On the Use of ON/OFF Traffic Models for Spatio-Temporal Analysis of Wireless Networks

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***Abstract*—The spatial and temporal distribution of active users across a given region greatly affects the activity of base stations (BSs) and the cumulative interference in a wireless network. In this letter, we propose a new approach for spatio-temporal analysis of wireless networks wherein stochastic geometry is used for the spatial domain and ON/OFF traffic models are used for the temporal domain. We illustrate the proposed approach through a mix of file transfer protocol (FTP) and video streaming (VS) traffic. With the aid of semi-Markov process, we derive the stationary probability for a given service request. Further, we develop a joint spatio-temporal model for the distribution of *active* users under a random BS.**

***Index Terms*—FTP, ON/OFF, semi-Markov, spatio-temporal, video streaming.**

I. Introduction

SPATIO-TEMPORAL modeling and analysis is an emerging frontier in wireless networks research. The integration of the two domains has helped researchers in analysis of more critical performance metrics such as delay outage and unstable queue probability which are difficult to capture through spatial analysis alone. Recent studies on spatio-temporal analysis [1]–[3] are mainly focused on the use of Poisson point processes (PPPs) for spatial modeling of base stations (BSs) and Bernoulli process for capturing temporal arrival of packets during a time-slot. While the PPP assumption for spatial analysis has been found to be accurate [4], the use of Bernoulli process for temporal arrival of packets does not precisely capture the intensity of generated traffic either for a given service (application) or for a mix of different service requests. In this work, we advocate the use of ON/OFF traffic models for spatio-temporal analysis of wireless networks. The ON/OFF traffic models are preferred for modeling of Internet protocol (IP) traffic [5] and, according to a recent report [6], within next five years, 20% of the global IP traffic would be carried by mobile networks. By exploiting ON/OFF traffic models, the Noah effect i.e., high variability or infinite variance, can be created which results in an aggregate traffic that exhibits the Joseph effect i.e., self similar or long range dependent [7]. Moreover, these models are more realistic and provide the capability of application-specific or mixed traffic analysis.

The Interrupted Poisson Point (IPP) process and Alternating State Renewal Process (ASRP) are the types of ON/OFF traffic model *with* and *without* self transitions, where exponential and general distributions are assumed for the transition time, respectively [8]. Thus, in this work, we exploit a two state ON/OFF model, which inherits some of the features from IPP i.e., self transition, and others from ASRP model i.e., general distributions, for estimating the activity of a user, by assuming two different service requests i.e., File transfer protocol (FTP) and video streaming (VS). By using semi-Markov process, we derive the stationary probability of a user for being in ON state, which is also termed as the active probability of a user, during a time-slot. Moreover, for illustrating the effect of ON/OFF traffic model, we develop a joint spatio-temporal model for the distribution of *active* users, given that single flow is generated per user. To the best of our knowledge, this is the first study that investigates the use of ON/OFF traffic model for spatio-temporal analysis of wireless networks. We discuss the results by assuming two different traffic scenarios i.e., homogeneous and heterogeneous, and also benchmark our model against state-of-the-art studies.

II. Joint Spatio-Temporal Model

A. Network Model

We assume a single-tier cellular network, where a PPP Φ_b, with intensity λ_b, has been used for drawing the location of BSs within a given region. The user equipments (UEs) are assumed to be distributed according to another PPP Φ_u, with intensity λ_u. We consider a downlink channel model, where at least single user is associated with a BS.[1] The constant power transmitted by BSs has been denoted by $\mathcal{P}_t$ and frequency re-use factor of unity has been assumed for the entire network. The time axis has been divided into slots of fixed length T_s and, for simplification, we consider that single time-slot is required for the transmission of a packet with fixed length L. The arrival(departure) of a packet occurs immediately after(before) the slot boundary. We further assume that the BS maintains a separate buffer, of infinite capacity, for accumulation of packets of each associated user, where a user can generate request for either FTP or VS service.

B. Temporal Domain

In this work, we consider a homogeneous and a heterogeneous traffic scenario. In homogeneous case, all users generate

[1]The presented approach can be readily extended for the uplink analysis.

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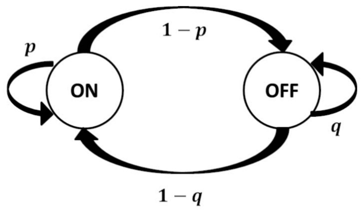


Fig. 1. A two-state Markov chain representing ON/OFF traffic model.

request for same service i.e., FTP or VS. In heterogeneous case, the users generate request for either FTP or VS with certain probability termed as weight (w_i); here subscript i represents the type of service. Thus, the general formulation for the active probability (ξ) of a user, during a time-slot, has been defined as

$$\xi = w_f \Pi_f^{on} + w_v \Pi_v^{on}, \tag{1}$$

here Π_i^{on} represents the active probability of a user for service type $i \in \{f, v\}$.

1) FTP: We assume that a user, when using FTP service, generates a request for a file whose size follows Pareto distribution with mean υ_x, shape ϱ_x, and scale k_x. Assuming a fixed size of packet with L bytes and time-slot duration T_s, the mean ON duration $(\hat{\upsilon}_x)$ can be obtained as

$$\hat{\upsilon}_x = \frac{\upsilon_x \times T_s}{L}, \tag{2}$$

and by following a similar process, $\hat{k}_x$ can also be obtained.

Lemma 1: Given a user, with FTP service request, remains in ON and OFF state with probability p and q, respectively, the stationary probability of the user for being in ON state can be defined as

$$\Pi_f^{on} = \frac{\overline{q}}{\overline{p} + \overline{q}}, \tag{3}$$

where

$$\overline{p} = 1 - \left(\frac{\hat{k}_x}{\tau_x}\right)^{\varrho_x}, \quad \overline{q} = 1 - \exp\left(-\frac{\tau_y}{\mu_y}\right), \tag{4}$$

$\tau_x = \mu_y$ and $\tau_y = \hat{\upsilon}_x$ denote the thresholds for ON and OFF states, respectively.

Proof: We are assuming a two-state Markov chain, as shown in Fig. 1, with two random variables X and Y distributed according to Pareto and exponential distribution, respectively. As the time-axis has been divided into slots of fixed duration (T_s), and in practical scenarios $T_s << \hat{\upsilon}_x$, μ_y, the probability that during a time-slot a user remains in ON or OFF state approaches unity. This condition violates the rules of Markov chain, resulting in two states with self-transition only. Therefore, in order to solve the mentioned issue, we define thresholds $\tau_x = \mu_y, \tau_y = \hat{\upsilon}_x$ for two states of the Markov chain. In this way, we are setting the transition probabilities of two states relative to each other. Thus, when $\mu_y \gg \hat{\upsilon}_x$ it means a user remains in OFF state for a longer duration compared to its ON state.

The process under consideration is semi-Markov as Pareto distribution is used for defining the ON state [9]. As the two-state Markov chain, shown in Fig. 1, is irreducible and aperiodic, the stationary distribution $\Pi_f = \Pi_f \mathbb{P}_f$ can be obtained [10]. Here, $\mathbb{P}_f$ denotes the transition matrix and can be defined as

$$\mathbb{P}_f = \begin{bmatrix} p & 1-p \\ 1-q & q \end{bmatrix}, \tag{5}$$

hence

$$\Pi_f^{on} = p\Pi_f^{on} + (1-q)\,\Pi_f^{off}. \tag{6}$$

As $\Pi_f^{on} + \Pi_f^{off} = 1$, after rearranging, substitution, and simplification, we get final result (3). ■

TABLE I

DETAILS FOR ON AND OFF STATES OF FTP AND VS SERVICE [5]

Service	State	Distributions and general parameters
FTP	ON	Pareto distributed file size with mean υ_x in MB, shape $\varrho_x = 1.5$, and scale k_x can be obtained through υ_x and ϱ_x.
	OFF[2]	Exponentially distributed with mean μ_y in seconds.
VS	ON	Deterministic frame duration F_d in ms; Number of slices per frame $S_n = 8$; Slice size is distributed according to a truncated Pareto distribution with shape $\rho_x = 1.2$, $x_{min} = 1500$B, and $x_{max} = 3$MB.
	OFF[3]	Inter-arrival time between slice is distributed according to a truncated Pareto distribution with shape $\rho_y = 1.2$ and $y_{min} = 1$ms.

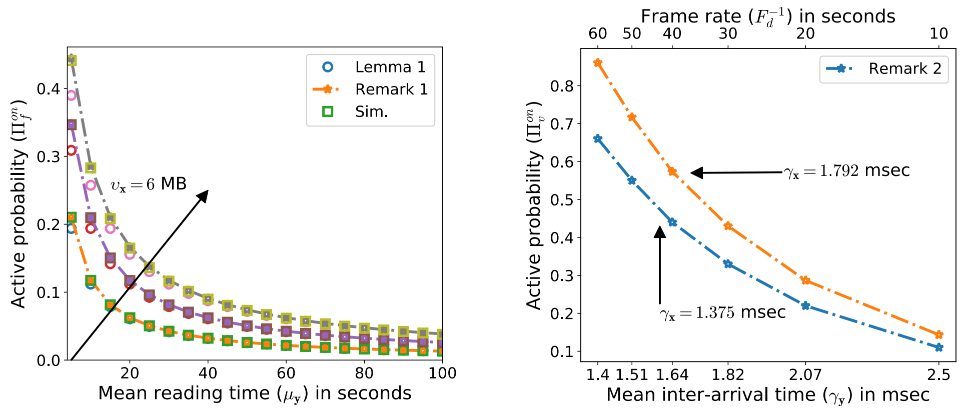
Remark 1: By exploiting the mean ON and OFF duration, we can obtain the active probability of a user, during a time-slot, as follows

$$\overline{\Pi}_f^{on} = \frac{\hat{\upsilon}_x}{\hat{\upsilon}_x + \mu_y}. \tag{7}$$

This is in accordance with the ASRP model [8], where general distributions are assumed for defining ON and OFF states.

For validation of Lemma 1 and Remark 1, we generated the simulation results, using distributions and parameters as listed in Table I for FTP service, by creating around 10^6 instances, where each instance includes the size of a file and corresponding reading time. The number of required time slots, and hence the time duration, for complete transmission of the file has been obtained by exploiting (2). As we are interested in the active probability, in the end, the results are averaged over all the instances. Please note that, this work is focused around the transmission over the access link i.e., from BS to user. As clear from Fig. 2a, compared to Lemma 1, the results obtained through Remark 1 are closer to the simulated ones. This suggests that, irrespective of the distribution being used for defining states, we can exploit the mean duration in order to define the active probability of a user, which is in accordance with the ASRP model [8]. Moreover, the activity of a user increases as a function of file size and decreases as a function of reading time.

2) Video Streaming: According to the details given in [5], the slice size (X) and the inter-arrival times (Y) for VS are distributed according to a truncated Pareto distribution. The frame duration and the number of slices per frame are defined deterministically. We can derive the stationary probability for a user by following a process similar to Lemma 1. However, as already clear from Remark 1, the active probability of a user can also be obtained with the help of mean ON



(a) (b)

Fig. 2. Active probability of a user: (a) for FTP as a function of mean off duration (μ_y) assuming mean file size as $v_x = 2, 4, 6$ MB, (b) for VS as a function of mean inter-arrival time (γ_y).

and OFF durations. Hence, by exploiting this finding, in the following Remark we discuss the active probability of a user for VS service request.

Remark 2: Given a user generates a service request for VS, the active probability of the user, during a time-slot, can be defined as

$$\Pi_v^{on} = \frac{S_n \gamma_x}{F_d}, \tag{8}$$

here S_n and F_d denote the number of slices per frame and frame duration, respectively, whereas γ_x represents the mean of random variable X which is distributed according to a truncated Pareto distribution and it can be obtained as

$$\gamma_x = \frac{x_{min}^{\rho_x}}{1-\left(\frac{x_{min}}{x_{max}}\right)^{\rho_x}} \left(\frac{\rho_x}{1-\rho_x}\right) \left(\frac{1}{x_{min}^{\rho_x - 1}} - \frac{1}{x_{max}^{\rho_x - 1}}\right). \tag{9}$$

In Fig. 2b, the active probability of a user for VS service (8) has been plotted against mean inter-arrival time γ_y, which is basically function of frame rate i.e., $1/F_d$. It must be clear that, as the frame rate decreases, the inter-arrival time between successive slices increases; hence, the activity of a user decreases. Moreover, the active probability of a user increases as a function of slice size.

C. Distribution of Active Users

Under following Lemma, we derive the probability mass function (PMF) for the distribution of active users under a random BS.

Lemma 2: Let $\mathcal{N}_r$ and $\mathcal{N}_r^a$ represent the spatial and active number of users in a Voronoi cell of a random BS. Given that single flow of service type $T = t$ is being generated by a user with active probability of Π_t^{on}, the PMF for overall active users under the BS can be obtained as

$$\mathbb{P}(\mathcal{N}_r^a = \kappa) = \sum_{n=\kappa}^{\infty} \sum_{t \in \{f,v\}} \mathbb{P}\left(\mathcal{N}_r^a = \kappa | \mathcal{N}_r = n, T = t\right) \times \mathbb{P}\left(\mathcal{N}_r = n\right) \mathbb{P}(T = t), \tag{10}$$

where

$$\mathbb{P}\left(\mathcal{N}_r^a = \kappa | \mathcal{N}_r = n, T = t\right) = \binom{n}{\kappa} \left(\Pi_t^{on}\right)^{\kappa} \left(1 - \Pi_t^{on}\right)^{n-\kappa}. \tag{11}$$

Proof: Here, we assume that the request generated by each user is independent of the other users' locations and service requests. Therefore, the joint probability is the product of independent random variables i.e., $\mathbb{P}(\mathcal{N}_r = n, T = t) = \mathbb{P}\left(\mathcal{N}_r = n\right) \mathbb{P}(T = t)$, where the PMF for n spatial users under a random BS has been defined in [11] as

$$\mathbb{P}\left(\mathcal{N}_r = n\right) = \frac{3.5^{3.5}\Gamma(n + 3.5) \left(\lambda_u/\lambda_b\right)^n}{n!\Gamma(3.5) \left(\lambda_u/\lambda_b + 3.5\right)^{n+3.5}}, \tag{12}$$

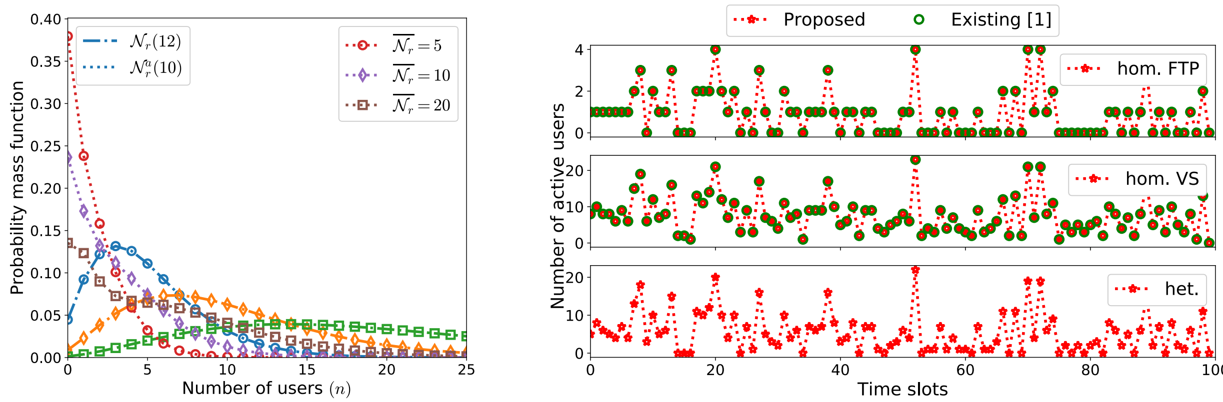
and the average load per BS is $\overline{\mathcal{N}_r} = \frac{\lambda_u}{\lambda_b}$. The probability for generating a service request of type t is w_t, which is actually the weight associated with service t. Moreover, we have exploited Binomial distribution in order to obtain κ active users, during a time-slot, out of n spatial users, for a given service request t. In the end, the results are summed over all the service types and possible combination of n spatial users, and we get (10). ∎

The results obtained through the PMF of spatial (12) and active (10) users are reported in Fig. 3a, by assuming a heterogeneous traffic scenario with parameters specified in Section III. Although the number of spatial users is significant, the number of active users is very small, due to their active probability which is less than unity. As the number of active users is small, during a time-slot, the probability that a random BS remains active is also low. As a result, in contrast to saturated model, the cumulative interference reduces and the overall SIR coverage improves [3]. Thus, the modeling and analysis of the activity of users can greatly help in coverage analysis of practical scenarios. Moreover, it can also help in accurate modeling of more critical performance metrics like delay outage and stable queue probability.

III. Results and Discussion

Unless otherwise specified, the parameters used for generating results are: $\Pi_f^{on} = 0.05, \Pi_v^{on} = 0.4, w_f = 0.3, w_v = 0.7, T_s = 1$ms, $L = 1500$B. As video traffic is predicted to be dominant [6], a large weight has been assigned to VS. The active probabilities for FTP and VS service requests have been chosen from the reported results in Fig. 2.

The statistical patterns are shown in Fig. 3b, for homogeneous and heterogeneous scenarios, by assuming $\overline{\mathcal{N}_r} = 20$.



(a) (b)

Fig. 3. (a) The PMF for the number of spatial and active users, under a random BS, in a heterogeneous scenario. (b) The statistical pattern for the active users in homogeneous and heterogeneous scenarios, and the comparison with existing literature [1].

The patterns are also compared with existing approach [1], where the PMF for spatial users with packet arrival rate $\xi \leq \xi_o$ has been defined as

$$\mathbb{P}(\mathcal{N} = n) = \frac{(2n+5)!!}{15.n!}\left(\frac{C_o}{2}\right)^n (C_o+1)^{-n-3.5} \tag{13}$$

and

$$C_o = \frac{\xi_o - \xi_{min}}{\xi_{max} - \xi_{min}} \frac{2}{7} \frac{\lambda_u}{\lambda_b}. \tag{14}$$

The authors in [1] assumed that ξ is uniformly distributed in the range $[\xi_{min}, \xi_{max}]$. Moreover, as clear from (14), the cumulative distribution function (cdf) of uniform distribution has been used for obtaining the PMF of spatial users with $\xi \leq \xi_o$. Thus, the existing approach provides the PMF of spatial users with arrival rate less than or equal to ξ_o, and when $\xi_o = \xi_{max}$, the (13) becomes equal to the PMF of overall spatial users (12). For the results reported in Fig. 3b, the chosen parameters for (13) are: $\xi_{min} = 0, \xi_{max} = 1, \xi_o = \Pi_f^{on}$ for FTP, and $\xi_o = \Pi_v^{on}$ for VS. Although the statistical patterns produced through proposed model are visually same to those of (13), for homogeneous scenario, the interpretation is different. As per (13), the pattern represents the fraction of spatial users with $\xi \leq \xi_o$, and according to proposed approach, the pattern represents the total number of active users. Thus, with the aid of proposed model, we can obtain the number of active users, during a time-slot, which directly affects the activity of BSs, and hence, the cumulative interference. The statistical pattern has also been plotted for a heterogeneous scenario by exploiting the proposed approach. It must be noted that, under homogeneous case, compared to FTP, the number of active users for VS service is large. For heterogeneous case, the number of active users is slightly less than the VS as a certain percentage of the users is using FTP service and they have smaller active probability.

IV. Conclusion and Future Work

Considering the impact of spatial and temporal distribution of active users on various performance metrics, we have developed a joint spatio-temporal model for the distribution of active users under a random BS. The proposed approach is generalized, as it can be exploited for obtaining the PMF of active users, when homogeneous or heterogeneous service requests are being generated in a given region. With the help of statistical patterns, we have showed that, for a given average spatial load, the number of active users for VS is large as compared to FTP because the users' active probability for VS service is higher. Moreover, we discussed the limitation of existing approach which does not provide the PMF of active users. The future work includes the extension of this approach for multiple traffic flows per users and derivation of the PMF for active user under a serving BS.

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