Two-layer modeling of IEEE 802.11x channel occupancy

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Low power IoT communication signals (e.g., Bluetooth and ZigBee) may seriously suffer from the presence of high-power co-channel interference like wireless local area network (WLAN) signal. They may effectively avoid WLAN interference by exploiting dynamic characteristics of WLAN traffic. Representing the arrival/departure of WLAN users using an M/M/m/m queueing structure, we consider the characterization of large-scale dynamics of WLAN channel occupancy. We also consider the characterization of small-scale dynamics of WLAN channel occupancy by generating WLAN signal using a two-state semi-Markovian process. Simulation results show that the proposed model generates WLAN signal having similar statistical characteristics to those of real WLAN signal.

Introduction: Low-power wireless communication systems (WCSs) operating in unlicensed frequency band (e.g., ZigBee and Bluetooth) may noticeably be affected by the presence of co-channel interference. They may seriously suffer from the presence of IEEE 802.11x wireless local area network (WLAN) traffic [1, 2]. The channel occupancy ratio (COR) of WLAN signal, defined by the portion of time that WLAN signal presents, may significantly vary over the time even in a time scale of minutes [3]. It may be desirable for low-power WCSs to employ a transmission scheme that can make communications while effectively avoiding major interference [4–6]. We may design such a transmission scheme by exploiting the COR of WLAN signal.

Traffic workload models may well characterize large-scale dynamics of WLAN channel occupancy [7]. However, they may not properly characterize small-scale dynamics (e.g., the inter-packet arrival time) of WLAN signal [8]. Previous works consider the characterization of small-scale dynamics of WLAN channel occupancy taking into consideration of packet transmission protocols (e.g., the back-off, transmission, and inter-frame spacing) [8, 9]. They may well approximate the distribution of inter-packet arrival time in a long-time interval using a generalized Pareto distribution (GPD). However, they may not properly characterize the time-varying behavior of WLAN channel occupancy.

Based on the analysis on WLAN traffic [10, 11], we consider the modeling of WLAN channel occupancy using a two-layer stochastic process. Representing the arrival/departure of WLAN users as an M/M/m/m queueing process, we may characterize large-scale dynamics of WLAN channel occupancy. Assuming that the traffic of WLAN users has similar characteristics to each other, we may generate WLAN signal using a two-state semi-Markovian process with parameters associated with the number of WLAN users. The inter-arrival time of WLAN signal generated by the two-state semi-Markovian process may have similar statistical characteristics to those of real WLAN signal, providing small-scale dynamics of WLAN channel occupancy.

Previous works: The WLAN traffic workload can be characterized by so-called sessions that represent WLAN users, the number of traffic flows generated by a session and the inter-arrival time between the traffic flows [7]. The arrival of sessions can be represented by a time-varying Poisson process and the traffic flow arrival by a bi-Pareto distribution [7]. It may well characterize large-scale behavior of WLAN channel occupancy, but it may not well characterize the inter-arrival time of WLAN signal since it does not consider the medium access control (MAC) of WLAN.

The WLAN channel occupancy can be represented using a single-layer semi-Markovian process in consideration of WLAN MAC [8, 9], where the transition between the states is deterministic and depends on the data size, as illustrated in Figure 1. The medium may be in an idle

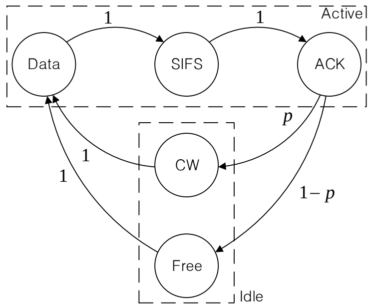


Fig 1 *Semi-Markovian modeling of WLAN channel occupancy [8, 9]*

state when WLAN devices are in a back-off state to avoid collision or has no data to transmit, referred to free-time (FT). The probability density function (pdf) of sojourn time in the idle state can be represented as [8]

$$f_I(\tau) = p f_C(\tau) + (1-p) f_F(\tau) \tag{1}$$

where $p \in [0,1]$ is a mixture variable, $f_C(\tau)$ denotes the pdf of the contention window for random back-off that follows uniform distribution, and $f_F(\tau)$ denotes the pdf of FT. Considering bursty nature of WLAN signal, $f_F(\tau)$ can be represented using a heavy-tailed pdf which has longer tail than the exponential distribution (ED) (e.g., GPD) as [8]

$$f_F(\tau) = \frac{1}{\sigma}\left(1 + \xi\frac{\tau}{\sigma}\right)^{(-1-1/\xi)} \tag{2}$$

where the shape parameter ξ and the scale parameter σ depend on WLAN traffic. It was shown that the semi-Markovian modeling of WLAN channel occupancy is effective for statistical characterization of WLAN signal [8, 11]. However, the semi-Markovian modeling may not effectively characterize time-varying nature of WLAN signal due to the use of fixed shape and scale parameters.

Proposed WLAN channel occupancy model: Based on characterization of WLAN users [11], we may assume that the usage pattern of WLAN users is similar to each other and that the COR of WLAN signal is a function of the number of WLAN users, which solely depends on the arrival/departure of WLAN users. We may characterize the inter-arrival time by an ED parametrized with time-varying COR of WLAN signal, achieving heavy-tail characteristics. The memoryless property of ED makes it easy to analyze and simulate WLAN signal.

We may represent the WLAN channel occupancy in a two-layer process as illustrated in Figure 2, where the upper and the lower layer process represent the arrival/departure of WLAN users and the generation of WLAN signal, respectively. The arrival and departure of WLAN users can be represented by a Poisson process since WLAN users may come in and out independently of each other. The number of WLAN users at time t denoted by n_t, can be represented by an M/M/m/m queueing process with parameters λ_A and μ_D, representing the arrival rate and the departure rate of WLAN users, respectively. Letting N_C^{max} be the maximum number of WLAN users, it can be shown that the average number of WLAN users can be represented as [12]

$$\bar{N}_C = \frac{\sum_{n=0}^{N_C^{max}} n\left(\lambda_A/\mu_B\right)^n/n!}{\sum_{n=0}^{N_C^{max}} \left(\lambda_A/\mu_B\right)^n/n!} \tag{3}$$

Letting $\rho_t = \xi(n_t)$ be the COR of WLAN signal at time t and $\xi(n_t) = \rho_C n$, the average COR of WLAN signal in the steady state can be represented as $\bar{\rho} = \rho_C \bar{N}_C$.

The lower layer process can be represented as a two-state semi-Markovian process where the state “Active” represents Data, SIFS and ACK, and the state “Idle” represents CW and FT [9]. Since WLAN signal is present only in Active state, the duration of Active state depends on the size of WLAN packets [7]. Provided that the sojourn time of Active state does not significantly vary in time, the sojourn time of Idle state (i.e., the inter-arrival time of WLAN signal) can be represented by an ED with mean $\lambda_I^{-1}(t)$. Letting $\bar{T}_A$ be the average time duration of Active state, the COR of WLAN signal at time t can be represented as

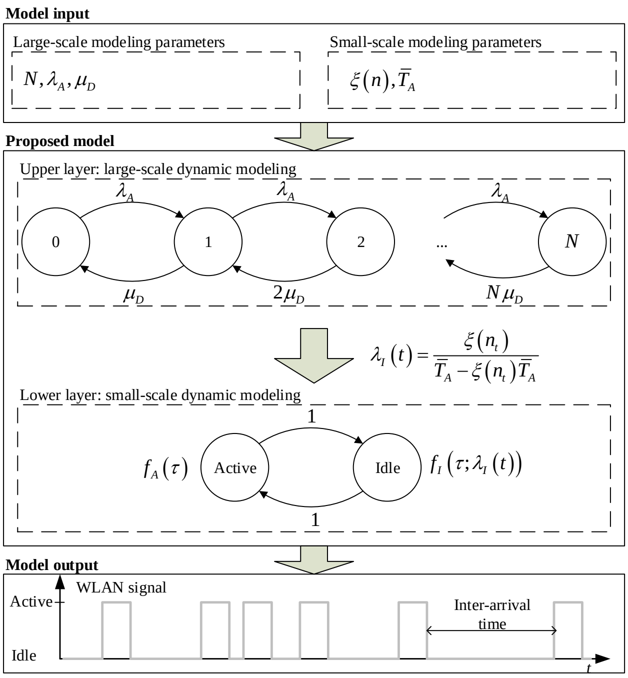


Fig 2 *Proposed two-layer modeling of WLAN channel occupancy*

$$\rho(t) = \rho_C n_C(t) = \frac{\bar{T}_A}{\bar{T}_A + \lambda_I^{-1}(t)}. \tag{4}$$

We evaluate the validity of the proposed model by computer simulation. Table 1 summarizes parameters of the proposed model for the evaluation, where we assume that the departure rate is once a 30-second, which may represent a highly dynamic operation scenario. We generate the WLAN signal for an interval of 10^4 seconds. To verify the validity of the proposed model, we perform Kolmogorov-Smirnov test on the empirical distribution of inter-arrival time of WLAN signal and the GPD fitting [13].

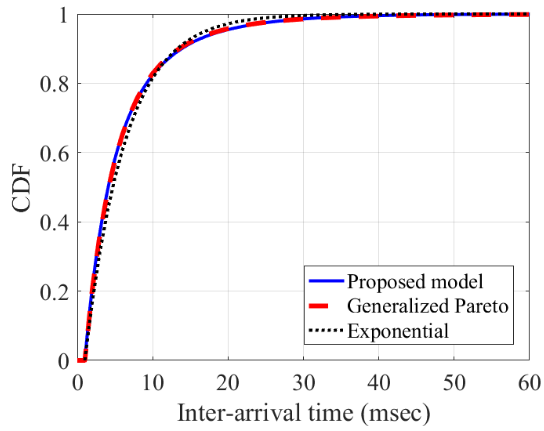
Figure 3 depicts the empirical CDF when $\bar{\rho} = 0.1$ and $\bar{\rho} = 0.3$. The fitting parameters and its goodness-of-fit of GPD are summarized in Table 2 and 3. It can be seen that the empirical distribution is well approximated by a GPD. It can also be seen that the GPD fitting works well when $\bar{\rho} = 0.3$ because the variance of COR of WLAN signal increases as $\bar{\rho}$ increases, which agrees well with the result in [10].

Figure 4 and 5 depict WLAN signal generated by the proposed model and the single-layer semi-Markovian model [9], respectively, where (a) depicts the WCOR measured in one-second bins, and (b) and (c) depict the presence of WLAN signal when the measured COR of WLAN signal is the highest and the lowest, respectively. It can be seen that the inter-arrival time of WLAN signal generated by the two models may well be approximated by a GPD in a long-time interval. It can also be seen that the proposed model generates WLAN signal showing time-varying nature of COR of WLAN signal, while the single-layer semi-Markovian model does not.

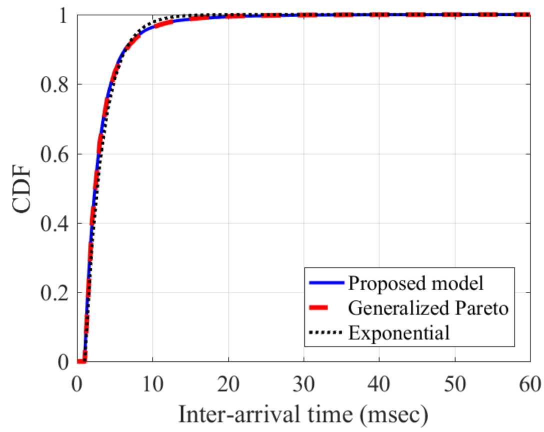
Conclusions: In this letter, we have considered the modeling of WLAN channel occupancy. The proposed model can represent the time-varying property of COR of WLAN signal by modeling the arrival/departure of WLAN users and generating WLAN signal using the parameters associated with the number of WLAN users. Computer simulation with Kolmogorov-Smirnov test has shown that the inter-arrival time of WLAN signal generated by the proposed scheme may be approximated using GPD in a long-time interval.

Table 1. Modeling parameters for the verification

Symbol	Value
N_C	5
	$0.0334\ s^{-1}$ ($\bar{\rho} = 0.1$)
λ_A	$0.0696\ s^{-1}$ ($\bar{\rho} = 0.2$)
	$0.1192\ s^{-1}$ ($\bar{\rho} = 0.3$)
μ_D	$0.0333\ s^{-1}$
$\bar{T}_A$	$1ms$
$\xi(n)$	$0.1n$



(a) $\bar{\rho} = 0.1$



(b) $\bar{\rho} = 0.3$

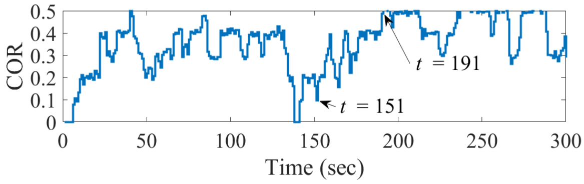
Fig 3 *Empirical CDF of inter-arrival time of WLAN signal*

Table 2. Fitting parameters for GPD over the distribution of inter-arrival time of WLAN signal

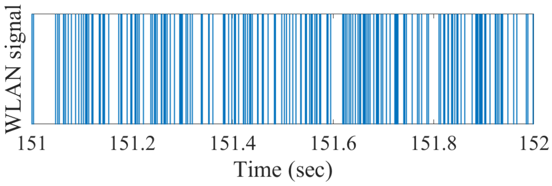
Average COR $\bar{\rho}$	0.1	0.2	0.3
Shape parameter ξ	0.2256	0.2609	0.3024
Scale parameter σ	0.0091	0.0036	0.0021

Table 3. Goodness-of-fit of the GPD fitting under Kolmogorov-Sminorv test

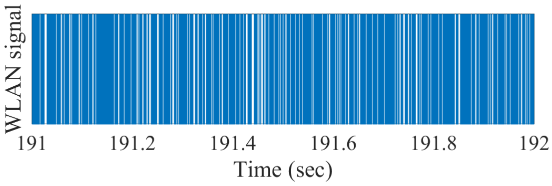
Average COR $\bar{\rho}$	0.1	0.2	0.3
p-value	0.0040	0.2873	0.7165
D-value	0.0134	0.0073	0.0050



(a) COR measured in one-second bins

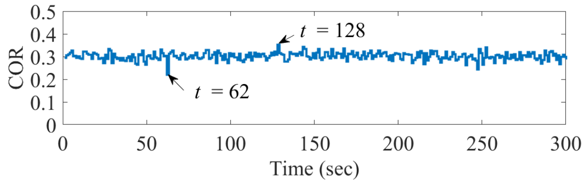


(b) WLAN signal generated in $t \in [151, 152]$

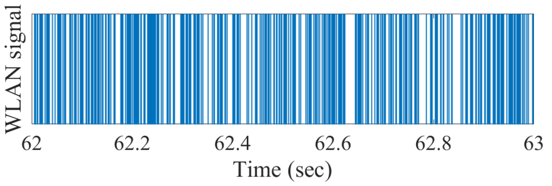


(c) WLAN signal generated in $t \in [191, 192]$

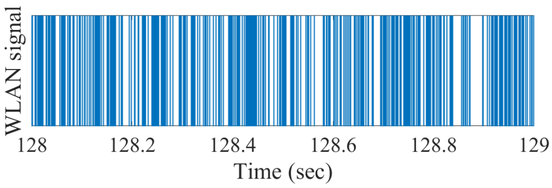
Fig 4 *WLAN signal generated by the proposed model with* $\bar{\rho} = 0.3$



(a) COR measured in one-second bins



(b) WLAN signal generated in $t \in [62, 63]$



(c) WLAN signal generated in $t \in [128, 129]$

Fig 5 *WLAN signal generated by [9] with* $\bar{\rho} = 0.3$

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