Towards Repeatable Wireless Network Simulation Using Performance Aware Markov Model

Zhiwei Zhao[1], Wei Dong[2,*], Geyong Min[3], Gonglong Chen[2], Tao Gu[4] and Jiajun Bu[2]
[1]School of Computer Science, University of Electronic Science and Technology of China, China
[2]College of Computer Science, Zhejiang University, China
[3] College of Engineering, Mathematics and Physical Sciences, University of Exeter, UK
[4]College of Computer Science, RMIT University, Australia
zzw@uestc.edu.cn; g.min@exeter.ac.uk; {dongw,chengl,bjj}@zju.edu.cn; tao.gu@rmit.edu.au

***Abstract*—Wireless network simulation is a fundamental service aiming at providing controlled and repeatable environment for protocol design, performance testing, etc. The existing simulators focus on reproducing the packet behaviors on individual links. However, as observed in some recent works, individual link behaviors alone are not enough to characterize the protocol performance. As a result, while the existing works can mimic the link behaviors very closely, they often fail to simulate protocol level performance. In this paper, we propose a novel performance-aware simulation approach which can preserve not only the link-level behaviors but also the performance-level behaviors. We first devise an accurate performance model by combining link quality and the spatial-temporal link correlation. Based on the performance modeling, we then propose a Performance Aware Hidden Markov Model (PA-HMM), where the protocol performance is directly fed into the Markov state transitions. PA-HMM is able to simulate both link-level behaviors and high-level protocol performance. We conduct extensive testbed and simulation experiments with broadcast and anycast protocols. The results show that compared to the state-of-the-art work, 1) the performance model is able to accurately characterize wireless communication performance and 2) the protocol performance is closely simulated as compared to the empirical results.**

I. Introduction

Wireless network simulation is a fundamental service aiming at providing controlled and repeatable environment for protocol design, performance testing, algorithm analysis, etc [1]. A good simulator is designed to generate the packet traces, based on which the *end-to-end protocol performance* could be close to the empirical performance. Some research efforts have been devoted to repeatable simulation such as TOSSIM [2] and M&M [3]. These works try to reproduce and simulate the link-level behaviors of the empirical traces in order to simulate the repeatable protocol performance. Specifically, TOSSIM [2] employs the SNR model to simulate packet traces for individual links. M&M [3] uses multi-level Markov model to simulate both long term and short term behaviors of individual links. The rationale behind is that the protocol performance can be characterized if the individual links are closely simulated.

However, many recent studies have shown that the individual link behaviors are not enough for capturing the wireless protocol performance, especially for anycast and broadcast/multicast [4]–[6]. The spatial correlation among adjacent links is also highly impactive. As a result, the simulation of individual link behaviors can hardly provide repeatable performance simulation for the protocols involving multiple links (analyzed in Section III). In this paper, we aim at designing repeatable wireless network simulation, which can simulate both link-level behavior and the end-to-end protocol performance.

There are two key challenges as follows: First, accurately modeling the end-to-end performance for network protocols, especially for protocols involving multiple links (anycast and broadcast/multicast). Second, generating packet reception sequences that yield repeatable protocol performance, based on the proposed performance model. As to the first challenge, most protocol performances are determined by each single-hop performance and the propagation path in the network. Since the propagation path is controlled by the simulated routing protocol, modeling the single-hop performance becomes the essential key problem. Similar to [7], [8], we choose the expected number of transmissions (ETX) as the key metric for protocol performance since most of other performance metrics can be derived with ETX [7]. Specifically, we separately define the ETX metrics for the three transmission modes for single-hop communications [9]: uETX for unicast, aETX for anycast, and bETX for broadcast/multicast. The detailed definitions are described in Section II.

While modeling uETX is straightforward, it is much more challenging to model aETX and bETX, which involves multiple links. Although some existing works use packet reception ratio (PRR) on individual links to model aETX/bETX, many recent studies [5], [10] indicate that the temporal and spatial correlations among links also have a significant impact on anycast/broadcast besides individual PRRs. However, combining all three kinds of information (PRR, temporal and spatial correlations) is a non-trivial task. The reason is that the metrics for them essentially contain overlapped information (as analyzed in Section II). For example, given one link PRR and its correlation with an adjacent link, we are able to infer the other link's PRR. If we separately take the PRRs of both links and the correlation between them in the modeling, one link's PRR is actually

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calculated twice. The existing works such as [11], [12] account such overlapped information multiple times during the model iteration, which can lead to largely inaccurate performance characterization. To deal with the overlapping problem, the independent link metrics κ factor [4] and β factor [13] are potential alternatives. Unfortunately, the isolation of different dimensional information leads to too complex metric designs, which can hardly be directly utilized for ETX modeling.

As to the second challenge, Markov model has been proved to be effective for packet trace simulation [3]. When the ETX performance is accurately characterized, the packet traces can be generated using a Markov model fed with the derived performance states. Hence the key problem is to 1) define the appropriate Markov states representing both link-level and performance level behaviors and 2) obtain appropriate parameters to generate packet sequences preserving the performance states.

To address the above two challenges, we first propose an accurate performance modeling approach for anycast and broadcast/multicast (aETX and bETX), which considers PRR, temporal and spatial link correlations. Based on this new modeling approach, we devise a Performance Aware Hidden Markov Model (PA-HMM), in which the aETX/bETX combinations are used as the underlying unobserved performance states and an abstraction of link features containing both spatial and temporal link correlation is used as the observed states. With the accurate performance models and PA-HMM, the proposed work can simulate not only the link-level behaviors but also the protocol performance, providing a more repeatable and reliable simulation environment for wireless protocols.

We implement the performance model and PA-HMM. The experimental results show that, (1) The performance model provides more accurate single-hop aETX/bETX modeling than the existing works. (2) Compared to the existing simulators (TOSSIM [2] and M&M [3]), the proposed work can achieve more repeatable wireless network simulation in terms of both link-level behaviors and protocol performance.

The main contributions of this paper are summarized as follows:

1) We propose an accurate performance model for anycast and broadcast/multicast, which jointly considers PRR, spatial and temporal link correlation. With the model, aETX and bETX can be accurately obtained from the packet traces.
2) Based on the performance model, we propose a Performance Aware Hidden Markov Model (PA-HMM) for wireless network simulation, which can simulate both link level and performance level behaviors of wireless networks.
3) We implement PA-HMM and evaluate the simulation based on PA-HMM. The results show that more repeatable simulation is achieved compared to the existing works in terms of protocol performance.

The rest of the paper is organized as follows: Section II presents related works on wireless network simulation and performance characterization. Section III analyzes the necessary link features that should be considered for accurate performance modeling with measurement study. Section IV presents the performance modeling and PA-HMM in detail. Section V evaluates the performance model and the simulation with PA-HMM in comparison with the state-of-the-art works. Section VI concludes this work.

II. Related Works

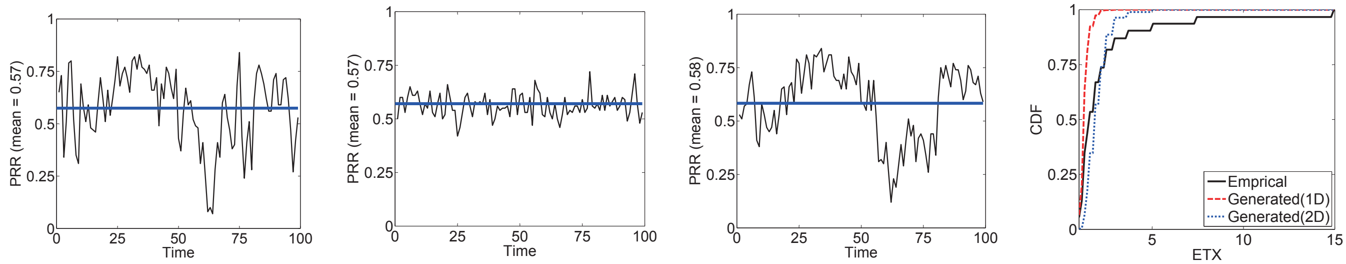
Simulation has always been one of the most important means to study protocol behaviors and evaluate protocol performance in wireless networks. To this end, the existing works have utilized different techniques to simulate packet reception/loss manners on the individual links. However, the protocol performance cannot be simulated solely by reproducing individual link behaviors. In this section, we will review the existing works on wireless simulations as well as the modeling of wireless communication performance. The comparison between our work and the existing works will also be discussed.

A. Wireless network simulation

Many existing works utilize Markov model for network simulation [3], [14]–[16]. The Gilbert model [14] is a probabilistic model for simulating burst noise in wireless channels. A hidden Markov model with two states is employed, where the first state has a zero transmission error rate (perfect link quality) and the other state has a given nonzero probability of transmission error rate (intermediate link quality). The transition probabilities control the duration spent in each state, thus the burst links can be simulated. Nguyen et al. [15] proposed to employ the exponential and Pareto distributions to model the packet traces. Markov-based trace analysis decomposed the packet trace with non-stationary properties into stationary pieces consisting of lossy and error-free states. Khayam et al. [16] focused on 802.11b networks in terms of both bit errors and packet errors. From these works, we can see that wireless simulation needs to consider both long-term and short-term link variations. The simulated traces should also be close to the input traces.

TOSSIM TOSSIM [2] is a discrete-event simulator for wireless sensor networks operating the TinyOS system. The input of TOSSIM is the physical layer signal powers (RSSI) for each link and background noise, where the RSSIs are set by simulation users and the background noise is generated based on the historical environmental noise traces with the Closest Pattern Matching (CPM) model. The packet reception/loss traces are then generated using the SNR model.

M&M M&M [3] is a Markov model based approach, which is directly based on the packet traces instead of the physical layer indicators. A multi-level Markov model is employed in M&M, where the higher level states capture the long-term link behavior and the lower level states capture the short-term link behavior. The transition probabilities control the durations of long-term and short-term behaviors and are extracted from the collected traces in real environments.



(a) Empirical PRR trace (b) Generated trace with 1D(PRR) (c) Generated trace with 2D (d) ETX of empirical/generated trace

Fig. 1: Characterizing single link performance.

We can see that the existing works focus on simulating single links. The rationale behind is that once the individual links are simulated, the protocol performance can be simulated as well. However, many recent studies observed that the spatial correlation between adjacent links can significantly affect the communication performance (anycast and broadcast). Srinivasan et al. [4] observed correlation on the packet receptions and losses among different links and analyzed the impact of link correlation on broadcast performance. Many following works [5], [17], [18] also confirmed the impact of link correlation on anycast and broadcast/multicast performance. As a result, simulation of individual links is not enough to simulate the protocol performance.

Different from the aforementioned works, we directly adopt both end-to-end performance and link-level behaviors into the proposed simulation model. Both the link-level behaviors and the end-to-end performance can be preserved.

B. Performance characterization

The expected number of transmissions (ETX) has been widely used as the performance metric for various protocols. While ETX for unicast (uETX) is easy to calculate, it is challenging to characterize the ETX of anycast and broadcast/multicast. We denote the ETX for anycast and broadcast/multicast as aETX and bETX. Specifically,

- aETX is the ETX for a sender to successfully deliver one packet to *at least one* of its receivers.
- bETX is the ETX for a sender to successfully deliver one packet to *all* of its receivers.

aETX for a sender s is often calculated as $\frac{1}{P^s_{S_R}}$, where $P^s_{S_R}$ is the probability that at least one node in its receiver set (S_R) receives the packet. To calculate $P^s_{S_R}$, the work [11] uses the multiplication of the link quality of all outbound links of s. However, due to the spatial link correlation, the result is often over estimated as the correlated information is accounted multiple times. In [10], link correlation is additionally considered for accurate aETX calculation. The calculation of bETX is more complex as given by:

$$bETX = \sum_{k=1}^{+\infty} kP(X=k) \tag{1}$$

where $P(X=k)$ denotes the probability that all nodes in S_R receive the packet after k transmissions. The existing approaches [5], [19] differ from each other mainly in the way of calculating $P(X=k)$. In [19], topology and link quality are considered and in [5], link correlation is additionally considered. However, the overlapped information between link correlation and individual link quality is also accounted multiple times in the model iteration.

The modeling of aETX/bETX in this paper differs from these performance models in the following ways. First, we jointly consider link quality and the temporal-spatial link correlation. To improve the model efficiency, we propose a packet trace abstraction scheme, which can efficiently extract the three kinds of information without explicit link metric calculations. Second, in addition to the aETX/bETX, we further analyze the model and identify how to reversely generate the link metrics using the aETX/bETX sequences.

III. Measurement Study on Link Features for Modeling Wireless Communication Performance

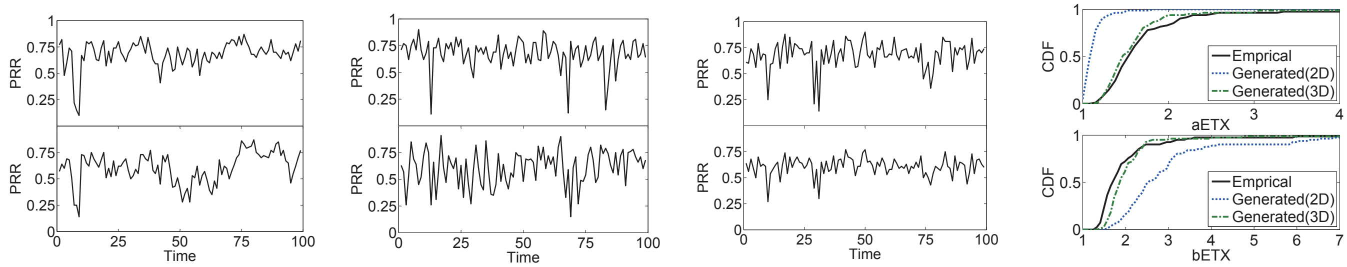
In this section, we analyze the impacting factors of unicast, anycast and broadcast/multicast performance and find the necessary information required for uETX/aETX/bETX modeling.

A. Characterizing single link performance (uETX)

Link quality (1D). Link quality is one of the most widely identified impacting factors for wireless communication performance. Packet reception ratio (PRR) is a typical characterizing metric for link quality. It is a link-wise long term property, indicating the probability that a packet can be successfully received. We denote link quality as the one-dimension (1D) link feature.

Figure 1(a) shows an empirical PRR trace of a wireless link. If we simulate this link using the average PRR value (0.57) with random variations, the generated PRR is shown in Figure 1(b). Now with the two packet traces generated based on the two links, we check whether the uETX is characterized. The uETX is obtained from the packet traces as $n_{tx} = n_{loss} + 1$, where n_{loss} is the number of losses before a packet reception. We repeat the experiments 100 times and obtain the average uETX values for both links.

Figure 1(d) shows the CDF of uETX values for both empirical and the 1D generated traces (1D). We can see that, the uETX values using 1D information are largely different from the empirical uETX. The reason is that the average PRR



(a) Empirical trace of a link pair (b) Generated trace with 2D (c) Generated trace with 3D (d) ETX of empirical/generated trace

Fig. 2: Characterizing broadcast/anycast performance.

captures long term link behaviors, which could derive the long term overall uETX of the empirical trace. However, due to the PRR variations and the nature of reciprocal relationship between PRR and ETX, the fine-grained short term uETX cannot be captured, resulting in the inaccurate performance characterization. For example, the average PRR of 0.2 and 0.8 is 0.5. The ETX is normally calculated as $\frac{1}{0.5}$=2. However, the actual ETX should be $\frac{1}{2}(\frac{1}{0.2}+\frac{1}{0.8})=3.125$, which is quite different from the result directly obtained by the average PRR. Therefore, a long-term PRR metric is not enough to accurately capture the uETX performance.

PRR and its temporal distribution (2D). It has been observed by many recent works that both packet receptions and losses have clear temporal behaviors [13], [20], [21]. These works try to characterize the temporal distribution using various metrics such as μ [22], β [13], etc. To see the impact of the temporal features on the protocol performance, we manually generate packet traces for the simulated link preserving both PRR and the temporal packet distributions (using the metric μ and a simulation approach similar to [3]). Figure 1(c) shows the generated PRR trace, preserving 2D properties (the long term PRR and temporal distributions). Intuitively, it is much more close to the original link in Figure 1(a) than the 1D simulated link in Figure 1(b). Figure 1(d) shows the uETX comparison between the empirical trace and the 2D generated trace. We can see that uETX is also characterized more accurately. Preserving the 2D properties (i.e., PRR and its temporal distribution) seems good enough for characterizing uETX.

B. Characterizing the performance for multiple links (aETX/bETX)

Next, we study whether the above 2D information can characterize transmission performance involving multiple links (aETX and bETX). Figure 2(a) shows the empirical PRR traces of a link pair. We can see that these two links have a high positive correlation. Figure 2(b) shows the simulated link pair preserving both PRR and the temporal distributions of the links in Figure 2(a). Obviously, the correlation between the links is not captured by the generated link pair. Then we further investigate whether aETX and bETX are characterized by the simulated link pair. Using the packet reception traces for the two links, we can directly obtain the number of transmissions for delivering one packet to at least one receiver (aETX) and the number of transmissions for delivering one packet to both receivers (bETX). Figure 2(d) depicts the CDF of the aETX/bETX values for the empirical traces and the generated traces with simulated link pair. We can see that there exist large errors on both aETX and bETX with 2D. The reason is that, anycast and broadcast can be greatly affected by spatial correlation, which is not captured by the 2D link features. For example, if the receptions of two links are strongly correlated, aETX tends to be large [10] and bETX tends to be small [4] for the same generated packet traces on both links.

PRR and the temporal-spatial distributions (3D). The spatial distribution of PRRs essentially reflects the relationship among different links, which has been observed by the existing works [4]. Now we manually set packet traces for the simulated link pair preserving PRR, temporal and spatial distributions. Figure 2(c) shows the generated traces. We can see that the relationship between two links is similar to that in Figure 2(a). As shown in Figure 2(d), both aETX and bETX are much more accurately characterized with 3D information.

We also repeat the experiment under various different environments (e.g., indoor, outdoor, WiFi-interfered, pedestrians, etc.) and obtain similar observations to the above results.

C. Short summary on characterizing link features

From the above study, we can see that 1) PRR characterizes the long term property of a link; 2) The temporal distribution characterizes the how a link's PRR variates. These two-dimension information can accurately characterize single link performance. 3) The spatial distribution characterizes the relationship between different links. With the three-dimension information, each link's PRR, PRR variations and its correlation with other links can be determined, which essentially determines the performance of anycast and broadcast/multicast.

Therefore, to *accurately* infer the link behaviors as well as wireless communication performance in terms of uETX, aETX and bETX, we need to consider all the three kinds of information. In the next section, we will present our performance modeling approach and the simulation approach based on the performance model.

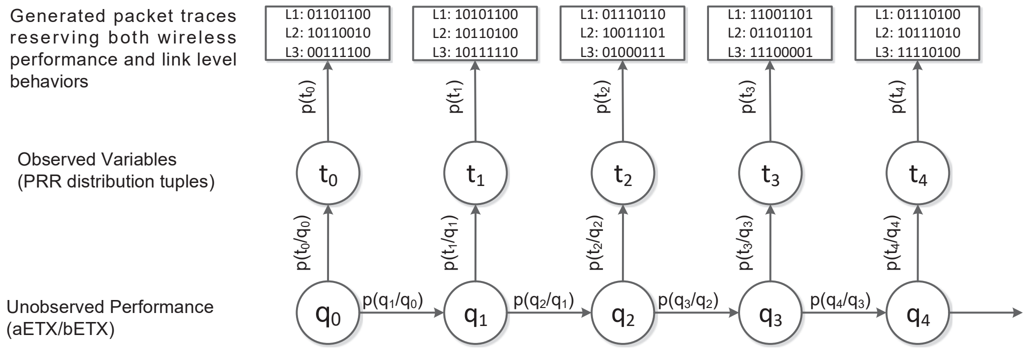


Fig. 3: The PA-HMM. The unobserved q states capture the performance state transitions (with aETX and bETX). The observed t states capture the link level behavior transitions (with PRR tuples, where a tuple indicates the PRR distribution at multiple receivers).

IV. The Performance Aware Markov Model for Wireless Simulation

Now we present the Performance Aware Hidden Markov Model (PA-HMM) for repeatable wireless network simulation, which is based on the performance modeling considering the aforementioned link features. The proposed work can preserve both wireless communication performance and the link-level behaviors. We will first present the overview of the simulation based on HMM and then present the details of each building block of PA-HMM including the wireless communication performance modeling and the HMM.

A. Overview

The performance aware hidden Markov model (PA-HMM) is shown in Figure 3. We denote the packet receptions and losses on each links with binary sequences, where a "0" denotes a packet loss and a "1" denotes a packet reception. The binary sequences on multiple links of a sender are generated at the same time using the PRR tuples represented by t_n as shown in the figure, where n denotes the n-th time window. Each performance state q (unobserved) is a combination of aETX and bETX and has its own probability distribution $p(t_n/q_n)$ of emitting the PRR tuple distributions (t_n). The performance states (q) capture the performance-level behaviors and the link states (t) capture the link-level behaviors (as will be described in Section IV-C). The transition probability of the performance states controls the performance variations. For each performance state q_n, the emission distribution contains m component for the m links in t_n (m is the number of outbound links of a sender). Each component contains d elements controlling the PRR temporal variation in a duration of $d \times W$ slots, where W denotes the number of packets sampled in one PRR window. It is worth mentioning that wireless communication is inherently based on broadcast and packet receptions/losses happen at the same time. Hence, compared to the existing "link-wise" approaches, a more reasonable simulation manner is to generate the packet traces for multiple adjacent links at the same time.

As most wireless protocols are based on anycast and broadcast/multicast, in PA-HMM, single-hop protocol performance is denoted by the performance states using aETX/bETX combinations (q). The link level behavior is captured by the PRR tuple distributions (t), where both link correlation and link quality are preserved. The input parameters include: 1) Performance states (aETX/bETX pairs); 2) PRR distribution tuples (as will be described in Section IV-C); 3) The transition probability matrix between performance states, $p(q_n/q_{n-1})$; 4) The emission probability distribution for each performance state, $p(t_n/q_n)$. These parameters can be either manually set by the simulation users or extracted from the target empirical traces (the simulated results will have similar performance and link-level behaviors with those of the empirical trace). Next, we will present how to model aETX/bETX and obtain the necessary parameters.

Table 1: Notations

Parameter	Description
aETX	ETX required to deliver one packet to at least one receiver
bETX	ETX required to deliver one packet to all receivers
t_n	the n-th PRR tuple
q_n	the n-th performance state in the PA-HMM model, which is a combination of aETX and bETX
$p(t_n/q_n)$	the emission probability from state q_n to PRR tuple t_n
$p(q_n/q_{n-1})$	the transition probability from state q_{n-1} to state q_n

B. Performance modeling for aETX and bETX

aETX. Recall that aETX is the number of transmissions for a sender to deliver one packet to at least one node of its receivers. Similar to the existing works [10], [11], the aETX is calculated as:

$$aETX = \frac{1}{p^s_{S_R}} \tag{2}$$

where $p^s_{S_R}$ is the probability that at least one node in S_R receives the packet. Since we extract the metric from packet reception/loss traces, $p^s_{S_R}$ can be obtained as follows:

$$\begin{aligned} p^s_{S_R} &= 1 - p_{0*} \\ &= 1 - \sum_{\forall t_i \in T} p(t_i) p_{t_i}(0*) \end{aligned} \tag{3}$$

where p_{0*} denotes the probability that all receivers lose the packet ("0" stands for a packet loss), T denotes the PRR tuple

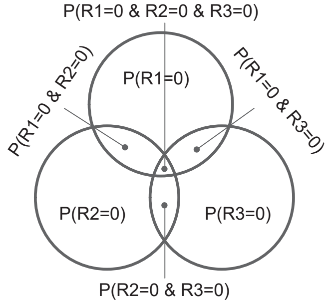


Fig. 4: Calculation of bETX: The case of three receivers.

set, $p(t_i)$ denotes the probability of PRR tuple t_i, and $p_{t_i}(0*)$ denotes the probability that all receivers lose the packet given the PRR values in tuple t_i.

bETX. Recall that bETX is the expected number of transmissions for a sender to deliver one packet to all its receivers. *Note that the receivers are not restricted to receive the packet at the same time.*

For simplicity, we start from the case of three receivers R1, R2, and R3. Basically, bETX can be calculated as:

$$bETX = \sum_{k=1}^{+\infty} kP(X=k) \tag{4}$$

where $P(X=k)$ is the probability that k transmissions cover all three receivers. It can be calculated as

$$P(X=k) = P(X>k-1) - P(X>k) \tag{5}$$

where $P(X>k)$ is the probability that after k transmissions, at least one receiver has not received the packet.

The calculation of $P(X>k)$ turns out to be an inclusion-exclusion problem as shown in Figure 4. Note that P(R1=0) denotes the probability that *after k transmissions*, R1 has not received the packet, P(R1=0&R2=0) denotes the probability that after k transmissions, both R1 and R2 have not received the packet, and P(R1=0&R2=0&R3=0) denotes the probability that after k transmissions R1, R2, and R3 have not received the packet. With the above information,

$$\begin{aligned}&P(X>k) = P(R1=0)+P(R2=0)+P(R3=0)-\\&P(R1=0\&R2=0)-P(R1=0\&R3=0)-P(R2=0\&R3=0)+\\&P(R1=0\&R2=0\&R3=0)\\&=P_{n_0=1}-P_{n_0=2}+P_{n_0=3}\end{aligned} \tag{6}$$

where $P_{n_0=1}$ denotes the probability that n_0(=1) receivers lose the packet k times. With the input, we get:

$$\begin{aligned}P_{n_0=1} =&(p_{000}+p_{001}+p_{010}+p_{011})^k+\\&(p_{000}+p_{001}+p_{100}+p_{101})^k+\\&(p_{000}+p_{010}+p_{100}+p_{110})^k\\P_{n_0=2} =&(p_{000}+p_{001})^k+\\&(p_{000}+p_{010})^k+\\&(p_{000}+p_{100})^k\\P_{n_0=3} =&(p_{000})^k\end{aligned} \tag{7}$$

where p_{ijk} denotes the probability that $R1=i, R2=j, R3=k$ $(i,j,k \in [0,1])$. Combining Eqs. (4)-(7), we can obtain the bETX to cover the three nodes.

***n*-receivers case for bETX**. Now we move to calculate the bETX for n receivers, which is an extension of Eq. (4). The key is to calculate $P(X>k)$, the probability that not all n receivers received the packet after k transmissions. We use an n-bit bitmap to denote the case of packet reception distribution. For example, a bitmap of "0101" denotes the case in which the first and third receivers lose the packet and the second and the fourth receivers receive the packet. Then $P(X>k)$ is given as:

$$\begin{aligned}P(X>k) &= \sum_{m=1}^{n}(-1)^{m-1}P_{n_0=m}\\&=\sum_{m=1}^{n}(-1)^{m-1}\sum_{\forall S_m} e_{S_m}^k\end{aligned} \tag{8}$$

where $P_{n_0=m}$ is the probability that m receivers do not receive the packet by k transmissions, S_m is set of bitmaps with m "0"s and e_{S_m} is the probability with m uncovered receivers. e_{S_m} is calculated as:

$$e_{S_m} = \sum_{\forall b \in S_m} p_b = \sum_{\forall b \in S_m}\sum_{\forall t_i \in T} p_{t_i}(b) \tag{9}$$

where b is a bitmap with m "0"s and $p_{t_i}(b)$ denotes the probability of the bitmap b given the PRR tuple of t_i.

Combining Eqs. (4), (5) and (8), the bETX to cover n receivers is given by:

$$\begin{aligned}bETX &= \sum_{k=1}^{+\infty} kP(X=k)\\&=\sum_{m=1}^{n}(-1)^{m-1}\sum_{\forall S_m}\frac{1}{1-e_{S_m}}\end{aligned} \tag{10}$$

The combinations of the extracted aETX and bETX values are then used as the performance-level states.

C. Link-level states: PRR tuple distribution

Link level states are responsible to represent the link level metrics including PRR, temporal and spatial correlations. Different from the existing modeling approaches, we do not utilize separate link metrics such as κ for link correlation or β for burstiness. Instead, we abstract a PRR tuple distribution from the packet reception traces on multiple links, which essentially stores the PRR and temporal-spatial distributions. With the PRR tuples, link-level behaviors can be preserved.

Given packet reception traces on different links, we first slice time into many short periods and obtain a series of PRR values for each link. The period length can be set according to user's granularity requirement. After that, we combine PRR values at the same period in a PRR tuple and account the overall probability of each different PRR tuples. After that, we obtain a table storing PRR tuples and its distribution probabilities. One different PRR tuple represents one different spatial distribution for a short period. The probabilities for PRR tuples represent the temporal distributions and variations.

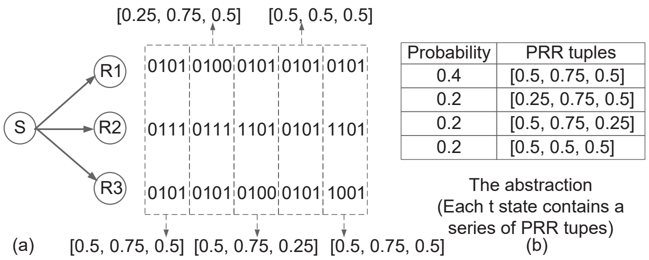


Fig. 5: Illustration of the packet trace abstraction.

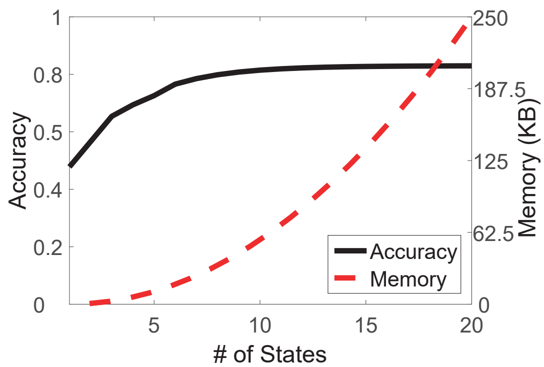


Fig. 6: Impact of states number on modeling accuracy and memory overhead.

Figure 5(a) shows an illustrating example, where S is a sender; $R1, R2$ and $R3$ are three receivers. The "0" and "1" represent packet losses and receptions. Taking the packet reception traces as input, we first slice the traces into several windows (each window contains 4 packets). In each window, we can obtain a PRR tuple, e.g., the PRR tuple of the first window is [0.5,0.75,0.5], indicating that PRRs on the three links are 0.5, 0.75 and 0.5 within the window. After that, we can obtain the probabilities of all different PRR tuples as shown in Figure 5(b). This table is the packet trace abstraction and used as the states for link features (t). We can see that PRR values, spatial distributions and temporal distributions are all covered the abstraction. For each aETX/bETX state, there are several corresponding link states of PRR tuples and probability distributions. It is worth noting that, *during the abstractioneach packet reception/loss is accounted only once*, inherently avoiding the information overlapping problem.

D. Optimization

With the performance modeling approach, we can obtain the performance states (aETX/bETX pairs) from the packet traces (It is also worth noting that the states can be set manually for the simulation users to explore all possible performance space). However, there will be infinite values for aETX/bETX states, which will significantly increase the complexity for PA-HMM. For example, if we divide the range of aETX/bETX values into 100 sections, there will be 100×100 different (aETX,bETX) states. The transitional matrix size will be $(100\times100)^2$. To reduce the overhead, we can decrease the number of performance states using k-means clustering. The cluster centers can then be used as the performance states.

Fig. 7: The 8×10 testbed with TelosB/TinyOS nodes.

Apparently, there exists a tradeoff between accuracy and the computational overhead. With a small k, the model accuracy decreases and memory overhead decreases. With a large k, the model accuracy increases yet the memory overhead increases. We determine k experimentally. Figure 6 shows the model accuracy of presenting the aETX/bETX states and memory overhead with varying k values. We can select k=7 to achieve a good tradeoff between efficiency and accuracy because it achieves relatively high accuracy (nearly 0.8) while incurring a smaller memory overhead. Please refer to our technical report for detailed experimental settings[1]. Similarly, the link level states (PRR tuples) can also be optimized by clustering the traces into k states. We will continue explore schemes for improving the space efficiency in our future work.

V. Evaluation

In this section, we evaluate the proposed performance modeling approach as well as the PA-HMM based simulation.

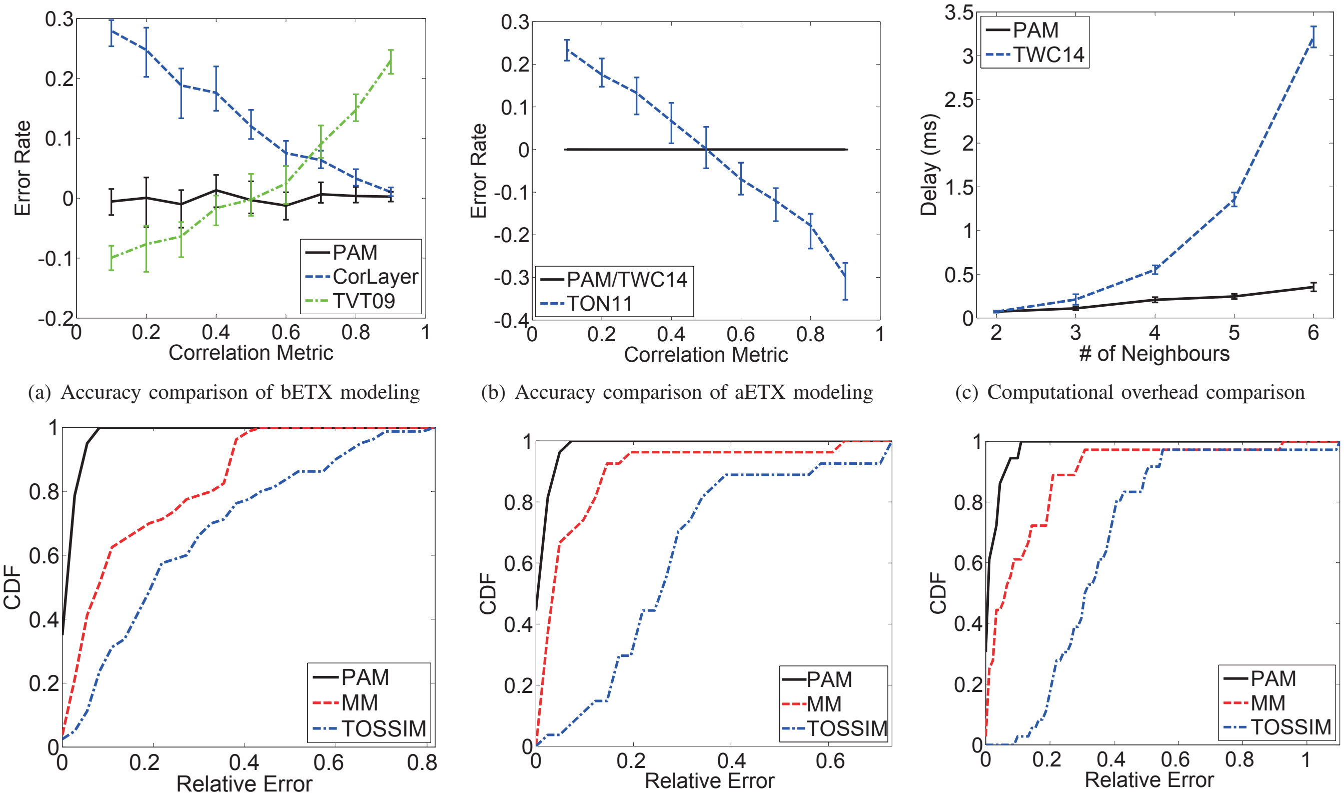
We use our 8×10 TelosB nodes testbed (Figure 7) to collect packet traces. The radio power is set to -32.5 dBm to enable a 6-10 hop network. Each node periodically broadcasts packets and records the packet receptions from neighboring nodes. The packet receptions on each link are sent to the PC via USB cables. It is worth noting that the packet traces can be from any networks or generated according to the user demands. With the traces, we then study the model accuracy as well as the repeatable simulation performance. In order to explore the full potential of the PA-HMM simulation we utilize the exact aETX/bETX values as performance states.

A. Performance modeling

We study the model accuracy of both aETX and bETX for anycast and broadcast by repeating experiments with varying number of receivers. We manually tune the PRR, temporal and spatial distributions by introducing intentional packet losses to compare the modeling accuracy under various environments. Performance models of aETX and bETX are separately evaluated, in terms of accuracy and computation overhead.

Baseline approaches. For the performance model, We use the approaches introduced in Section II as baseline approaches. Specifically, for aETX we compare 3DW with two existing works TON11 and TWC14 [10], [11]. TON11 considers only

[1]http://mobinets.org/pub/wSim-tech-rep.pdf



(a) Accuracy comparison of bETX modeling

(b) Accuracy comparison of aETX modeling

(c) Computational overhead comparison

(d) Comparison on representing link correlation

(e) Comparison on opp. routing performance

(f) Comparison on dissemination performance

Fig. 8: Evaluation results on the aETX/bETX performance modeling.

link quality and TWC14 considers both link quality and link correlation. For bETX, we also compare 3DW with two existing works TVT09 and CorLayer [5], [19]. TVT09 [19] considers only link quality and CorLayer considers both link quality and link correlation. For repeatable simulation, we compare our work with TOSSIM [2] and M&M [3].

Figure 8(a) compares the bETX modeling accuracy of the proposed work (denoted as PAM) and other approaches. We can see that, (1) TVT09 [19] is accurate only when link correlation is around 0.5, i.e., the spatial distribution is random. The reason is that it does not consider the spatial distributions and implicitly assumes that the PRRs are independently distributed at different receivers. (2) CorLayer [5] is accurate when link correlation is strong and inaccurate when link correlation is weak. The reason is that it is based on the assumption that receivers of the better-quality links receive the packets earlier than other receivers. When link correlation is 1, it can be treated as the case that all receivers receive the packet at the same time, which minimizes the negative impact of the assumption.

Figure 8(b) compares the aETX modeling accuracy. We can see that (1) the proposed model is more accurate than the approach in [11]. The reason is the spatial and temporal link characteristics are additionally considered. (2) The proposed model and TWC14 have the same accuracy. The reason is that TWC14's modeling essentially takes 2^n link correlation values for n links, which implicitly takes the spatial distribution as well as its temporal distributions. Therefore, although they do not explicitly reduce the overlapped information, the modeling results are as accurate as our work PAM. We further compare the computation overhead of PAM and TWC14 on the MSP430 platform. Figure 8(c) compares the computation overhead of the proposed model and TWC14 [10]. We can see that when the number of receivers increases, TWC14 incurs much more delay. The reason is that in the proposed model, the probability of all zeros can be directly extracted by p_{0*} (Eq.(3)) while TWC14 has to translate the PRR and link correlation metrics for calculating the aETX.

B. Comparison with TOSSIM and M&M simulation

Using the collected packet traces at all links, we can simulate the network using PA-HMM based simulation (denoted as PAM in the figures). For fair comparison, we use the same measured traces to drive the M&M and PA-HMM. For TOSSIM, we measure the noise traces on our testbed and feed it into the TOSSIM simulation. We first study whether the packet traces can be characterized by letting nodes periodically transmit packets in both the testbed experiments and all the three simulations Since both PA-HMM and M&M consider PRR and the temporal distribution, the key is to check whether link correlation among different links on the testbed can be preserved and simulated. We run the protocols 1000 times and the results are shown in Figure 8(d), where the relative-errors between the empirical and simulated link correlation by different simulation approaches are demonstrated. We can see that, most of the simulation errors of PA-HMM are smaller than 9%. Conversely, Only about 50% cases in M&M simulates the transmission count with relative errors smaller than 9%. The relative error of TOSSIM is even larger.

Next we compare our work with M&M and TOSSIM in terms of protocol performance. We test two popular protocols: opportunistic routing [23] and data dissemination [24], which are based on anycast and broadcast/multicast respectively. We initiate the PA-HMM, TOSSIM and M&M using the same packet traces collected from our testbed. Then we study whether the simulated packet traces can support repeatable protocol performance (number of transmissions).

Figure 8(e) shows the comparison of PA-HMM, TOSSIM and M&M for opportunistic routing protocol. Figure 8(f) shows the comparison of PA-HMM, TOSSIM and M&M for bulk data dissemination protocol. We can see that for both opportunistic routing and dissemination, the protocol performance based on PA-HMM is much more closer to the empirical results (the relative error between simulation results and empirical results are greatly reduced compared to the other approaches). The reason is that 1) Our work explicitly use wireless communication performance (aETX and bETX) as the underlying performance states, thus the generated trace can preserve the single hop wireless communication performance. 2) The aETX/bETX errors in the other works can further lead to incorrect routing decisions, which makes the difference between simulated performance and the empirical performance even larger in TOSSIM and M&M. Due to the page limit, we have moved some technical contents and evaluation results to our technical report[2].

VI. Conclusion

In this paper, we investigate the problem of repeatable wireless network simulation. We first propose a performance model that considers spatial-temporal link correlation to accurately characterize the single-hop ETX performance. And then based on the performance model, we further propose a novel Performance Aware Hidden Markov Model (PA-HMM) for wireless network simulation. The evaluation results show that the performance model achieves more accurate ETX modeling for both anycast and broadcast/multicast, and the PA-HMM based simulation can simulate both the link level behaviors as well as the protocol performance (ETX).

Acknowledgment

This work was supported by the National Natural Science Foundation of China (No. 61602095, No. 61772465 and 61472360), the National Key Research and Development Program of China (2017YFB1400102), the Fundamental Research Funds for the Central Universities (No. ZYGX2016KYQD098, No. ZYGX2016J079 and No. 2017FZA5013), National Postdoctoral Program for Innovative Talents of China, Zhejiang Provincial Key Research and Development Program (No. 2017C02044), and the EU FP7 CLIMBER project under Grant Agreement No. PIRSES-GA-2012-318939.

[2] http://mobinets.org/pub/wSim-tech-rep.pdf

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