

*Consiglio Nazionale delle Ricerche*



**WiQoS-M: An Integrated QoS-Aware Mobility  
and User Behavior Model for Wireless Data  
Networks**

G. Resta, P. Santi

IIT TR-11/2006  
**Technical report**

**Novembre 2006**



**Istituto di Informatica e Telematica**

# WiQoS-M: An Integrated QoS-Aware Mobility and User Behavior Model for Wireless Data Networks\*

Giovanni Resta<sup>†</sup>      Paolo Santi<sup>†</sup>

## Abstract

Modeling mobility and user behavior is of fundamental importance in testing the performance of protocols for wireless data networks. While several models have been proposed in the literature, none of them can at the same time capture important features such as geographical mobility, user generated traffic, and wireless technology at hand. When collectively considered, these three aspects determine the user-perceived QoS-level, which, in turn, might have an influence on mobility of those users (we call them QoS-driven users) who do not display constrained mobility patterns, but they can decide to move to less congested areas of the network in case their perceived QoS-level becomes unacceptable.

In this paper, we introduce the WiQoS-M model which collectively considers all the above mentioned aspects of wireless data networks. WiQoS-M is composed of *i*) a user mobility model, *ii*) a user traffic model, *iii*) a wireless technology model, and *iv*) a QoS model. Components *i*), *ii*), and *iii*) provide input to the QoS model, which, in turn, can influence the mobility behavior of QoS-driven users. WiQoS-M is very simple to use and configure, and can be used to generate user and traffic traces at the APs composing a wireless data network.

Based on WiQoS-M, we perform an extensive simulation-based analysis of network usage under different combinations of network parameters, which discloses interesting insights

---

\*A preliminary version of this paper appeared in Proc. ACM/IEEE International Symposium on Modeling, Analysis and Simulation of Wireless and Mobile Systems (MSWiM), 2006.

<sup>†</sup>Istituto di Informatica e Telematica del CNR, Pisa, ITALY. email:{giovanni.resta, paolo.santi}@iit.cnr.it

and shows that WiQoS, despite its simplicity, is able to capture important properties observed in real-world network deployments.

**Index terms:** Mobility modeling, user behavior modeling, QoS-driven mobility, wireless data networks.

## 1 Introduction

Thanks to the increasing popularity of 802.11-based products, wireless data networks have become widespread in recent years: medium- to large-scale WLAN deployments are nowadays common in campuses, enterprises, and so on, and also public areas such as airports, shopping malls, and parks, are becoming increasingly covered by wireless access points (APs). The proliferation of wireless data networks is expected to increase even further when the recently introduced wireless Mesh technology will become mature [7].

In order to fulfill the promise of ubiquitous connectivity, forthcoming wireless data networks must face several challenges, including the design of appropriate congestion control mechanisms and interference mitigation protocols, whose performance should be carefully optimized depending on the scenario at hand. Given the high costs of on-the-field testing, simulation is often the preferred option to test the performance of network protocols.

There are several factors that influence performance of a wireless data network, including infrastructure (number and location of the APs), number of active users, their mobility and traffic patterns, the wireless technology at hand, and so on. This implies that, in order to obtain an accurate estimation of the performance of a certain protocol for wireless data networks, none of these aspects should in principle be neglected at the simulation stage. Furthermore, a mobility and user behavior model should be relatively simple, while at the same time general enough to allow the simulation of a wide range of network settings.

Despite the considerable amount of research devoted to mobility and user behavior modeling in recent years, to the best of our knowledge none of the models introduced in the literature so far considers all the above mentioned aspects at the same time. On one hand, we have synthetic models aimed at resembling user registration patterns observed in a certain real-world deployment (e.g., the Dartmouth college [13, 19, 20], or the ETH Zurich campus [26]). While

these models allow some flexibility in the choice of some parameters, such as number of users and APs, they do not consider user traffic patterns. Most importantly, these models are tailored to a very specific network deployment, and cannot be used to test the performance of wireless data network protocols in different scenarios. On the other hand, we have ‘general purpose’ random models that typically account for only one of the above mentioned aspects influencing wireless data network protocols performance. For instance, we have separate synthetic models for user mobility (such as the well-known random waypoint model [15]), traffic pattern, radio channel characteristics, and so on. However, these models (especially for what concerns mobility) are often considered too general, and not representative of any real-world scenario.

In light of the above, the need of more realistic, yet simple, mobility and user behavior models for testing the performance of wireless data network protocols, which is mentioned in [3] as one of the challenges related to the realization of ubiquitous wireless connectivity, has not been satisfied yet. In this paper, we make a first step in this direction introducing WiQoS, an integrated mobility, user behavior, and wireless technology model which can be used in the performance evaluation of wireless data network protocols.

A salient and novel feature of WiQoS is that it allows mimicking a situation in which a fraction of users displays constrained movement patterns (e.g., because they have to move to a certain specific location within a certain time), while the remaining users are mainly stationary, but they could decide to move to another location in case their perceived QoS degrades considerably. In the remainder of this paper, we call users of the former type *mobile users*, and users of the latter type *QoS-driven users*. We believe distinguishing users into mobile and QoS-driven is representative of many WLAN or wireless Mesh deployments in public areas such as airports, parks, shopping malls, and so on, as acknowledged also in [2, 24]. For instance, consider the case of a public park. In this situation, a fraction of users might be seated somewhere in the park, using their wireless devices to browse the Web, sending emails, downloading music files to listen with the iPod, and so on. For this class of users, what is relevant is the perceived QoS: as long as the QoS is satisfactory, there is no reason to move to another location. However, if the QoS degrades below an acceptable level, a typical user of this class may decide to look for a better location in the park, becoming stationary again when the perceived QoS is restored to an adequate level. It is not difficult to imagine similar scenarios

in other environments such as airports, shopping malls, campuses, and so on.

WiQoS is composed of four components: a mobility model, a user traffic model, a wireless technology model, and a QoS model. The mobility model implements weighted random waypoint mobility, where the next waypoint is chosen according to an AP popularity metric. The fact that different APs in a wireless data network display very different popularity degrees (i.e., number of registered users) has been recently observed in different types of wireless data networks [4, 17, 25]. As such, we believe accounting for the popularity degree when choosing the next waypoint contributes to improving the accuracy of our model. To model user traffic behavior, we classify users into three classes depending on the amount of load offered to the network. Note that this classification of users based on the offered load is (in principle) orthogonal to their classification into mobile or QoS-driven. The third fundamental building block of WiQoS is the wireless technology model, which is in turn composed of a channel access and a radio propagation model. Currently, we have implemented two channel access methods (data polling and time polling), and two radio propagation models (free space and log-normal shadowing), but other models can be easily integrated in our framework. The mobility, user traffic, and wireless technology models provide input to the QoS model, which estimates the degree of satisfaction for each user in the network according to a simple criteria. If a user is QoS-driven, he/she can decide to change its AP association and/or physical location depending on the perceived QoS-level. The block diagram of our WiQoS model is reported in Figure 1.

WiQoS generates user and traffic traces which can be easily fed to custom simulators used to evaluate the performance of a specific wireless data network protocol. We believe using WiQoS-generated traces can considerably improve the accuracy of wireless data network protocols' performance estimation, in contrast to the current habit of using purely random approaches (e.g., the traffic observed at an AP is generated uniformly at random between an upper and lower bound).

Another interesting feature of WiQoS is that the generated traces are accompanied by a set of metrics such as balance index, user prevalence and persistence in AP association, average data delivery rate, and so on, that can be used to assess relevant features of the generated traces. For instance, the network designer might be interested in testing the performance of a certain congestion relief protocol under different degrees of unbalancing of the observed load.

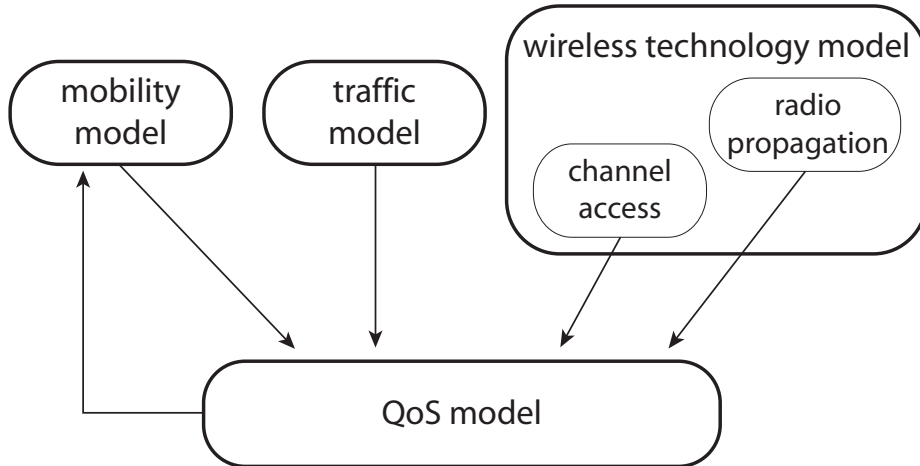


Figure 1: Block diagram of the WiQoS model.

By appropriately tuning WiQoS input parameters, the designer can assess the average degree of unbalancing of the generated traces through the balance index, and feeds the ones with the desired degree of unbalancing to the custom simulator used to test the performance of the designed protocol.

As a concrete example of WiQoS utilization, we perform an extensive simulation-based analysis of network usage under a wide range of different conditions in terms of number of users, number of deployed APs, percentage of QoS-driven users, and wireless technology. The main findings of our analysis are that the presence of QoS-driven users can significantly increase the QoS-level in the network (especially when combined with the time polling channel access method), and that, in order to avoid resource wastage, network designers should carefully consider both the channel access method and the estimated fraction of QoS-driven users before deploying additional (possibly scarcely utilized) resources. Most importantly, our analysis shows that, despite its simplicity, WiQoS is able to reproduce an important phenomenon which has been observed in real-world network deployments, i.e. the loose correlation between the number of registered users and the load observed at the APs.

The rest of this paper is organized as follows. In Section 2, we survey related work and discuss the main contributions of this paper. In Section 3, we introduce the WiQoS mobility

and user behavior model, and in Section 4 we describe how WiQoS can be used to generate user/traffic traces for wireless data networks. In Section 5 we use WiQoS to perform an extensive simulation-based analysis of network usage under different settings. Finally, Section 6 concludes and discusses possible ways of extending/improving our model.

## 2 Related work and contribution

The characterization of user behavior in wireless data networks has been subject of intensive research in recent years. By analyzing user traces collected at the various access points in campuses [16, 17], corporate buildings [4], or conferences [1], typical user behaviors have been analyzed, and phenomena such as different popularity levels of the APs, occasional network congestion, low correlation between the number of users and load, and so on, have been observed. More recently, some authors have derived synthetic models of user behavior which try to mimic the observed user behavior in a certain environment. This is the case, for instance, of the ModelT model proposed in [13], which is based on the traces collected from the Dartmouth College campus over a period of 2 years. This model has been recently extended to account for spatio-temporal correlation in the user registration patterns [20]. Other examples of synthetic mobility models based on real-world traces are proposed in [19, 26]. While allowing the network designer to have a certain degree of freedom in setting some network parameters such as number of users and access points, synthetic models based on real-world traces have the disadvantage of being representative of a very specific scenario (the one from which the traces were collected). Furthermore, these models are built to capture the characteristics of existing or past wireless networks, and it is not clear to what extent these models are representative of future wireless network deployments.

Another related active area of research in recent years is the analysis of existing ‘general purpose’ synthetic mobility models, such as the random waypoint and the random direction model, which, mostly due to their simplicity, are the most commonly used in the simulation of wireless ad hoc network protocols. Recent studies have characterized the long term node behavior in these types of mobile networks [5, 18, 21, 23, 27, 28], outlining some undesired phenomena such as node concentration in the center of the deployment region [5], and long term decay

of the average nodal speed [27]. These phenomena could impair the accuracy of simulations based on these synthetic mobility models, essentially because the initial network conditions can be very different from the long term network conditions. Another acknowledged weakness of random waypoint/direction -like mobility is that it is too general, and not representative of any real-world scenario. In order to address some of the criticisms raised against random waypoint/direction mobility, some authors have recently proposed more realistic and/or more accurate synthetic mobility models, such as the obstacle model proposed in [14], and those proposed in [6, 12, 22, 28]. For a survey on mobility models for wireless ad hoc networks the reader is referred to [8].

Despite the considerable amount of research efforts referred above, to the best of our knowledge none of the existing synthetic models of user behavior in wireless networks jointly considers the three aspects that influence performance of wireless data network protocols, i.e., *i*) geographical user mobility, *ii*) user traffic patterns, and *iii*) wireless technology at hand. Furthermore, none of the existing models accounts for the fundamental observation that a fraction of users might not display constrained movement patterns, but they could decide to move to a better location in case their perceived QoS level drops below an acceptable level. We want to remark that the fact that some users might be willing to move to another location to improve their QoS has already been observed in [24], and explicitly suggested as a method to alleviate congestion in [2]. In the latter paper, the authors introduce the concept of network-directed roaming, which can be briefly explained as follows: if the required QoS cannot be guaranteed to a certain user, the network itself indicates to the user where to roam in order to obtain the desired level of service. This technique, combined with explicit channel switching, is shown to considerably improve load balancing in the network.

The main contribution of this paper is the proposal of an integrated QoS-aware mobility and user behavior model that jointly considers *i*), *ii*), and *iii*) above. The need of estimating the degree of user satisfaction complicates a lot the model definition, since aspects such as user offered load and channel access method have to be carefully modeled. To keep the complexity of our proposed model to a reasonable level, we have decided to simplify the mobility part as much as possible, while at the same time accounting for relevant aspects such as degree of AP popularity. This explains our choice of modeling user movements according to the well-known



RWP model, suitably modified to choose the waypoints according to an AP popularity metric.

As a concrete example of WiQoS utilization, we also present an extensive analysis of network usage under different scenarios. Note that, differently from [2], in this paper we are not proposing any explicit congestion relief technique. Instead, motivated by previous work showing the beneficial effect of QoS-driven users on load balancing [2], our aim is to carefully investigate the effects on network congestion of having a *fraction* of QoS-driven users. This outlines another major difference with respect to [2], in which it is implicitly assumed that *all* the users are QoS-driven. We believe that in most real world scenarios only a fraction of the users can be classified as QoS-driven, while other users display a constrained movement pattern. Another difference with respect to [2] is that we are not assuming network-directed roaming, in which a users decide to move after an explicit roaming message sent by the network manager. Instead, in our model we assume that it is the user himself, based on the perceived QoS level, who decides when to start moving, and the destination of the movement.

In order to achieve our goal of investigating the effect of QoS-driven mobility on network congestion, we consider a wide range of parameter settings, including not only the relative fraction of QoS-driven users, but also the number of users, the number of APs, the channel access method, and so on. To the best of our knowledge, this is the first such study presented in the literature.

### 3 WiQoS

In this Section we introduce our mobility and user behavior model, which we call WiQoS (Wireless QoS-aware Mobility). The model is composed of four main components: mobility modeling, user traffic modeling, wireless technology modeling, and QoS modeling (recall Figure 1). We describe each of these components in a separate subsection.

#### 3.1 Mobility model

As mentioned in the previous sections, in WiQoS we assume that a certain fraction  $f$ , with  $0 \leq f \leq 1$ , of the  $n$  network users is QoS-driven, while the remaining  $(1 - f) \cdot n$  users display constrained movement patterns.

Movement of QoS-driven users obeys the following rules. Users in this class are mostly stationary, i.e. they are not willing to move unless their perceived QoS level drops below an acceptable threshold. The determination of whether a certain QoS level is acceptable for the user is left to the QoS model (see Section 3.4).

Since we assume that QoS-driven users are ‘lazy’, and that the only reason forcing them to move is low QoS level, in our model we assume that an unsatisfied QoS-driven user first tries to do a ‘virtual movement’ by simply changing AP association. Using the terminology introduced in [2], we call this action *channel switching*.

In case channel switching is possible, user  $u$  changes AP association, selecting the AP which provides him/her the best QoS. Estimating the QoS level achieved by surrounding APs is not immediate, since the user perceived QoS depends not only on the quality of the wireless channel connecting to the AP, but also on the load offered by the other users registered at that AP. Hence, estimating the QoS achieved by surrounding access points requires information exchange between the user and the APs, which might not be allowed or implemented in certain network deployments. For this reason, in WiQoS we simply assume that the user selects the AP to switch to based on the signal quality, preferring the AP with the best signal (and, consequently, data rate).

Note that in WiQoS we are assuming that a typical network user is essentially selfish, i.e., he/she tries to improve his/her own QoS level, without considering possible degradation of the QoS level of other users. An alternative is to assume that users are naturally willing to cooperate with each other in order to optimize network performance, as it is assumed, for instance, in [2]. However, cooperative user behavior is a reasonable assumption only in networks composed of ‘homogeneous’ users, such as corporate networks. On the other hand, networks deployed in public areas are likely to be used by very ‘heterogeneous’ users, and assuming spontaneous cooperation between users seems a bit optimistic. This explains our choice of assuming selfish user behavior, which can be considered as a sort of ‘worst-case’ behavior.

In case channel switching is not possible (because there is no overlapping of APs in the current user’s position, or because also the other AP is overloaded and QoS level remain low), an unsatisfied QoS-driven user decides to do a physical move. Again, there are many different options to model movement of an unsatisfied user. To keep the model simple, we assume

that unsatisfied QoS-driven users move according to the same rules governing the movement of mobile users, i.e. AP popularity weighted RWP movement (see below).

Let us now consider mobile users. In order to reduce the complexity of our model, we assume that mobile users follow a weighted waypoint mobility model similar to that proposed in [12]<sup>1</sup>. Mobile users alternate between pause times at waypoints and traveling periods between successive waypoints. Initially, a user is assigned a certain waypoint according to a weighted, non uniform distribution which resembles the different popularity of APs. The fact that APs in a wireless data network display different popularity degrees is well documented in the literature [1, 4, 17]. In our model, we initially assign each AP  $a$  with a popularity degree  $p(a) \in [0, 1]$  according to a probability distribution resembling a power law (as suggested in [13]). Alternatively, it is possible to manually specify popularity degrees (in the  $[0, 1]$  range) for each AP.

When selecting the initial or a new waypoint for a certain mobile user (or for an unsatisfied QoS-driven user), first an AP is selected with a probability proportional to its popularity, then a waypoint is selected uniformly at random within the coverage area of the selected AP. The pause time at waypoints is chosen according to a Poisson distribution with intensity  $\lambda_p$ . In order to avoid degenerate situations of excessively long or short pause times, we have imposed an upper and lower bound to the pause time at the waypoints. The trajectory between consecutive waypoints is linear, and the velocity is chosen uniformly at random in an interval  $[v_{min}, v_{max}]$ .

### 3.2 User traffic model

In WiQoS, users are divided into three different classes of offered load: *low*, *medium*, and *high* load. The lowest class of traffic accounts for users who are using the network for emailing, chatting, and light web browsing. The average bandwidth requirement of this class of users is a tunable parameter, but the actual bandwidth requirement is very variable, since users in

---

<sup>1</sup>We are aware that more realistic mobility models such as, for instance, the obstacle model of [14], could have been used in WiQoS. However, this would have increased a lot the complexity of the simulator and the simulation running time. For this reason, we have opted for a simple model such as random waypoint mobility, but enriched with ‘more realistic’ salient features such as weighted choice of waypoints according to AP popularity.

this class typically generate bursty traffic. In the study reported in Section 5, the average bandwidth requirement of this class of users is set to 64 Kb/sec.

The medium class of traffic accounts for users who are using the network for intensive web browsing, file downloading, audio streaming, and so on. The average user bandwidth requirement in this case is also a tunable parameter, and the generated traffic displays a more uniform pattern. To maintain the complexity of the simulator at a reasonable level, we assume users in this class generate UDP-like traffic. In the study reported in the following, we have set the average bandwidth requirement of medium users to 256 Kb/sec.

Finally, the highest class of traffic accounts for users who make an intensive use of the network, such as video streaming. The average user bandwidth requirement is again a tunable parameter. Similarly to the case of medium traffic, also high traffic users typically display a relatively uniform bandwidth usage. Hence, we assume UDP-like traffic for these users, with a rate which is set to 2 Mb/sec in the study reported in the following.

The allocation of users to the various traffic classes is performed according to a certain mix  $l, m, h$ , where  $l$  is the fraction of low traffic users,  $m$  is the fraction of medium traffic users, and  $h = 1 - (l + m)$  is the fraction of heavy traffic users. These fractions can be different for QoS-driven and mobile users.

### 3.3 Wireless technology model

The wireless technology model is composed of two sub-models: radio channel model and channel access model.

The radio channel model is as follows. For given user  $u$  and AP  $a$ , we estimate the quality of signal between  $u$  and  $a$  according to a radio propagation model. In the current version of the model, we have considered free-space and log-normal shadowing propagation, but other propagation models can easily be integrated into WiQoSM. The quality of signal is used to determine the achievable data rate between  $u$  and  $a$ , if  $u$  is actually within the coverage range of AP  $a$ . We have considered the eight possible data rates available in 802.11a, i.e. 6, 9, 12, 18, 24, 36, 48 and 54Mbs. The nominal radio range of an AP at the various data rates is set according to what reported in the data sheets of the CISCO Aironet 1240AG access point

Nominal (Mbs)	Actual (Mbs)
54	25
48	24
36	19.5
24	16
18	12.8
12	9.6
9	7.2
6	5.4

Table 1: Actual data rates achieved with 802.11a.

[9]. The nominal ranges are used in combination with the free space radio propagation model to determine the highest possible available data rate between  $u$  and  $a$ . In case of log-normal shadowing, the distance between  $u$  and  $a$  cannot be directly converted into a data rate value, due to the random component in the signal attenuation caused by shadowing. Hence, the geographical distance between  $u$  and  $a$  is converted into a ‘virtual distance’ accounting for the actual signal attenuation between  $u$  and  $a$ , and the highest available data rate is obtained by comparing this ‘virtual distance’ with the nominal radio ranges.

As mentioned in the Introduction, WiQoS implements two channel access methods: *data polling* and *time polling*. Data polling is similar to the 802.11 a/b/g MAC layer with PCF coordination: registered users are polled by the AP. In case a polled user  $u$  has a packet to send/receive to/from the AP  $a$ , the packet is sent at the highest possible data rate available between  $u$  and  $a$ . If a polled user has nothing to send/receive, the next registered user is polled, and so on. Note that, from a high level point of view, there is little difference between DCF and PCF coordination in 802.11, since DCF is designed to give the same long term probability of accessing the channel to contenders [11]. Hence, our data polling model is representative also of 802.11 a/b/g networks with DCF coordination.

In order to keep the complexity of simulation at a reasonable level, in WiQoS we have not implemented any exchange of control messages. However, we have accounted for the overhead caused by control message exchange and channel access time by using an actual data rate for sending packets which is significantly lower than the nominal data rate. In particular, we have used the actual data rates reported in Table 1, which are obtained from the measurements reported in [10].

The current implementation of the 802.11 a/b/g MAC layer is known to have major ineffi-

ciencies. In particular, both DCF and PCF access methods suffer when registered users have different data rates, because the slowest user reduces the throughput of the other users down to the value of the slowest user<sup>2</sup>. This performance anomaly, which has been observed in [11], is caused by the data polling approach, in which a user, once gained access to the channel, transmits a packet, independently of his/her data rate. Hence, the *time* allotted to each user can be very different, and slower users tend to use the channel for longer times, driving down the throughput of faster users.

The second access model used in WiQoS, time polling, solves this problem by assigning to each polled user a *time slot*, instead of whatever time is necessary to send a packet. With this approach, all the users gain access to the channel for an approximately equal share of time, and faster users can transmit more packets than slower ones. Time polling resembles the basic functioning of the 802.11e MAC extension for QoS support, which is in the final stage of standardization.

A final consideration about channel access in WiQoS is that we assume adjacent APs use different (orthogonal) channels, so that interference between users registered at adjacent APs is not an issue.

### 3.4 QoS model

To determine whether the QoS level is acceptable for a certain user  $u$ , we measure the number of buffer overflow/underflow (depending on whether we are sending or receiving packets) experienced by  $u$  during the last  $\Gamma$  seconds, where  $\Gamma$  is a tunable parameter which can be used to smooth temporary variations in the QoS level. The status of the buffer is checked every  $\gamma$  seconds, with  $\gamma \ll \Gamma$ , where a check is successful if there is no overflow/underflow, unsuccessful otherwise. If at least a fraction of  $rq(u)$  checks are successful, where  $rq(u)$  is a tunable parameter modelling the minimum QoS level that user  $u$  considers acceptable, then  $u$  is satisfied, otherwise it is unsatisfied.

Note that the degree of user satisfaction is evaluated for both mobile and QoS-driven users. In case the user is mobile, the experienced QoS level is simply tracked and returned as one of

---

<sup>2</sup>This is true under the assumption that all the registered users always have a packet to send in their queues.

the output parameters of the model. In case the user is QoS-driven, the experienced QoS level can influence user mobility (recall Section 3.1).

## 4 Using WiQoS

WiQoS is written in C++ under a Linux environment. This section describes how WiQoS can be used to generate user and traffic traces for wireless data networks.

### 4.1 Network deployment and user distribution

Two options are available for AP deployment: *guided random* and *manual*. In case of guided random deployment, a number  $m$  of APs is distributed in a square deployment region  $R$ , which is assumed to have a 1Km long side (this parameter can be arbitrarily set). APs are distributed according to a ‘guided uniform’ distribution, which is designed to provide at least a certain degree of coverage of the deployment region. More specifically,  $R$  is divided into 25 squares of side 200m, and approximately  $m/25$  APs are distributed uniformly at random in each square. If  $m$  is below 25,  $m$  squares are randomly selected in the deployment region, and one AP is distributed uniformly at random in each of the selected squares. Each deployed AP  $a$  is then assigned with a degree of popularity  $p(a) \in [0, 1]$ , which reflects its potential of attracting network users. The degree of popularity of APs is computed according to a probability distribution resembling a power law (see [13]). In case of manual deployment, both the location and the popularity degree (in the  $[0,1]$  interval) for each AP are provided as input parameters.

After AP deployment, a number  $n$  of users is distributed in the network according to the following rules. First, each user is assigned a mobility class (QoS-driven/mobile) and a traffic class (low/medium/high) according to the defined parameters  $f, l, m$ , and  $h$ . Then, he/she is assigned with an initial position by first randomly selecting an AP according to the popularity metric, and then choosing a position uniformly at random in a bounded vicinity (within the coverage area) of the selected AP. To model users joining/leaving the network, we assume that each user is randomly assigned an active/sleep state, where the active/sleep transition is governed by a Poisson law with parameter  $\lambda_a$ , and the sleep/active transition is governed by a

Poisson law with parameter  $\lambda_s$ . Hence,  $n$  must be intended as the maximum possible number of network users, and the actual number of users using the network at a given time is in general lower. In order to avoid degenerate situations of excessively long or short transition times, we have imposed an upper and lower bound to the active/sleep and sleep/active transition time.

Once all the input parameters has been set and network deployment has been done, WiQoS can be instructed to generate traffic traces for a certain period of simulated network time.

## 4.2 Performance metrics

An interesting feature of WiQoS is that the generated traces are accompanied by a set of metrics which can be useful to the network designer to assess some of their relevant features. The metrics computed by WiQoS are the following:

- *total network load (NL)*: total number of packets exchanged in the network during the simulated time interval.
- *data delivery rate*: we trace the average data delivery rate experienced by network users during the last log interval. The data delivery rate is defined as the ratio between the number of bytes correctly sent/received to the number of bytes offered to the network. We also compute the average data delivery rate experienced by network users during the entire simulated time interval.
- *balance index*: let  $L_i$  denote the load observed at the  $i$ -th AP. The balance index [2] is defined as

$$\beta = \frac{(\sum_{i=1}^m L_i)^2}{m \cdot \sum_{i=1}^m L_i^2} .$$

The balance index is used to measure the deviation in utilization of the different APs: if the load is equally divided amongst the APs, we have  $\beta = 1$ ; conversely, with highly unbalanced network load we have  $\beta \approx 1/m$ . Similarly to the data delivery rate, the balance index is averaged both in the log interval, and in the entire simulation time.

- *prevalence* and *persistence*: these metrics, which are used also in [4], model the mobility of users independently of the duration of simulation and of the amount of time a user



spends in the network. Prevalence of user  $u$ , denoted  $prev(u)$ , measures the overall fraction of time user  $u$  spends with the AP is registered with for a longer time. Prevalence accounts for the total registration time with a certain AP, and does not take into account the duration of each session with the given AP. To account for this, we consider also persistence, denoted  $pers(u)$ , which measures the average amount of time user  $u$  stays associated with an access point before being forced to move to another AP or leaving the network. We separately compute these metrics for QoS-driven and mobile users.

The many parameters used in WiQoS, and their setting in the network usage analysis reported in Section 5, are summarized in Table 2.

Parameter	Meaning	Values
$m$	number of APs	25, 30, 40, 50
	simulated time interval	14400 sec (4 hours)
$p(a)$	degree of popularity of AP $a$	chosen according to a power law (guided random) manually set (manual)
$n$	maximum number of users	100 – 800
$\lambda_a$	intensity of Poisson law governing active/sleep transition	5 min. (min) - 90 min. (avg) - 180 min. (max)
$\lambda_s$	intensity of Poisson law governing sleep/active transition	5 min. (min) - 20 min. (avg.) - 90 min. (max)
$rq(u)$	required QoS value for user $u$	0.90
$\Gamma$	window length to determine user satisfaction at current location	5 sec.
$\gamma$	buffer check interval	0.05 sec
$\lambda_p$	intensity of Poisson law governing pause times at waypoints	5 min. (min) - 60 min. (avg) - 120 min. (max)
$v_{min}, v_{max}$	min and max velocity of mobile users	$v_{min} = v_{max} = v = 1m/sec$
$f$	fraction of QoS-driven users	0, 0.125, 0.25, 0.5
$l, m, h$	relative fraction of low, medium, and high traffic users	0.33, 0.33, 0.33
$pathLoss$	radio propagation model	free space, log-normal shadowing
$packSize$	packet size (in the data polling model)	1Kb
$timeSlot$	time slot length (in the time polling model)	200 $\mu sec$
$NL$	total network load	
$DDR$	data delivery ratio	
$\beta$	balance index	
$prev_q(u)$	prevalence of QoS-driven user $u$	
$pers_q(u)$	persistence of QoS-driven user $u$	
$prev_m(u)$	prevalence of mobile user $u$	
$pers_m(u)$	persistence of mobile user $u$	

Table 2: Parameters used in the WiQoS model, and their setting in the network usage analysis of Section 5.

### 4.3 Input/output

A typical input file of the WiQoS model is reported in Figure 2. The user can specify the number of AP or, in case of manual deployment, the name of an ASCII file containing a set of

(*location, popularity degree*) pairs (one for each access point). The second row of the input file selects the channel access method, and the packet size (in case of data polling), or the time slot duration (in case of time polling). Then, the user can specify the (maximum) number of active users, and their relative subdivision into QoS-driven/mobile and in the three traffic classes. This subdivision is expressed through six numbers: the first group of three numbers corresponds to QoS-driven users with low/medium/high traffic, respectively; the second group of number has similar meaning for mobile users. For instance, if we set the traffic fractions as 121 233, we have  $1/12=8.3\%$  of QoS-driven users with low traffic and high traffic, and  $2/12=17\%$  of QoS-driven users with medium traffic, for a total of  $4/12=33\%$  QoS-driven users in the network. Similarly, we can obtain the relative fraction of mobile users and their subdivision into the three traffic classes. Next, the user can choose the average data rate for the three classes of traffic considered, the buffer size for users in the three classes of traffic, and the interval at which packets arrive in the buffer (the number of packets arriving in the buffer is determined by the data rate of the user's traffic class). The next parameter is the probability that a user is in sleep state at the beginning of the simulated time interval. The user can then specify the number of available data rates, their (actual) values, the corresponding theoretical transmitting radius assuming free space propagation, and the radio propagation model. We then have a set of parameters determining the average pause, sleep and awake time of a user, with lower and upper bounds which are used to avoid extremal values. Then, there is a group of parameters concerning the QoS model, i.e. the length of the window used to check QoS level, and the fraction of successful packet insertion/removal operations in the buffer which is considered acceptable by QoS-driven users. Finally, the user can set the log interval, the duration of the simulated time interval, and the random seed.

WiQoS produces three types of output traces, which are identified by suffix `*.alog`, `*.Tr`, and `*.log`, respectively.

`*.alog` traces (see Figure 3 for a sample) reports, for each log interval, a 3-tuple for each AP. The first value of the tuple is the number of registered users at the expiration of the last log interval. Then, we have the load (in Mb) observed at the AP in the last log interval, and the cumulated load (also in Mb) since the beginning of the simulation.

`*.Tr` traces give a finer view of what is happening in the network. A sample `*.Tr` trace

```

-----
# Number of APs or name of a file containing APs locations and popularity
25
# TimePolling = 0 DataPolling = 1 and duration (sec) or packet size (bytes) (0
# 0.2 / 1 1024 are default values)
0 0.2
# Number of users
300
# Qos-driven LMH and mobile LMH traffic class (fractions)
1 1 1 1 1 1
# The 3 data rates for the 3 class (L,M,H) (Kb/sec)
64 256 2048
# the 3 buffer size for the 3 class (Kb)
256 1024 8192
# data arrive step (sec)
0.05 0.05 0.05
# Probability of being initially sleepy
0.25
# Number of Data Rates
8
# Data rates (Mb/sec)
25
24
19.5
16
12.8
9.6
7.2
5.4
# Radii corresponding to data rates (m)
30
91
130
152
168
183
190
198
# Radio propagation (0 Free space, 1 LogNormal - if LogNormal, specify also path loss exponent and variance)
0
# Min and max user velocity (m/sec)
1 1
# Min ave max PauseTime (minutes)
5 60 180
# Min max sleep time (minutes)
5 20 90
#min max Awake time (minutes)
5 60 120
# qos window (sec)
10
# qos ratio (move if less than this value).
0.90
# log every seconds
60
# stop after seconds
300
# random seed (0 = time dependent)
0
-----

```

Figure 2: WiQoS input file.

```

-----
1 1 105 105 2 113 113 1 8 8 4 12806 12806 2 12692 12692
2 1 105 211 2 113 227 1 8 16 4 12816 25622 2 12702 25395
3 1 105 317 2 113 341 1 8 24 4 12817 38439 2 12702 38098
4 1 105 423 2 113 455 1 8 32 4 12816 51256 2 12702 50801
5 1 105 529 2 113 569 1 8 40 4 12817 64073 3 12702 63503
-----

```

Figure 3: Sample \*.alog trace. The first column reports the progressive log interval index. Then, we have a 3-tuple of each AP.

is reported in Figure 4. Initially, the trace reports a summary of the current model settings. Then, for each log interval, the following information are reported:

- Data delivery rate, during the last log interval and cumulated since the beginning of the simulation;
- Balance index, during the last log interval and cumulated since the beginning of the simulation;
- Prevalence and persistence of QoS-driven and of mobile users;
- Number of (active) QoS-driven users who are currently moving;
- Number of active users who are currently disconnected;
- Number of registered users at each access point;
- Number of users in sleep state;
- Total number of network users (disconnected+registered+sleep);
- Total number of (active) moving users, and their subdivision into QoS-driven and mobile users;
- Number of active QoS-driven users, and number of them who are satisfied;
- Number of active mobile users, and number of them who are satisfied.

```

-----
AP = 25
Channel access method is TimePolling
TimeSlot = 200 microsec
800 Users
qos LQ:MQ:HQ = 33 33 33
mob LM:MM:HM = 235 233 233
Users data classes: 64 256 2048
Buffers in Kb: 256 1024 8192
Data incr every 0.05 0.05 0.05 sec.
Initial prob. of sleep 0.25
8 datarates (nominal range):
25(30), 24(91), 19.5(130), 16(152), 12.8(168), 9.6(183), 7.2(190), 5.4(198),
PauseTime min ave max = 5 60 180
SleepTime min ave max = 5 20 90
WakeTime min ave max = 5 60 120
QosWindow 10 sec.
Qos Ratio 0.9
Log every 60 sec.
Stop after 14400 sec.
Random Seed 732761
Ok
APs init Ok
Users Init Ok
sleepy = 186

Sec. 60
DDR=19019/28292 (0.672255) cumDDR=19019/28292 (0.672255) Bal (act/cum)=0.387753 0.387753
qprev = 1 qpers = 15.8983 mprev = 0 mpers = 0 qosmoving 3 disc = 0
AP/users : 10 52 6 10 36 11 58 20 6 19 13 16 10 29 11 70 53 47 23 16 25 13 21 30 9
Sleep: 186 TotalUsers = 800 mov:3=3+0 qos/sat (76/73) mob/sat (538/415)

Sec. 120
DDR=19485/28315 (0.688153) cumDDR=38505/56608 (0.680207) Bal (act/cum)=0.383973 0.387422
qprev = 1 qpers = 15.8983 mprev = 0 mpers = 0 qosmoving 3 disc = 0
AP/users : 10 52 6 10 36 11 58 20 6 19 13 16 10 29 11 70 53 47 23 16 25 13 21 30 9
Sleep: 186 TotalUsers = 800 mov:3=3+0 qos/sat (76/73) mob/sat (538/409)
-----

```

Figure 4: Sample \*.Tr trace.

The \*.log trace is a spreadsheet friendly version of the \*.Tr trace, in which the raw data are reported without descriptions. Actually, the information reported in a \*.log trace is slightly different from the one reported in a \*.Tr. For each log interval, it is reported, in order: log interval progressive number, DDR, cumulated DDR, Balance index (current/cumulated), qprev, qpers, mprev, mpers, min and max number of registered users at an AP, QoS-driven users who are currently moving, number of users in sleep state, total number of registered users, number of QoS-driven users, number of satisfied QoS-driven users, number of mobile users, and number of satisfied mobile users. The \*.log trace corresponding to the \*.Tr trace reported in Figure 4 is reported in Figure 5.

```

-----
1 19019 28292 0.672255 19019 28292 0.672255 0.387753 0.387753 1 15.8983 0 0 6 70 3 186 614 76 73 538 415
2 19485 28315 0.688153 38505 56608 0.680207 0.383973 0.387422 1 15.8983 0 0 6 70 3 186 614 76 73 538 409
-----

```

Figure 5: Sample \*.log trace.

## 5 Analysis of network usage

In this section, we report an extensive study of network usage under different scenarios performed using our proposed WiQoS model.

### 5.1 Increasing number of users

In the first set of experiments, we have analyzed network usage as the number of APs is fixed to 25, and the maximum number of users increases from 100 to 800. We have considered both channel access methods, and different fractions of QoS-driven users. Radio channel propagation is free space. The other simulation parameters are summarized in Table 2. The purpose of these experiments is to investigate how network usage changes as the network becomes more and more saturated (the number of AP is fixed, and the number of users increases). Due to the relatively long simulation time<sup>3</sup> and the many different parameter settings used in our experiments, we have used a sample size of 10 simulation runs<sup>4</sup>.

Figure 6 reports the average data delivery rate at the end of the 14400 seconds of simulated time for increasing values of  $n$  and different values of  $f$ . As seen from the graphics, QoS-driven users have a beneficial effect on the DDR: as  $f$  varies from 0 to 0.5, the DDR value increases from 0.66 to 0.75 with data polling channel access and 800 users (14% increase), and from 0.69 to 0.83 in case of time polling (20% increase). Hence, time polling channel access has the potential of getting more benefits than data polling from having a fraction of QoS-driven users in the network. Concerning the relative performance of time polling vs. data polling access method, using time polling increases DDR of about 4% with respect to data polling with 800

<sup>3</sup>Depending on the channel access method (time polling is about twice as fast as data polling) and the machine, the simulation time of a single instance with 800 users varied between 24min. and 90min.

<sup>4</sup>We have verified in preliminary simulation runs that the variance is already acceptable with a sample size of 10 runs.

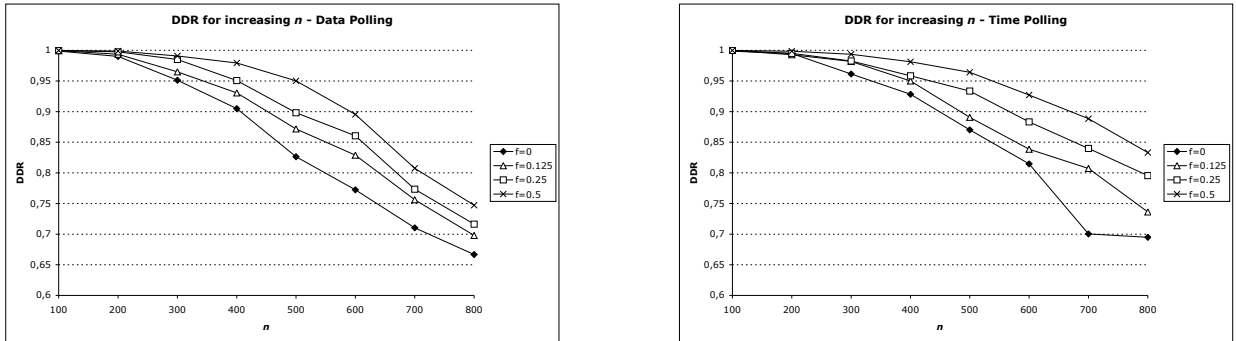


Figure 6: Data Delivery Rate for increasing values of  $n$  and different values of  $f$ . Channel access method is Data Polling (left) and Time polling (right). Free space radio channel propagation.

users when  $f = 0$ , and of about 12% when  $f = 0.5$ .

Similar trends can be observed for the total network load, which is reported in Figure 7. In this case, the performance increase of having a fraction 0.5 of QoS-driven users is 12% in case of data polling, and 19% in case of time polling (when  $n = 800$ ). Concerning the relative advantage of time polling over the data polling channel access method, it is about 4% when  $f = 0$ , and about 11% when  $f = 0.5$ .

The balance index at the end of the simulated time interval for increasing values of  $n$  and different values of  $f$  is reported in Figure 8. As seen from the plots, the major factor influencing  $\beta$  is the number of users  $n$ , while the channel access method and the fraction of QoS-driven users seem to have little influence on  $\beta$ .

The balance index shows a decreasing trend until  $n$  is 200/300, then it starts to increase with  $n$ . This behavior is displayed independently of the channel access method and of the fraction of QoS-driven users. A possible explanation for this behavior is the following. When the number of users is relatively low ( $n \leq 200$ ), the network is far from saturation, and the difference between the maximally and the minimally loaded AP (which clearly influence the value of  $\beta$ ) tends to increase with  $n$  (and, consequently, the balance index decreases). This can be understood by observing that, due to the different popularity degree of APs, the minimally loaded AP is likely to have close to zero load, and the maximally loaded AP is likely to have

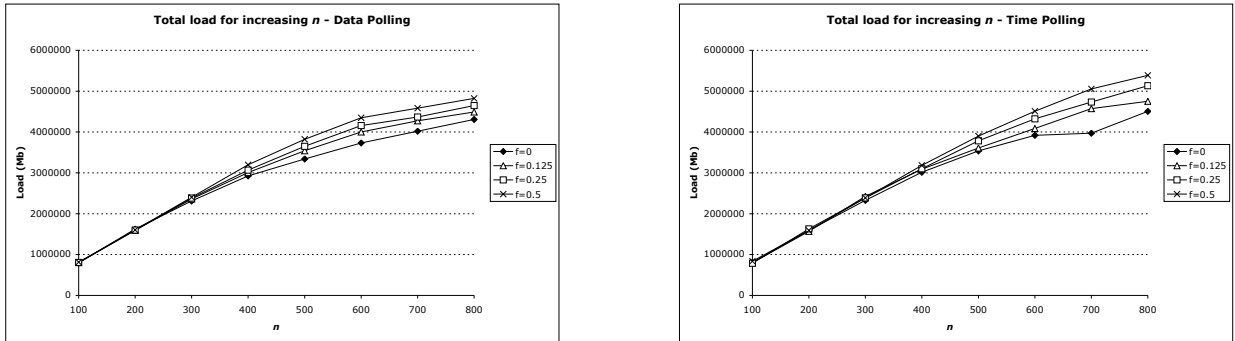


Figure 7: Total network load for increasing values of  $n$  and different values of  $f$ . Channel access method is Data Polling (left) and Time polling (right). Free space radio channel propagation.

a load which increases with  $n$ . However, when a relatively large number of users ( $n \geq 300$ ) is present in the network, the maximally loaded AP is likely to be close to saturation, while the minimally loaded AP is likely to observe an increasing load with  $n$ . Hence, the difference between the maximally and minimally loaded AP decreases (implying a higher value of  $\beta$ ) with  $n$  if  $n$  is sufficiently large.

It is also interesting to observe that when the network is in the “increasing  $\beta$ ” regime ( $n \geq 300$ ), the fraction of QoS-driven users present in the network begins to play a significant role. More in particular, when the network approaches saturation (this happens when  $n$  is about 500 in case of data polling channel access, and when  $n$  is about 600 in case of time polling), many QoS-driven users are likely to be unsatisfied, and begin to move (or perform channel switching) to increase their QoS level. Interestingly, as clearly seen from Figure 8, these “selfish” actions of QoS-driven users aimed at increasing their own level of satisfaction have a positive effect on network-wide load balancing.

Although referring to a quite different scenario, it is worth qualitatively discussing the results concerning the balance index obtained in our simulations and those reported in [2]. The simulation setting of [2] is the following: 100 users, 6 APs, data polling channel access scheme. The authors show that the balance index is increased of about 30% when the fraction of QoS-driven users increases from 0 to 1. We recall that in [2] unsatisfied QoS-driven users



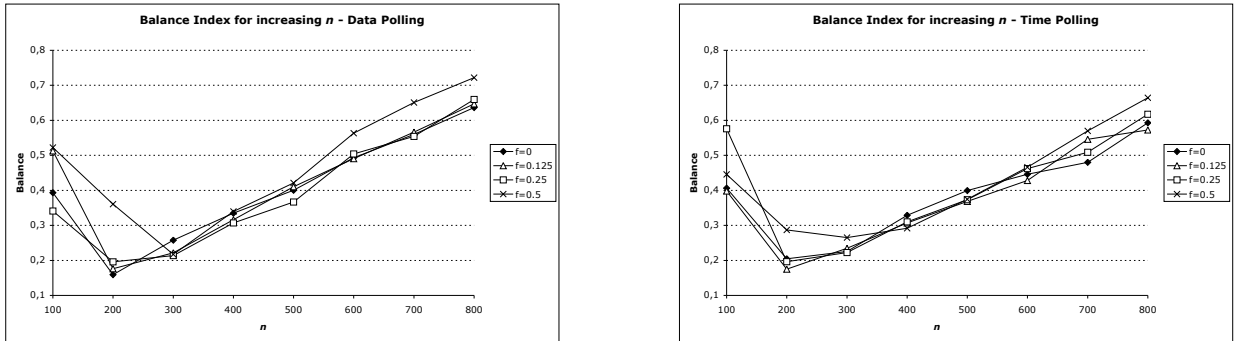


Figure 8: Balance index for increasing values of  $n$  and different values of  $f$ . Channel access method is Data Polling (left) and Time polling (right). Free space radio channel propagation.

are explicitly directed to another area of the network, so that network capacity is maximized (directed roaming). In our experiments, the fraction of QoS-driven users is at most 0.5 and, most importantly, QoS-driven users are not explicitly directed to ‘optimal’ network locations, but they instead move ‘at random’ (if channel switching is not possible), according to the popularity degree based RWP model described in Section 3.1. Nevertheless, when  $n = 800$  and channel access method is data polling, increasing the fraction of QoS-driven users from 0 to 0.5 results in a 14% improvement of the balance index (12% in case of time polling), which is about half of the improvement reported in [2] (which, however, referred to the case  $f = 1$ ). This seems to indicate that somewhat random movement of QoS-driven users is in principle sufficient to achieve significant load balance increase.

Figure 9 shows the prevalence and persistence of QoS-driven and mobile users for increasing values of  $n$  when the fraction of QoS-driven users is  $f = 0.5$ . Both prevalence and persistence of mobile users are not influenced by  $n$ , nor by the channel access method. This is reasonable, since the movement pattern of mobile users is not influenced by the perceived QoS-level, nor by the number of active users in the network. The situation is different for QoS-driven users, who decide to change AP association and/or to move when the perceived QoS level is not satisfactory. Hence, we can expect that both prevalence and persistence are proportional to the fraction of satisfied QoS-driven users in the network. This behavior can actually be observed in

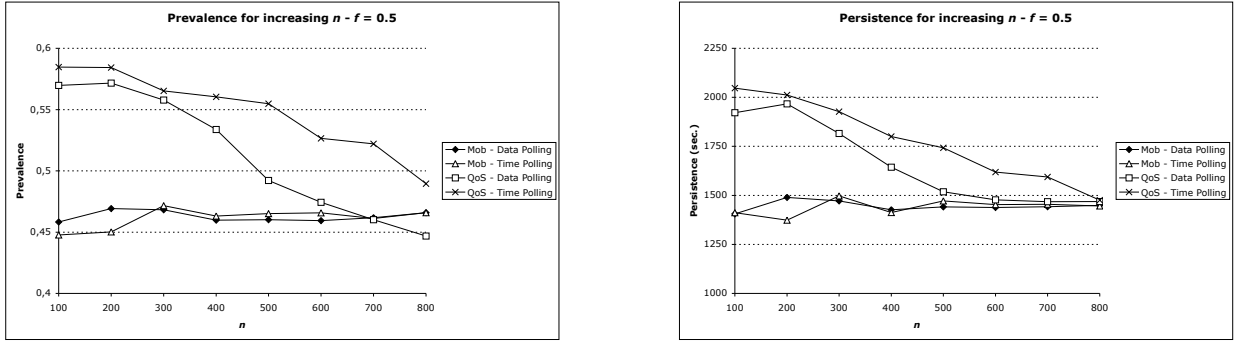


Figure 9: Prevalence (left) and persistence (right) for increasing values of  $n$  with  $f = 0.5$ . Free space radio channel propagation.

Figure 9: as  $n$  increases, the network load gets closer to the saturation point, and the fraction of unsatisfied QoS-driven users increases. As a consequence, both prevalence and persistence of QoS-driven users decrease with  $n$ . Comparing data polling with time polling channel access method, we observe a relatively higher prevalence and persistence with the time polling method, which reflects the fact that the average QoS level in the network is higher with time polling with respect to the case of data polling (see Figure 6).

In order to get a better understanding of the network usage evolution with time, we report the traces obtained from a single simulation run, referring to the following scenario:  $n = 800$ ,  $f = 0.5$ , time polling channel access method. Figure 10-left reports the load vs. time registered at the maximally loaded (max AP), minimally loaded (min AP), and ‘close to average’ AP (avg AP) at the beginning of the simulated time interval. The ‘close to average’ AP is chosen by first computing the average AP load at the beginning of the simulated time interval, and then selecting the AP whose load is closer (in absolute value) to the computed average. Figure 10-right reports the number of registered users vs. time for the same three APs. It is interesting to note that the load at the max AP changes a lot during the simulated time interval, and shows a decreasing trend. We believe this relatively unstable load observed at the max AP is due to the presence of QoS-driven users: when the load is very high, users becomes unsatisfied, and if a few of them are QoS-driven they decide to change AP association, causing a sudden decrease

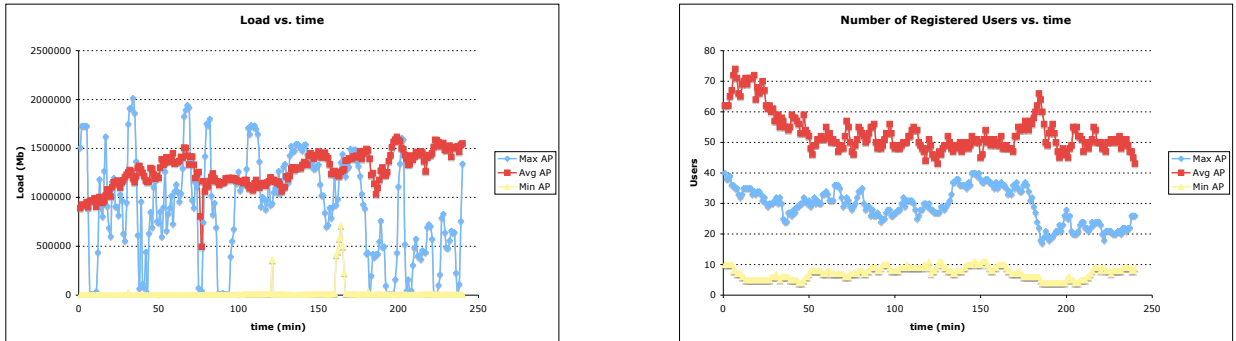


Figure 10: Total load (left) and number of registered users (right) at the maximally loaded, minimally loaded, and ‘close to average’ loaded access point, as a function of the simulated time. Parameter  $n$  is set to 800,  $f$  is 0.5, and channel access method is time polling.

of the max AP load. However, the max AP is likely to have a relatively high popularity degree, attracting a relatively high number of mobile and/or newly activated users. Thus, the load at the max AP tends to increase again, until saturation is reached again, and so on. On the other hand, the observed load at the avg AP is more stable, and shows a slightly increasing trend. Combining the fact that the load observed at the max AP shows a decreasing trend, and the load at the avg AP shows an increasing trend, we can conclude that load balancing is improved with respect to the initial network conditions. As mentioned above, this better load balancing at the end of the simulated time interval is due to the presence of QoS-driven users.

Another interesting observation is the relatively low correlation between the observed load at the AP (Figure 10-left) and the number of registered users at the same AP (Figure 10-right): while the number of registered users at the avg AP is consistently higher than that observed at the max AP<sup>5</sup> (62 vs. 40 at the beginning of the simulated time interval), the observed load at the max AP is often considerably higher than that observed at the avg AP. We want to remark that the fact that the load observed at the APs and number of registered users are only loosely correlated have been observed in several papers that have analyzed user traces collected from real-world network deployments [1, 4, 17, 25]. Thus, our WiQoS model is

<sup>5</sup>We recall that max and avg refers to the load, not to the number of users.

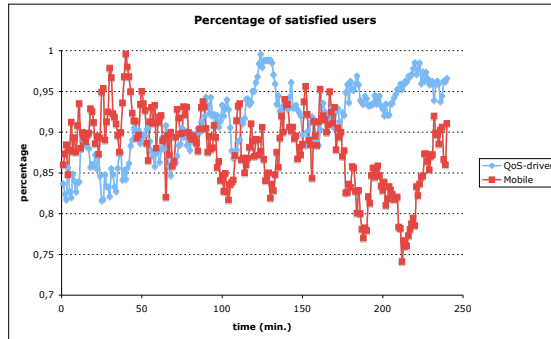


Figure 11: Fraction of QoS-driven and mobile satisfied users, as a function of the simulated time. Parameter  $n$  is set to 800,  $f$  is 0.5, and channel access method is time polling.

able to reproduce one of the most important behaviors observed in real-world deployments of wireless data networks, i.e. the low correlation between the number of registered users at an AP and the observed load at the AP.

Figure 11 reports the fraction of satisfied QoS-driven users over the total number of active QoS-driven users vs. time, and the same fraction vs. time relative to mobile users<sup>6</sup>, for the same simulation run as above. It is interesting to note that, while at the beginning of the simulated time interval QoS-driven users have approximately the same degree of satisfaction of mobile users, as time goes by QoS-driven users increase their degree of satisfaction, which becomes considerably higher than that observed by mobile users. This is a consequence of the fact that, contrary to mobile users, QoS-driven users change their behavior depending on the experienced QoS-level.

In order to investigate the effect of the radio propagation model on network usage, we have repeated the experiments (10 runs for each parameter setting) using the log-normal radio propagation model with path loss exponent equal to 2 and  $\sigma = 4$ .

The average data delivery rate for increasing values of  $n$  is reported in Figure 12. There are two notable differences with respect to the case of free space radio propagation: *i*) the benefit

---

<sup>6</sup>We recall that our simulator computes the perceived QoS level also for mobile users, although QoS has no influence on their behavior.

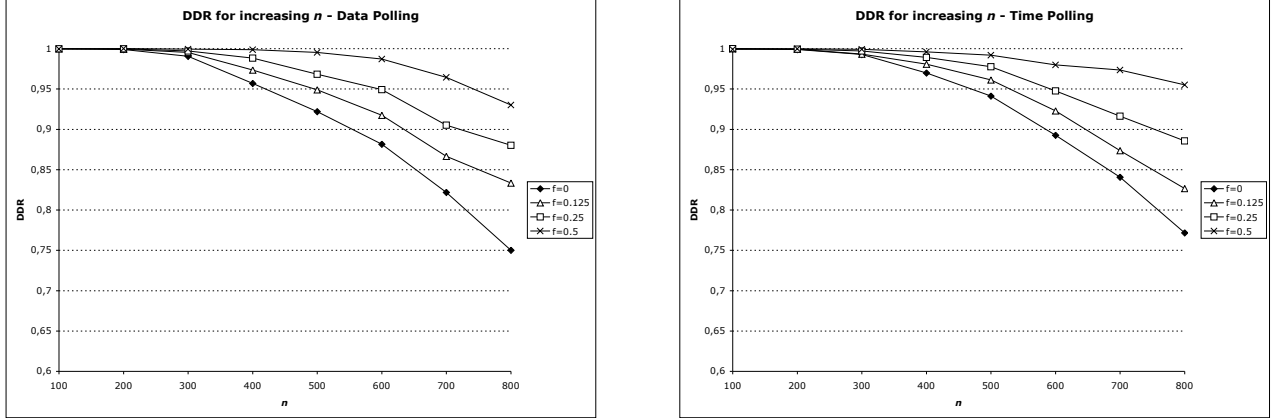


Figure 12: Data Delivery Rate for increasing values of  $n$  and different values of  $f$ . Channel access method is Data Polling (left) and Time Polling (right). Log-normal radio channel propagation.

of using time polling channel access is only marginal (about 2.6% DDR increase with respect to the case of data polling), and *ii*) QoS-driven users have a more beneficial effect on DDR with respect to the case of free space radio propagation (about 24% increase in DDR when  $n = 800$  and  $f = 0.5$  with respect to the case of  $f = 0$ , with both data and time polling channel access). Similar trends can be observed for the total network load.

The balance index for increasing values of  $n$  is reported in Figure 13. The trend is similar to the one observed with free space radio propagation: independently of the value of  $f$ ,  $\beta$  initially decreases with  $n$ , and, after reaching a minimum value around  $n = 300-400$ , it starts increasing again. With respect to the case of free space propagation, we observe relatively higher values of  $\beta$  for small values of  $n$ , and relatively lower values of  $\beta$  for large values of  $n$ .

## 5.2 Increasing AP density

In the second set of experiments, we have fixed the number  $n$  of users to 800, and considered four different values  $m$  of deployed AP (25, 30, 40, 50). The purpose of this second set of experiments is to investigate the effect of different AP deployment densities on network usage. Similarly to the results presented in the previous section, all the results presented in this section are averaged over 10 simulation runs. Radio channel propagation is free space.

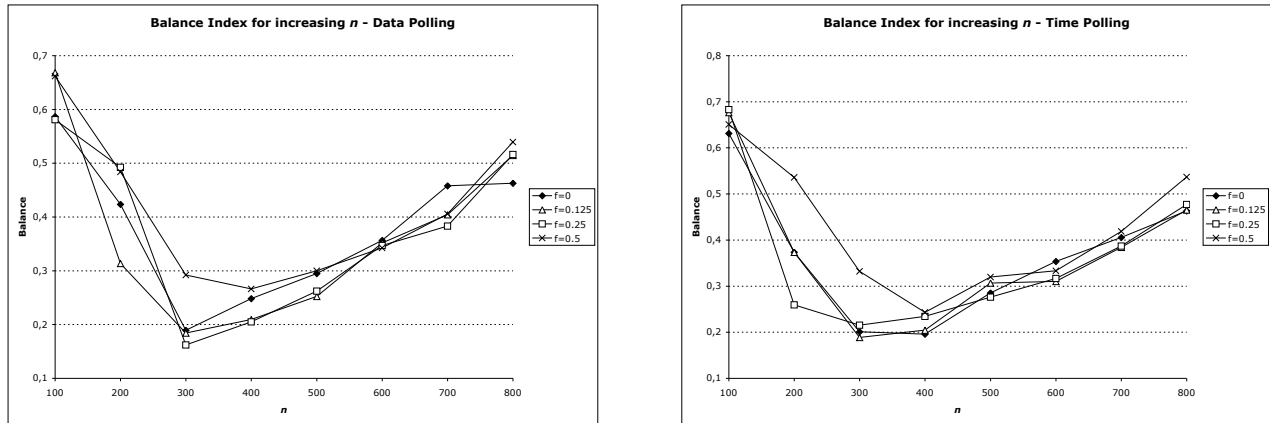


Figure 13: Balance index for increasing values of  $n$  and different values of  $f$ . Channel access method is Data Polling (left) and Time Polling (right). Log-normal radio channel propagation.

Figure 14 reports the average data delivery rate (left) and the total network load (right) for increasing AP deployment densities, and different values of  $f$ . It is interesting to note that a 100% increase in the number of deployed resources (50 instead of 25 APs) results at most in a 36% increase in both DDR and total network load when  $f = 0$  and the channel access method is data polling. The relative benefit of deploying more APs becomes lower as the fraction of QoS-driven users increases to 0.5, and the channel access method is time polling: when  $f = 0.5$  and channel access method is time polling, a 100% increase in deployed resources results in only a 18% increase in DDR and total network load.

The above described results have interesting implications on network planning, as they suggest that, in order to avoid resource wastage, network designers should carefully consider both the channel access method and the estimated number of QoS-driven users in the network before deploying additional, possibly scarcely utilized, network resources.

Figure 15 reports the balance index for increasing AP density and different values of  $f$ . We can observe a decreasing trend of  $\beta$  for increasing number of deployed APs, which can be explained as follows: as the number of AP increases and the number of users is fixed, QoS-driven users tend to become more and more satisfied, i.e. stationary. Hence, as a consequence of the different popularity degree of the APs, the relative difference between the maximally and

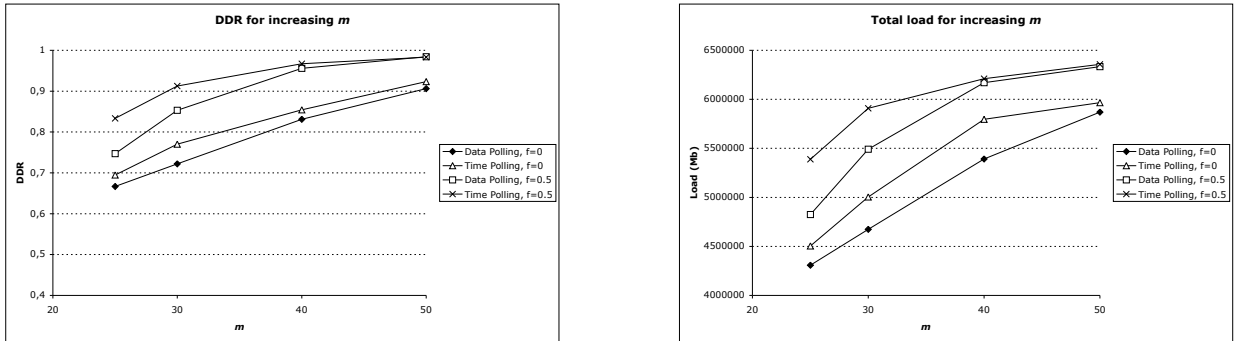


Figure 14: Data Delivery Rate (left) and total network load (right) for increasing density of AP deployment and different values of  $f$ .

minimally loaded AP becomes larger as  $m$  increases.

Finally, Figure 16 reports the prevalence (left) and persistence (right) of QoS-driven and mobile users as the number  $m$  of deployed AP increases. As expected, as  $m$  increases, both prevalence and persistence of QoS-driven users increases, since QoS-driven users tend to be more satisfied when the number of deployed APs increases. On the other hand, the movement and AP registration pattern of mobile users is not influenced by the average QoS level in the network. It is also worth noting that the time polling channel access method displays higher prevalence and persistence with respect to the data polling method, as a consequence of the fact that the average QoS-level in the network is higher with time polling channel access.

## 6 Conclusions

In this paper, we have introduced the first synthetic mobility and user behavior model which explicitly takes the degree of user satisfaction into account. In particular, in our WiQoS model a fraction  $f$  of the users is assumed to change AP association and/or to move in case the perceived QoS-level drops below an acceptable level.

Based on WiQoS, we have performed an extensive investigation of network usage under different conditions, which has disclosed interesting insights, and has shown that our model is

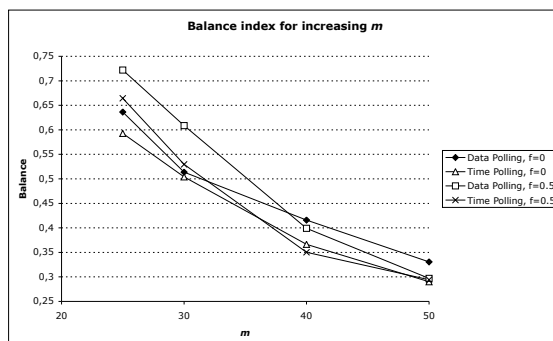


Figure 15: Balance index for increasing density of AP deployment and different values of  $f$ .

able to reproduce phenomena which have been observed in real-world deployments (different AP popularity degrees, low correlation between number of registered users and load observed at the APs). As such, we believe our model can be successfully used in the simulation of wireless data networks, such as public area WLAN and wireless Mesh deployments. In this respect, our model can be considered as a response to the need of more realistic, yet simple, mobility and user behavior models for wireless hotspots outlined in [3]. With respect to recent models such as those proposed in [13, 19, 20, 26], our model is more general and flexible, as several parameters such as number of users and APs, traffic mix, fraction of QoS-driven users, and wireless technology at hand can be easily modified.

WiQoS is intended to be an open source model which can be freely used by the wireless networking community in the simulation of wireless data networks. For this reason, the source code of the model, as well as a very simple user manual, is available on the web at the following URL: <http://www.iit.cnr.it/staff/giovanni.resta/WiQoS>. We encourage other researchers to extend and improve WiQoS in order to incorporate more accurate models of user mobility and/or traffic, other wireless technologies, different QoS models, and so on. In this sense, the model described in this paper must be intended as a starting point, rather than a complete and mature model for wireless data network simulation.

On our side, we are currently working on modeling bursty traffic for users belonging to the low load class. Furthermore, we are planning to use the traces generated by WiQoS to accu-



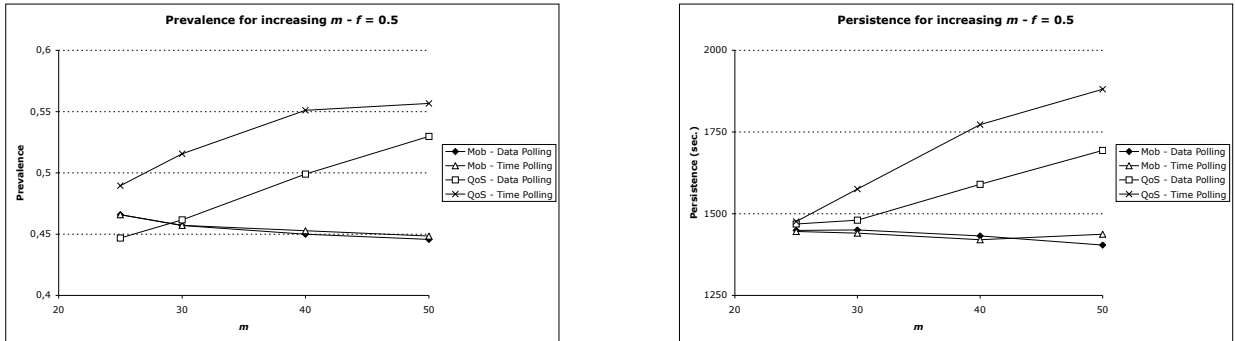


Figure 16: Prevalence (left) and persistence (right) for increasing density of AP deployment with  $f = 0.5$ .

rately investigate the performance of different WLAN and wireless Mesh networks protocols.

## 7 Acknowledgements

The authors wish to thank Mauro Leoncini for actively participating in many discussions in the early stage of WiQoS definition, and Doug Blough for reading a first draft of this paper, and giving several useful suggestions for improving our model.

## References

- [1] A. Balachandran, G.M. Voelker, P. Bahl, P. Venkat Rangan, “Characterizing User Behavior and Network Performance in a Public Wireless LAN”, *Proc. ACM Sigmetrics 02*, pp. 195–205, 2002.
- [2] A. Balachandran, P. Bahl, G.M. Voelker, “Hot-Spot Congestion Relief and User Service Guarantees in Public-Area Wireless Networks”, *Proc. IEEE Workshop on Mobile Computing System and Applications (WMCSA)*, 2002.
- [3] A. Balachandran, G.M. Voelker, P. Bahl, “Wireless Hotspots: Current Challenges and Future Directions”, *Mobile Networks and Applications*, Vol. 10, pp. 265–274, 2005.
- [4] M. Balazinska, P. Castro, “Characterizing Mobility and Network Usage in a Corporate Wireless Local-Area Network”, *Proc. ACM MobiSys 03*, pp. 303–316, 2003.

- [5] C. Bettstetter, G. Resta, P. Santi, “The Node Distribution of the Random Waypoint Mobility Model for Wireless Ad Hoc Networks”, *IEEE Trans. on Mobile Computing*, Vol. 2, n.3, pp. 257–269, July-Sept. 2003.
- [6] C. Bettstetter, “Smooth is Better than Sharp: A Random Mobility Model for Simulation of Wireless Networks”, in *Proc. ACM Intern. Workshop on Modeling, Analysis, and Simulation of Wireless and Mobile Systems (MSWiM)*, (Rome, Italy), pp. 19–27, July 2001.
- [7] R. Bruno, M. Conti, E. Gregori, “Mesh Networks: Commodity Multihop Ad Hoc Networks”, *IEEE Communications Magazine*, Vol. 43, n. 3, pp. 123–131, March 2005.
- [8] T. Camp, J. Boleng, V. Davies, “Mobility models for ad hoc network simulations”, *Wireless Communication & Mobile Computing (WCMC)*, special issue on mobile ad hoc networking, Wiley, 2002.
- [9] *Cisco Aironet 1240AG data sheets*, available at <http://www.cisco.com/en/US/products/hw/wireless>.
- [10] I. Haratcherev, J. Taal, K. Langendoen, R. Legendijk, H. Sips, “Automatic IEEE 802.11 Rate Control for Streaming Applications”, *Wireless Communications and Mobile Computing*, Vol. 5, pp. 421–437, 2005.
- [11] M. Heusse, F. Rousseau, G. Berger-Sabbatel, A. Duda, “Performance Anomaly of 802.11b”, *Proc. IEEE Infocom 03*, 2003.
- [12] W. Hsu, K. Merchant, H. Shu, C. Hsu, A. Helmy, “Preference-based Mobility Model and the Case for Congestion Relief in WLANs using Ad Hoc Networks”, *Proc. IEEE VTC 04*, 2004.
- [13] R. Jain, D. Lelescu, M. Balakrishnan, “Model T: and Empirical Model for User Registration Patterns in a Campus Wireless LAN”, *Proc. ACM Mobicom*, pp. 170–184, 2005.
- [14] A. Jardos, E. M. Belding-Royer, K. Almeroth, S. Suri, “Towards Realistic Mobility Models for Mobile Ad Hoc Networks”, *Proc. ACM MobiCom*, pp. 217–229, 2003.
- [15] D.B. Johnson, D.A. Maltz, “Dynamic Source Routing in Ad Hoc Wireless Networks”, *Mobile Computing*, Kluwer Academic Publishers, pp. 153–181, 1996.
- [16] M. Kim, D. Kotz, “Modeling Users’ Mobility among WiFi Access Points”, *Proc. WiTMeMo 05*, 2005.
- [17] D. Kotz, K. Essien, “Characterizing Usage of a Campus-Wide Wireless Network”, *Proc. ACM Mobicom*, pp. 107–118, 2002.
- [18] J.Y. LeBoudec, M. Vojnovic, “Perfect Simulation and Stationarity of a Class of Mobility Models”, *Proc. IEEE Infocom 05*, pp. 2743–2754, 2005.
- [19] J.K. Lee, J. Hou, “Modeling Steady-State and Transient Behaviors of User Mobility: Formulation, Analysis, and Application”, *Proc. ACM MobiHoc 06*, pp. 85–96, 2006.

- [20] D. Lelescu, U. Kozat, R. Jain, M. Balakrishnan, “Model T++: An Empirical Joint Space-Time Registration Model”, *Proc. ACM MobiHoc 06*, pp. 61–72, 2006.
- [21] M. McGuire, “Stationary Distributions of Random Walk Mobility Models for Wireless Ad Hoc Networks”, *Proc. ACM MobiHoc 05*, pp. 90–98, 2005.
- [22] M. Musolesi, S. Hailes, C. Mascolo, “An Ad Hoc Mobility Model Founded on Social Network Theory”, *Proc. ACM MSWiM 04*, pp. 20–24, 2004.
- [23] W. Navidi, T. Camp, “Stationary Distributions for the Random Waypoint Mobility Model”, *IEEE Transactions on Mobile Computing*, Vol. 3, n. 1, pp. 99–108, 2004.
- [24] M. Satyanarayanan, “Pervasive Computing: Vision and Challenges”, *IEEE Personal Communications*, Vol. 8, n. 4, pp. 10–17, August 2001.
- [25] D. Tang, M. Baker, “Analysis of a Local-Area Wireless Network”, *Proc. ACM Mobicom*, pp. 1–10, 2000.
- [26] C. Tudeuce, T. Gross, “A Mobility Model based on WLAN Traces and its Validation”, *Proc. IEEE Infocom 05*, pp. 664–674, 2005.
- [27] J. Yoon, M. Liu, and B. Noble, “Random Waypoint Considered Harmful”, *Proc. IEEE Infocom*, (San Francisco, CA), pp. 1312–1321, April 2003.
- [28] J. Yoon, M. Liu, and B. Noble, “Sound Mobility Models”, *Proc. ACM MobiCom*, (San Diego, CA), pp. 205–216, Sept. 2003.