Framework for resource allocation in heterogeneous wireless networks using game theory

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Abstract. This is a framework for resource allocation in a heterogeneous system composed of various access networks, for instance Third Generation wireless networks (3G) and WLAN, in the presence of multimedia traffic, namely voice and data. Our aim is to present a game theoretical modeling of routing and load-balancing strategies along with admission control and pricing in cooperative and non-cooperative settings.

1 Introduction

In a heterogeneous environment composed of more than one access network, say third generation (3G) [1] [2] and IEEE802.11-based WLAN [3] networks, the question is that of how to allocate resources in a way that is optimal both to the user and operator (see Figure 1).

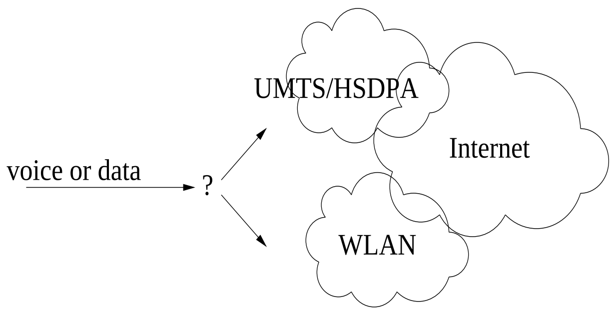

Fig. 1. Reference model.

The answer is multi-fold. On the user side, the issue is that of routing. Optimality in this case refers to the best QoS, according to the type of traffic, at the best price. On the operator side, the issue is that of admission control and pricing so as to maximize revenue which is proportional to resource utilization itself subject to granted QoS and the prices assigned to each type of resources as well as their cost.

Game theory [4] [5] studies interactions and winning strategies for parties involved in situations where their interest conflict with each other. It has applications to real games, economics, commerce, politics and recently telecommunications. The research area of networking games and their application in telecommunications has known rapid developments through the last years [6]. Since optimization theory is unable to take into account interactions between different actors, be they users, protocols, nature or other, game theory has shown to be a useful tool allowing to study behavior and eventual equilibrium of complicated and interacting systems.

Inspired from economical environments, game theoretical modeling proved to be a powerful tool to study resources allocation in homogeneous as well as heterogeneous systems presenting contending users or classes for those resources. More specifically, it has been used in power control [7] and access to a common shared link, but also to study flow control problems and to find structural properties of equilibrias in systems involving routing into links with different capacities ([8], [9]). For a survey on applications but also on methodologies and challenges of networking games in telecommunication, the reader is refered to Reference [6].

Our aim in this work is to model interaction between different, non-homogeneous types of traffic, namely voice and data, with eventually different radio conditions, competing for the use of resources in heterogeneous networks offering different QoS. The dynamic sharing nature of wireless protocols in recent networks, particularly Medium Access Control (MAC) protocols, makes the game theoretical tool suitable to study interaction and resulting strategies of involved players, be they the end users asking for resources and subsequently a QoS level, and the network strategies for admitting those calls and pricing them after admission.

At this point, we have to distinguish between cooperative and non-cooperative settings, both on the user and operator side. On the user side, users may cooperate so as to achieve the best global utility function. This is not very probable. Often, users are non-cooperative wherein only maximizing the individual utility function is at sake.

On the operator side, cooperation is typically given when the heterogeneous access networks belong to one operator and the objective is again to maximize some global utility function. If different players own the different networks, the problem becomes a game where each one tries to maximize its own utility function.

Now, taking the problem as a whole, with both users and operator(s), the resource allocation problem may be solved through some classical Nash equilibrium [5], defined as being the players actions from which no player has an incentive to unilaterally deviate, or may be brought to some optimal operation point through for example incentives by the operator to guide users to choices that simultaneously maximize their utility function as well as his.

The remainder of this work is organized as follows. In section II, we give a basic introduction for the tool of game theory. In Section III, we investigate the routing and show the distinction between cooperative versus the non-cooperative cases. The same distinction pertains for admission control and pricing too and is presented in Section IV. Section V presents a cross-layer modeling of the two systems under consideration. Eventually, Section VI concludes the paper.

2 Game theory primer

A strategic game has three components:

- A set of players $\mathbf{Pl}$
- A set of possible actions A_{pl} for each player $pl \in \mathbf{Pl}$
- A set of utilities $\mathbf{U}$, where for each player $pl \in \mathbf{Pl}$, the utility for each player is a function of the action profile $\mathbf{a} = (a_g, a_{-g})$, a_g being the action of player pl and a_{-g} the vector of all other players strategies. An action profile belongs to the set of actions profiles denotes by $\mathbf{A} = \prod_{pl \in \mathbf{Pl}} A_{pl}$. In other words a utility function is a mapping from the set of all actions profiles $\mathbf{A}$ to the set of real numbers $\mathbf{R}$.

Two settings may arise in a system involving several players. Players may cooperate and the problem reduces to an optimization problem where a single player drives the system to a social equilibrium. A standard criterion used in game theor to express efficiency of such equilibrium is Pareto efficiency. A strategy profile $\mathbf{a}$ is called *Pareto efficient* if there is no other strategy $\mathbf{a}'$ for which:

- 1) all users do at least as well
- 2) at least one user does strictly better.

Another important setting is that of non-cooperative players where each decision maker selfishly chooses its strategy. In this case, the equilibrium reached, when it exists, is called a Nash equilibrium and is defined as the point from which no player finds it beneficial to unilaterally deviate.

Pareto efficiency is a desirable operating point for a given system in general, however non-cooperative equilibria are in general Pareto inefficient.An important question that arises is how to drive a system where decision makers have a non-cooperative behavior to the system's optimal point. This question has been addressed in [10].

3 User side : routing/load-balancing

We consider a QoS-based routing, where each type of traffic, broadly classified into streaming versus elastic and each further decomposed into classes according to various radio conditions, chooses the proportion of flows to be sent to each subnetwork.

At this point, two situations arise. One can imagine some cooperative behavior of different classes, where the routing controller wants to achieve in a social manner, the best global utility, QoS divided by a given price in this case, for different classes in a fair manner. Another case arises when non-cooperative classes behave as selfish players, each player trying to choose individually its routing strategy so as to optimize its individual utility, i.e., its own perceived QoS normalized to the price.

Recall that in the cooperative case, Pareto-optimal points are defined as points corresponding to equilibria from which any deviation will lead to a degradation in the performance of at least one player in the cooperative game. It should be noted that in a multi-class environment, there is an infinite number of solutions, so-called Pareto-optimal strategies. The notion of fairness is then introduced to select a unique operating point. In the theory of cooperative games this is known as the Nash arbitration scheme.

In the non cooperative case, however, every class acts selfishly to optimize its own performance measure regardless of others' performance. Such games are characterized by the Nash equilibrium point, when it exists, defined as the (routing) strategy profile from which no player finds it beneficial to unilaterally deviate. This can arise in situations where a decentralized routing decision is adopted and where end users choose their subnetwork in a selfish manner so as to optimize their individual performance measure.

From an operator point of view, it is more beneficial to operate on Pareto-optimal points since Nash equilibrium points are in some cases inefficient compared to Pareto-optimal solutions.

In what follows, we first present utility functions, the measure that assesses the user degree of satisfaction from a given setting.

3.1 User utilities

We consider a set of voice and data users, with index $j \in \mathbf{J} = \{v, d\}$ denoting their respective types and an index $k \in \mathbf{K} = \{1, ..., K\}$ denoting each type's radio conditions. Let these users share resources in a set of $n \in \mathbf{N} = \{1, ..., N\}$ possible parallel subnetworks.

We consider probabilistic routing of calls according to their type of traffic and radio conditions. A type-(j,k) selects the n-th subnetwork with a probability $r_n^{j,k}$. Let $\lambda^{j,k} = \sum_{n=1}^{N} \lambda_n^{j,k}$ be the total flow demand of class-(j,k) users, where $\lambda_n^{j,k} = r_n^{j,k}\lambda^{j,k}$ is the mean rate of class-(j,k) flow that is routed through subnetwork n.

The utility function $J^{j,k}$ of class-(j,k) is the utility achieved by that class and depends on its own strategy given by the rate vector $\Lambda^{j,k} = (\lambda_n^{j,k})_{n \in \mathbf{N}}$, but it also depends on other classes routing decisions, denoted by $\Lambda^{-(j,k)}$. Or:

$$J^{j,k} = J^{j,k}(\Lambda^{j,k}, \Lambda^{-(j,k)})$$

For a QoS-based routing, the natural candidate for utility functions is some performance measure seen by the call, blocking probability for voice $B_n^{v,k}$, and the mean transfer time for data $M_n^{d,k}$, normalized to the unitary price p_n of resources of each subnetwork n (p_n corresponds to the price per unit time for the case of voice and to a price per unit volume for the case of data). In this work, we define the utility function of an individual (j,k)-class by :

$$J^{j,k}(\Lambda^{j,k}, \Lambda^{-(j,k)}) = -\sum_{n=1}^{N} \lambda_n^{j,k}(1 - B_n^{j,k})X_n^{j,k} \times p_n$$

where $X_n^{j,k}$ is equal to the blocking probability $B_n^{v,k}$ for voice traffic and mean transfer time $M_n^{d,k}$ for data.

Remark 1. Other utility functions are possible. For instance, the one where a subclass tries to maximize some utility related only to the throughput or mean transfer time, while maintaining its blocking probability below a given acceptable limit. In this case, we are in the presence of a constrained optimization/game problem where the weights on the blocking probabilities are the Lagrange multipliers.

Remark 2. Stability conditions are required in the case where no admission control is implemented in the networks. In this case the admissible region should be specified.

The remainder depends on whether strategies are cooperative or not.

3.2 Non-cooperative routing

In a non-cooperative setting, different classes are considered as selfish players where each class implements a routing strategy so as to maximize its own net utility function as a response to others' strategies without any concern about others utilities. For a (j,k)-class user, the set of all possible strategies is given by:

$$\mathbf{F}^{j,k} = \{(\Lambda^{j,k}) \in \mathbb{R}^N : \lambda_n^{j,k} \geq 0 \text{ for } n \in \mathbf{N};\ \sum_{n=1}^{N} \lambda_n^{j,k} = \lambda^{j,k}\}$$

In this case, optimality cannot be well defined. The Nash equilibrium is considered as a specific form of optimality [5]. When it exists, the Nash equilibrium is a routing strategy profile from which no class finds it beneficial to unilaterally deviate, i.e., no class finds it beneficial for its perceived QoS to unilaterally change the amount of load it is sending to each subnetwork. More precisely, a $(\Lambda^{j,k})$ vector is a Nash equilibrium if for all (j,k), $j \in \mathbf{J}$, $k \in \mathbf{K}$:

$$\Lambda^{j,k} \in \underset{f^{j,k} \in \mathbf{F}^{j,k}}{\operatorname{argmax}}\, J^{j,k}(f^{j,k}, \Lambda^{-(j,k)})$$

meaning that $\Lambda^{j,k}$ is the best strategy of class-(j,k) player while other players strategies are fixed.

If the above-mentioned utility functions are convex in the routing strategy $\Lambda^{j,k}$, the Kuhn-Tucker optimality conditions are applicable and imply that the response of users of class-(j,k) given by $\Lambda^{j,k}$ is the optimal response to other classes strategies given by $\Lambda^{-(j,k)}$ if and only if there exist Lagrange multipliers $l^{j,k}$ and $(s_n^{j,k})_{n\in N} = (s_1^{j,k}, ..., s_N^{j,k}))$ such that [9][8]

$$\begin{aligned} \frac{\partial J^{j,k}}{\partial \lambda_n^{j,k}}(\Lambda^{j,k}, \Lambda^{-(j,k)}) - l^{j,k} - s_n^{j,k} = 0 \qquad n = 1, ..., N \\ \sum_{n=1}^{N} \lambda_n^{j,k} = \lambda^{j,k} \\ s_n^{j,k}\lambda_n^{j,k} = 0 \\ l^{j,k} \geq 0, \quad s_n^{j,k} \geq 0, \quad \lambda_n^{j,k} \geq 0 \qquad n = 1, ..., N \end{aligned} \tag{1}$$

3.3 Cooperative routing

We now turn to the cooperative case where for instance a central operator assigns calls to each subnetwork in a probabilistic manner ensuring fairness in terms of the QoS perceived by different classes. In this case, user classes are considered as cooperative players trying to share resources so as to optimize an overall utility function. The JK-dimensioned cooperative game reduces then to an optimization problem where the central decision maker (the router) maximizes a global utility function built of individual ones.

The routing strategy is a routing vector $(\lambda_n^{j,k})_{n\in\mathbf{N},j\in\mathbf{J},k\in\mathbf{K}}$. The set of all possible routing vectors is given by:

$$\mathbf{F} = \{\Lambda = (\lambda_n^{j,k})_{n\in\mathbf{N},j\in\mathbf{J},k\in\mathbf{K}} : \lambda_n^{j,k} \geq 0 \text{ for } n \in \mathbf{N},\, j \in \mathbf{J}\,,\, k \in \mathbf{K};\; \sum_{n=1}^{N} \lambda_n^{j,k} = \lambda^{j,k}\}$$

We are interested in Pareto optimality. In this setting, the solution provides that no player can increase its utility without adversely affecting the others [11]. Pareto optimility leads to a set of $P-1$ equations for P players, therefore an infinite number of operating points called Pareto boundary. To choose one operating point, the notion of fairness is introduced. The cooperative game can be formulated as follows:

$$\begin{array}{c} \max\limits_{\Lambda\in\mathbf{F}} \mid J(\Lambda) \mid \\ J.J^{-1} = \gamma \end{array} \tag{2}$$

where γ ($\mid \gamma \mid = 1$) is a JK's dimensioned vector defining the direction in which the Pareto point is required. The Pareto boundary can be found by evaluating Pareto points in all possible directions γ, in other words γ refers to the fairness degree that a centralized decision maker might give to different classes.

4 Network side : Admission Control and pricing

While end users, if given the right to decide on their routing strategy, are only interested in the QoS they perceive regardless of the good use of resources, the network operator(s) do care about the way resources are utilized. In other words, supposing that a call of type $(j,k) \in \mathbf{J} \otimes \mathbf{K}$ has a revenue p^j, the operator should choose its prices as well as its Call Admission Control (CAC) strategy so as to maximize its total revenues R given by:

$$R(\Lambda, CAC, p) = \sum_{j\in\mathbf{J},k\in\mathbf{K}} (p-I)\lambda^{j,k}(1-B^{j,k})$$

where I represents the cost of the investment made by the operator for the given technology.

Please note that in the above expression the revenues of the network are a result of both the offered load, the price and the implemented admission strategy. For every routing strategy, be it cooperative or not, and in order to maximize its revenue, the operator must offer an attractive price and implement some intelligent admission control to make the best profit of his resources given that load is dictated by end users.

Remark 3. If no fairness considerations towards different classes of users are taken into account from the operator side, maximizing revenues only may lead to very unfair situations where for instance users experiencing bad radio conditions are constantly blocked.

We now consider cooperative versus non-cooperative configurations. For the sake of simplicity, we adopt a threshold-based admission control leading to closed-form expressions. Nevertheless, our framework is general and can be used for other families of admission control strategies such as trunk reservation.

4.1 Cooperative case

To make the best use out of the network resources, the strategy of the operator is to choose a threshold parameter $T_n^{j,k}$ for each class (j,k). The set of all possible strategies for admission control is given by :

$$\mathbf{T} = \bigotimes_{n \in \mathbf{N}} \bigotimes_{j \in \mathbf{J}} \bigotimes_{k \in \mathbf{K}} \mathbf{T}_n^{j,k}$$

where

$$\mathbf{T}_n^{j,k} = \{0, ..., N_n^{j,k}\}$$

and $N_n^{j,k}$ is the maximum number of admitted users of class-(j,k) assuming that this class is the only one served in network n. The dimension of this set is given by $\mid \mathbf{T} \mid = \prod_{j \in \mathbf{J}} \prod_{k \in \mathbf{K}} N^{j,k}$.

In the case of a wireless network where capacity is shared in a nonlinear manner, determining the set $\mathbf{T}$ of all possible strategies for admission control is more complex. The set of threshold strategies is a subset of the above-mentioned $\mathbf{T}$ containing elements corresponding to feasible states, i.e., the set of all possible strategies where all admitted users obtain sufficient resources (at the MAC layer) so as to satisfy their QoS.

Similarly, the same analysis holds for the pricing strategy. In the cooperative case, a centralized decision maker chooses a vector of prices $(p)_{n \in \mathbf{N}}$ in a finite set of possible prices $\mathbb{P}$.

In the case of a single operator implementing admission control, the objective function is as follows

$$\max_{T \in \mathbf{T}, p \in \mathbf{P}} R(\Lambda, T, p) \tag{3}$$

4.2 Non-cooperative case

In this case, each network has its own utility function and each network optimizes its CAC parameters and chooses its prices independently of other networks. Formally, each network $n \in \mathbf{N}$ solves selfishly the following maximization problem, considering other network admission strategies fixed to T_{-n} and prices to p_{-n}:

$$\max_{T_n \in \mathbf{T}_n, p_n \in \mathbf{P}_n} R_n(\Lambda, T_n, T_{-n}, p_n, p_{-n}) \tag{4}$$

where $(\mathbf{T})_n$ is the set of all possible network n strategies given by:

$$\mathbf{T}_n = \bigotimes_{j \in \mathbf{J}} \bigotimes_{k \in \mathbf{K}} T_n^{j,k}$$

and each subnetwork chooses its own price p_n from a finite set of possible prices $\mathbf{P}_n$.

4.3 Optimal strategies

The set of all possible strategies is a finite set limited to the threshold values guaranteeing some QoS to the admitted users as well as prices. An extensive search algorithm is used to find the optimal threshold parameters [12]. Some algorithms accelerating the search for the optimal threshold parameters can be run by ordering traffic classes according to their revenues.

Admission as well as pricing strategies need not be run on the same time scales. The operator may well fix the price first and then optimize according to admission control.

5 Performance metrics

The above-mentioned utility functions, both for network and user, have been formulated in terms of performance metrics: mean transfer time and blocking probabilities. These performance metrics are derived as follows.

Consider a subnetwork n where the arrival of (j, k)-class users is Poissonian with mean rate $\lambda_n^{j,k}$ for fresh users and $h_n^{j,k}$ for handoff users. The service is exponential with mean rate $\mu_n^{j,k}$. The mean service time of voice users is constant; it depends on the share of resources for data transfers. In what follows, index n will be suppressed for clarity.

In 3G networks, voice calls shall be assigned to constant rate dedicated links whereas data ones shall share the leftover power on shared links implementing High Speed Downlink Packet Access (HSDPA). At the MAC layer, HSDPA implements, among other mechanisms, opportunistic scheduling, typically through the use of the Proportional Fair Scheduling (PFS) algorithm.

The service rate of a class-(k) data call in such a system is given by:

$$\mu^{j,k}(x) = \frac{\psi^k (C - \sum_{k=1}^{K} x^{v,k} \phi^{v,k})^k G(x^d)}{\mid x^d \mid}$$

where ψ^k is an attenuation factor related to radio conditions of class-k users, C is the overall system capacity, $\phi^{v,k}$ is the share of resources for voice users out of the total resources and $G(.)$ is the scheduling gain [13].

In IEEE802.11 WLAN, the MAC layer is based on CSMA/CA, and all flows, voice and data, are subject to competition. Voice frames are however severely affected by aggressive data sources as the latter are typically saturated ones, i.e., always with a frame to send. The share of voice and data users in this case is a nonlinear function of the number of users of each type in the system and is explicitly given in References [14] and [15].

The overall system can be described by a Markov process. It is however irreversible which makes product form expressions for the steady-state distribution impossible. As proposed in [16], we consider a quasi-stationary regime, where data calls would reach steady states between voice calls arrivals and departures. Accordingly, the marginal distribution of voice calls in the system is given by an M/M/c/c queueing system with steady state distribution of the number of ongoing voice calls given by [17]:

$$\pi(x^v) = \frac{1}{G} \prod_{k=1}^{K} q^k(x^{v,k}) \quad (5)$$

where

$$q^k(x^{v,k}) = \begin{cases} \frac{\left(\frac{\lambda^{v,k}+h^{v,k}}{\mu^{v,k}}\right)^{x^{v,k}}}{x^{v,k}!} & \text{if } x^{v,k} \leq T^{v,k} \\ \frac{\left(\frac{\lambda^{v,k}+h^{v,k}}{\mu^{v,k}}\right)^{T^{v,k}} \left(\frac{h^{v,k}}{\mu^{v,k}}\right)^{x^{v,k}-T^{v,k}}}{x^{v,k}!} & \text{if } T^{v,k} < x^{v,k} \leq H^{v,k} \end{cases}$$

and

$$G = \sum_{x^v \in \mathbb{X}^v} \prod_{k=1}^{K} q^k(x^{v,k})$$

is the normalization constant. $\mathbb{X}^v$ is the state space of voice users for which QoS is guaranteed on the packet level, $T^{v,k}$ is the threshold value above which no new voice arrival is admitted and $H^{v,k}$ is the threshold value above which no voice call in handover is admitted.

As of data, it can be modeled as an M/G/1-Processor Sharing (PS) queue with steady-state probabilities given by:

$$\pi(x^d \mid x^v) = \frac{1}{H} \prod_{k=1}^{K} f^k(x^{d,k}) \quad (6)$$

where

$$f^k(x^{d,k} \mid x^v) = \begin{cases} \frac{\left(\frac{\lambda^{d,k}+h^{d,k}}{\mu^{d,k}(x)}\right)^{x^{d,k}}}{x^{d,k}!} & \text{if } x^{d,k} \leq T^{d,k} \\ \frac{\left(\frac{\lambda^{d,k}+h^{d,k}}{\mu^{d,k}(x)}\right)^{T^{d,k}} \left(\frac{h^{d,k}}{\mu^{d,k}(x)}\right)^{x^{d,k}-T^{d,k}}}{x^{d,k}!} & \text{if } T^{d,k} < x^{d,k} \leq H^{d,k} \end{cases}$$

where H is the normalization constant obtained by setting the sum of all joint probabilities to one, $T^{d,k}$ and $H^{d,k}$ are defined similarly to $T^{v,k}$ and $H^{v,k}$.

These joint steady-state probabilities $\pi(x^v, x^d)$ are given by:

$$\pi(x^v, x^d) = \pi(x^d \mid x^v) \cdot \pi(x^v) \quad (7)$$

Now, the performance measures are given as follows.

The blocking probabilities of a class-k fresh arrival voice or data user is given by:

$$B^{j,k} = \sum_{x^{-(j,k)}} \sum_{x^{j,k}=T^{j,k}}^{H^{j,k}} \pi(x^{-(j,k)}, x^{j,k})$$

and for calls in handover

$$B_h^{j,k} = \sum_{x^{-(j,k)}} \pi(x^{-(j,k)}, H^{j,k})$$

The mean file transfer time W^k of a class-k data call is given by the a phase-2 type distribution taking into account the service received in both subsystems in case of a handover. The sojourn time S in each subsystem is given by the minimum between the dwell time V in the subsystem and W ($\frac{1}{S} = \frac{1}{V} + \frac{1}{W}$) [18]:

$$S^k = \frac{\bar{x}^{d,k}}{\lambda^{d,k}(1 - B^{d,k}) + h^{d,k}(1 - B_h^{d,k})}$$

where $\bar{x}^{d,k}$ is the mean number of data flows of class$-k$ in the subnetwork.

6 Conclusion

We presented in this work a framework for modeling the relationships between users, operators as well as the relationship between them in a heterogeneous environments where several wireless networks share the access of some Internet cloud. We covered the cases of cooperative optimization and non-cooperative games between the different players as these cases arise in real.

Our new step shall be devoted to the numeric analysis of such strategies in an attempt to quantify network-oriented issues, such as what the best options for voice and data users are, whether it is better for network operators to cooperate or not and do users interest correspond to the network's one.

References

1. 3GPP TS 25.855 High Speed Downlink Packet Access (HSDPA); Overall UTRAN description.
2. 3GPP TS 25.856 High Speed Downlink Packet Access (HSDPA); Layer 2 and 3 aspects.
3. IEEE standard for information technology- telecommunications and information exchange between systems- local and metropolitan area networks- specific requirements Part II: wireless LAN medium access control (MAC) and physical layer (PHY) specifications.
4. Drew Fudenberg, Jean Tirole. Game Theory. 1991.
5. T. Basar, G. J. Olsder, Dynamic Noncooperative Game Theory, Academic Press, London/New York, January 1995.
6. E. Altman, T. Boulogne, R. El Azouzi, T. Jimenez and L. Wynter , A survey on networking games , Computers and Operations Research, 2004.
7. T. Alpcan, T. Basar, R. Srikant, and E. Altman, "CDMA uplink power control as a noncooperative game," Wireless Networks, vol. 8, pp. 659–669, November 2002.
8. Y. A. Korilis, A. A. Lazar, and A. Orda, Capacity allocation under non-cooperative routing, IEEE Transactions on Automatic Control, 42(3):309-325, March 1997.
9. E. Altman, R. El-Azouzi, and V. Abramov, Non-Cooperative Routing in Loss Networks, Performance Evaluation 49(1–4), 43-55, 2002.

10. Yannis A. Korilis, Aurel A. Lazar, and Ariel Orda, ”Achieving network optima using Stackelberg routing strategies,” IEEE/ACM Transactions on Networking, vol. 5, no. 1, pp. 161–173, 1997.
11. Z. Dziong, L. G. Mason, Fair-efficient call admission control policies for broadband networks: a game theoretic framework, IEEE Trans. on Net., February 1996.
12. J. Ni, D. H. K. Tsang, S. Tatikonda, B. Bensaou, Threshold and reservation based call admission control policies for multiservice resource-sharing systems, Infocom’2005.
13. T. Chahed, M. Dirani, Cross-layer modeling of capacity of UMTS/HSDPA networks under a dynamic user setting, VTC-Fall, Montreal, September 2006.
14. M. Dirani, T. Chahed, A MAC/flow level modeling of data and voice intergation in WLANs, Globecom’2006, December 2006.
15. N. Hegde, A. Proutiere, J. Roberts, Evaluating the voice capacity of 802.11 WLAN under distributed control, IEEE LANMAN 2005.
16. N. Benameur, S. Ben Fredj, F. Delcoigne, S. Oueslati-Boulahia and J.W. Roberts, Integrated Admission Control for Streaming and Elastic Traffic, QofIS 2001, Coimbra, September 2001.
17. K. W. Ross, Multiservice Loss Networks for Broadband Telecommunications Networks, Springer-Verlag, 1995.
18. S-E. Elayoubi, T. Chahed, G. Hbuterne, Mobility-aware admission control schemes in the downlink of third generation wireless systems, to appear, IEEE Transactions on Vehicular Technology, January 2007.