OPTIMIZING IEEE 802.11 DCF USING BAYESIAN ESTIMATORS OF THE NETWORK STATE

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ABSTRACT

The optimization mechanisms proposed in the literature for the Distributed Coordination Function (DCF) of the IEEE 802.11 protocol are often based on adapting the backoff parameters to the estimate of the number of competing terminals in the network. However, existing estimation algorithms are either inaccurate or too complex. In this paper we propose an enhanced version of the IEEE 802.11 DCF that employs an estimator of the number of competing terminals based on a sequential Monte Carlo (SMC) or a approximate maximum a posteriori (MAP) approach. The algorithm uses a Bayesian framework, optimizing the backoff parameters of the DCF based on the predictive distribution of the number of competing terminals. We show that our algorithm is simple yet highly accurate even at small time scales. We implement our proposed new DCF in the ns-2 simulator and show that it outperforms existing methods. We also show that its accuracy can be used to improve the results of the protocol even when the nodes are not in saturation mode.

1. INTRODUCTION

In [1], we developed several Bayesian estimators for the number of competing terminals in an IEEE 802.11 network, that outperform the existing best estimator based on the extended Kalman filter (EKF) [2]. In particular, we developed an accurate and easy to implement MAP estimator whose computational load and memory requirements are equivalent to those of the Viterbi algorithm. In this paper we propose an optimization mechanism that makes use of the predictive distribution of the number of competing terminals to maximize the throughput of the IEEE 802.11 DCF. We show that the accuracy of our algorithms is particularly good at small time scales, which makes our proposal attractive to optimize the protocol when the terminals are in a non-saturating regime, a problem rarely addressed.

Existing work on the optimization of the IEEE 802.11 DCF consist either in a change of the contention resolution algorithm [3], or in the adaptation of the parameters of the protocol (e.g., backlog parameters) to an estimate of the network status (e.g. number of competing terminals). This estimate can be a rough approximation [4] or an *accurate* estimate relying on advanced filtering mechanisms [2]. The estimation-based mechanisms have a benefit over their protocol modification counterparts since they only involve adjusting the contention window parameters, while the rest of the protocol remains unchanged. However, existing methods based on the estimation of the number of competing terminals exhibit two problems. First, the number of competing terminals is a non-Gaussian nonlinear dynamic system that is difficult to track accurately with conventional filters. Advanced estimators such as the EKF-based from [2] provide better results but they are subject to critics due its complexity. Second, the performance of the IEEE 802.11 DCF is extremely sensitive to the number of competing terminals. This makes the simple approximation methods to yield suboptimal results compared with the theoretical optimal. In our opinion, there is a need for an accurate estimation algorithm that is able to efficiently track the number of competing terminals in an IEEE 802.11 network, and, at the same time, is easy to implement.

2. ESTIMATION OF THE NUMBER OF COMPETING TERMINALS

Let us consider an IEEE 802.11 network with DCF operating in the basic access mode. It is shown in [5] that when the terminals transmit in a saturation regime, i.e., they always have something to send, the normalized throughput is a function of the number of competing terminals x_t and the DCF backoff parameters, namely the minimum contention window CW_{min} and the maximum backoff stage m, i.e.,

$$S = S(x_t, CW_{min}, m). \qquad (1)$$

Once the number of competing terminals x_t has been estimated, the optimization problem involves a selection of the backoff parameters to maximize the system throughput. It is also shown in [5] that when the system reaches a steady state, the number of competing terminals x_t can be expressed as a monotonic increasing function of the collision probability p_c, $x_t = f(p_c)$. Hence an inverse function $p_c = h(x_t) = f^{-1}(x_t)$ exists. The estimation of x_t can

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therefore be derived from a noisy observation of p_c that each terminal can acquire by monitoring the channel activity.

We use the proportion of busy slots in a given period as an indication of the collision probability, since any attempt of transmission in a busy slot would result in a sure collision. Our observation variable of the collision probability can be defined at each time step t as $y_t = \sum_{i=(t-1)B}^{tB-1} C_i$, where $C_i = 0$ if the i^{th} time slots is empty or corresponds to a successful transmission (i.e., no collision), and $C_i = 1$ if the i^{th} basic time slot is busy or corresponds to an unsuccessful transmission; B is the number of slots that compose the *observation slot* for the measurement. It is easy to see that y_t follows a binomial distribution $\mathcal{B}(B, p_c)$ with B trials and probability of success p_c. The state-space representation of our problem is as follows:

$$x_t \sim \mathcal{MC}(\boldsymbol{\theta}), \qquad y_t \sim \mathcal{B}(B, h(x_t)), \tag{2}$$

where $\mathcal{MC}(\boldsymbol{\theta})$ denotes a discrete-time Markovian model with some unknown parameters $\boldsymbol{\theta}$; x_t is the state realization of the Markovian model at time t.

In this paper we consider two advanced methods developed in [1] for estimating x_t based on y_t: a sequential Monte Carlo (SMC) and an approximate MAP estimator.

SMC-based Estimator: In [1], it is assumed that the number of competing terminals evolves according to a first-order Markov chain with unknown transition probability matrix $\boldsymbol{A} = [a_{i,j}]$, i.e., $p(x_{t+1} = j | x_t = i) = a_{i,j}$ where $a_{i,j} \geq 0$ and $\sum_{j=1}^{N} a_{i,j} = 1$, N being the maximum number of terminals, and initial probability vector $\boldsymbol{\pi} = [\pi_1, \cdots, \pi_N]$, i.e., $p(x_0 = i) = \pi_i$. Denote the observation sequence up to time t as $\boldsymbol{y}_t \triangleq [y_1, y_2, \cdots, y_t]$ and the network state sequence up to time t as $\boldsymbol{x}_t \triangleq [x_1, x_2, \cdots, x_t]$, and denote the unknown parameters as $\boldsymbol{\theta} = \{\boldsymbol{\pi}, \boldsymbol{A}\}$. We are interested in obtaining a Bayesian estimate of the posterior distributions $p(\boldsymbol{x}_t|\boldsymbol{y}_t)$ and $p(\boldsymbol{\theta}_t|\boldsymbol{y}_t)$.

The usual SMC approach is not well-suited for parameter estimation (here $\boldsymbol{\theta}$) [6], and the key to the approach developed in [1] is to see that the complete information about the transition matrix can be carried over through some sufficient statistics. A well-known strategy for Bayesian inference is to choose the prior distributions with a suitable form so that the posteriors belongs to the same functional family as the priors. By assuming that the prior distributions of $\boldsymbol{\theta} = \{\boldsymbol{\pi}, \boldsymbol{A}\}$ are given by multivariate Dirichlet distributions, it is shown in [1] that the posterior distributions of $\boldsymbol{\theta}$ given $\boldsymbol{x}_t$ and $\boldsymbol{y}_t$ are also multivariate Dirichlet distributions:

$$\begin{aligned} p(\boldsymbol{\pi}|\boldsymbol{x}_t, \boldsymbol{y}_t) &= p(\boldsymbol{\pi}|x_1, y_1) = \mathcal{D}(\boldsymbol{\pi}_i; \rho_1, \rho_2, \cdots, \rho_N), \\ p(\boldsymbol{a}_i|\boldsymbol{x}_t, \boldsymbol{y}_t) &= \mathcal{D}(\boldsymbol{a}_i; \alpha_{i,1,t}, \alpha_{i,2,t}, \cdots, \alpha_{i,N,t}), \\ & \qquad i = 1, \cdots, N, \end{aligned} \tag{3}$$

where $\mathcal{D}(.; \ldots)$ denotes the Dirichlet probability density function. We get the following update procedure:

$$\alpha_{i,j,t} = \alpha_{i,j,t-1} + \mathbb{I}(x_{t-1} - i)\mathbb{I}(x_t - j). \tag{4}$$

From Bayes theorem we have

$$p(\boldsymbol{x}_t|\boldsymbol{y}_t) = p(y_t|\boldsymbol{x}_t, \boldsymbol{y}_{t-1}) p(x_t|\boldsymbol{x}_{t-1}, \boldsymbol{y}_{t-1}) p(\boldsymbol{x}_{t-1}|\boldsymbol{y}_{t-1}), \tag{5}$$

and $p(\boldsymbol{x}_t|\boldsymbol{y}_t)$ can thus be updated analytically:

$$p(\boldsymbol{x}_t|\boldsymbol{y}_t) = \mathcal{B}(y_t; B, h(x_t)) \frac{\alpha_{x_{t-1}, x_t, t-1}}{\sum_{j=1}^{N} \alpha_{x_{t-1}, j, t-1}} p(\boldsymbol{x}_{t-1}|\boldsymbol{y}_{t-1}). \tag{6}$$

We can now derive the deterministic SMC estimator. Suppose a set of weighted samples containing no duplicate and representing $p(\boldsymbol{x}_{t-1}|\boldsymbol{y}_{t-1})$ is available at time $(t-1)$,

$$p(\boldsymbol{x}_t|\boldsymbol{y}_t) \approx \sum_{k=1}^{K} w_t^{(k)} \mathbb{I}(\boldsymbol{x}_t - \boldsymbol{x}_t^{(k)}). \tag{7}$$

Based on (6) and (7), $p(\boldsymbol{x}_t|\boldsymbol{y}_t)$ can be approximated by:

$$p^{ext}(\boldsymbol{x}_t|\boldsymbol{y}_t) \propto \sum_{k=1}^{K} \sum_{j=1}^{N} w_t^{(k,i)} \mathbb{I}(x_t - i) \mathbb{I}(\boldsymbol{x}_{t-1} - \boldsymbol{x}_{t-1}^{(k)}), \tag{8}$$

where the weight update procedure is given by

$$w_t^{(k,i)} \propto w_{t-1}^{(k)} \mathcal{B}(y_t; i) \frac{\alpha^{(k)}_{x^{(k)}_{t-1}, i, t-1}}{\sum_{j=1}^{N} \alpha^{(k)}_{x^{(k)}_{t-1}, j, t-1}}. \tag{9}$$

A selection step is then performed to retain a fixed number of samples.

Approximate MAP Estimator: By using these sufficient statistics, we developed in [1] a modified Viterbi algorithm to fit the unknown transition matrix scenario. In this approximate MAP approach, the objective is to recursively maximize $p(\boldsymbol{x}_t|\boldsymbol{y}_t)$ with respect to $\boldsymbol{x}_t$. With this goal, the Viterbi algorithm uses

$$\begin{aligned} \delta_t(i) = \max_{\boldsymbol{x}_{t-1}|x_t = i} p(\boldsymbol{x}_t|\boldsymbol{y}_t) = p(y_t|x_t = i) \max_{x_{t-1}|x_t = i} \\ \max_{\boldsymbol{x}_{t-2}|x_{t-1}, x_t = i} [p(\boldsymbol{x}_{t-1}|\boldsymbol{y}_{t-1}) p(x_t|\boldsymbol{x}_{t-1}, \boldsymbol{y}_{t-1})], \end{aligned} \tag{10}$$

that can recursively be computed if the transition matrix is known by taking $p(x_t|\boldsymbol{x}_{t-1}, \boldsymbol{y}_{t-1}) = a_{x_{t-1}, x_t}$ out of the inner max. The estimate of x_t at time t is then given by $\max_i \delta_t(i)$. When the transition matrix is unknown, even if the probability of any path can be analytically computed as in (6), such a recursion cannot directly be used because $p(x_t|\boldsymbol{x}_{t-1}, \boldsymbol{y}_{t-1})$ depends on $\boldsymbol{x}_{t-2}$. However if the approximation that $p(\boldsymbol{x}_{t-1}|\boldsymbol{y}_{t-1}) p(x_t|\boldsymbol{x}_{t-1}, \boldsymbol{y}_{t-1})$ is maximized

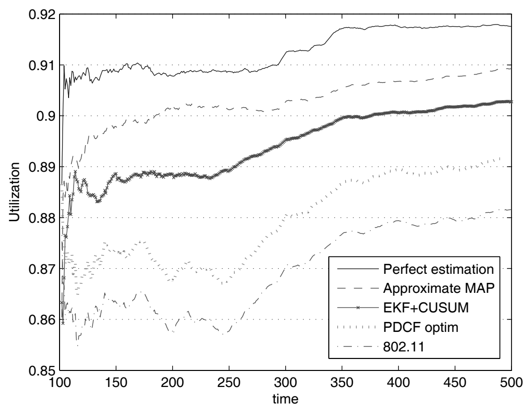


Fig. 1. Utilization with saturating nodes and Markovian node activation.

when $p(\boldsymbol{x}_{t-1}|\boldsymbol{y}_{t-1})$ is maximized is done, an approximation $\hat{\delta}_t(i)$ of $\delta_t(i)$ can be computed recursively as:

$$\hat{\delta}_t(i) = p(y_t|x_t = i) \max_j \left[\hat{\delta}_{t-1}(j) p(x_t = i|\boldsymbol{x}_{t-1}^{(j)}, \boldsymbol{y}_{t-1})\right]$$
$$= \mathcal{B}(y_t; B, h(i)) \max_j \left[\hat{\delta}_{t-1}(j) \cdot \frac{\alpha_{j,i,t-1}^{(j)}}{\sum_{k=1}^{N} \alpha_{j,k,t-1}^{(j)}}\right], \quad (11)$$

where $\boldsymbol{x}_{t-1}^{(j)}$ corresponds to the retained path ending at $x_{t-1} = j$ and $\alpha_{j,\cdot,t-1}^{(j)}$ is the corresponding sufficient statistics (4).

3. OPTIMIZATION OF IEEE 802.11 DCF

In this section we propose a novel optimization algorithm based on the estimators described in the previous section. Our simulations in ns-2 shows that the effect of CW_{max} greater that 1024 has no effect on the network performance for $x_t \leq 40$. So in order to simplify the problem we impose m to be fixed such as $CW_{max} = 2^m CW_{min} = 1024$, and CW_{min}[1] takes values from a set $\mathcal{W}$. This set can be fixed or it can be constructed, i.e, using the method in Section 3.2. Then, assuming m is no longer a variable, a simple formulation of the backoff window choice is given by

$$W_{t+1}^{*} = \arg\max_{W \in \mathcal{W}} \mathbb{E}_{p(x_{t+1}|\boldsymbol{y}_t)} \left\{\Psi_u\big(S(x_{t+1}, W, m) - S(x_{t+1}, W_t, m)\big)\right\}, \quad (12)$$

where Ψ_u is a utility function of the difference in throughput, and $S(\cdot)$ is given in (1). Ψ_u will typically be a non-decreasing function and should be convex on the positive part and concave on the negative part. We propose $\Psi_u(\Delta S) = (\Delta S)^3$ but any other sensible function could be used.

[1]We use the term CW_{min} and W interchangeably.

Note that our utility function in (12) makes use of the distribution of the number of competing terminals if available. In [4] a similar optimization scheme was introduced but a hard estimate of the number of terminals was used to make a range estimation. To prevent frequent switching, the authors used overlapping ranges. We believe that our Bayesian criterion is more natural to make a soft decision.

3.1. Predictive Distribution Based on SMC Samples

As shown in our criterion (12), we need to have access to the predictive distribution $p(x_{t+1}|\boldsymbol{y}_t)$ in order to perform an optimal control of the protocol.

Given a set of samples and weights $\left\{\boldsymbol{x}_t^{(k)}, w_t^{(k)}\right\}_{k=1}^{K}$ representing $p(\boldsymbol{x}_t|\boldsymbol{y}_t)$ at time t, (12) is approximated as

$$\hat{W}_{t+1}^{SMC} =$$
$$\arg\max_{W \in \mathcal{W}} \sum_{k=1}^{K} \sum_{i=1}^{N} \Psi_u(\Delta S(x_{t+1} = i, W)) p(x_{t+1} = i, \boldsymbol{x}_t^{(k)}|\boldsymbol{y}_t)$$
$$= \arg\max_{W \in \mathcal{W}} \sum_{k=1}^{K} \sum_{i=1}^{N} \Psi_u(\Delta S(i, W)) \frac{\alpha_{x_t^{(k)},i,t}}{\sum_{j=1}^{N} \alpha_{x_t^{(k)},j,t}} w_t^{(k)}$$
$$= \arg\max_{W \in \mathcal{W}} \sum_{k=1}^{K} \frac{w_t^{(k)}}{\sum_{j=1}^{N} \alpha_{x_t^{(k)},j,t}} \sum_{i=1}^{N} \Psi_u(\Delta S(i, W)) \alpha_{x_t^{(k)},i,t} \quad (13)$$

where $\Delta S(x_{t+1}, W) = S(x_{t+1}, W, m) - S(x_{t+1}, W_t, m)$.

For the case in which we only have access to an hard estimate of the number of competing terminals, the backoff window choice (12) is simply approximated by

$$W_{t+1}^{MAP} = \arg\max_{W \in \mathcal{W}} \Psi_u\left(S(\hat{x}_{t+1|t}, W, m) - S(\hat{x}_{t+1|t}, W_t, m)\right), \quad (14)$$

where $\hat{x}_{t+1|t} = \arg\max_{x_{t+1}} p(x_{t+1}|\hat{\boldsymbol{x}}_t, \boldsymbol{y}_t) \approx \arg\max_{x_{t+1}} p(x_{t+1}|\boldsymbol{x}_t, \boldsymbol{y}_t)$ is an approximate MAP estimate of x_{t+1} with $\hat{\boldsymbol{x}}_t$ being the current MAP estimate of $\boldsymbol{x}_t$. For the EKF algorithm, $p(x_t|y_t, y_{t-1}, ..., y_1)$ is approximated by a Gaussian $p(x_t|y_t, y_{t-1}, ..., y_1) \approx \mathcal{N}(x_t; h(x_t), P_t)$. This would involve complex numerical integrations, so we use the hard estimate of the number of competing terminals as in (14).

3.2. Choice of Backoff Window Size Set $\mathcal{W}$

Having discussed how to perform an optimal choice of the backoff window within a given set $\mathcal{W}$, we can now give some insight on the choice of this set. It will be chosen such that the optimal throughput can always be approached and such that its cardinality remains low. Indeed a small number of configurations will allow a more stable system and an easier implementation. Here we assume that m is not fixed and can also be chosen in the set of backoff windows.

Our design criterion can thus be written as

$$\forall i \in [1, \cdots, N],$$
$$|\max_{W \in \mathbb{N}^*} S(i, W, m) - \max_{W \in \mathcal{W}} S(i, W, m)| < \Delta S_{max}, \quad (15)$$

where ΔS_{max} is the maximum throughput loss to optimality we allow. ΔS_{max} will typically be chosen small, for instance 2.5%. Within this constraint, we would like to have as few points in $\mathcal{W}$ as possible. Because of the regularity of $S(.)$, such a set can be constructed by performing the following operations:

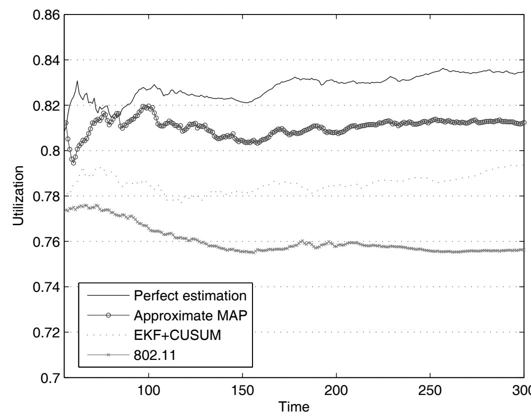
- Let $i_{mid} = 1$
- Choose the greatest integer j_{ref} such that $S_{opt}(i_{mid}) - S(i_{mid}, W_{opt}(j_{ref}), m) < \Delta S_{max}$, where $W_{opt}(k) = \arg\max_{W \in \mathbb{N}^*} S(k, W, m)$ and $S_{opt}(k) = S(k, W_{opt}(k), m)$. Let j_{ref} be in $\mathcal{W}$.
- Find the smallest integer i_{mid} such that $S_{opt}(i_{mid}) - S(i_{mid}, W_{opt}(j_{ref}), m) > \Delta S_{max}$.
- If $i_{mid} < N$ and $j_{ref} < N$, go back to step 2.
- If $i_{mid} \geq N$ and $j_{ref} \geq N$, remove j_{ref} from $\mathcal{W}$ and let N be in $\mathcal{W}$.

4. SIMULATION RESULTS

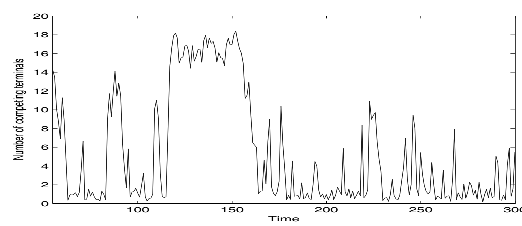
We use the ns-2 network simulator version 2.27 to compare our Bayesian approach with existing estimators. The parameters used in the simulation are classical for a 1 Mbps WLAN. No packet fragmentation occur, and the nodes are located close to each other to avoid capture or hidden terminal problems. Only the basic access is used.

Fig. 1 shows the instantaneous utilization of the protocols when saturating nodes arrive with an on-off exponential process in continuous time with an average of 6 nodes. We compare the effect of the estimation for $B = 50$, to keep the estimation within the granularity of the change in the number of terminals. We also compare with an optimized version of the PDCF protocol [3] for the range of 1–10 terminals (reset probability is 0.9). The approximate MAP algorithm outperforms both the EKF and the modified PDCF algorithm at all times, and all stay below the perfect estimation, which is an indication of the benefits of the accurate estimates in the IEEE 802.11 operation.

If we relax the saturation assumption, [2] shows that the number of competing stations fluctuates heavily under non-saturation conditions. This effect can be observed in Fig. 2(b). In this scenario, the effect of a highly accurate and fast estimate of the number of competing terminals is crucial to the optimal operation of the protocol; for that reason we select $B = 10$. Intuitively we can think of n terminals in non-saturation regime as a process of $x(t)$ saturating nodes (those who have something to transmit in the allowed slots) that fluctuates very fast. Fig. 2(a) show that our algorithm performs extremely well in the non-saturation regime. We



(a) Instantaneous utilization.



(b) Evolution of the number of competing terminals.

Fig. 2. Utilization with non-saturating nodes.

see that the accuracy and the speed of the estimation of the number of competing terminals in a 802.11 network has a significant impact on the network performance.

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