Abstract

The Third Wireless Network Generation includes two kinds of mobility. The micro and the macro-mobility. In this environment as it is a best-effort service no quality of service is guarantee. To ensure the quality of service, a new protocol MIR (Mobile IP Reservation) is developed [1] that takes into account the user mobility and provides a quality of service to the user. To show the benefit of the protocol, we do in this study the performance evaluation. Thus, in this study, we propose to compute bound on dropping handover by building a bounding model with smaller state space size, which is easier to solve than the original one. We compute the considered performance measure on the bounding model using an analytic method. We prove, using stochastic comparison, that the bounding model provides an upper bound for the dropping handover. To show, the quality of these bounds, we have made a numerical resolution for the bounding model since it is simpler to solve whereas for the original model we have made simulation by using a new approach based on the multi-agent structure.

Key words : Wireless networks, Mobility, Quality of Service, Performance evaluation, Stochastic method, Upper bound

1 Introduction

The third Wireless Network Generation including IMT2000 and UMTS take into account data at high throughput in the air interface. W-CDMA is also used to maximize the bandwidth utilization and to reduce the interference. The introduction of IP in the third wireless network as Mobile IP for the Macro-Mobility and Cellular IP for Micro-Mobility is also taken into account. These new protocols introduced new needs particularly in term of Quality of Service where the goal of these systems is to reach a QoS that allows us to include services as multimedia or video in the air interface. The major problems in wireless environment is the poverty bandwidth in the air interface, the signal attenuation, frequency allocation, interference, reliability, security, throughput and mobility. Performance evaluation of this kind of network is difficult because we take into account a lot of parameters such as the cell number, buffer size for data, connection voice number in a cell, handover, etc .... Thus, the mathematical model associated to this network is hard to solve by a numerical method due to the explosion of the state-space of Markov chain.

In this study, we propose to study a performance evaluation of this kind of networks. In this performance evaluation, we focus on the dropping handover as it is one of the most QoS indicators in this type of environment. To do this, we develop an analytic model that models the component of the MIR protocol [1]. The originality of our approach is based on an upper bound on dropping handover computed on a bounding model with smaller state-space size, which is easier to solve than the original one.

This paper is organized as follows. In section 2, we describe the considered model of wireless network. In section 3, we present in details the bounding model and we give the proof using the stochastic comparison that it provides an upper bound for performance measures. Finally, in section 4, we present numerical results that show that the bounding model gives a good results. Last section summarized the main contribution of this study.

2 The Analytic Model

We consider a model in which the users move along an arbitrary topology of K cells (see figure 1). Each cell has the same capacity of N channels. Each channel can be used by voice or data packets. If data packet arrives and all the channels are occupied, the data is stored in the buffer that has a limited capacity B. If the buffer is full, the data is lost. If the voice arrive and all the channels are occupied, the voice is lost (see figure 2). When a voice uses a channel, it uses it until the connection is finish or a handover happens but if an application arrives, it is decomposed into packets and when a channel is free, only one packet has a service and not all the application is served.

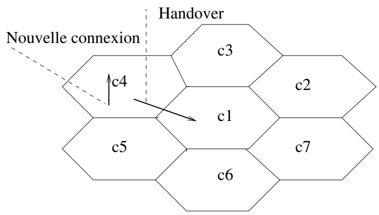

FIG. 1 – *The considered Network*

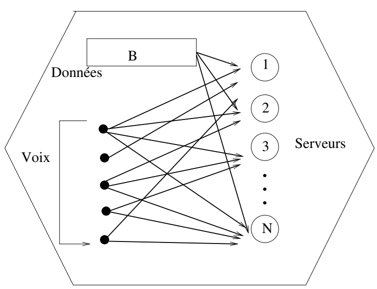

FIG. 2 – *Cell i of the network*

We suppose according to studies in [10] [8], the arrivals of voice connection follow a Poisson process with rate λ_{v_i}. The distribution of the communication time for voice is assumed to be an exponential distribution with rate μ_{v_i} and the rate that a user will leave the network is $\mu^*_{v_i}$. The arrivals of handoff voice from cell j to cell i follow a Poisson process with rate $\gamma_{v_{ji}}$. The total rate of departure from cell i is given by:

$$\mu_{v_i} = \mu^*_{v_i} + \sum_{j=1,j\neq i}^{K} \gamma_{v_{ij}}$$

Thus, a user will move from cell i to cell j with probability $\gamma_{v_{ij}}/\mu_{v_i}$.

The arrivals of data packet connection follow a Poisson process with rate λ_{d_i}. The distribution of the communication time for data is assumed to be an exponential distribution with rate μ_{d_i}.

The considered model can be described by a Markov chain in continuous time. To describe this chain, we define, the state $e^{\rightarrow}$ by

$(j_1,k_{d_1},k_{v_1},j_2,k_{d_2},k_{v_2}....,j_K,k_{d_K},k_{v_K})$, where:

- j_i is the number of data packets in the buffer in the cell i,
- k_{d_i} is the number of occupied channels by the data in the cell i,
- k_{v_i} is the number of occupied channels by the voice in the cell i.

We have $0 \leq k_{d_i} + k_{v_i} \leq N$.

Thus, $e^{\rightarrow}$ constitutes Markov chain of $[(B+1)*(N+1)*(N+2)/2]^K$ size states.

We denote by $\pi(e^{\rightarrow})$ its steady state probabilities.

If we just take for different parameters the following values $K = 5$, $N = 9$ and $B = 9$, the size of the Markov chain is upper than 10^{13} states. We can remark how the resolution of this model is very difficult.

We give now the equilibrium equations but before, we define some functions:

The function α allows to test if there is a free channel in cell i

$$\alpha(i) = \begin{cases} 1 & \text{if } (k_{v_i} + k_{d_i}) < N \\ 0 & \text{else} \end{cases}$$

The function β allows to test if there is a free channel or if the buffer is not full in cell i.

$$\beta(i) = \begin{cases} 1 & \text{if } (k_{v_i} + k_{d_i} < N) \;\; or \;\; j_i < B \\ 0 & \text{else} \end{cases}$$

The function ω allows to test that all the channels are occupied but the buffer is not full.

$$\omega(i) = \begin{cases} 1 & \text{if } (k_{v_i} + k_{d_i} = N) \;\; and \;\; j_i < B \\ 0 & \text{else} \end{cases}$$

The function φ tests if at least one channel is occupied by voice where the function ε tests if at least one channel is occupied by data.

$$\varphi(i) = \begin{cases} 1 & \text{if } k_{v_i} > 0 \\ 0 & \text{else} \end{cases}$$

$$\varepsilon(i) = \begin{cases} 1 & \text{if } k_{d_i} > 0 \\ 0 & \text{else} \end{cases}$$

The function $\theta(i)$ tests if the buffer is empty.

$$\theta(i) = \begin{cases} 1 & \text{if } j_i = 0 \\ 0 & \text{else} \end{cases}$$

Now, we give the equilibrium equations that allow us to understand the behavior of the studied model: We remmerber that:

- λ_{v_i} is the rate of new call arrivals
- λ_{d_i} is the rate of new data packets arrivals
- $\mu^*_{v_i}$ is the rate of departure of call completion
- μ_{d_i} is the rate of departure of data packet
- $\gamma_{v_{ji}}$ is the rate of handover from cell j to cell i

The equilibrium equations are:

$$\pi(j_1,k_{d_1},k_{v_1},...,j_K,k_{d_K},k_{v_K}) * [\sum_{i=1}^{K} \lambda_{v_i}\alpha(i) +$$

$$\sum_{i=1}^{K}(k_{v_i}\mu^*_{v_i} + k_{v_i}\gamma_{v_{ij}})\varphi(i) +$$

$$\sum_{i=1}^{K}\lambda_{d_i}\beta(i) + \sum_{i=1}^{K} k_{d_i}\mu_{d_i}\varepsilon(i)]$$

$$= \sum_{i=1}^{K}\lambda_{v_i}\varphi(i)\pi(j_1,k_{d_1},k_{v_1},...,j_i,k_{d_i},k_{v_i} - 1,...) +$$

$$\sum_{i=1}^{K} \lambda_{d_i}\alpha(i)\theta(i)\pi(j_1,k_{d_1},k_{v_1},...,j_i,k_{d_i}-1,k_{v_i},...)+$$

$$\sum_{i=1}^{K} \lambda_{d_i}\omega(i)\pi(j_1,k_{d_1},k_{v_1},...,j_i-1,k_{d_i},k_{v_i},...)+$$

$$\sum_{i=1}^{K} \alpha(i) \sum_{l=1,l\neq i}^{K} k_{v_l}\varphi(l)\gamma_{li}\pi(j_1,k_{d_1},k_{v_1},...,j_l,k_{d_l},k_{v_l}+1,...,j_i,k_{d_i},k_{v_i}-1,...)+$$

$$\sum_{i=1}^{K} k_{d_i}\mu_{d_i}\varepsilon(i)\theta(i)\pi(j_1,k_{d_1},k_{v_1},...,j_i,k_{d_i}+1,k_{v_i},...)+$$

$$\sum_{i=1}^{K} k_{d_i}\mu_{d_i}\varepsilon(i)\pi(j_1,k_{d_1},k_{v_1},...,j_i+1,k_{d_i},k_{v_i},...)+$$

$$\sum_{i=1}^{K} k_{v_i}\mu^*_{v_i}\varphi(i)\pi(j_1,k_{d_1},k_{v_1},...,j_i+1,k_{d_i},k_{v_i},...)+$$

$$\sum_{i=1}^{K} k_{v_i}\mu^*_{v_i}\varphi(i)\theta(i)\pi(j_1,k_{d_1},k_{v_1},...,j_i,k_{d_i},k_{v_i}+1,...)$$

3 Bounding Model, Stochastic Bounds and Proof

3.1 Bounding model

We consider in the original model a topology of K cells. We have shown in the previous section how the numerical solving of the original model is very difficult, and for the moment quite impossible. The bounding model, that is easier to evaluate, provides upper bound on the considered performance measures. To build this bounding model, we simplify the original system by deleting the input buffer in the K cells, and we replace them by sources [3]. An equivalent view is that these buffers are never empty. The bounding model is given in figure 3. The resolution of the bounding system will be easier since we do not consider the evolution of the cell numbers at these input buffers.

3.2 Stochastic ordering

In this section, we give only the basic definitions and theorems of the strong (sample-path) ordering that will be used in this paper. We refer to the book of Stoyan [11] for an excellent survey of stochastic bounding techniques applied in queuing theory.

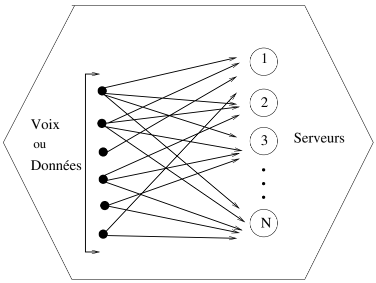

FIG. 3 – *A cell i from the bounding model*

First, let us give the definition of the sample path stochastic comparison of two random variables X and Y defined on a totally ordered space ε, (a subset of R or N), since it is the most intuitive one.

Definition 1 *X is said to be less than Y in the sense of the sample-path (strong) ordering ($X \leq_{st} Y$) if and only if*

$$X \leq_{st} Y \Leftrightarrow Prob(X > a) \leq Prob(Y > a), \quad \forall a \in \varepsilon.$$

In other words, we compare the probability distribution functions of X and Y: it is more probable for Y to take larger values than for X. Moreover, $X =_{st} Y$ means that X and Y have the same distribution.

The generic definition of a stochastic order is given by means of a class of functions. The strong stochastic ordering is associated with the increasing functions. We now give the generic definition in the general case: the random variables are defined on a space ε, endowed with a relation order $\preceq$ (pre-order or partial order):

Definition 2

$$X \preceq_{st} Y \Leftrightarrow Ef(X) \leq Ef(Y)$$

for every function $f : \varepsilon \rightarrow R$ $\preceq$-increasing, whenever the expectations exist.

f is $\preceq$-increasing if and only if, $\forall x,y \in \varepsilon, \quad x \preceq y \rightarrow f(x) \leq f(y)$.

We state only the sample-path properties of the strong stochastic ordering that will be applied to demonstrate the existence of stochastic comparison.

Theorem 1 *$X \preceq_{st} Y$, if and only if there exist random variables $\bar{X}$, $\bar{Y}$ defined on the same space, $\bar{X}$ and X have same distribution and such that:*

– *$\bar{X} =_{st} X$ and $\bar{Y} =_{st} Y$*

– $\bar{X} \preceq \bar{Y}$ *almost surely* $\quad (Prob(\bar{X} \preceq \bar{Y}) = 1)$.

In this work, we find bounding model on a reduced state space, thus the state space of the considered system and the bounding one are not the same. Therefore we compare them on a common state space. To do this, we first project the underlying spaces into this common one, and then compare the images on this space. This type of comparison is called *comparison of images or comparison of state functions* [2]. In the sequel, since our main goal is to compare Markov chains, we assume that the considered state spaces are discrete.

Definition 3 *Let X (resp. Y) be a random variable that takes values on a discrete, countable space E (resp., F), and G is a discrete, countable state space endowed with a pre-order $\preceq$; $\alpha : E \rightarrow G$ (resp., $\beta : F \rightarrow G$) be a many-to-one mapping. The image of X on G is less in the sense of $\preceq_{st}$ than the image of Y on G if and only if*

$$\alpha(X) \ \preceq_{st} \ \beta(Y).$$

The comparison of the images may be defined more intuitively by representing the projection applications by matrices. Let M_α, M_β denote the matrices representing the underlying mappings, and the probability vectors p, q represent, the random variables X, Y respectively. If

$$M_\alpha[i,j], \ i \in E \ \text{ and } \ j \in G = \begin{cases} 1 & \text{if } \alpha(i) = j \\ 0 & \text{otherwise} \end{cases}$$

then

$$\alpha(X) \preceq_{st} \beta(Y) \Leftrightarrow p\ M_\alpha \preceq_{st} q\ M_\beta. \tag{1}$$

Let us now assume that the state space comparison G be $\{1, \ldots n\}$; then, the comparison of images (equation 1) is defined by partial sums:

$$\forall i, \sum_{k=i}^{n} \ \sum_{j=1}^{n} p[j] \times M_\alpha[j,k] \ \leq \ \sum_{k=i}^{n} \ \sum_{j=1}^{n} q[j] \times M_\beta[j,k]$$

Obviously, the stochastic comparison of random variables is extended to the comparison of stochastic processes. There are two definitions; one of them corresponds to the comparison of one-dimensional increasing functional, while the other is the comparison of the multidimensional functional. We give both definitions in the context of Markov chains; nevertheless, they are more general. Let $\{X(t), t \in T\}$ and $\{Y(t), t \in T\}$ be two

Markov chains with discrete state space ε (time parameter space may be discrete $T = N^+$, or continuous $T = R^+$).

Definition 4 *$\{X(t), t \in T\}$ is said to be less than $\{Y(t), t \in T\}$ with respect to $\preceq_{st}$ ($\{X(t)\} \preceq_{st} \{Y(t)\}$) if and only if*

$$X(t) \preceq_{st} Y(t), \qquad \forall t \in T$$

that is equivalent to

$$E(f(X(t)) \leq E(f(Y(t)), \quad \forall t \in T$$

for every $\preceq$-increasing functional f, whenever the expectations exist.

3.3 Proof

In this section, we prove that the bounding model gives an upper bound on the voice dropping handover. To do this, we have used stochastic method that is based on the stochastic comparison [7] [5] [11].

First, we define the state space of comparison ε and the pre-order $\preceq$ defined on this space.

We define state by $s = (k_{d_1},k_{v_1},k_{d_2},k_{v_2},...,k_{d_K},k_{v_K})$, where: for $1 \leq i \leq K$

$$\begin{cases} k_{d_i} & \text{number of channels occupied by the data} \\ k_{v_i} & \text{number of channels occupied by the voice} \end{cases}$$

with $0 \leq k_{d_i} \leq N$ and $0 \leq k_{v_i} \leq N$.

Thus, the comparison space is:

$$\varepsilon = 0, \ldots, N \times 0, ldots, N \times .... \times 0, ldots, N$$

where $\times$ is the Cartesian product. The size of this space is $(N + 1)^K$.

Now, we defined the pre-order $\preceq$ on ε that we are going to use for our comparison:

Let $x = (x_{d_1},x_{v_1},x_{d_2},x_{v_2},...,x_{d_K},x_{v_K})$ and

$y = (y_{d_1},y_{v_1},y_{d_2},y_{v_2},...,y_{d_K},y_{v_K}) \in \varepsilon$ such that:

$$\begin{cases} x \preceq y & if\ x_{d_1} \leq y_{d_1},...,x_{d_K} \leq y_{d_K} \\ x = y & if\ x_{d_1} = y_{d_1},...,x_{d_K} = y_{d_K}\ and\ x_{v_1} = y_{v_1},...,x_{v_K} = y_{v_K} \end{cases}$$

This pre-order has been chosen for the comparison of the considered performance measure, i.e., the voice dropping handover.

Intuitively, if x, y are two states such $x \preceq y$, we can say that in state x, the number of lost voices will be less than or equal to, the number of lost voices at state y because in state y, we have more channels occupied by data than in state x. So, when a voice handover arrives in state x, it can find a free channel; however, in state y, this channel can be occupied by data because the priority of the voice in the original model is lost in the bounding one.

We have defined a comparison space and a pre-order on this state space. Now, we are going to compare the images of the considered models, i.e., original and bounding models on ε using the pre-order $\preceq_{st}$.

Let $s(t)_t$ be the Markov chain of the original model and $s^{sup}(t)_t$ the Markov chain of the bounding model. The comparison of Markov chains is defined to be as a conservation of stochastic ordering on initial distributions at each step. We have to prove the stochastic ordering relations between the chain images defined by:

$$\alpha(s(t)_t) \preceq_{st} \beta(s^{sup}(t)_t) \forall t \geq 0$$

with α and β projection applications on this space ε.

We now give an outline of the proof:

1. Step 1: To build the bounding model, we have simplify the original model by deleting the buffers in each cell and replacing them by sources. An equivalent view is to consider that these buffers are never empty. The resolution of the bounding model will be easier since we do not consider the evolution of the buffers in all the cells.

   $$if \;\; x_{d_i}(0) \leq x_{d_i}^{sup}(0) \Longrightarrow x_{d_i}(t) \leq x_{d_i}^{sup}(t), \forall t$$

   In the bounding model, when a data arrive, it takes the first channel which is free. Thus, we lost the priority between the voice and the data. So, we can say that we have most channels occupied by data in the bounding model than in the original one.
2. Step 2: The stochastic ordering $\preceq_{st}$ between the images follows as a consequence from the first step. Moreover, if there are steady-state distributions of the chains,

   $$\alpha(\Pi) \preceq_{st} \beta(\Pi^{sup})$$

   where Π is a steady-state distribution.
3. Step 3: We have to prove the inequalities between the rewards on the steady-state distributions of the chains:

   $$R \leq R^{sup}$$

   For this step, we use the following definition of $\preceq_{st}$ ordering:

   $$X \preceq_{st} Y \Leftrightarrow E(f(X)) \leq E(f(Y))$$

$\forall f : increasing\ function.$
The function R for the cell 1 is given by:

$$R = \sum_{s/k_{v_1}+k_{d_1}=N} \sum_{j=2}^{K} \pi(s)\gamma_{v_1} p_{j1}$$

The function R that corresponds to the dropping handover voice is an increasing function. So, this step is proved.

In the next section, we give the simulation results of the original and the bounding models by using multi-agent method.

4 Simulation Model Based on Agent Mobile and Results

It is not worth noting that previous work on multi-agent methods has been proposed [6] [9] to solve the problem of path allocation in fixed networks. In our case, we propose a multi-agent method for wireless networks. To evaluate the model, we propose a multi-agent structure composed of two types of agents: station-agents and user-agents (see figure 4). A station-agent is associated to each cell of the network. This agent manages the input and output user flows. To each user corresponds one agent that is called user-agent. The user moves from one cell to another one due to the information exchanges between station-agents and user-agents. Connections of the user-agents to the network are managed by the station-agents that may accept or refuse them in their cells.

User-agents and station-agents communicate by exchanging messages which contain information on: requests for voice or data connection, handover to a cell, acceptation or refusal connection, etc.

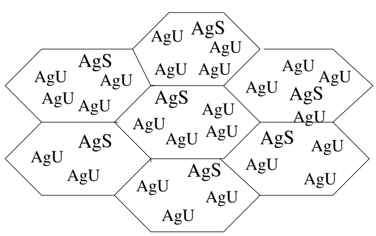

FIG. 4 – *User-agents and station-agents in the model*

When a user-agent asks for a connection, the station-agent can accept, refuse or temporize this request according to the type of desired connection and the number of users that are already connected. The station-agent confirms its decision to the user-agent by sending a message. When the user-agent receives the acceptation of the connection, it can communicate in the cell controlled by the station-agent, during its communication in this cell.

When the user-agent finishes its communication, it sends a disconnect message to the station-agent that updates the available resources. If the user-agent moves during its communication, it needs to change its current cell. Thus, it sends a request message for a handover. If the neighboring station-agent accepts the handover, the user-agent moves to the this new cell and it disconnects from the current cell. The station-agents give higher priority to the handover than new connection.

When all the resources of the cell are used, the station-agent temporizes the user-agents, asking for a new connection, during a certain period waiting for available resources (see figure 5).

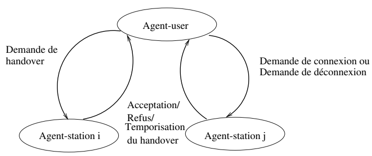

FIG. 5 – *User-agents and station-agents interactions*

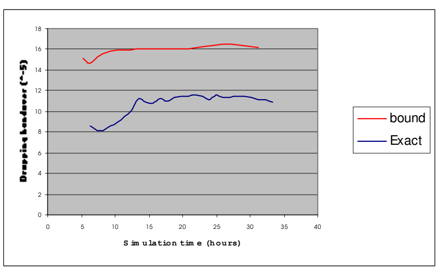

FIG. 6 – *Dropping handover at 1 Mb/s*

In figures 6 and 7, we plot the dropping handover for different time of simulation. We have considered a model with $K = 7$ cells and each cell has $N = 20$ channels. We plot in figure 6 the dropping handover in a cell with new voice call evry 10 secondes and a data packet throughput at a 1Mb/s. In figure 7 we consider that we have a new voice call evry 10s with a data packet throughput at 1,5 Mb/s. We can see at first that the dropping handover of the original (Exact) model is upper bounded by dropping handover of our bounding model. We can see that this dropping handover is under 10^{-4}, this value is under the tolerate threshold (i.e., 10^{-2}).

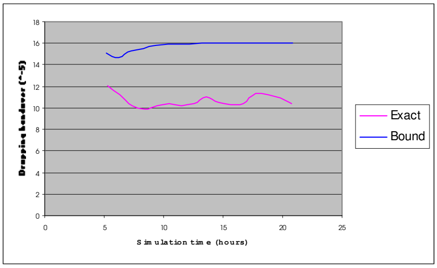

FIG. 7 – *Dropping handover at 1.5 Mb/s*

5 Conclusion

In this study, we have proposed a method based on stochastic comparaisons for performance evaluation of third generation wireless networks. The problems with this kind of networks is the size of the state- space which prevents numerical solutions. Thus, we propose a bounding model with a reduced state-space. We compute the performance measures on the bounding model. We give the proof using stochastic method that the performance measures on the bounding model are bounds on the performance measures of the original model. In order to show the quality of the bounds, we have simulated the two models using multi-agent method. The results show the quality of the upper bound. In future work, we will propose to use a multi-agent negotiation model in order to reduce the dropping handover.

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