Throughput prediction in wireless networks using statistical learning

Claudina Rattaro and Pablo Belzarena

Facultad de Ingeniería, Universidad de la República
Montevideo, Uruguay

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Outline

Motivation (1)

1. Wireless Local Area Networks (WLANs) have become increasingly popular.

Motivation (2)

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2. In 802.11 protocols, the fundamental medium access method is DCF (Distributed Coordinated Function).
3. Most research works in this area have been developed to model IEEE 802.11 DCF and evaluate its performance analytically but there are few works that focus on the problem of estimating quality of service (QoS) parameters by measurements in WLAN.

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3. As a result we obtain a continuous **non intrusive** methodology that allows to determine the maximum throughput of a wireless connection only knowing some characteristics of the network.
4. The methodology proposed can be also used to estimate other QoS parameters seen by the application traffic (like delay or jitter for example).

Model

We consider the regression model: $Y = \Phi(X) + \epsilon$

- Y represents the new connection throughput
- X is an estimation of the state of the wireless link
- ϵ is the error

Environment

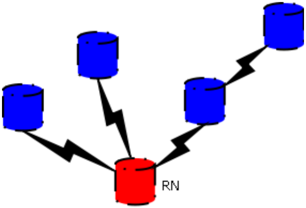

Figure: RN + constellation

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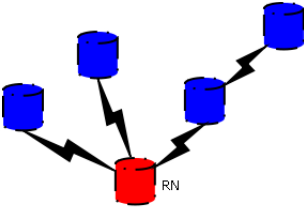

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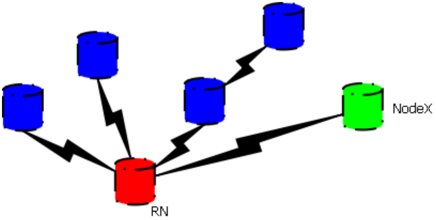

Figure: RF + constellation + NodeX

Method

1. Learning phase
2. Monitoring phase

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We estimate the function Φ using SVM with the set of samples (X_i, Y_i). We call $\widehat{\Phi}$ the estimation of the function Φ.

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The throughput of the new connection $\widehat{Y}$ is estimated using the function $\widehat{\Phi}$ by $\widehat{Y} = \widehat{\Phi}(X)$.

Estimator X

There are many factors that influence the state of the wireless link, but the most important of them are the collision probability (p) and the channel interference (I). 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 time t_n^o.

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

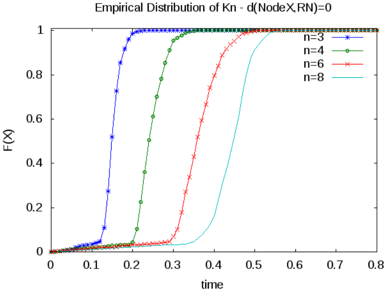
- P packet's size
- D latency of the link
- $C_n(p,I)$ free capacity of the link
- $V_n(p,I)$ represents the delay caused by retransmissions

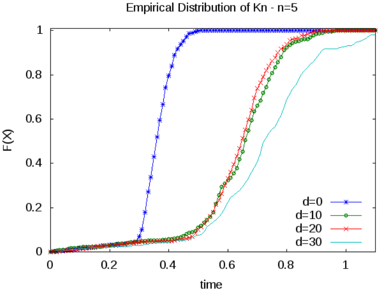
Working with equation (1) we can obtain

$$K_n = K_0 + \sum_{j=1}^{n} [(t_j^o - t_{j-1}^o) - (t_j^i - t_{j-1}^i)] \tag{2}$$

Equation (2) allows us to estimate the probability distribution of the variable component of the delay using only the arrival times and departure times.

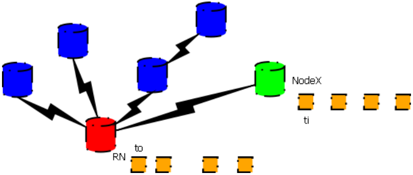
In the following figures we show the empirical distribution of K_n for different states of the wireless link.





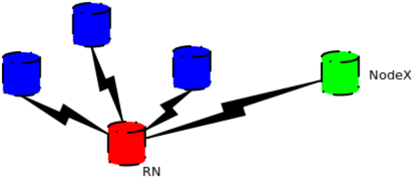
Estimator

We will use as variable X (estimator of the wireless link's state) some statistics of K_n like the expected value, variance, etc..



General characteristics

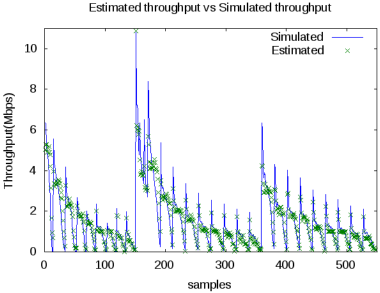
Topology



1. All simulations were done using the Ns-2 simulator
2. The training and the prediction using SVM were done with the libsvm library

Estimation and Results

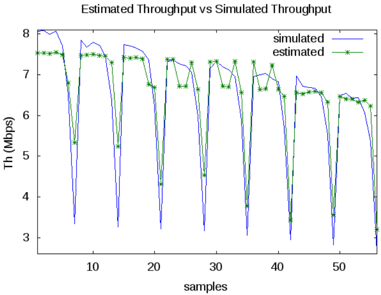
$X=$ mean value of K_n



Mean squared error	0.282229
Squared correlation coefficient	0.868246

Estimation and Results

$X=$ mean, variance, and minimum delay



Mean squared error	0.371387
Squared correlation coefficient	0.897626

Results

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2. We propose a estimator of the wireless link state and a methodology that uses SVM and probe packets in order to predict the maximum throughput of a new connection.
3. The proposed methodology is a non intrusive procedure.
4. This statistical learning approach gives accurate throughput prediction in both situations: saturated and non-saturated traffic conditions.

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2. Predicting other QoS parameters seen by applications in wireless networks (like delay, jitter, etc.)
3. Applying the previous methodology to 802.11e wireless networks.
4. Improving the estimation for the case of unsaturated traffic conditions.

Questions?