Statistical Tools for Admission Control Decisions in Wireless Networks

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Abstract. The family of IEEE 802.11 protocols has become the most popular wireless access method. In recent years, other technologies have started to complement 802.11 networks, for example, for Internet access in rural networks. Specifically, point-to-point links based on WiMAX and on TV White Space Dynamic Spectrum Access technologies are used to connect a wired Internet access with a set of 802.11 end users. These heterogeneous and multi-hop networks face many challenges in order to provide QoS guarantees. One of these challenges is the design of admission control algorithms. In this paper we develop a blackbox approach for designing admission control algorithms suitable for these kind of networks. The methodology is based on a combination of active measurements and statistical learning tools. The results obtained during simulation and testing in a laboratory testbed show that show that the methodology achieves good accuracy.

Keywords: Statistical learning, Support Vector Machines, Wireless Communications, Admission Control, Quality of Service, IEEE 802.11e, WiMax

1 Introduction

Wireless technologies have become increasingly popular as methods to provide flexible broadband connectivity. The main reasons are their low cost, and their fast and easy deployment. In particular, the family of IEEE 802.11 [1] protocols has become the most popular access method. In recent years, other technologies have started to complement 802.11 networks, for example, for Internet access in rural area networks (e.g. [2]). Specifically, point-to-point links based on WiMax (IEEE 802.16 [3]) and on TV White Space Dynamic Spectrum Access technologies. These technologies are typically used to connect with point-to-point links a wired Internet access with a rural community. At the end of these wireless hops, the users are connected using 802.11 links. This architecture is an heterogeneous and multi-hop network with two or more different technologies. This kind of networks must face many challenges to guarantee a certain level of Quality of Service (QoS). One of these challenges is the design of admission control algorithms. There are different proposals to implement admission control mechanisms in wireless networks [4,5], however, in heterogeneous networks the algorithms cannot be implemented based on one specific technology and so, a blackbox approach is needed.

In this paper we extend the results of our previous work [6] in different directions. In our previous work we presented a methodology to estimate QoS parameters seen by applications in 802.11 networks. In this work we extend this methodology for developing admission control algorithms for QoS sensitive networks, including multi-hop and heterogeneous networks.

Other previous works focus on the problem of estimating QoS parameters by active measurements in the network (see for example [7] and the references therein), but our methodology is based on a combination of active measurements and the application of statistical learning tools. It consists in training the system (as a blackbox) during short periods with application flows and probe packets bursts. After the system has been trained, the QoS parameters of the blackbox can be estimated by sending the probe packets only. Although our proposal is valid for any broadband wireless network, some specific architectures of wireless rural networks were analyzed in the simulations and in the test-bed experiments.

We found that in a wireless multihop heterogeneous network it is possible to estimate the QoS parameters of a future connection by observing the statistical behavior of a light probe packet burst, and hence to decide on the convenience of accepting the connection. In simulations and testbed experiments our methodology proved to be accurate enough for practical use.

1.1 Organization of the paper

The rest of the paper is structured as follows. In section 2 we introduce the methodology. In section 3 we describe the network's state estimator. In section 4 we describe the statistical learning tool used in this work. In section 5 we show the performance of our proposal in different simulation scenarios and in section 6 we discuss experimental results based on a laboratory testbed. Finally, we conclude and discuss future works in section 7.

2 Methodology

Our methodology is based on the estimation of the network state using probe packets and on inferring the QoS seen by applications using statistical learning algorithms. We are interested on inferring the end-to-end QoS seen by an application from the behavior of the probe packets, so the probe packets should generate a traffic similar to the one the application generates (e.g. TCP traffic if it is a file download). Since the volume of this traffic may overload the network, we proposed a trade-off solution in which the system is trained during short periods with application flows and probe packets bursts. After this training period, the system sends only light probe packets that do not overload the network. We used an statistical learning approach to decide if a connection should be accepted or not from its QoS requirements and the behavior of the probe packets.

For example a new connection will be accepted if its delay is less than certain threshold, otherwise it will be blocked.

The main assumption is that the probe packets give an estimation of the state of the wireless path. If the state of the network is such that there are virtually no queues at the links, a low collision probability and low interference, the probe packets will not suffer major changes and their interarrival times will be almost the same as the periods between departures. However, if the network has for example many collisions, the interarrival times of probe packets will suffer strong modifications. This is illustrated in Figure 1.

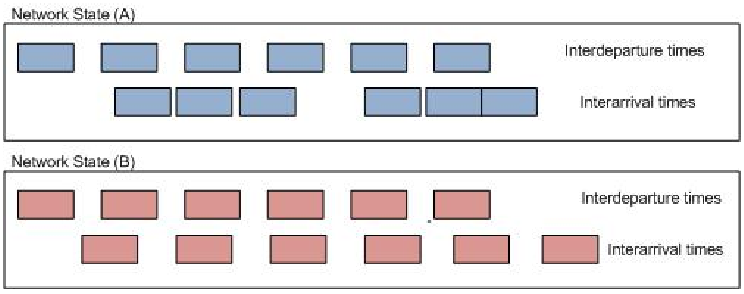

Fig. 1. Interarrival times of probe packets in two different network states. A: High collision probability and/or high interference. B: Low collision probability and low interference.

We proposed a binary classification problem, the idea is to predict the associated label $Z \in \{+1, -1\}$ from any new sample X, where Z is a binary variable that indicates if the connection is accepted ($Z = 1$) o not ($Z = -1$), and X is an estimation of the state of the wireless path. We use Support Vector Machines (SVM) as the statistical learning tool, therefore the objective is to find the maximum margin classification function (Φ). To estimate this function we divide the algorithm into two phases (learning and monitoring).

During the learning phase, when a new connection arrives to the network and starts sending traffic we measure the QoS parameters (e.g. delay) of the new connection. Afterwards, when this transmission finishes, the system sends a burst of probe packets with fixed size and interdeparture times. We build the variable X_i by measuring in each experiment i the interarrival times of the probe packets burst. Therefore, in each experiment of the learning phase we have a pair (X_i, Z_i). Z_i is a binary sequence obtained by comparing the QoS parameters with their thresholds. After we have collected a set of samples (X_i, Z_i) we use SVM to obtain the estimation of the classification function ($\widehat{\Phi}$). After the system is trained in the learning phase, the second one begins. During the monitoring phase, the new connection sends probe packets only and we build the variable X in the same way as in the learning phase. Using $\widehat{\Phi}$ we can decide if the connection is accepted or not.

We point out that this procedure does not load the network during the monitoring phase because it does not send the application packets to measure the QoS parameters.

3 The estimator of the state of the wireless link, X

X will be estimated from the probability distribution of the variable component of the delay seen by the probe packets. We first consider a single wireless link, and then a network path.

We consider a probe packet n that arrives to the queue of the wireless link at time t_n^i and leaves the link at the time t_n^o (in practice, these can be obtained with timestamps). If the latency of the link is D, the free capacity is $C_n(p, I)$ (we consider the general case of adaptive multirate where the link capacity varies with p (collision probability) and I (channel interference)), P is the packet's size, tq_n is the waiting time in the queue and $V_n(p, I)$ represents the delay caused by retransmissions, the difference between t_n^o and t_n^i is such that:

$$t_n^o - t_n^i = \frac{P}{C_n(p, I)} + D + V_n(p, I) + tq_n \tag{1}$$

Some factors in (1) are constant and other depend on n, so we can express equation (1) as:

$$t_n^o - t_n^i = K + K_n(p, I) \tag{2}$$

Applying equation (2) recursively for n probe packets we have:

$$K_n = K_0 + \sum_{j=1}^{n} [(t_j^o - t_{j-1}^o) - (t_j^i - t_{j-1}^i)] \tag{3}$$

Equation (3) allows us to estimate the probability distribution of the variable component of the delay using only the arrival and departure times (K_0 is a constant independent of n).

The previous analysis can be generalized to the case of a multi-hop path. In that case, the difference between the arrival time of packet n to the first queue and the time that this packet leaves the multi-hop path has a constant part and other that depends on n. Therefore, this difference can be written as in equation (2), and equation (3) follows for the multi-hop case.

It is important to note that we didn't use the fact that the interdeparture times of the test packets are constant, so this result is valid for any distribution.

In order to give an insight on how K_n or its statistics depends on the state of the network, in figures 3 and 4 we show the empirical distribution of K_n for different states of the wireless link using 802.11. These simulations were done using the topology shows in figure 2 in saturated traffic condition. In the first, we can see that when the number of nodes in the network m increases the mean value of K_n increases too.

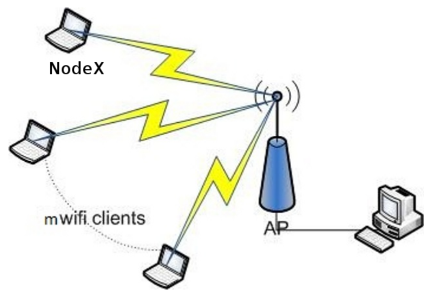

Fig. 2. IEEE 802.11 network. The network consists in a reference node (AP) and $m+1$ nodes generating traffic to the AP. The distance between AP and NodeX (which generates the probe packets to estimate the state of the link) is the same in all the simulations.

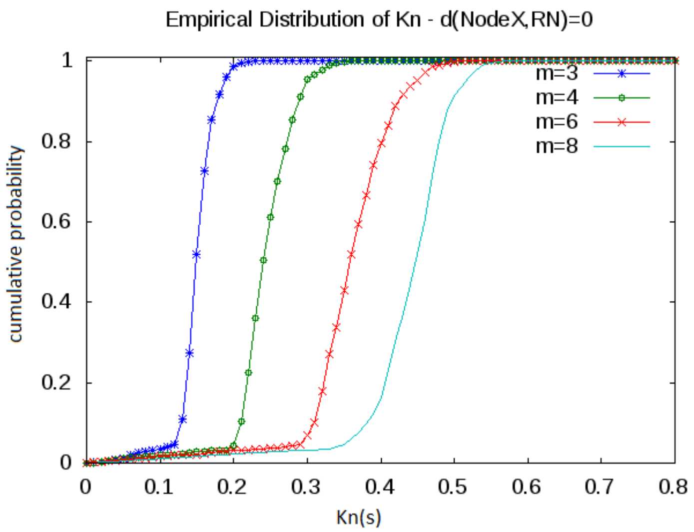

Fig. 3. Empirical distribution of K_n for different states of the wireless link, changing the number of fixed nodes (m) in a Wireless Local Area Network (see figure 2).

On the other hand, in figure 4 the number of fixed nodes is the same in all the simulations. In this case we varying the distance between the RN and NodeX. Figure 4 shows, varying d varies the mean and variance of K_n.

Following the previous analysis we propose to use some statistics of K_n (expected value, variance, etc..) as an estimator of the state of the wireless network path (X).

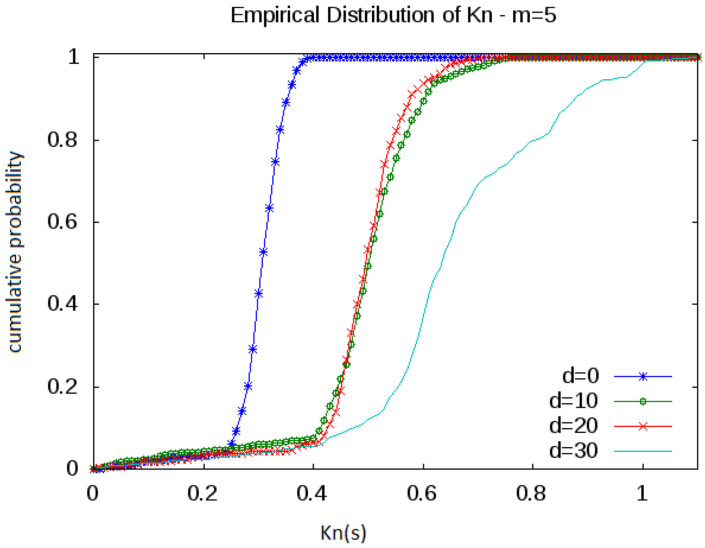

Fig. 4. Empirical distribution of K_n for different states of the wireless link, changing the distance (d) between NodeX and AP.

4 Support Vector Machines

There are several supervised statistical learning tools. We have selected Support Vector Machines (SVM). SVM is a set of classification and regression techniques, introduced in the early nineties by Vladimir Vapnik [8]. A complete description of the method can be found in [9]. SVM is a supervised learning tool well known for its discriminative power and has shown very good performance in different applications. In networking it has been used in several works showing very good performance (see for example [10]).

In this work, training and prediction were done with the LIBSVM library [11]. In particular, we use a radial basis function (rbf) kernel due to the good performance shown in different applications.

5 Simulations

We ran several sets of simulations using ns-2 simulator [12]. This simulator has been used in several works for simulating 802.11 networks (see for example [13,14,15]). In particular we used ns-2.28 simulator[4].

We considered two topologies. Topology I (figure 5) is a basic scenario that consists of two wireless 802.11e nodes (the distance between the nodes is 30

[4] We had to use that version of ns-2 to use the existing EDCA patch developed for TKN group [16] (it was used in other papers, an example is [17])

meters). Topology II (figure 6) represents a multi-hop network. In this case, all wireless links were configured using the same frequency band and the average distance between an AP with its clients is 10 meters. Please note traffic is bidirectional in both cases.

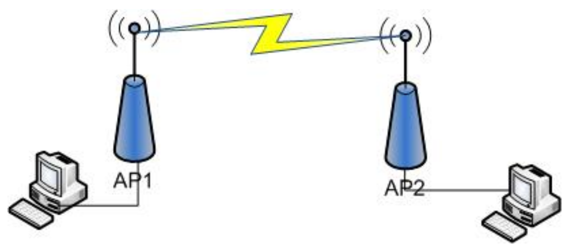

Fig. 5. Topology I: wireless link

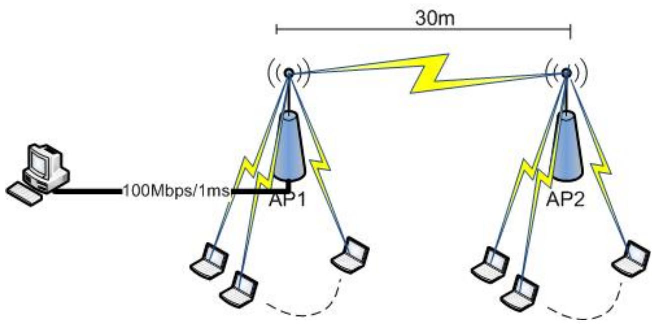

Fig. 6. Topology II: two wireless hop and a wired segment consisting of a duplex-link ($C = 100$ Mbps and $delay = 1$ ms)

We considered EDCA (802.11e), and to simplify, we only included two access categories (ACs) in our networks using their default EDCA parameters in ns-2 (AC_VI and AC_BE).

Network traffic was generated as follows: to model video flows we used an exponential on-off process over UDP, and best effort traffic was modeled as FTP/TCP connections. We considered 1500-byte packet size in both cases.

To estimate the state of the wireless path we injected UDP packets as probing packets. There is a trade-off between the size and interarrival time of these probe packets, since the objective is not to affect the network performance. We did several tests and we concluded that the values: Packet Size (payload)= 10 bytes and Interval Time= 10 ms are sufficient to achieve good results without affecting the system (these may be sent by either AC).

As an example we will show the results where the new connection is of AC_VI and we classified according to the delay. In order to get sufficient statistics for training and to verify the model, in each case we ran several simulations varying the number of flows in the network (the number of TCP and UDP connections).

In both scenarios we built the variable Z that we defined in sec.2 choosing an arbitrary threshold as *maxDelay*. $Z = 1$ if the new connection's delay is less than *maxDelay*, otherwise $Z = -1$. Using the mean value of K_n as the estimator X[5], in both scenarios we obtained more than 90% of accuracy.

Note: accuracy means the proportion of verification samples that were classified correctly.

6 Testbed for Experimental Validation in Heterogeneous Networks

The proposed methodology was tested experimentally using several topologies typical in rural networks. As a representative example, we present the case of a heterogeneous network that consists of two segments, one with WiMAX and another with WiFi (see Figure 7).

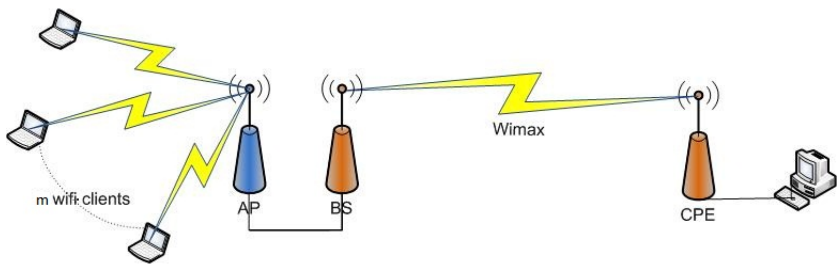

Fig. 7. Hybrid network WiMAX(5 GHz) and WiFi(2.4 GHz). The WiMAX segment consisted of a BS ARBA-556 and a CPE-56-PROA (Albentia Systems [18]). In the WiFi segment we used ALIX boards ([19]) with Voyage Linux v0.6.5 OS [20], one board worked as an Access Point and the other as clients (generating and receiving traffic). In addition, we have used miniPCI 802.11 a/b/g radio interfaces model Mikrotik R52H with 802.11e EDCA support, Atheros chipset and MadWiFi driver.

We have used D-ITGv2.8.0-rc1 [21] to generate and measure traffic. As in previous simulations, we used only two access categories of EDCA (in this case we chose AC_VI and AC_BE) with its default driver parameters. All flows of the class AC_BE were TCP, the other ones, trying to emulate real-time applications, were UDP. We did several tests varying the number of flows of each class in the network (considering bidirectional traffic). The tests were conducted reproducing the steps performed in the simulations.

[5] We have tested the system using other statistics like the variance or quantiles of K_n but the improve on the accuracy of the system is negligible

In order to build the estimator of the state of the network, a burst of probe packets with fixed size and interdeparture times was injected: packet size (payload)= 10 bytes, interdeparture time= 10 ms, duration= $60s$. This causes an overload on the network less than 0.1% which allow us to affirm that the methodology is not invasive.

We used a binary classification based on thresholds. For example for a AC_BE new connection, it will be accepted if its throughput is greater than $minTh$, otherwise it will be blocked. Applying this criteria, we obtained 85% of accuracy using the mean value of $K(n)$ as the estimator of the state of the network.

7 Conclusion

The main contributions of this paper are the proposed estimator of the wireless network state and the methodology presented that uses SVM and probe packets in order to decide whether a connection should be admitted by the network or not. In addition, the proposed methodology is only marginally intrusive. This was verified in the real experiments. The results obtained in the validation process (simulations and experimental testbed) show that the methodology has a good accuracy. It is important to note that the technique is independent of the wireless technology of the network. This allows its use in heterogeneous networks.

This work has many future lines of research like: extending it for more complex topologies and applying the methodology to real networks, in particular, in rural areas (ej: Long-Distance Wireless Links). Also, we are interested in investigating other features of K_n that help raise the accuracy of the estimation and the classification.

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