B_y(p)$$

$B_g(p)$ is the guaranteed part of bandwidth that cannot be canceled by the SPC whereas $B_y(x)$ quantifies the allocated part of the bandwidth that can be preempted if the SPC needs it for another usage. They are referred to as the *green* and the *yellow* bandwidth parts, respectively.

Now, let N be the number of SRCs realizing the game, that is competing for a part of the resource of the SPC X. After several game steps, and by learning about concurrent strategies, the paradigm achieves a pure Nash equilibrium. It find the best strategy to play by aN SRC to reach a stable situation, where the strategy of every SRC is optimal at a specific game step. Thus, an SRC utility depends on:

- his request, which expresses the needed bandwidth quantity, and depends on customer profile, connection and QoS needs, $\ldots$,
- the requests of the other players in the game,
- the decisions of the SPC, that is, the allocated bandwidth and connection types.

The request of each player i, $i \in [1, N]$, to an SPC $p \in [1, P]$ consists of a pair of values for each connection type, that is, the guaranteed (*green* bandwidth) or the non guaranteed (*yellow* bandwidth). Each pair of values consists of the minimum and the maximum quantity of bandwidth type needed. These are noted, respectively, $m_i^{X_p}$ and $M_i^{X_p}$, X being the connection type. The choice of these values will constitute the strategy s_i^p of the player regarding SPC p. Let s_i be the strategy set of SRC i regarding all SPCs on its path, that is $s_i = \{s_i^1, \ldots, s_i^P\}$ such that:

$$s_i^p = \{(m_i^{G_p}, M_i^{G_p}), (m_i^{Y_p}, M_i^{Y_p})\}$$

G and Y refer to *green* (guaranteed) and *yellow* (non guaranteed) bandwidth, respectively.

The choice of a strategy to apply by a player is a probabilistic choice. The purpose of the model's learning phase is to update the probability vector of the strategies. A strategy probability increases if the gain that the requester customer can obtain from the SPC, using this strategy, is maximal. The learning algorithm stops when the probability of a strategy is equal to 1.

The gains of an SRC is quantified using an utility function U. According to a set of requests $\Pi = \{s_1, s_2, ..., s_N\}$ of SRCs, the utility of an SRC is defined within the bandwidth allocation politic of the SPC. The utility of SRC i, noted $U_i(s_i)$, depends mainly on his profile and the response he/she receives from the SPC. The response, noted $R_i =< X, bw_i >$, consists of the connection type and the bandwidth quantity granted. Thus, the utility is expressed as:

$$U_i(s_i)(= \frac{|bw_i - \mathcal{M}_i^X|}{M_i^X - m_i^X} \tag{1}$$

where $\mathcal{M}_i^X$ is the bandwidth quantity that the player tolerates to receive. This parameter depends on the SRC profile. If the SRC is sensitive to the QoS then the minimum of bandwidth he/she tolerates to receive is the maximum of the strategy played, that is, $\mathcal{M}_i^X = M_i^X$. If he/she is more sensitive to the resource price, the minimum of bandwidth he/she tolerates to receive is $\mathcal{M}_i^X = m_i^X$.

The presented model allows to guarantee a fair access to a femtocell between the SRCs and the femtocell owner (SPC). However, a synchronization between players must exist in the game since every player must know the available capacity. Moreover, the learning phase makes the model slow to react, and needs a lot of interactions between the service requester and the provider customers. Thus, a realistic implementation of this model becomes not easy to achieve if we consider the short time allowed to the handover procedure between femtocells and the random arrivals of the mobile requesters.

B. The Mobility Prediction Model

To guarantee the offer of continuous services for mobile clients, and to shorten handoff latency in wireless cellular network, mobile operators try to know the next mobile's location using mobility prediction. It consists in locating in advance the next connection point in order to anticipate the initiation of the handover process at the predicted point.

Most mobility prediction models are based on Markov chains exploiting the mobility trace of the mobile user, that is, a sequence of cells that a mobile crosses during an interval of time. In this paper, we consider the Markov chains-based prediction model that has been proposed, in the context of LTE architecture, in [6, 7]. This model has been proved to be efficient enough to predict the movements changes of a mobile user. The model is based on two complementary prediction algorithms, the Global Prediction Algorithm (GPA), and the Local Prediction Algorithm (LPA). Both algorithms use the mobility trace of the users as follows.

- **GPA** allows predicting the regular movements of a mobile client. It is based on the user's mobility trace and a second order continuous-time Markov chain, whose discrete states are the cells of the network. Thus the transition probability to the next cell to be visited by a mobile user depends not only on its current cell but also on the previously visited cell. The mobility trace consists of the identity of all cells crossed by the mobile user, during a fixed time period.
  For each mobile user, the GPA computes the transition probabilities from its current cell C_i to each cell in its neighborhood (adjacent cells) noted $\Gamma(C_i)$. For that, for each cell C_i, a tuple (M, N, r) is defined where:
  - for each pair of cells C_j and C_k in $\Gamma(C_i)$, $M(C_kC_i, C_j)$ is the number of transitions of the mobile user from cell C_i to cell C_j in the past, knowing that each time such a transition occurred the mobile user was previously in cell C_k.
  - $N(C_k, C_i)$ is the number of transitions of the mobile user from cell C_k to cell C_i.
  - $r(C_i)$ indicates the average residence time of a mobile user in cell C_i.

  Let $L = C_1C_2C_3...C_{n-1}C_n$ be the mobility history trace of a mobile user. Let $X = C_{n-1}C_n$ be the sequence, in L, of the previously visited cell and the current cell of the mobile user. Assuming that $Y = C_nC_{n+1}$ is the sequence of the current cell and the future cell to be visited, the estimated transition probability P_e is given by:

$$P_e = P(X_{n+1} = Y/X_n = X) = \frac{M(X, C_{n+1})}{N(C_{n-1}, C_n)} \tag{2}$$

- **LPA,** when the GPA is unsuccessful, the approach proposes to use a first order continuous-time Markov chain. The transition probability from the current cell C_n to each adjacent cell C_{n+1} is given by:

$$P_m = P(X_{n+1} = Y/X_n = X) = \frac{N(C_n, C_{n+1})}{Z(C_n)} \tag{3}$$

  where $Z(C_n)$ is the number of times cell C_n appears in the mobility trace. The prediction based on first order Markov chain may fail if the current cell C_n appears for the first time in the trace. In this case, the visits frequency $H(C_n)$ to C_n from adjacent cells is used. If K is the total number of adjacent cells to C_n,

$$H(C_n) = \sum_{j=1}^{j=K} Z(C_j)$$

  So, the transition probability to an adjacent cell is given by:

$$P_m = \frac{Z(C_n)}{H(C_n)} \tag{4}$$

The complete mobility prediction model proceeds as follows. At every entred cell C_n, the algorithm computes the transition probability to every adjacent cell of C_n. For that, the algorithm checks if there are enough information in the mobility trace to predict the next cell:

- if enough informations, the GPA is used and P_e is computed (Equation 2),
- otherwise, the LPA is used and P_m is computed using Equation 3 or Equation 4, according to the value of $N(C_n, C_{n+1})$.

This prediction procedure just needs to know the adjacent cells. This information can be provided by the knowledge of the operator's network topology, or by analysing the intensity of received signals.

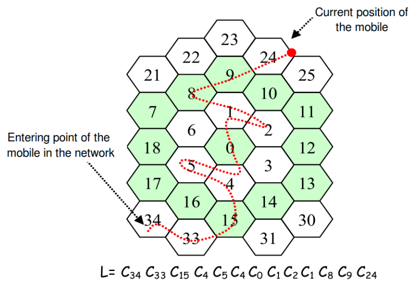

Fig. 1: Example of mobility trace.

IV. Femtocell Sharing Mangement using Mobility Prediction

The bandwidth sharing model in Section III-A2 does not allow the convergence of the learning algorithm because of the small size of the femtocells, the mobile users velocity and, more importantly, their random arrivals. In order to overcome the real-time constraint faced by the bandwidth sharing model, we propose to use the mobility prediction model in Section III-B. Indeed, knowing the next visited cell provides more time to mobile users to negotiate with the access provider and to generate synchronized resource reservation requests maximizing the gain.

In the following, we first define the main actors in the model and their characteristics. Then, we present the general model and the interactions between the actors. Finally, we describe the scenarios we use to evaluate the performances of the model.

A. Actors

We consider two main actors: the mobile user and the femto base station to which the mobile is connected. The user is an SRC who moves between the network's cells. These cells have small base stations with low power. They provide resources for mobile clients and can guarantee the QoS during their movements. When SRC enters a new cell, a new stage t in its mobility begins.

- **Mobile Client:** Every mobile client has a unique identifier id. It is characterized by:
  - A requested resource capacity $cap_{req}(id,t)$, at every stage t. The resource can be guaranteed or not during the client movement. We use a green color for a guaranteed resource and yellow color for non guaranteed one. For all stage t, cap_{req} is constant.
  - A QoS sensitivity parameter α_{id}, and a price sensitivity parameter β_{id}.
  - A reattachment femtocell $cell(id,t)$, at every stage t.
  - An allocated capacity $cap_{alloc}(id,t)$ such that $0 \leq cap_{alloc}(id,t) \leq cap_{req}(id,t)$
    - **If** $\mathbf{cap_{alloc}(id,t) = cap_{req}(id,t)}$, the mobile's request is totally satisfied.
    - **If** $\mathbf{cap_{alloc}(id,t)) = 0}$ then the mobile's request is not satisfied.
  - An adopted strategy $s_{id}(t)$ to formulate his/her service request at each new reattachment cell.
  - An utility $U_{id}(t)$ that client id gets for the application of his/her strategy $s_{id}(t)$ and considering those adopted by the concurrent mobiles.
  - A mobility trace L which contains all visited cells by the client during T stages, $0 \leq T \leq t$.
- **Femtocell:** a femtocell $cell$ is characterized by:
  - A total resource capacity $cap(cell)$ such that $cap(cell) = cap_g(cell) + cap_y(cell)$ where:
    - $*$ $cap_g(cell)$ is the guaranteed resource capacity (green),
    - $*$ $cap_y(cell)$ is the non guaranteed resource capacity (yellow).
  - A pre-emption risk P_{pre}, which is the probability that the connection is interrupted by the base station. If the connection is green then $P_{pre} = 0$, otherwise $P_{pre} > 0$.
  - A maximum number of mobile clients $nb_{max}(cell)$ that $cell$ can satisfy simultaneously.
  - A neighborhood graph $V(cell)$, which models the network coverage. Each vertex v_i in the graph is a cell and each edge $[v_i, v_j]$ indicates that cells v_i and v_j overlap, $i, j \in [0, R]$, R being the graph size.
  - A sharing resources policy that defines the way cells attribute their resources to the different mobile clients.

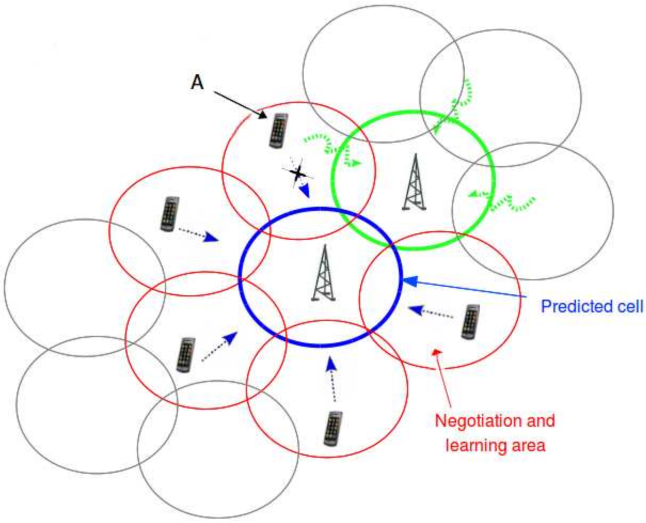

Fig. 2: Mobility prediction for femtocell sharing

We consider two resource sharing policies, a FIFO based-policy and priority-based policy. In the former, there is no distinction between mobiles who had a successful prediction at the previous stage $t-1$, and those who had a wrong prediction at that stage. In the latter policy, the priority assigned to a mobile user depends on the success of its prediction at the previous stage $t-1$. A mobile who had a successful prediction, at stage $t-1$, will be in the predicted cell at stage t. In this case, he/she will have a higher priority to be satisfied, because he/she has prepared his resource request maximizing his gain. A mobile who made a wrong prediction will joint a cell for which he did not prepare his request, unlike some of his concurrent who had success predictions. In this case, he/she will be assigned a low priority to be satisfied by the femtocell.

B. The Algorithm of the Complete Approach

At every stage t, the mobile client id is attached to a femtocell $cell(id,t)$. Its terminal executes the mobility prediction algorithm in order to compute the transition probability from the current $cell(id,t)$ to every adjacent cell v in $V(cell)$. The procedure continues as follows:

- The mobile terminal communicates his prediction results to the base station. The results of id consist of a probability distribution over a set of predicted cells $Pred(id,t+1)$.
  - If $|Pred(id,t+1)| = 1$ then id has predicted a single cell.
  - Otherwise, the base station determines the next cell that will be visited by client id.
- With the help of its current base station, mobile client id initiates the negotiation process with the base station of the predicted cell. The negotiation makes the mobile client part of a game where C mobile clients play the access to the same resources.
- Client id determines the best strategy $s_{id}(t+1)$ to play during the next phase $t+1$, which maximizes its utility.

At stage $t+1$, mobile client id enters a new cell $cell(id,t+1)$. Two scenarios are then possible:

a. **Wrong prediction:** the mobile is not in the predicted cell, that is $cell(id,t+1) \neq Pred(id,t+1)$. Consequently, he is in a cell for which he did not prepare a request strategy. In this case, mobile client id can play either the strategy already prepared, but for another cell, or play a strategy $s_{id}(t+1)$ that he will determine using a uniform distribution.

b. **Successfull prediction:** the mobile id is in the predicted cell, that is $cell(id,t+1) = Pred(id,t+1)$. The mobile uses the strategy $s_{id}(t+1)$ already prepared. In the last

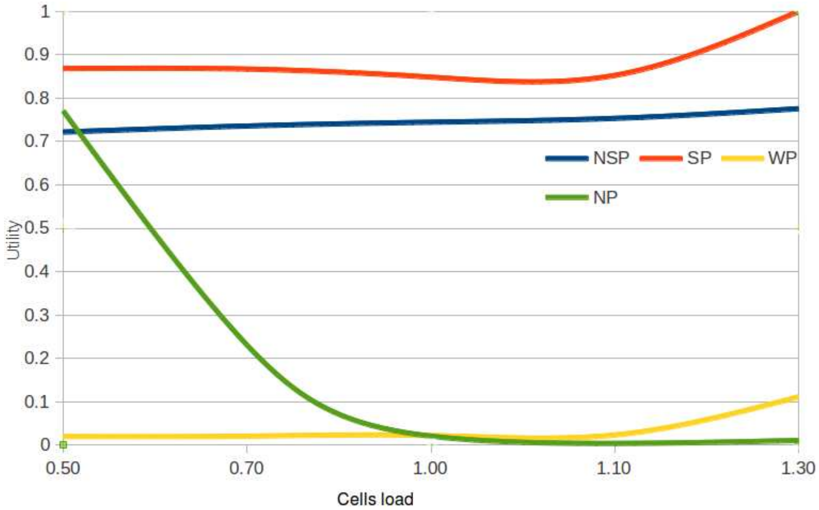

Fig. 3: Utility satisfaction rate of mobile user $n1$

scenario, we consider two cases:

b1. One of the other players c that client id finds in the new cell made was not supposed to be there ; c made a wrong prediction. The new mobile client c may or may not play his strategy $s_c(t+1)$. Moreover, another player that is supposed to be in the cell and against which mobile client id has played has vanished because he/she made also a wrong prediction. In this case, the context of the new cell has changed for mobile client id.

b2. All players against which mobile client id has played are in the new cell. Thus the context of the new cell has not changed for mobile client id.

V. Performances Analysis

In order to assess the performances of our approach, we observe mobile clients (targeted users) requesting resources while moving in a defined environment. This one consists of a total of twelve (12) mobile users competing for a femtocell radio resource access. The data sets of the targeted users are field data collected in a major US urban area (Rice). These data sets are measured on WiFi enabled GSM cellular phones [17]. Using these data sets, a mobility trace representing all visited cells during the time period of the collection, has been extracted for each targeted user.

The performance measures we are interested in are the prediction success rate and the utility satisfaction rate. Prediction success rate $PSR_{id}(t)$ is the ratio between the number of successful predictions and the total number of predictions made by user id. Utility satisfaction rate $USR_{id}(t)$ is the ratio between the utility obtained with strategy $s_{id}(t)$ and the utility that could have been obtained with the optimal strategy $s^*_{id}(t)$.

To perform these assessments we use simulation which results are obtained for a confidence level of 95%.

We consider four different simulation scenarios, noted NP, WP, SP and NSP:

- **NP** scenario: the mobility prediction is not used and mobile users run the learning algorithm within, at most, 90 learning steps (the average number of sufficient game steps to converge is 115). This models the fact that without prediction, the converging time is limited since the learning algorithm can only be run when handovers occur.

- **WP** scenario: the mobility prediction mechanism is used and the targeted user makes a wrong prediction. This is the case of user A in Fig.2

- **SP** scenario: the mobility prediction mechanism is used and all the users, including the targeted user, make a successfull prediction.

- **NSP** scenario: the prediction mechanism is used. The targeted user makes a good prediction

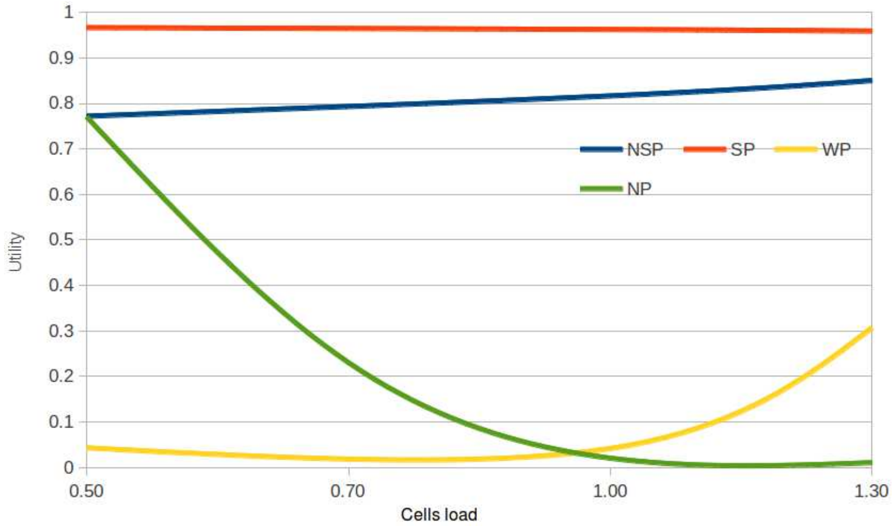

Fig. 4: Utility satisfaction rate of mobile user $n2$

and some other users make wrong predictions, considering a 20% prediction failure rate on the 11 other users.

Figures 3, 4 and 5 show the utility satisfaction rate obtained for targeted user $n1$ using his mobility trace and considering different cells loads.

When the cells load is low (0.5), the scenario NP provides good performances since the provider has enough resources to satisfy all requesters. Whereas, when the cells load increases, the utility decreases until reaching 0 when the load is 1.5, and the limited number of steps (90) becomes insufficient to converge to a good utility state.

The use of mobility prediction in the learning algorithm increases the obtained utility and the QoS obtained when prediction is successful (scenario SP), for different levels of cells load. Indeed in this case, the learning algorithm has enough time to converge towards good utility state. Note that other simulation results have shown that the time to cross a cell is sufficient for the game to converge. This explains why the utility satisfaction rate and the QoS obtained can reach value 0.9 and 24, respectively if the prediction is successful, for all targeted mobiles. If the targeted user makes a wrong prediction (WP curves), the obtained utilities are lower than the ones obtained when good predictions are made, since strategies have not been chosen for the corresponding crossed cells and the other mobile users having predicted these cells have priority on the resources. Indeed, the targeted user obtains a lower QoS (Fig6). Moreover, when wrong predictions are made by the targeted user, the cells load used in the simulation are considered static in the model. Thus, even if the provider has enough resources, he/she will not exceed the load that he fixed beforehand. This explains why the utility in WP scenario is smaller than the utility in NP scenario for low loads.

If at least one of the concurrent mobiles makes a wrong prediction, the utility satisfaction rate of the targeted mobile decreases also the QoS. Indeed, in this case, on the one hand, the strategy initially chosen by the targeted user is not the optimal one anymore and that is why the utility satisfaction rate decreases.

On the other hand, since the cells are overloaded, according to the policy of the mobile operator to satisfy the providers before the mobile users, there are users that are not served at all initially. Thus, when users do not show up in the predicted cell, there are more available resources, and the provider chooses to satisfy the minimum quantity requested by the not served mobiles. For that the provider decreases the capacity affected to the users that have already been served in the cell among which is the targeted user. That can

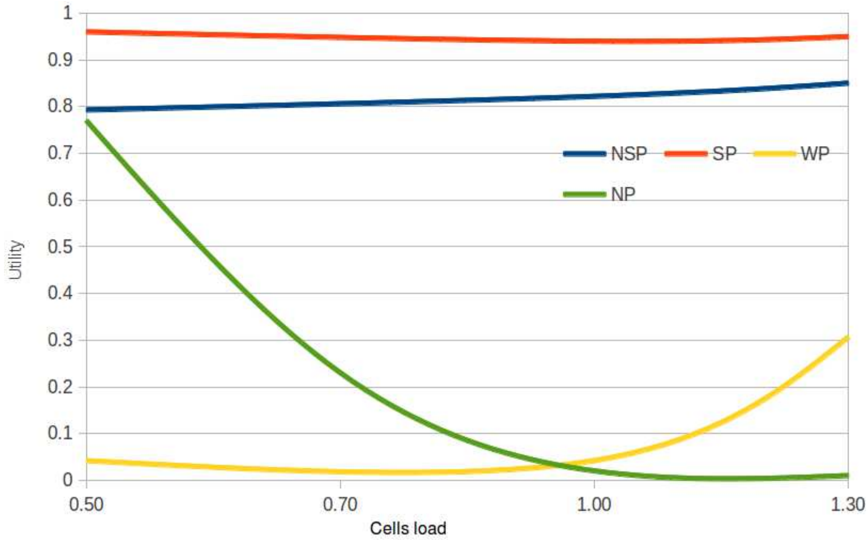

Fig. 5: Utility satisfaction rate of mobile user $n3$

be seen by observing the used strategies and the obtained capacities by the users in the cell.

Targeted mobile user $n1$ has an average prediction ratio equal to 0.6 (see Fig.3); he alternates between regular movements (i.e. predictable ones), for which utility success ratio is about 0.83 during 60% of the time, and irregular movements (difficult to predict), for which utility averages 0.05 in heavily loaded cells. In such cases, when WP scenario is considered the utility rate is 0.01.

In the case of a trace (1629 cells) of irregular movements solely, the prediction success rate of targeted user $n3$ (Fig.5) does not exceed 0.3. If the visited cells are heavily loaded, the utility rate is most of the time at 0.17, and 0.04 otherwise.

But, if the mobile user has regular movements and is able to make successful predictions, like user $n2$ (Fig.4) who has a mobility trace of 7286 cells, the prediction success rate reaches 0.8. That is, most of the time, this mobile has an utility satisfaction rate of 0.95. Its resource request is not satisfied in 20% of the crossed cells (utility rate at 0.3) which corresponds to wrong predictions.

VI. Conclusion

The objective of this paper is to improve a techno-economic model for sharing femto access by anticipating the handover process using mobility prediction. We have assessed the performances of our approach, in terms of utility satisfaction rate and QoS. We focused on the behavior of different targeted users when they make successful/wrong predictions and the impact of the successful/failed prediction of their concurrents on their utility rate. We compared the obtained results with the ones obtained if no mobility prediction is used. These results show that we have effectively enhanced the utility obtained using the basic model for all cells loads. They also show that this enhancement depends on movements type of the users (regular, irregular, mixed). Indeed, the mobility prediction approach we have used was penalizing for irregular movements. In the future, we plan to use a mobility prediction approach designed for such type of movements, like mobility prediction based on user profiles [3, 4]. We also plan to investigate the behavior of our algorithm in a green Femto-Macro cells network.

Bibliography

[1] S. H. A. Ahmad, C. Tekin, M. Liu, R. Southwell, and J. Huang. Spectrum sharing as spatial congestion games. volume abs/1011.5384, 2010.

[2] J. G. Andrews, H. Claussen, M. Dohler, S. Rangan, and M. C. Reed. Femtocells: Past, present, and future. *IEEE Journal on Se-*

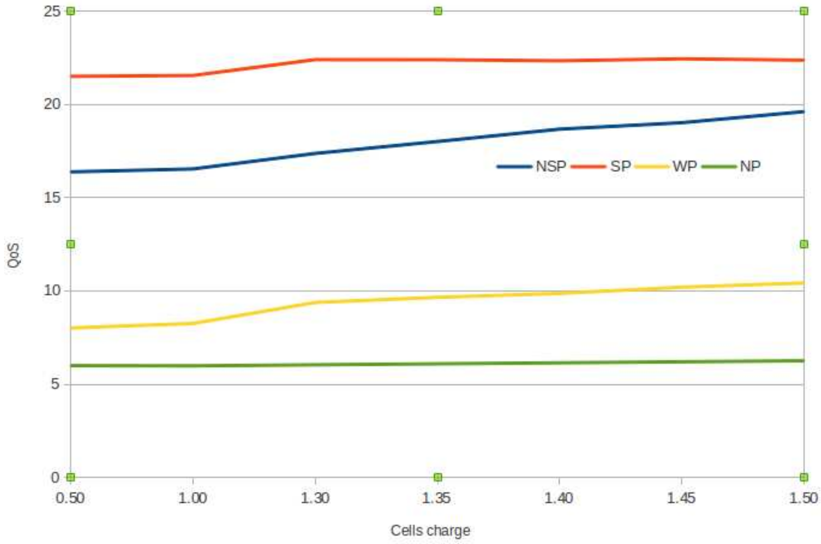

Fig. 6: QoS obtained for targeted user $n1$

lected Areas in Communications, 30(3):497–508, 2012.

[3] D. Barth, S. Bellahsene, and L. Kloul. Mobility prediction using mobile user profiles. In *19th IEEE MASCOTS, Singapore*, Singapore, 2011.

[4] D. Barth, S. Bellahsene, and L. Kloul. Combining local and global profiles for mobility prediction in LTE femtocells. In *15th ACM MSWiM*, Paphos, Cyprus, 2012.

[5] S. Bellahcene. *Prédiction de la mobilité pour la gestion des handovers dans les réseaux IP : modèles et algorithmes*. PhD thesis, Université de Versailles, Mai 2011.

[6] S. Bellahsene and L. Kloul. A new markov-based mobility prediction algorithm for mobile networks. Bertinoro, Italy, 2010.

[7] S. Bellahsene, L. Kloul, and D. Barth. A hierarchical prediction model for two nodes-based ip mobile networks. In *12th MSWiM*, Canary Islands, Spain, 2009.

[8] J. Chan, S. Zhou, and A. Seneviratne. A qos adaptive mobility prediction scheme for wireless networks. In *IEEE GLOBECOM*, volume 3, pages 1414–1419, 1998.

[9] F. Chinchilla, M. Lindsey, and M. Papadopouli. Analysis of wireless information locality and association patterns in a campus. In *IEEE 23*$^{rd} INFOCOM, HongKong, China,$ 2004.

[10] M. Z. Chowdhury, Y. M. Jang, and Z. J. Haas. Network evolution and QoS provisionning for integrated femtocell/macrocell networks. *International Journal of Wireless & Mobile Networks (IJWMN)*, 2(3), 2010.

[11] F. Giannotti and D. Pedreschi. *Mobility, Data Mining and Privacy - Geographic Knowledge Discovery*. Springer, 2008.

[12] M. Gonzàlez, C. Hidalgo, and A.-L. Barabàsi. Understanding individual human mobility patterns. volume abs/0806.1256, pages 779–782, 2008.

[13] M. Krichen, J. Cohen, and D. Barth. Model for sharing femto access. In *5th ICST VALUETOOLS*, Paris, France, 2011.

[14] G. Liu and J. G. Maguire. A class of mobile motion prediction algorithms for wireless mobile computing and communication. *Mobile Networks and Applications*, 1(2):113–121, 1996.

[15] M. Liu, S. Haji, A. Ahmad, and Y. Wu. Congestion game with resource reuse and applications in spectrum sharing. volume abs/0910.4214, 2009.

[16] D. Niyato and E. Hossain. Microeconomic models for dynamic spectrum management

in cognitive radio networks. In E. Hossain and V. Bhargava, editors, *Cognitive Wireless Communication Networks*, pages 391–423. Springer US, 2007.

[17] A. Rahmati and L. Zhong. Crawdad data set rice/context (v. 2007-05-23), May 2007.

[18] S. Rinzivillo, D. Pedreschi, M. Nanni, F. Giannotti, and N. Andrienko. Visually driven analysis of movement data by progressive clustering. *Information Visualization*, 7(3-4):225–239, 2008.

[19] P. S. Sastry, V. V. Phansalkar, and M. A. L. Thathachar. Decentralized learning of nash equilibria in multi-person stochastic games with incomplete information. *IEEE Trans Systems, Man, and Cybernetics*, 24:769–777, 1994.

[20] T. Simonite. Qualcomm proposes a cell-phone network by the people, for the people, 2013.

[21] L. Song, D. Kotz, R. Jain, and X. He. Evaluating location predictors with extensive wi-fi mobility data. In *IEEE 23*$^{rd} INFOCOM, HongKong, China,$ 2004.

[22] Y. Xing, C. Mathur, M. Haleem, R. Chandramouli, and K. Subbalakshmi. Real-time secondary spectrum sharing with qos provisioning. In *3rd IEEE CCNC*, Las Vegas, 2006.