On the Effects of Cognitive Mobility Prediction in Wireless Multi–hop Ad Hoc Networks

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Abstract—In this paper, we address an important problem in mobile ad hoc networks, namely, the intrinsic inefficiency of the standard transmission control protocol (TCP), which has not been designed to work in these types of networks. After an initial training phase, we predict the mobility status of the network through a probabilistic approach, and we propose a series of ad hoc strategies to counteract the TCP inefficiency based on this prediction. Via simulation, we show the performance improvements in various wireless scenarios, in terms of increased average throughput and decreased length of the outage intervals. The significant performance improvements shown here will be verified in a future work by implementing our approach in a real testbed.

Index Terms—MANET, OLSR, statistical inference, Bayesian networks, TCP

I. INTRODUCTION

The massive proliferation of mobile devices, along with the ever-increasing data demand, has been pushing interest in the use of multi-hop ad hoc networks for more than a decade. The last-mile multiple hops crossed by each connection before reaching their respective destinations can be seen as a “wireless appendix” which is attached to the worldwide (wired) web. These types of networks are named mobile ad hoc networks (MANETs). A MANET is characterized by a self-configuring infrastructureless architecture, which can handle the communications in a highly dynamic network topology. It can provide connectivity also in areas with no network infrastructure, and can be a valuable and inexpensive solution for many networking problems. For these reasons, a broad set of research contributions has been carried out in this area.

One of the main issues that should be addressed in order to design a MANET is the fact that a fast changing topology creates significant problems to the standard transport layer protocol. Indeed, the transmission control protocol (TCP), which is the standard for reliable connection-oriented communications, was designed for wired networks. In a MANET, it shows degraded performance, since the congestion control and avoidance mechanisms were modeled assuming i) static nodes, i.e., a stable topology, and ii) packet losses caused by buffer overflow, i.e., network congestion. Conversely, in a MANET there may be mobile nodes and rapidly changing channels, thus most packet losses are due to channel errors or link layer contention, as pointed out in [1]. Furthermore, the network topology can rapidly change due to mobility. Thus, the routing protocols should adapt to this highly dynamic scenario. Anyway, a temporary link breakage due to mobility

can seriously affect TCP performance, since this protocol was not designed to keep into consideration this kind of events.

In this work, we aim at designing a light-weight cross-layer framework to counteract the aforementioned TCP limitations, and to propose a valid solution to some specific problems of the TCP and routing protocols that we observed in highly mobile scenarios. Our approach, differently from many other works in the literature, is based on the cognitive network paradigm [2]. It includes an observation phase, i.e., a training set in which the network parameters are collected; a learning phase, in which the information to be used for network improvement is extracted from the data; a planning phase, in which the strategy, in terms of protocol modifications exploiting the learned information, is decided; and an acting phase, which corresponds to running such strategies in the network and observing the resulting communication performance improvement. The general workflow behind our contribution is structured as follows.

1) We observe the overall TCP throughput degradation by means of simulations performed with ns3 [3], an open-source discrete-event network simulator for Internet systems. We consider both a static scenario and a mobile scenario, and we vary the channel characteristics to simulate different realistic scenarios. We identify a set of critical network states, and in this phase we also collect the values of some network parameters as a function of time, which are stored in a training dataset.

2) We exploit the training dataset to learn the probabilistic relationships among the communication parameters, and we organize this probabilistic information in a Bayesian network (BN). The BN is designed in order to provide real-time information on the mobility status of the network.

3) We define a set of actions to be adaptively taken in order to address the problem of each critical network state, once the network state has been inferred by means of the BN.

4) Finally, we design a cross-layer framework that allows to dynamically take actions at the TCP and IP levels, i.e., to apply the corresponding strategy defined in 3). We also perform a simulation campaign to show the performance improvements in terms of increased average throughput and decreased length of the outage intervals, i.e., the time intervals in which the communication is frozen due to topology or network problems.

The rest of the paper is organized as follows. In Sec. II we
briefly overview the state-of-the-art dealing with the degradation of TCP performance over MANETs and the proposed solutions. In Sec. III we detail the network scenario and the main communication problems we observed. In Sec. IV we describe our system model, including the probabilistic graphical model approach for learning and the strategies to address the main communication problems we identified. Then, in Sec. V we validate our framework through a simulation campaign and we show the performance improvements. Sec. VI concludes the paper and proposes some future work.

II. RELATED WORK

In wireless networks, TCP suffers from poor performance because of packet losses and transmission errors due to the wireless channel [4]. In [5], [6], a comprehensive overview of the main limitations of TCP over MANETs is provided, and the performance of different TCP techniques is evaluated by simulation. We report here a few examples addressing these issues from different perspectives. An adaptive congestion control mechanism based on link layer measurements and performed by each node along the path is proposed in [7]. In [8], a dynamic slow start threshold mechanism, as a function of the number of outstanding packets, is designed. In [9], the maximum congestion window is adapted as a function of the channel bandwidth and the packets’ delay profiles; in [10], instead, a comparative analysis of several end-to-end, link-layer or split-connection techniques to improve the performance of TCP over lossy wireless hops is provided. Alternatively, in [11] some reliable transport protocols, optimized to better support MANETs, are detailed. Moreover, other contributions deal with the TCP degradation due to node mobility [12]–[14], where unnecessary retransmissions are triggered because of route failures or route changes. To address this problem, modifications of the routing protocol are proposed in [15], [16], in order to better support mobility during the topology discovery phase. In addition, a number of trajectory prediction techniques are reviewed in [17]. The high complexity of such approaches motivated us to design an on-off mobility prediction rather than estimating the location of the future positions of the nodes. Finally, there are many experimental studies of TCP performance in a MANET with mobility, e.g., see [18]–[21].

In our previous work, we have applied the cognitive network approach [2] to a various set of networking problems. We adopted a learning phase similar to the one used in this paper, which makes use of Bayesian networks (BN), in order to infer the presence of congestion in a multi-hop static network [22], to learn the information needed by a game theoretical inter-network node sharing strategy [23], and for a call admission control protocol in LTE [24].

III. SCENARIO OVERVIEW

As a first step, in order to more easily assess the effects of mobility, we consider a scenario with six nodes, connected through a chain topology with five wireless hops, where the inter-node distance is 100 m.1 We simulate an FTP file transfer, where the data is sent via TCP New Reno from node 0 to node 5.

During the simulation time there are a series of mobility events, in which two adjacent nodes switch positions, by moving in opposite directions at a constant speed of 2 m/s. Two nodes are disconnected if their distance becomes approximately larger than 130 m. During these events, the connections among the nodes break and the network topology needs to be reconstructed once all the nodes are connected again. We also noticed that the effects of these mobility events on the communications among the nodes change as a function of the channel variability, thus we consider in our simulations different Nakagami-m fading channel models, in which the variance of the received power2 decreases for increasing values of the parameter M, as depicted in Fig. 1.

We make use of the optimized link state routing (OLSR) network protocol [25], which is the most popular open source proactive routing protocol for MANETs, accepted as experimental Request For Comments (RFCs) by the Internet Engineering Task Force (IETF). OLSR builds a route for data transmission thanks to the dissemination of two types of periodic control messages. HELLO messages are broadcast by each node to find all the one-hop and two-hop neighbor nodes. Then, topology control (TC) messages are broadcast by each node with the list of its neighbor nodes [19].

In a scenario with wireless links and mobile nodes, as noted in [4], there is room for improvement at both the transport and the network layers in order to adapt to the network dynamics. We consider as a performance metric the TCP throughput \( k \), which is defined as the number of bits acknowledged by the sender during a time interval \( k \) and divided by the length of the time interval (equal to 0.1 seconds). In particular, in this paper we seek a solution to the following network problems.

Problem 1. In a scenario with or without mobility, the measured TCP throughput \( \ell(k) \) can go to zero for a certain time

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1We plan to evaluate random deployments of the nodes in a real testbed, as part of our future work.

2Evaluated on 500 samples, extracted from a 50 s long simulation
interval, as shown in Fig. 2-(a) in the case of a static scenario. We observed in our simulations that these transmission holes are due to route failures, which occur when the TC messages of the OLSR protocol are dropped due to failures in the wireless transmission. This results in a topology breakage, which blocks the data transmission for a few seconds.

Problem 2. In the presence of mobility, there can be a route failure when a node falls out of the connection range of its neighbors; e.g., in Fig. 2-(b), two nodes switch positions in the time interval between 40 and 90 seconds. In this example, the time needed to restore the data transmission is significantly longer than the time spent to restore the topology.

Problem 3. In both static and mobile scenarios there is another problem due to the nature of the TCP protocol, which was not designed for a wireless multi-hop network. TCP regulates the retransmission mechanism assuming that an unacknowledged packet has been dropped because of congestion. Thus, at each retransmission, the retransmission timeout (RTO) timer is doubled to prevent further congestion. Nevertheless, packet losses in wireless networks are dominated by link failures. Therefore, increasing the RTO value at each retransmission may not be a suitable solution, and can turn out to be highly inefficient, since data transmissions might be prevented despite a good channel and a stable topology.

We design a light-weight flexible approach that aims at dynamically detecting whether the network is in a static or in a mobile scenario, and at taking specific actions to mitigate TCP degradation based on such prediction. More in detail, the core of our proposed framework relies on learning network parameters’ statistical dependencies for an accurate prediction of mobility. To collect an observable data set, we perform a number of simulations characterized by the parameters reported in Table I. Then, we propose a set of strategies to adaptively counteract the main TCP limitations, by detecting mobility, and by appropriately modifying some key aspects of the transport and network layer protocols.

IV. SYSTEM MODEL

Our cognitive framework has been designed to address the problems highlighted in Sec. III by means of a probabilistic approach, which can infer a mobility event, and ad hoc solutions at the transport and network layers, which exploit such knowledge. The framework, depicted in Fig. 3, is divided into two modes, an offline and an online (real-time) mode.

The offline mode involves an initial analysis of the data, which can be collected during a training period in a real network \(^3\). It is composed of three points: 1) the TCP, IP and MAC parameters are observed at each node of the network during a training period; 2) the probabilistic relationships among these parameters are learned through a probabilistic graphical model approach, which allows to infer the presence of a mobility event as a function of the observation of certain network parameters; and 3) a set of strategies to address specific network problems as a function of the presence or absence of a mobility event is defined. The probabilistic graphical approach is detailed in Sec. IV-A, while the network strategies are outlined in Sec. IV-B.

The second part of the cognitive framework involves a real-time (online mode) action on the network. It is composed of three points: 1) a subset \(S\) of the network parameters is observed; 2) the presence of a mobility event is inferred in real time, as a function of the observation of the network parameters in \(S\), using the probabilities learned in the offline mode; and 3) the corresponding strategies are applied to the

\(^3\)The training period is executed only at the beginning of the transmissions.
time interval of following variables: ar and o mv ariable. The network parameter are represented as independent samples of a node, with the exception of the source and the destination such probabilistic relationships in a Bayesian Network (BN) among the set of network parameters available. We represent the presence of mobility is divided into two phases. During the first phase, we study the conditional independence relationships among the set of network parameters available. We represent the probabilistic relationships among the variables, that defines the structure of the joint probability among these variables. We use a structure learning algorithm [26] to select the DAG that best represents the probabilistic relationships among the variables, using the samples in the training dataset. Unfortunately, the number of DAGs grows super-exponentially with the number of variables, so we need to exploit a local search algorithm, the hill climbing (HC) random search [27], which is not optimal, but provides a good approximation of the best fitting DAG. Furthermore, in order to choose the DAG that best fits the data, we use the Bayesian information criterion (BIC) scoring function [28]. We assign a score to each DAG as a function of how well it fits the data in the training dataset, and penalizing it based on the number of edges of the DAG, thus favoring simpler DAG structures. The best fitting DAG is denoted by $\mathcal{D}$ and is shown in Fig. 4.

In the second phase of our approach, we select from $\mathcal{D}$ the set of nodes $S$ which separate the parameter to infer ($v$) from the rest of the graph according to the d-separation rule [26]. According to this rule, the observation of the parameters in $S$ is sufficient to make the variable $v$ independent of the other variables in $\mathcal{D}$ or, in other words, to make the inference of $v$ depend only on the observation of the variables in $S$. Given the structure of $\mathcal{D}$, we obtain $S = \{m_t, m_r\}$.

We can now build a simplified probabilistic model, i.e., a Conditional Bayesian network (CBN) in order to study how, by observing the variables in $S$, it is possible to infer the value of $v$. This is a simplified model, in which there is an arrow from each variable in $S$ pointing to $v$. A CBN does not contain the information on the joint probability distribution among all the variables, i.e., $P(c_w, q, m_t, m_r, r_t, v)$, but only on the conditional probability $P(v|m_t, m_r)$, which is simpler to learn and can be approximated more accurately from the observation of a finite dataset.

The parameters of the CBN are learned from the data with a maximum likelihood approach and can be summarized in a tabular conditional probability distribution (TCPD), which is a probability matrix that indicates the probability of $v = 1$, for each value of $m_t$ and $m_r$. In particular, the values of $m_t$ and $m_r$ are quantized to 3 and 5 levels, respectively, with a uniform quantization. We provide a numerical example of the TCPD in Tab. II, where the columns represent the quantized values of $m_r$, while the rows represent the quantized values of $m_t$.

The information is exploited by our online framework. At each time sample $k$, we observe $m_t$ and $m_r$ for each link, read the corresponding probability value for the TCPD, and infer the status of the network (static network or presence
of a mobility event). According to the inferred status of the network, we can apply the corresponding network strategy, which is detailed in the next section.

B. Strategies definition

In this section we describe the two strategies which can be adopted as a function of the scenario inferred by the probabilistic graphical model approach.

Strategy 1. If the probabilistic model recognizes a static scenario, we increase the holding time of the topology from the default value of 6 s to 100 s, in order to make sure that the topology does not rely on discovery messages, since we expect the scenario to be static. In this way, we aim at reducing the probability of a route failure due to Problem 1.

Strategy 2. In the presence of mobility, we increase the HELLO and TC generation rate by a factor of 10, from the default values of 0.5 and 0.2 messages per second, respectively, to 5 HELLO messages and 2 TC messages per second. Thanks to these modifications, once the physical connections are re-established, the OLSR protocol can recover the network topology more quickly, thereby reducing the long interval with zero TCP throughput observed in Fig. 2-(b).

Furthermore, we also adopt an ad hoc solution to Problem 3. Both in the case of route failures for a static network and in the presence of mobility, at each packet loss we do not increase the RTO until the overall topology is restored. In this way, we make sure that the retransmission is performed as soon as the complete topology is re-established.

A possible drawback of our approach is that, since we modify the TCP protocol to promptly react in a mobile wireless multi-hop scenario, it may not behave properly when congestion really occurs. Dealing with the occurrence of congestion is out of the scope of this paper. Anyway, it is possible to design a cognitive approach which can also predict the occurrence of congestion in the network, as in [22]. If congestion is detected, the standard TCP retransmission mechanisms should be applied.

V. PERFORMANCE EVALUATION

In this section, we evaluate the performance of our model to predict the mobility events in a simulated multi-hop wireless mobile scenario. Then, we show the performance improvements achieved by adopting our set of strategies in this scenario.

| $M = 5$ | 17/24 | 1 |
| $M = 10$ | 20/24 | 2 |
| $M = 20$ | 24/24 | 3 |
| $M = 50$ | 24/24 | 5 |
| $M = 100$ | 24/24 | 2 |

A. Prediction analysis

We evaluate the prediction accuracy of our probabilistic graphical network approach in 5 scenarios, which differ for the wireless channel adopted. In particular, we use a Nagakami-m fading channel model with a parameter $M \in \{5, 10, 20, 50, 100\}$. Our goal is to discriminate between two network conditions, i.e., a static network in which the topology is stable, and a mobile network, where a mobility event occurs. For each choice of the parameter $M$ we run a training simulation of length 2000 s. We observe the value of each network parameter for every time sample $k$, which corresponds to a time interval of length 0.1 s. The collected data becomes the input for the BN structure learning algorithm and then for inferring the probabilistic parameters of the CBN, as described in Sec IV-A. Then, we obtain the TCPD needed to predict the state of the network.

In order to discriminate between the two network conditions, we need to set up a probability threshold, which is used to make the decision after the observation of the parameters in $S$, and as a function of the corresponding TCPD. We have selected a threshold which represents the best tradeoff between the number of false positives, i.e., the prediction of a mobility event in the case in which the scenario is static, and the number of false negatives, i.e., the prediction of a static network when a mobility event occurs.

We evaluate the accuracy of this network status prediction by running 6 simulations (of 500 s each) for every Nakagami-m fading channel coefficient $M$, with 4 disruptive mobility events in each simulation. In Tab. III we show the results in terms of prediction accuracy, i.e., the fraction of mobility events detected, and in terms of false positives. We notice that for $M = 5$, which corresponds to an outdoor scenario in a residential area, the prediction is still good, but less accurate than in the case in which $M$ is larger, which corresponds to a scenario with more stable radio propagation conditions.

B. Performance improvements

Our approach is compared to the standard TCP with OLSR protocol stack in different wireless scenarios. The performance is evaluated in terms of the average TCP throughput, which is defined as

$$\bar{t} = \frac{1}{K} \sum_{k=1}^{K} t^{(k)},$$

where $t^{(k)}$ is the instantaneous throughput and $K$ is the total observation time. We also evaluate the outage probability $p_o$, which is defined as the fraction of time in which $t^{(k)}$ is below a throughput threshold $\tau$, i.e.,

$$p_o = \frac{1}{K} \sum_{k=1}^{K} \chi^{(k)}, \quad \text{where} \quad \chi^{(k)} = \begin{cases} 1, & \text{if } t^{(k)} < \tau, \\ 0, & \text{otherwise}. \end{cases}$$

In Fig. 5-(a) we compare the throughput obtained in a static scenario when adopting our proposed framework as opposed to standard procedures. We show also the percentage of throughput improvement obtained with our approach. Similarly, in

This ad hoc solution follows the rationale behind the explicit link failure notification (ELFN) technique for ad hoc networks proposed in [4].

In this paper, the TCP throughput threshold is set to $\tau = 1$ KB/s.
Fig. 5. Average throughput for different Nakagami-m fading channel coefficients ($M$) (a) in a static scenario, and (b) in the presence of mobility.

Fig. 5-(b) we show the same throughput comparison in the case of a scenario with mobility events. From these figures, we obtain three important insights. i) The throughput increases as $M$ increases, as expected, due to a more stable channel. ii) Our approach provides increasing gains at lower values of $M$. iii) By comparing the two scenarios, we observe that our model introduces better performance compared to the standard approach when mobility is introduced and the topology varies as a function of time. Thus, our approach shows a significant performance improvement in both a static scenario and in the presence of mobility events.

Before describing the performance improvement in terms of the reduction of the outage probability, we study the complementary cumulative distribution function (CCDF) of the duration of the outage intervals. In Fig. 6-(a) we show the CCDF in a static scenario for the standard protocols and for our approach, while in Fig. 6-(b) we show the CCDF for a scenario with mobility events. We show that our approach can decrease the duration of the outage intervals, which may be an important requirement to meet the requested quality of service (QoS) for some specific applications, in both civilian and military scenarios.

Fig. 6. CCDF of the length of the outage intervals for Nakagami-\textit{m} fading channel ($M = 5$) (a) in a static scenario, and (b) in the presence of mobility.

Finally, in Fig. 7 we show the reduction in the outage probability for the static scenario, in Fig. 7-(a), and in the presence of mobility events, in Fig. 7-(b). It can be noted that, in both cases, this probability is significantly reduced, thus corroborating the validity of our proposed model.

VI. CONCLUSIONS AND FUTURE WORK

In this paper we have adopted the cognitive network paradigm to address the intrinsic inefficiency of the standard TCP in mobile ad hoc networks. With our probabilistic approach, we have been able to identify in real time the presence of mobility events, and we have estimated also the prediction accuracy. Through a simulation campaign, for the case of a linear topology, we have shown that our approach can significantly outperform the standard TCP with OLSR protocol both in a static and in a mobile scenario, in terms of increased average throughput and decreased outage probability. In our future work, we plan to address more general topologies, and implement this framework in our mobile network testbed [29], in order to study its performance in realistic wireless scenarios.
Fig. 7. Outage probability for different Nakagami-m fading channel coefficients (M) (a) in a static scenario, and (b) in the presence of mobility.

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