# Impact of Protocols on Traffic Burstiness at Large Timescales in Wireless Multi-Hop Networks

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***Abstract*—We investigate the impact of the protocol stack on traffic burstiness at large time-scales in wireless multi-hop network traffic. Origins of traffic burstiness at large scales (like its LRD nature) have been mostly attributed to the heavy-tails in traffic sources. In wired networks, protocol dynamics have little impact on large time-scale dynamics. However, given the nature of wireless networks, the MAC and routing layers together can lead to route flapping or oscillations even in a static network. Hence, we explore whether these dynamics can lead to traffic burstiness and LRD. Using network simulations, we analyze traffic for two MANET routing protocols - OLSR and AODV. By varying the routing protocol parameters, we analyze their role in inducing or preventing route oscillations, and study their impact on traffic LRD. We find that, losses in OLSR control packets, due to congestion at the MAC, can lead to route oscillations and traffic burstiness at large timescales. By tuning the parameters, route oscillations and traffic LRD can be avoided. AODV dynamics show little evidence for traffic LRD, even though we cannot rule out this possibility. We also show that the route oscillations can have heavier body and tail than exponential distribution, and that the Markovian framework for route oscillations is inadequate to explain the observed traffic scaling. Lastly, we give a model that captures the MAC and OLSR routing protocol interactions and depending upon chosen protocol parameters and input load, correctly predicts the presence of traffic LRD. Thus, we use this model to design appropriate choice of protocol parameters to mitigate traffic burstiness at large-timescales.**

## I. Introduction

The existence of self-similarity in Ethernet LAN was established with the seminal work of Leland et al. [1]; self-similarity and the related phenomena of long-range dependence (LRD) characterized the unexpected burstiness and correlation of the network traffic at large-time scales. LRD nature of the traffic has significant impact on network performance through queue-occupancy, service times, packet losses, etc. Existence of LRD also invalidates the use of Poisson arrivals and Markovian queuing analysis. Since then, many works have shown the existence of traffic LRD in various data networks such as ATM, WAN, etc. [2]–[4]. In most of these networks, the high variability in traffic sources, characterized by heavy-tail distributions, has been attributed as one of the main causes of traffic LRD. In particular, heavy-tails in file sizes, connection or flow durations, inter-arrival times, etc., have been empirically verified [2], [5], [6]. And, through the fundamental result on *On/Off model* by Taqqu et al. [5], the causal link between heavy-tails and LRD in an idealized setting has been established. Even though idealized, the result and its variations, have been applied with great success in many real-measurements [5], [6] as well as simulation-based studies [7], [8]. The wide applicability of the model in various network settings has led to the belief that the network protocols themselves play little part in the large time-scale behavior of traffic, and that protocol dynamics affect only the small-time scale properties [3], [7], [9].

While the existence of LRD has been widely studied in wire-line networks, there are very few studies in wireless networks [10], [11]. Given the belief that network protocols won't affect large time-scale behavior, it is generally expected that wireless networks will yield similar results. However, we believe, LRD in wireless networks can be qualitatively and quantitatively different, as they include a number of new features such as shared wireless medium, fading as well as mobility. The lower-layer protocols are expected to have more pronounced impact in wireless networks. Due to variable link conditions in wireless networks, the routing protocol can also cause changes in multi-hop routes even in a static topology. The link 'failure' detection mechanisms are different for wireless networks; a certain number of consecutive packet drops is usually used as indicator of link failure, even though these packet drops can be due to fading or congestion. Thus, the wireless medium can introduce route changes which can potentially affect traffic burstiness at large timescales. Hence, we wish to re-examine the impact of protocols on the traffic LRD, in wireless multi-hop networks.

We carry out a simulation-based study to find the relation between traffic burstiness and the impact of protocols in multi-hop wireless networks. In particular, we focus on the role of routing protocols and contention-based MAC on traffic burstiness. We study two of the most popular routing protocols - OLSR [12] and AODV [13]. We observe that losses of OLSR routing control packets, at the MAC layer, can lead to route changes even in static networks. Such route changes, in turn, result in bursty traffic at intermediate nodes. Even though, the typical timescale of routing protocol packets is of the order of few seconds, we see that traffic burstiness is observed even at time-scales of up to several hours. Thus, unlike the wired networks studied before, the varying nature of wireless 'links' and their impact on routing protocols, result in traffic brustiness at much larger timescales.

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Our own preliminary experiments show that the performance of contention-based MAC, like 802.11, is affected by the traffic burstiness at large-timescales. Also, LRD or not, the observed traffic oscillations directly impact the carried load in the network. For some of the scenarios, we observed a throughput drop of up to 15 % due to avoidable route oscillations. Hence, it is important to characterize the large-timescale behavior of traffic for more accurate performance evaluation and network design. Otherwise, the actual QoS will be much worse than predicted by traditional models.

For the OLSR scenario, we also model the observed traffic burstiness phenomena using models in two steps. At first, using a simple On/Off packet train model, we explain how route oscillations can lead to traffic burstiness, and how a Markovian framework for route oscillations is not sufficient to explain the large-timescales burstiness. Using a simple 4-node scenario with a single connection, we provide evidence for sub-exponential On and Off durations, providing some evidence for protocol-induced 'heavy-tails'. In the second part, we model the 802.11 MAC and OLSR protocols to show how input traffic load levels can impact protocol dynamics and lead to topology changes even in a static network. We use approximate models to predict the presence of traffic burstiness at large timescales. In particular, we use the 802.11 MAC and OLSR models from [14], [15], to find the probability of topology changes; thereby, leading to traffic burstiness in at least some of the intermediate nodes. Lastly, while protocols can lead to traffic burstiness at large-timescales, appropriate tuning of protocol parameters can mitigate the effect. We use our models to correctly predict what choices of protocol parameters will results in traffic burstiness and what choices will not. Thus, we use the models not just to explain the observed phenomenon, but also to aid in network design.

The paper is organized as follows: In Sec. II, we provide some preliminaries for traffic analysis as well as the relevant protocol dynamics at play in our study. Sec. III includes our preliminary simulation studies which show evidence of traffic burstiness due to OLSR protocol and contention-based MAC. In Sec. IV, we give the details about the On/Off model for route oscillations. Sec. VI, provides a simplistic model linking load-levels, MAC failure probabilities and the resulting impact on OLSR routing. In Sec. VII, we test our models on newer scenarios and demonstrate how we can use them to tune the network parameters appropriately.

## II. Preliminaries

### A. Traffic Scaling and Wavelet Analysis

To analyze traffic at different timescales, a commonly used tool is based on the Discrete Wavelet Transform [9], [16]. The Multi Resolution Analysis consists of splitting a given sequence of observations $X = \{X_1 \dots X_n\}$ into the (low pass) *approximation* and the (high-pass) *details* :

$$X = \sum_{k=1}^{n/2^J} a_X(J,k)\phi_{J,k}(t) + \sum_{j=1}^{J}\sum_{k=1}^{n/2^J} d_X(j,k)\psi_{j,k}(t) \quad (1)$$

where $\phi_{j,k}(t)$ and $\psi_{j,k}(t)$ are shifted and dilated versions of the scaling function $\phi_0(t)$ and the mother wavelet $\psi_0(t)$.

The quantity $|d_X(j,k)|^2$ measures the amount of energy in signal X about time $t_0 = 2^j k$ and about the frequency $2^{-j}\lambda_0$ where $\lambda_0$ is a reference frequency which depends on the choice of $\psi_0$. And the expectation of energy that lies within a bandwidth $2^{-j}$ around the frequency $2^{-j}\lambda_0$, is denoted by $\mathrm{E}[E_j]$ and is approximated by $\frac{1}{n_j}\sum_{k=1}^{n_j}|d_X(j,k)^2|$, where $n_j$ is the number of wavelet coefficients at scale or octave $j$. The wavelet analysis is widely used to study the Long Range Dependence (LRD) properties of a time-series as well [17]. If X is an LRD process, then the wavelet coefficients satisfy:

$$y_j = \log_2\big(\frac{1}{n_j}\sum_{k=1}^{n_j}|d_X(j,k)^2|\big) \sim (2H-1)j + c, \quad (2)$$

where $c$ is a constant and $H$ is the Hurst parameter which characterizes the degree of LRD. From Eq. (2), a linear regression fit to the plot of $y_j$ against octave $j$ gives an estimate of $H$. However, to get a good Hurst estimate the region of scaling needs to be carefully identified [8]. Nevertheless, scaling over a finite range of octaves is indicative of traffic burstiness at corresponding timescales. And scaling at higher octaves is a good enough indicator for the presence of LRD.

### B. Routing Protocol Dynamics

For multi-hop scenarios, the routing protocol plays a role in shaping traffic. Even in a static topology, the routing protocol may change routes due to losses. Loss of routing protocol control packets at the MAC (due to congestion or physical layer losses) can lead to the inference of topology changes. This in turn, can result in route changes even for static topology. Such changes in the routes may lead to additional dynamics in the traffic at each node. In our simulations we either use the OLSR [12] or AODV [13] routing protocols. We summarize the details relevant to our study here.

OLSR is a proactive routing protocol. It relies on periodic HELLO and TOPOLOGY CONTROL (or TC) packets to discover local and global topology, respectively. Each node periodically broadcasts HELLO packets (with period $T$). Whenever a neighboring node receives a HELLO packet, the node assumes that the link to the sender is up. If $D$ consecutive HELLO messages are lost (timed-out), the node infers link failure. Based on the local neighborhood information from HELLO packets, TC packets are broadcast throughout the network, and each node stores its limited view of the global topology. Based on this topology, each node chooses the best next-hop for a given destination. Any changes in local topology, inferred due to HELLO packets, triggers network-wide updates in global topology. Thus, losses in HELLO packets (even due to congestion or fading) can result in changes in inferred topology and hence, the routes.

AODV is a reactive routing protocol. Whenever a new connection is arrives, the source attempts to find the best path to the destination. For a new destination, the source broadcasts Route Request (RREQ) packets which are propagated in the network. The destination node sends out Route Reply (RREP)

packets along the best path, using the information stored in the RREQ packets. Once a path has been established, the liveliness of the links on the path is determined using both explicit and implicit methods. Explicit methods rely on periodic HELLO packets on the active links. Implicit methods rely on MAC layer ACKs or control messages. Any of these packets could be dropped at the MAC and PHY layers.

In OLSR, nodes keep an updated view of the entire topology. In the event of a link failure, nodes will quickly route paths on newer links. If that new path becomes congested later, it might trigger more link 'failures'. Thus, it is possible that the routes keep oscillating between two paths, leading to traffic burstiness at the intermediate nodes. In AODV, in contrast, nodes only store active routes. In the event of link failure, there is route recovery. Compared to an OLSR scenario, it is more likely that the route recovery mechanism returns the old path, although route oscillations can occur in AODV as well.

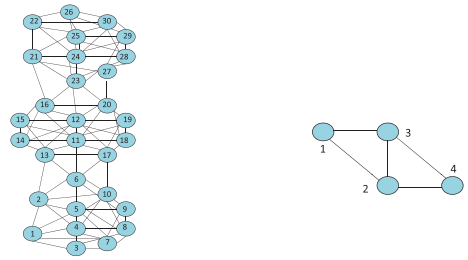
## III. Simulation Study

At first, we conduct some preliminary experiments to analyze the role of protocol dynamics in shaping traffic at large timescales. This serves as the motivation for a more detailed modeling and analysis that follows. We used OPNET [18], to study traffic scaling in wireless networks. We studied multi-hop scenarios using IEEE 802.11b MAC (DCF mode). MAC and PHY parameters were set to the standard values. However, to keep our focus on the MAC and higher layers, we set a unit-disc model for the communication range. To achieve this, we used a two-ray ground propagation model, and modified the CCK modulation scheme's BER curve to be either 0 or 1 depending upon the SNR. Thus, a pair of nodes within a given distance threshold can communicate without any physical layer errors. Even though we did not report the results here, we repeated our experiments with realistic PHY and SNR models, to obtain similar results qualitatively.

We used a 30-node topology as shown in Fig. 1(a). There are multiple short connections within the clusters, but there are some connections across the clusters as well. The traffic applications use TCP/IP protocols (we obtained similar results using UDP). We ran multiple simulations with varying load levels, and different random seeds for each load level. For each of the scenarios studied below, we ran each simulation for 1 day. At each node, we measured the MAC layer throughput every $\Delta = 0.1\ sec$. To study the impact of routing protocols, we ran two sets of simulations - one each with OLSR and AODV protocols. We initially chose the default parameters according to the respective RFCs. However, route oscillations were clearly visible in OLSR scenarios (and not so obvious for AODV). To study the OLSR route oscillations in more detail, we tuned the OLSR routing parameters as described later.

### A. Impact of Routing Protocols

For each connection, we used exponential file sizes (with mean 13715 Bytes) and exponential inter-request time, with mean 2 sec (for medium load) or 10 sec (for low load). For medium load (mean inter-request time = 2 sec), the total




(a) 30-Node Scenario (b) 4-Node Scenario

Fig. 1. Simulated Topologies

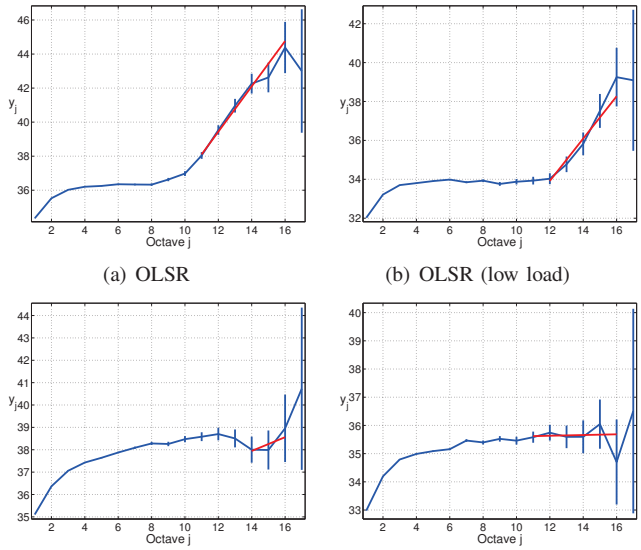
offered load was around 1.5Mbps. While it is difficult to characterize the capacity of the network, we call the load-level medium, because, for properly tuned routing protocols (as described later), all of the offered load was carried by the network. Even for the default OLSR scenario, the throughput was 99.6%.

Fig. 2 shows the wavelet analysis for the traffic successfully received at the MAC layer of a sample Node 25 (measured in bps). On the x-axis, octave $j$ corresponds to $t = 2^j * \Delta$, where $\Delta = 0.1$ seconds. Thus, $octave\ j = 10$ implies $t = 100$ seconds. Scaling at large timescales is indicative of traffic LRD. Fig. 2(a) shows that, the traffic at the intermediate Node 25 displayed LRD, when using the OLSR routing protocol. For exactly the same parameters, but using AODV, there was no clear evidence of traffic LRD (see Fig. 2(c)). We made similar observations for low load scenarios. While we may debate whether the finite series is actually LRD or is 'pseudo-LRD', the traffic is definitely bursty at scales from hundreds of seconds to several hours. Thus, to the best of our knowledge, unlike any other previous study, our simulations show for the first time that wireless network protocols can impact traffic at large timescales for several hours. This impacts the network performances as discussed before. For the sake of brevity, we call this traffic burstiness as traffic 'LRD' in the following discussions, although 'pseudo-LRD' will be more appropriate.

Fig. 3 shows the time series plot for traffic at sample node 25 for low-load scenario. Clearly, Fig. 3(a) shows that there were periods of very low traffic at node 25 when using OLSR. During the times when node 25 was carrying less traffic, neighboring nodes (especially node 24) carried more traffic (Fig. 3(b)). These results are evidence of route oscillations, in OLSR, leading to traffic LRD. At least for the scenarios studied, AODV induced little traffic burstiness.

### B. Impact of OLSR Parameters

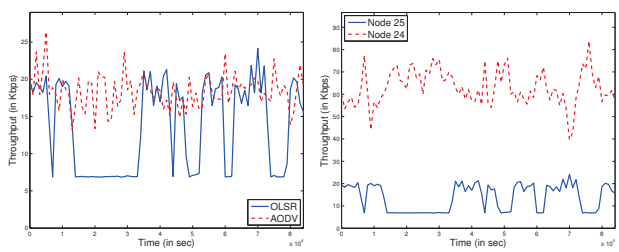
To study the impact of the OLSR protocol in inducing traffic LRD, we changed the OLSR protocol parameters. In OLSR, the default values of $T$ is 2 sec, and $D$ is 3 (Sec. II-B). That is, if $D = 3$ consecutive HELLO messages are lost (timed-out), the node infers link failure, which results in topology and route updates. In our scenario, even though the topology is static, periodic HELLO packets may be lost at the MAC layer. To test our hypothesis that route changes are due to




(a) OLSR (b) OLSR (low load)

(c) AODV (d) AODV (low load)

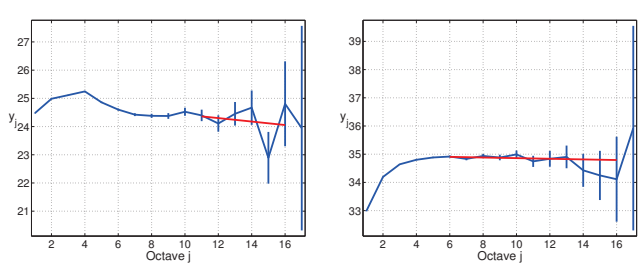
Fig. 2. LRD due to Routing Protocol




(a) Traffic at Intermediate Node 25 (b) Traffic Oscillation between Node 24 and 25 for OLSR scenario

Fig. 3. Evidence of Route Oscillations in OLSR scenario

drops of consecutive HELLO packets, we set $D = 10$. Hopefully, the probability of 10 consecutive packet drops (spread over $T * D = 20sec$) is low enough to avoid unnecessary route updates. We re-ran our simulation and analysis for the scenarios as above with $D = 10$ for OLSR. We denote these scenarios as *Tuned-OLSR*. Fig. 4 shows that there was no LRD in traffic. Also, there were no route or topology updates after the initial setup time. Clearly, by tuning the OLSR parameters, unnecessary route oscillations were avoided. This in turn, leads to absence of routing-protocol-induced LRD.




(a) Tuned-OLSR (b) Tuned-OLSR (low load)

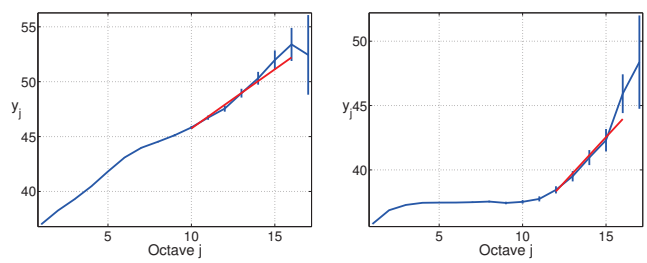
Fig. 4. Parameter tuning in OLSR to avoid route oscillations and traffic LRD

## IV. Traffic Burstiness due to Route Oscillations

In this section, we investigate the relationship of the observed traffic burstiness at large timescales to the presence of route oscillations. We attempt to model the route oscillations using a simple On/Off packet train model and use it to explain the observed traffic scaling.

*1) Analysis of Simple 4-node Topology:* We start with a simple topology (Fig. 1(b)). Nodes 1 and 4 are the source and destination. Nodes 2 and 3 forward traffic depending upon routes chosen by the protocols. OLSR will typically select route $1 \rightarrow 2 \rightarrow 4$ or else $1 \rightarrow 3 \rightarrow 4$. However, due to intermittent link losses of OLSR Control Packets, OLSR can infer the topology incorrectly. Hence, the chosen route (and forwarded traffic) oscillates between the two paths. For the intermediate nodes, then, the traffic at it's MAC layer depends on the chosen route at the source. And hence, incoming traffic can be modeled using an On/Off model packet train model. Since we are focusing on the large time-scale behavior, we can ignore the small time-scale dynamics (due to the source and the MAC layer). Hence, we assume a constant traffic rate during the On periods and no traffic during the Off periods.

We measured the traffic at intermediate nodes (2 and 3) and analyzed their scaling properties. Fig. 5 shows a few sample plots indicating a strong presence of traffic burstiness at large timescales. The high (low) load scenario corresponds to mean inter-arrival time was 0.06 seconds (0.8 seconds). We observed similar behavior for different load levels.

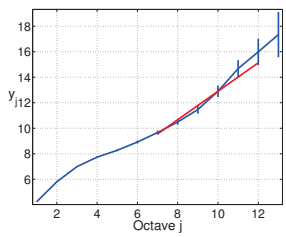



(a) High Load (b) Low Load

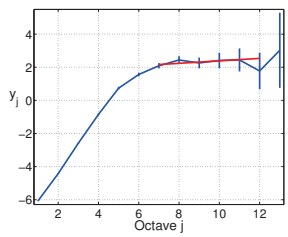
Fig. 5. Timescale of Traffic Burstiness in 4-Node Scenario

We also measured routing table statistics and deduced the On/Off durations for traffic at the intermediate nodes. For example, whenever node 2 is present on the chosen path, it corresponds to the On duration for node 2. And when the chosen path is $1 \rightarrow 3 \rightarrow 4$, it corresponds to the Off duration for node 2. Then, using the On/Off Model, we attempt to predict the traffic burstiness. Initially, motivated by the usual Markovian framework, we assumed i.i.d. Exponential distributions for the On and Off Durations with appropriate mean (17.48 and 23.67, respectively) corresponding to the observed values. Fig. 6(b) shows that the Markovian model for route oscillations cannot explain the observed traffic burstiness (Fig. 6(a)) at large timescales of several hours, which is 3-4 orders of magnitude higher than the mean. However, if we use the empirical distributions, the prediction about traffic scaling is accurate (Fig. 6(c)). Note that, Fig. 6 uses $\Delta = 1$ (unlike

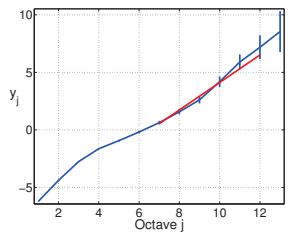
$\Delta = 0.1$) seconds as the sampling interval, hence the shift in the x-axes.




(a) Observed Traffic




(b) On/Off Model with Exponential Duration Distributions




(c) On/Off Model with Empirical Durations

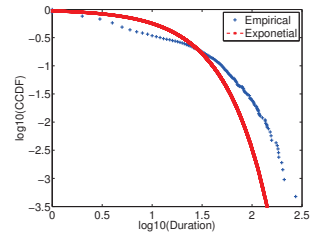
Fig. 6. On/Off Model and Traffic Burstiness

In Fig. 7, we plot the On and Off duration distributions for the high load scenario (mean inter-arrival time of 0.06 seconds). It shows the CCDF and quantile-quantile (QQ) plot for the On and the Off (empirical) distributions compared to exponential distributions with respective means. As can be seen, the On durations have much heavier-body, and slightly fatter tail compared to the exponential. Note that the CCDF plot is on a log-log scale. Repeated experiments with different load conditions and different random seeds yielded similar observations. These observations are in line with sub-exponential tails leading to burstiness at much higher scales. Whether the empirical distributions are true heavy-tails, needs more detailed evaluation.

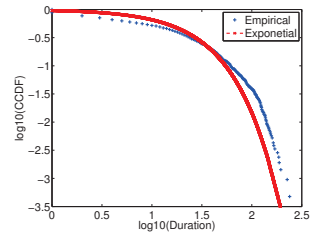
## V. Modeling the MAC Collisions and OLSR Link Failures

### A. MAC Model

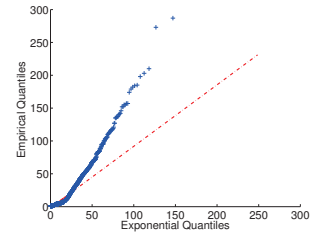
Starting with the seminal work by Bianchi et al. [19], there are some works [14], [20], [21] in throughput modeling for networks using 802.11 MAC. They are abstract MAC models for estimating the average transmission attempt rates, collision rates, service times and throughput. They model the detailed working of the collisions and back-offs to get good approximations to average throughput. In this paper, we use our considerably more realistic model introduced in [22] and improved in [14]. In our model, given the input load, the $MAC\ model$ approximates the average MAC frame drop probabilities $\beta$ over various links. We use these MAC frame drop probabilities as the probabilities of OLSR control packets losses, which form the input to our $OLSR\ model$.



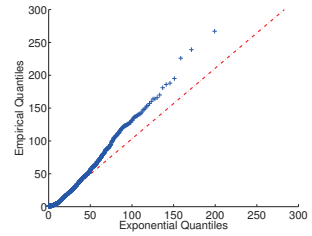

(a) CCDF for On Durations




(b) CCDF for Off Durations




(c) QQ plot for On Durations




(d) QQ plot for Off Durations

Fig. 7. Empirical On and Off Durations Distribution Compared With Exponential

### B. OLSR Model

Here, we present a model for the working of OLSR route calculations. In particular, given the packet transmission failures (MAC frame drop probabilities), our model tries to find out the probability of topology change (and route recalculations). For this, we use our earlier component-based performance models from [15]. However, we modify the models for our new metric of interest: the probability of topology changes.

The Neighbor Discovery Component (NDC) of OLSR is responsible for detection of changes in a node neighborhood. NDC relies on periodic transmission of HELLO messages for detection of neighbors. From the HELLO messages, a node can detect its neighbors. This local information about bidirectional links is flooded through out the network using TOPOLOGY CONTROL messages. The controlled flooding for TOPOLOGY CONTROL messages along with the HELLO messages, help nodes to construct a global view and discover routes.

We model the NDC as a Finite State Machine (FSM). The Markov chain model for the link between nodes $i$ and $j$ is depicted in Figure 8. The parameter $s_{ij}$ is the probability of success in sending HELLO messages and $f_{ij}$ is the probability of failure. The design (or control) parameters for NDC are the $U$ and $D$ parameters that can be set to achieve the desired performance. In OLSR, the value of $U$ is fixed to 1.

Let $\pi_k$ be the steady state probability that NDC is in state $k$ of the Markov chain. Then, the probability of detecting a directional link to node $j$ at node $i$ is:

$$q_{ij} = \sum_{k=U}^{U+D-1} \pi_k, \tag{3}$$

where $\pi_k$ and $q_{ij}$ are functions of $s_{ij}$ and $f_{ij}$.

We assume that the probability of successful transmission from $i$ to $j$ and from $j$ to $i$ are independent from each other.

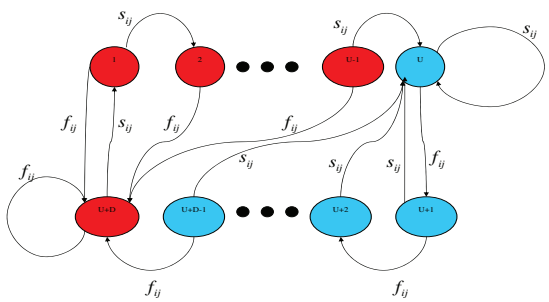



Fig. 8. Markov chain model for the neighbor discovery mechanism

Then the two FSMs at nodes $i$ and $j$ (for directional links $j \rightarrow i$ and $i \rightarrow j$, respectively), can be assumed to be independent. Then the bidirectional link state is UP ($BU$) if both FSMs are in directional UP states (otherwise $BD$). Thus, the probability of a bidirectional link detection is:

$$p_{ij} = q_{ij} \cdot q_{ji}. \tag{4}$$

For brevity, we assume $f_{ij} = f_{ji} = f$. (The general case of $f_{ij} \neq f_{ji}$ is a simple extension). The probability of change of bidirectional link status is, then:

$$p_{change} = p_{BU \rightarrow BD} \cdot p + p_{BD \rightarrow BU} \cdot (1 - p) \tag{5}$$

where

$$p_{BU \rightarrow BD} = \frac{2\pi_{U+D-1} \cdot f \cdot q - \pi^2_{U+D-1} \cdot f^2}{p} \tag{6}$$

And,

$$p_{BU \rightarrow BD} = \frac{2\pi_{U-1} \cdot s \cdot q + \pi^2_{U-1} \cdot s^2 - 2\pi_{U-1}\pi_{U+D-1} \cdot s \cdot f}{1 - p} \tag{7}$$

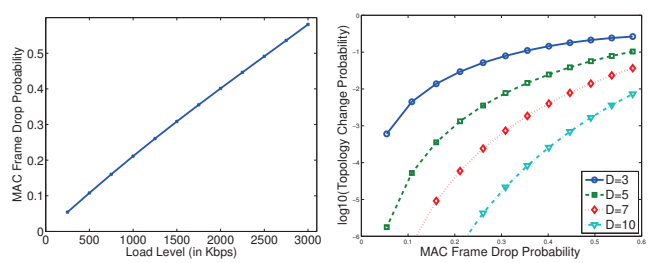
Thus, $p_{change}(f)$ gives the probability of state change for a particular link, as a function of it's MAC layer frame drop probability $f$. Change in any link status may results in global topology change and may lead to route calculations. Since, route recalculations are performed at every fixed intervals and aggregated for all link changes, we make another approximation. We assume that the probability of topology change $\nu$ is dominated by the probability of link status change of the most suspectible link. Hence, we assume $\nu = p_{change}(\beta_{max})$, where $\beta_{max}$ is the maximum of (vector) $\beta$ over all links, obtained from the $MAC\ model$ described previously.

## VI. Modeling Route Oscillations due to MAC Losses

In Sec. IV, we used the On/Off model to demonstrate how the route oscillations lead to traffic burstiness, in a simple scenario. In this section, we aim to predict when route oscillations may occur in a large topology, when using OLSR. Depending on the input load levels, and the choice of OLSR design parameter $D$, we model the 802.11 MAC losses due to congestion and resulting OLSR topology changes. For this purpose, we use the performance models developed in Sec. V. We present the model and simulation results here to demonstrate that the MAC and routing protocol dynamics are the origins for the observed traffic burstiness, and also this traffic burstiness can be mitigated by appropriate parameter choices. The $MAC\ model$ takes the offered load level and topology as inputs to predict MAC frame drop probabilities for various links. The $OLSR\ model$ uses these MAC loss probabilities as input to give topology change probability and predict route oscillations. Thus, in this section, we use our models to connect input load levels, with MAC frame drops and OLSR topology / routing changes. We use the 30-node topology to validate our models, and also demonstrate how we can design the protocol parameters to avoid traffic LRD.

### A. Link Losses and Topology Changes

*1) Packet Collisions due to Increasing Load Levels:* At first, using the $MAC\ model$ for 802.11, we find the MAC packet or frame drop probabilities depending upon the input load level. Depending upon the topology and different traffic demands, each wireless 'link' will have varying probability for MAC frame drop due to collisions. OLSR HELLO packets will suffer losses according to these probabilities. Since more MAC loss probability leads to more dynamism in OLSR link changes, the overall rate of OLSR topology changes will be mainly governed by the most susceptible link. Hence, amongst all the different links, we consider the link with highest MAC layer losses (as input to the OLSR model). In Fig. 9(a), we show the maximum (over links) average (over time) MAC failure probability as a function of input load. Clearly, as the load increases, there are more collisions at the MAC level.



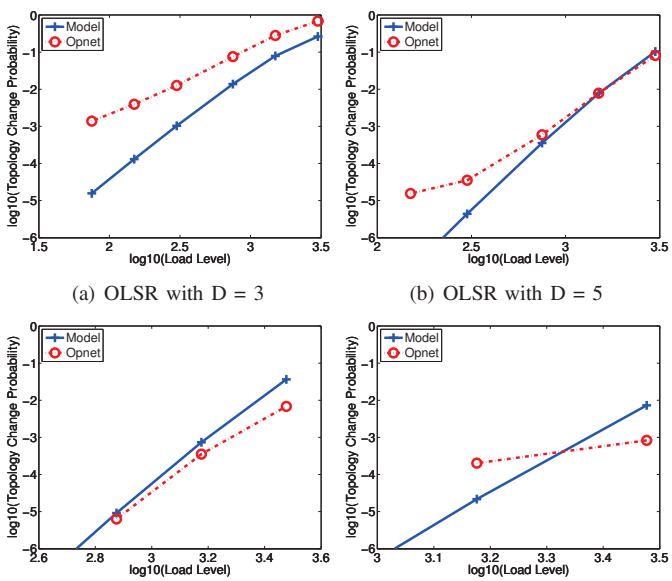

(a) (b)

Fig. 9. Load Level, MAC Losses and OLSR Topology Change Probabilities

*2) OLSR Link Failures due to Packet Collisions:* Now, using the maximum MAC failure probability $\beta_{max}$ as an input to $OLSR\ model$, we obtain the steady-state probability of OLSR link changes in the most susceptible link. Note that any local change in topology is likely to result in global topology changes and routes calculations. Also, changes at different links are aggregated and sent periodically. Hence, even if two links change in a slot, only one update will be propagated network wide. Thus, the rate or probability of OLSR global topology changes $\nu$ is mainly determined by the rate of link status change of the most susceptible link (see Sec. V). Hence, we assume that the $OLSR\ model$ output gives the probability of global route table calculations. Using the $OLSR\ model$, Fig. 9(b) shows the probabilities of OLSR topology changes as a function of MAC loss probabilities, for various choice of

OLSR parameter $D$. As conjectured in Sec. III-B, higher $D$ implies more resilience to MAC layer losses.

We compare the $OLSR\ model$ output with actual statistics obtained from OPNET simulations. For a given value of OLSR parameter $D$, Fig. 10 shows the model and OPNET probabilities of topology changes (and resulting route re-calculations), for various load-levels (normalized to 1 for maximum load of 3 Mbps). The topology change probabilities from OPNET are obtained as the fraction of instances when HELLO message exchanges (slotted) lead to topology changes. The y-axes are truncated to hide low data points. Also the missing data points for the OPNET dataset corresponds to $log(0) = -\infty$. The model output matches very closely with the OPNET results. There is some mismatch at higher levels of MAC loss probabilities, especially for $D = 3$. We believe that is due to the assumption about the most susceptible link dominating the network-wide topology changes. However, even other links can increase the topology change rate, and their impact can be higher at higher MAC loss levels. Nevertheless, the model predicts the order of topology change probability correctly.




(a) OLSR with D = 3 (b) OLSR with D = 5

(c) OLSR with D = 7 (d) OLSR with D = 10

Fig. 10. OLSR Topology Changes due to Increasing Load Levels

### B. Traffic LRD due to OLSR Topology Changes

Next, we turned our attention back to traffic burstiness and wavelet analysis. We ran wavelet analysis on traffic at intermediate nodes (as in Sec. III). For each value of D and different load-levels, we ran the simulation for 1 day, and repeated the experiment with 5 different random seeds. As before, we present the sample results for central node 25. However, instead of showing the numerous wavelet plots, we just list the results in Tab. I. The table should be read as follows: the value give the fraction of scenarios (out of the 5 random seeds), in which we observed traffic LRD according to the wavelet analysis. Clearly, we see that for low values of $D$, collisions at the MAC couple with OLSR to give rise to traffic LRD. And as we increase $D$, such traffic burstiness can be avoided. The last row also shows the results for AODV, validating the absence of traffic burstiness in any of the AODV scenarios.

| Load (in Kbps) | 75 | 150 | 300 | 750 | 1500 | 3000 |
|---|---|---|---|---|---|---|
| **D=3** | 0 | 1 | 1 | 1 | 1 | 1 |
| **D=5** | 0 | 0 | 0 | 0 | 0.6 | 1 |
| **D=7** | 0 | 0 | 0 | 0 | 0 | 0.4 |
| **D=10** | 0 | 0 | 0 | 0 | 0 | 0 |
| **AODV** | 0 | 0 | 0 | 0 | 0 | 0 |

TABLE I
LRD AT NODE 25 FOR DIFFERENT LOAD LEVELS IN 30-NODE SCENARIO

Combining the topology change probabilities from the $OLSR\ model$ and observed LRD in traffic, we look at traffic LRD as a function of topology change probabilities. In Fig. 11, shows the fraction (out of 5 random seeds) of scenarios where traffic was LRD at Node 25 (for all $D$). Thus, there is a strong relation between topology change and traffic LRD.

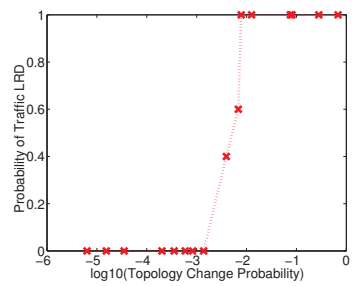
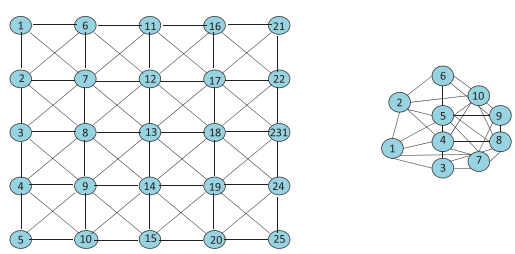



Fig. 11. Traffic LRD with Topology Change Probability Estimate from the Model

## VII. NETWORK DESIGN AND VALIDATION

We give additional evidence for traffic LRD. We, also, validate the models and their utility in choosing an appropriate value for OLSR design parameter $D$ to avoid traffic LRD. For these purposes, we used the topologies shown in Fig. 12.For the 25-node scenario, we setup three connections:$1 \rightarrow 20$, $5 \rightarrow 18$ and $18 \rightarrow 25$. For the 10-node scenario, we setup 10 connections: $1 \rightarrow 9, 2 \rightarrow 7, 3 \rightarrow 10, 4 \rightarrow 5, 5 \rightarrow 1, 6 \rightarrow 8, 7 \rightarrow 4, 9 \rightarrow 6, 10 \rightarrow 3$.



(a) 25-Node Grid (b) 10-Node

Fig. 12. Other Topologies

We used our model to justify a choice of design parameter $D$. In particular, given the topology and traffic demands, we

| **Load (in Kbps)** | | 36 | 360 | 720 | 1200 | 1800 |
|---|---|---|---|---|---|---|
| **MAC Failure Probabilities** | | 0.0219 | 0.2190 | 0.4152 | 0.6354 | 0.6913 |
| **Topology Change Probability** | D=3 | 4.1e-5 | 0.032 | 0.155 | 0.278 | 0.273 |
| | D=10 | 9.9e-17 | 7.9e-7 | 3.5e-4 | 0.015 | 0.03 |
| | D=20 | 2.5e-33 | 2.0e-13 | 5.4e-8 | 1.6e-4 | 7.6e-4 |
| **Traffic LRD** | D=3 | 0.4 | 1 | 1 | 1 | 1 |
| | D=10 | 0 | 0 | 0 | 0.2 | 1 |
| | D=20 | 0 | 0 | 0 | 0 | 0 |

TABLE II
ANALYSIS FOR 25-NODE SCENARIOS

| **Load (in Kbps)** | | 120 | 1200 | 2400 |
|---|---|---|---|---|
| **MAC Failure Probabilities** | | 0.0471 | 0.4303 | 0.7517 |
| **Topology Change Probability** | D=3 | 3.9e-4 | 0.167 | 0.242 |
| | D=10 | 2.0e-13 | 4.9e-4 | 0.053 |
| **Traffic LRD** | D=3 | 1 | 1 | 1 |
| | D=10 | 0 | 0 | 1 |

TABLE III
ANALYSIS FOR 10-NODE SCENARIOS

relied on our model to find: 1) the MAC failure probability, and 2) Topology change probability, for a given choice of D. If the probability of topology change is non-negligible, then we should see traffic LRD at least in some nodes (as in Fig. 11). Hence, the particular choice of D is not suitable. Tab. II and Tab. III give the results for 25-node and 10-node scenarios respectively. They show the model outputs - the MAC loss probabilities and topology change probabilities, for different input load levels and design choice $D$. Then, the last row also gives the presence (or absence) of traffic LRD as observed from simulation traces. The table, and Fig. 11, show that the model correctly predicts which values of $D$ will give rise to traffic LRD and which won't. In particular, if the topology change probability is too low, traffic will not be LRD. For high probability of topology change, traffic will be LRD (in atleast some of the intermediate nodes). The only exception seems to be at load level of 0.1 with $D = 3$. According to the model, the probability of topology change was negligible and hence we should not have observed traffic LRD. We believe this is due to the approximations of the model which seem to be inaccurate for low load levels and low value of $D$ (similar to the mismatch in Fig. 10(a)). Overall, the model predicts traffic LRD accurately, and can be used to chose the right $D$.

## VIII. CONCLUSIONS

We explored the impact of routing protocols in large time-scale traffic burstiness. In particular, we observed that packet losses at the MAC (even due to congestion) can lead to route oscillations in OLSR. Route oscillations, in turn, lead to traffic burstiness at large timescales and LRD. We showed that protocols in wireless multi-hop networks can induce traffic burstiness at timescales much larger than previously thought. We also showed that the route oscillations are not accurately modeled by relying on Markovian models for exponential durations. Lastly, we also used performance models for 802.11 MAC and OLSR routing, to correctly predict the MAC losses due to input load, and resulting route oscillations and traffic burstiness. Thus, using these models, we can design the network settings to avoid such phenomena.

## ACKNOWLEDGMENT

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