

Using a History-Based Approach to Predict Topology Control Information in Mobile Ad Hoc Networks

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Abstract. Several social computing participation strategies, such as crowdsensing and crowdsourcing, use mobile ad hoc or opportunistic networks to support the users activities. The unreliability and dynamism of these communication links make routing protocols a key component to achieve efficient and reliable data communication in physical environments. Often these routing capabilities come at expenses of flooding the network with a huge amount of topology control information (TCI), which can overload the communication links and dramatically increase the energy consumption of the participating devices. In previous works the authors have shown that predicting the network topology in these work scenarios helps reduce the number of control packets delivered through the network. This saves energy and increases the available bandwidth. This paper presents a study that extends the authors' previous works, by identifying the impact of predicting the TCI generated by routing protocols in these networks. The prediction process is done following a history-based approach that uses information of the nodes past behavior. The paper also determines the predictability limits of this strategy, assuming that a TCI message can be correctly predicted if it appeared at least once in the past. The study results show that the upper-bound limit of the history-based prediction approach is high, and that realistic prediction mechanisms can achieve significant ratios of accuracy. Mobile collaborative applications and routing protocols using mobile ad hoc or opportunistic networks can take advantage of this prediction approach, in order to reduce network traffic, and consequently, the energy consumption of their devices.

Keywords: Network Topology Prediction, History-Based Prediction, Routing Protocols, Mobile Ad Hoc Networks, Mobile Collaboration.

1. Introduction

Mobile computing and wireless networks are part of our life. Everyday more and more people are becoming a part of collaborative networks to share several information, such as the status of the vehicular traffic in an area, the security level of a city zone, or the location of interesting places to visit while performing touristic activities.

In many scenarios, the networks of these applications are wireless and ad hoc, and the provision of the applications' services makes sense only if the consumer (i.e. the end-user) is localized near to the service provider. For instance, during lunch time the restaurants located in a promenade area can deliver special offers to the smartphone of the passers-by, motivating them to take lunch in those places. If the service providers (i.e. the restaurants) use WiFi to irradiate these messages to the people, then this process will need to use message routing to reach the devices of potential clients that are located to more than one-hop of distance from the provider. This means more than 80-100 meters in open areas or more than 30-25 meters in build areas.

The routing protocols used in these mobile collaboration scenarios must be simple, efficient, reliable and they have to quickly adapt themselves to changes in the network topology [1, 2, 3, 4]. Moreover, these protocols should minimize the delivery of topology control information (TCI) to avoid consuming too much energy of the passers-by' devices. Link-state proactive-routing protocols could be used in these scenarios to support interaction among devices, since they have low latency when sending data through ad hoc networks. The latency is low because these protocols utilize an optimized and known data-path for delivering messages to the destination nodes [5]. However, this advantage comes at the cost of periodically flooding the network with TCI that negatively impacts the energy consumption of the nodes.

Medina et al. [6] and Meseguer et al. [7] show that the traffic generated by OLSR (Optimized Link State Routing protocol [5]) for different nodes densities, grows almost exponentially with the number of nodes. Therefore, for a large number of nodes, a huge amount of TCI should be delivered through the network. This not only overloads the communication links, but also increases the energy consumption of the nodes. The authors have also shown that the problem of delivering much control information through the network can be addressed using predictions [6, 8]. Particularly, the OLSRp (OLSR with prediction) protocol was proposed to eliminate redundant control information, and thus, to reduce CPU and energy consumption in mobile ad-hoc networks. This prediction mechanism is based on the assumption that the last TCI send by a node will probably be repeated during the next round of information delivery. The results of this prediction strategy show that this simple algorithm can reduce considerably the number of control packets (CP) transmitted through the network, saving computational processing and energy consumption, without affecting the routing capability of the protocol.

However, this prediction process sometimes introduces additional complexity to routing protocols, because additional hardware, software or both of them, must be devoted to make a prediction, and possibly to validate it. Moreover, the prediction can also introduce additional time-penalties to the system, mainly when the rate of mis-predictions is high. On average, if the percentage of right predictions is high enough, the overall performance of the routing protocols can be significantly improved at a reasonable hardware/software cost. The same concerns can be extended to computer networks, as they also have been aware of prediction techniques in several ways, such as energy-efficient routing [9, 10], nodes sleeping-state scheduling [11, 12], reliability [13, 14], link-quality tracking [15, 16] and routing-traffic reduction [6, 7, 8].

This paper extends the proposal described in [2, 4], by presenting and evaluating a new strategy for predicting TCI in mobile ad hoc and opportunistic networks. This new prediction approach uses a time window, in which the historical TCI of a node is considered to predict the next TCI. By using simulations, this proposal determines the performance of the history-based prediction in several mobile scenarios. The scenarios used in these simulations are representative of some everyday life activities, where people freely move around a certain area, and eventually interact with other people in these places. The obtained results help designers of both, routing protocols and mobile collaborative systems, to conceive more efficient ways to manage the TCI in these scenarios.

2. Predicting TCI Using Past Information

Although it seems to be a good idea to use historical TCI to make predictions of the next control packets [8], it is important to determine the performance and limits of this approach. Only after that, it would be possible to determine in which mobile computing scenarios this proposal can provide a real benefit.

The history-based prediction (HBP) approach considers that each node keeps updated locally (in a table) the recent history of the TCI received from its neighbors. The prediction process performed in such a node takes this information as input, and produces a prediction of TCI for each neighbor. Thus, it tries to guess the network topology without delivering control information. The prediction that a node makes for a TCI of a neighbor can be done whenever the recently TCI received from such a neighbor, matches with the previously TCI stored by that node. It is important to notice that the HBP approach is focused on predicting a state that has already appeared in the past.

In order to understand the performance of the HBP approach, we performed several simulations using unbounded tables with historical information. These unbounded tables give more flexibility to identify patterns in the nodes' movements, and thus to try guess the next topology of the network. This pattern identification can be done analyzing the tables with historical information that each node keeps for such a purpose. Each movement pattern corresponds just to a sequence of TCI packets (one or more), that the node making the prediction has seen in the past (and it has registered in its local table). Attached to every pattern stored in the table there is a list of all the packets that appeared after such a pattern. These packets could be predicted depending on the prediction strategy used by the node.

The table with historical information also records some statistical information that helps the prediction process to select one option among several candidate node mobility patterns; i.e., to determine which is the most suitable candidate (pattern) to match with the next TCI packet in the current prediction scenario. In short, an entry of the table will be composed by an input (TCI packets representing the pattern), an output (a list of control packets that appeared after each particular pattern) and statistical information (related to every output, which helps predict the next control packet). For every entry, it is maintained a list of all CPs that appeared after the pattern that is

under consideration by the prediction process. The statistics attached to the table establish both, the most frequent and the last packet of the pattern.

In order to analyze properly the usefulness of this historical information for the prediction process, we have defined the *history depth* (HD) metric. This metric can be calculated as the number of TCI packets that compose a movement pattern. In our study, the HD can assume values from 0 to 5. If we consider for instance a table with HD=1, this means that the number of packets that identify each pattern is one. Therefore, there will be one entry in the table for every control packet (CP) that appeared in the past. We believe that high HD means more accurate predictions, but few opportunities for predicting, because the packets sequences are long. Contrarily, low HD means more opportunities for predicting, but less accuracy in the predictions.

Based on the information stored in this table, we use and analyze the performance of three different flavors of the HBP approach: *last value* (it uses the last packet of the pattern to make the predictions), *most-frequent value* (it uses the most-frequent packet for predicting the next TCI) and *random value* (it uses any packet from the list, which is randomly selected). For instance, the OLSRp mechanism [6] assumes a last-value policy and HD=0 for predicting the next control packet with TCI. Probably, this is the most simple prediction mechanism, as just one control packet has to be stored and no statistics have to be maintained. Even this simple strategy has shown to be useful for reducing the traffic of TCI and energy consumption in mobile ad hoc networks [7, 8].

The different flavors of the HBP approach must not only succeed in their predictions, but also not predict when this success is not guaranteed. In our scenario, success reduces the network traffic and saves energy consumption, but incorrect predictions can skew the network topology map, and therefore decrease the reliability of the process. In this paper, we include a confidence mechanism to determine the likelihood that a prediction done using the HBP approach is correct. This could help both, maximize right and minimize wrong predictions. We assume a simple confidence mechanism, which determines if every packet of the output data list of a pattern was already predicted. If so, a counter is incremented by 1. Otherwise, it is decremented by 1. The counter is initialized as 1, and it can assume values in the range from 0 to 3. We consider that a prediction is confident, if the counter is equal or higher than 2.

Although this confidence mechanism can help us improve the prediction accuracy, if we assume a fixed HD, the opportunities for predicting TCI packets remain fixed. Therefore, in this article we analyze an additional flavor of the HBP approach, in which the HD is not initially fixed. We call this strategy as *prediction tree*. This strategy predicts the TCI assuming the maximum HD. Every time that it is not possible to do such an assumption (e.g. because there is not an entry or enough confidence), the HD will be decreased by 1. After that, the prediction tree attempts to make a new prediction, but using a shorter pattern. This will be repeated until the HD metric reaches 0. We analyze this approach with and without a confidence mechanism.

Finally, we quantify the repetition of TCI over time, in order to help understand predictability and prediction opportunity limits of this proposal. In one side, we determine the maximum prediction accuracy that these flavors of the HBP approach can reach, by counting if a certain TCI packet has ever appeared in the past. If it has appeared once, we assume that it could be correctly predicted. Moreover, we also quan-

tify the incorrect prediction of a pattern for each particular HD that could be correctly predicted as the correct prediction was in the list of control packets related to that pattern. Therefore, this information can help us identify the limits of the HBP approach, and also determine how far a particular prediction approach is from the best prediction performance. On the other side, this article also analyzes the representativeness of the most-frequent packets, respect to whole set of packets received by a node over time. This will give us a first understanding about how difficult is to make right predictions, and which is the amount of data (historical information) that must be tracked to make these predictions.

3. Experimental Framework

In order to determine the performance of the HBP approach, we designed and simulated several interaction scenarios using the NS-3 simulator [17]. This tool allowed us to model these scenarios, collect statistics, define initial network topologies, configure wireless network interfaces and set the mobility-patterns of the nodes. Every simulation performed in this study lasted 14,400 seconds (4 hours).

In these simulations we used the Optimized Link State Routing (OLSR) protocol, which is a well-known protocol for routing messages in ad-hoc networks [5]. The nodes of these networks periodically exchange control information to maintain a local map of the network topology. In order to do that, OLSR uses two types of control messages: HELLO and Topology Control (TC). HELLO messages allow a node to discover its neighbors and determine the quality of the links between them. TC messages allow a node to disseminate topology information with its neighbors. The simulations considered the delivery of a HELLO message every 2 seconds, and a TC message every 3 seconds.

The physical place available for interactions was a square open area of 300×300 meters, that could represent a beach or a park, where people are free to move throughout the whole space, and eventually interact with other people (e.g., friends, relatives or service providers). In these scenarios, the people can remain stationary (e.g. during a picnic), or walking with or without a clear direction. A mobile collaborative application, that detects the presence of related people in a physical area, can be eventually used to promote face-to-face encounters among them, as proposed in [18].

The simulations considered devices using Wi-Fi to detect other nodes and exchange control information among them. Using these interfaces, mobile networks composed of 10, 20, 30, and 40 nodes were simulated. The nodes were randomly deployed in the open area, and their behavior alternate between some stationary periods, and others in which they move up to 1 m/s (walking), 2 m/s (trotting), 4 m/s (running), and 6 m/s (bicycling).

The node movements can follow one of the following mobility models: *Random Walk*, *Nomadic* or *Self-similar Least Action Walk* (SLAW) [19, 20]. These mobility models are quite representative of the movement patterns of a person or a group that performs outdoor activities. The node mobility was implemented using the BonnMotion simulator [21]. The Random Walk model considers people moving randomly in

terms of direction and speed within a certain area; e.g. people in a park, where each person can move via walking, running or riding a bicycle without using formal paths. The Nomadic model considers people moving in groups, from one location to another. This is representative of guided tours, e.g. at a city downtown. This model considers a particular node per group (i.e., a reference node) that determines the next target point to be visited, and also a reference path and speed to reach such a place. This role can be played by the tour guide. Finally, in the SLAW model people move quite randomly, but they consider their previous movements (speed and direction) to determine the new ones. This is similar to the movements of people that use the walking paths in a park. This model is also effective to model casual encounters among community members; e.g., students at the university campus, or friends in a theme park. Unlike other models, the speed in this model cannot be parameterized, and it assumes a default value of 1 m/s (walking speed).

Finally, we have assumed that all nodes are similar, and their capabilities are equivalent to an iPhone 4. These devices have an effective WiFi range of approximately 80 meters in open areas. In such range, we can expect quite stable ad-hoc communication among devices and a bandwidth of at least of 50 Kbps, which is appropriate to support reliable interactions among mobile nodes.

4. Analysis of Obtained Results

4.1 Predictability Limits

In order to determine the upper-bound limit achievable by the HBP approach, we have assumed unbounded memory for the nodes, and also tracking if a TCI packet has ever appeared in the past. Figure 1 shows how the three mobility models behave when considering several nodes densities (from 10 to 40 nodes) and a similar average mobility speed (1 m/s) for the nodes in every model. Notice that for the scenario with 10 nodes, about 80% of the times the control packet to be predicted has already appeared in the past. This upper-bound limit is extremely high; therefore, the potential of predicting correctly the TCI is also high.

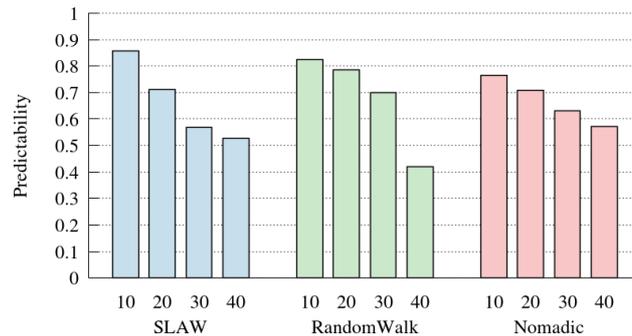


Fig. 1. Predictability limits

Besides that, we can see that there are no significant differences among the prediction capability in the three mobility models. This would be indicating that the prediction capability of the HBP approach does not depend on the mobility model being used by the nodes. In fact, we could expect similar results even in scenarios where the nodes use several mobility patterns.

The results also show that the prediction limits decreases when increases the node density. This is a result that can be expected, since a high-density network has many communication links that need to be correctly predicted; therefore, an important amount of control packets must delivered through the network, and a fewer number of patterns (in percentage) are identifiable by the nodes.

In order to determine the role that the nodes speed is playing in the obtained results, we established maximum speeds to the nodes. The nodes can randomly assume a certain speed (1 m/s, 2 m/s, 4 m/s or 6 m/s) for a short time periods, and then make a new assumption for the next period. The obtained results have shown that the nodes' speed does not affect the prediction upper-bound limit of the HBP approach. Therefore, we can say that this limit always ranges between 50% and 80%. Moreover, the predictability limit decreases when the node density increases, and there is not a significant difference among the mobility models used by the nodes.

4.2 Frequency of the Observed Control Packets

Concerning the control packets that appear most frequently in the history kept by the nodes, Figure 2 shows a curve illustrating the results. The curve considers, from left to right, the most frequent packets. The X-axis indicates (in percentage) the number of different packets that appear more frequently, respect to the total number of observed packets (i.e. packets that were recorded in the historical information of the nodes). For instance, in the scenario with 30 nodes, there are a 30% of different the control packets that represent 70% of the (total) observed packets. Notice that Y-axis and X-axis are both normalized.

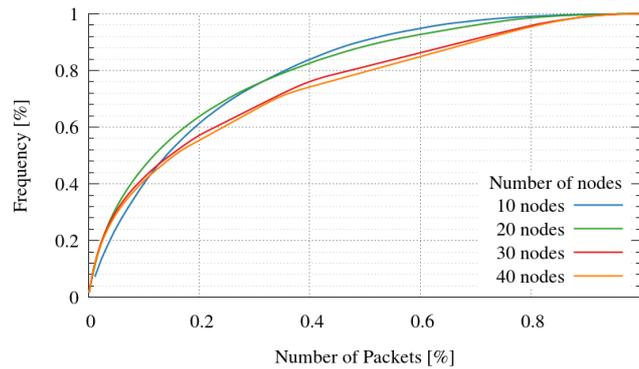


Fig. 2. Frequency of the observed control packets

The most important result shown in Figure 2 is that there is a small subset of packets that are representative of most packets delivered by the nodes through the network. In other words, the control packets belonging to this small subset traverse the network many times, therefore they have high representativeness. Although it seems that the combination of multiple nodes will produce a huge number of possibilities, in reality only with a few number of packets we can obtain most of the packets that a network produces. Notice that this result does not depend on the node density in the network.

Although the values shown in Figure 2 were obtained considering a SLAW mobility model and a speed of 1 m/s, the simulations done using the other mobility models have shown the same distribution for the results. Summarizing, these results and the predictability limits shown by the HBP approach are highly encouraging, as it provides many opportunities for predicting TCI packets, and these predictions would be focused on a small subset of the total packets delivered through the network.

4.3 History-Based Prediction

In order to perform a more comprehensive evaluation of the prediction performance, we have used several flavors of the HBP prediction approach. Moreover, we have identified four typical cases to analyze when making a prediction: (1) *nopred*, (2) *hit*, (3) *missNoPred*, and (4) *missPred*. In the first case (*nopred*), there is no prediction because there was no table entry that matches the current pattern. This would be the case with the lowest occurrence probably, as it only occurs the first time that a pattern appears. The second case (*hit*) means that there is a prediction (i.e., the pattern is in the table) and it is correct (i.e., the packet associated to that entry is the next expected packet). The third case (*missNoPred*) means that there is a prediction, and it is not correct, but it is impossible to do a correct prediction, as the next expected packet never appeared in the past with that pattern. Finally, the fourth case (*missPred*) means that there is a prediction, and it is not correct, however the packet could be correctly predicted, as the next expected packet appeared with that pattern at least once in the past.

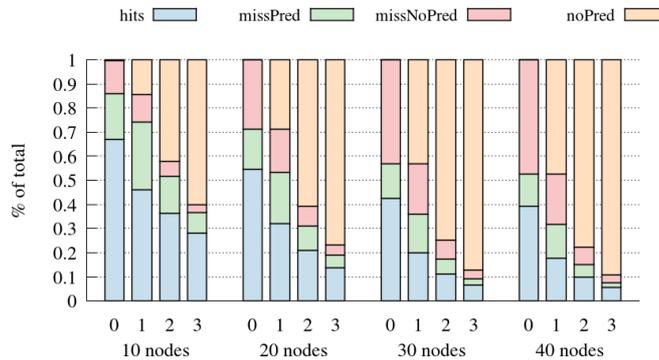


Fig. 3. History-based prediction using a SLAW mobility model and last value policy

Figure 3 shows the HBP performance considering these prediction cases in a scenario with a SLAW mobility and node density ranging from 10 to 40 nodes. The HBP approach assumes the last-value policy as the selected prediction mechanism, and a HD in the range from 0 to 3.

These results indicate that the largest percentages of *hits* are achieved with HD=0, but these cases also present important percentages of *misses* (i.e. *missPred* and *missNoPred*). The results also show the effects of the predictability limits (already seen in Figure 1), which reduces the number of *hits* and *misses* when the node density increases. The equivalence of *missNoPred* (HD=0) and *noPred* (HD=1) can be explained because for HD=1 the mechanism cannot predict the first time that a packet appears; i.e., this is *missNoPred* for HD=0.

Figure 4 shows the effect of using different prediction policies with a SLAW mobility model, for a network with 10 nodes. For this analysis we have considered three different sizes of history windows, corresponding to 1, 2 and 3 rounds of TCI delivery (X-axis). These windows sizes establish the amount of historical information used to identify the patterns.

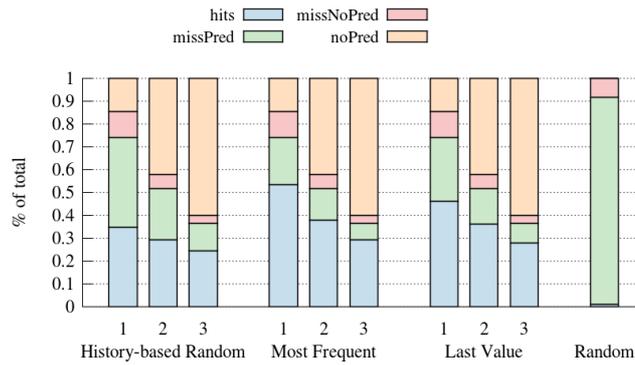


Fig. 4. History-based prediction using different prediction policies

When using pure Random policy it is always possible to make a prediction (even without history information), but most predictions are *missPred*. The use of historical information clearly allows achieving better results, even using a history-based Random strategy. This can be considered as the baseline and demonstrates the importance of utilizing the historical information to make more and accurate predictions.

Finally, Figure 5 shows the effect of using different mobility models with a speed of 1 m/s, for a network with 10 nodes. For this analysis we have considered three different sizes of history windows (1, 2 and 3). We can observe that the behavior of the 3 mobility models is quite similar (less than a 10% of difference), with a significant increase in *noPred* cases for large history values. These results confirm that there are no significant differences among the prediction capability in the three mobility models, as outlined in the analysis of predictability limits.

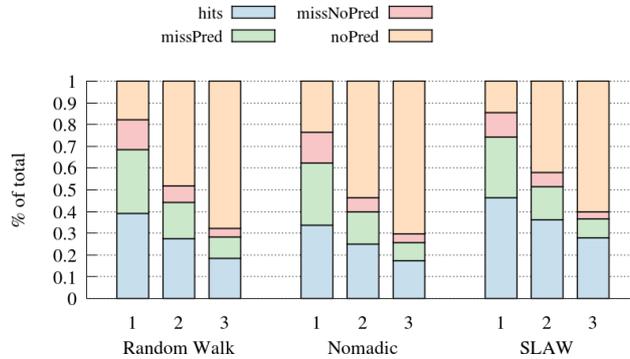


Fig. 5. History-based prediction using different mobility-models

4.4 History-Based Prediction Using a Confidence Mechanism

Notice also that in all the analyzed approaches a prediction is always done (besides the *noPred* case), and this prediction can be a hit or a miss. In the case of a hit, the direct benefit is a reduction of the network traffic and energy consumption, due to the producer will not send the control packet through the network, and the consumer will assume that its predicted control packet is correct. However, every miss prediction has a cost for the nodes, since the producer will detect that the prediction is not correct (due it has the current packet and this packet does not correspond to the one that returns the predictor). Therefore, this node will send the correct packet through the network. Meanwhile, the consumer will assume an incorrect prediction, as long as the correct packet does not arrive to the consumer node. This elapsed time would not be long, but it could be long enough to route some data packets, assuming a low accuracy of the network topology map. Therefore, the challenge to address is to always predict in certainty scenarios, and does not predict in other cases.

This strategy can be implemented by including a mechanism that adds two more cases to the previous four. Now a prediction is made if the predictor has enough confidence. In other case, the prediction would be a hit (*noConfidence/hit*) or a miss (*noConfidence/miss*). Our aim is to maximize *noConfidence/miss* with a minimum *noConfidence/hit*. Figure 6 shows the behavior of this confidence mechanism, considering the 6 cases (four of them consider no confidence). The results were obtained using a Nomadic mobility model, in a network with 10 nodes, which had a maximum speed 1 m/s. A last-value strategy was chosen to perform the predictions.

The results indicate that there are few predictions when using confidence; however, most of them are hits and there are few misses (the miss ratio is minimized). On the other hand, the most of the predictions were not made because there were not enough confidence (*noConfidence/miss* with little *noConfidence/hit*). This indicates that using a confidence mechanism we can minimize prediction errors.

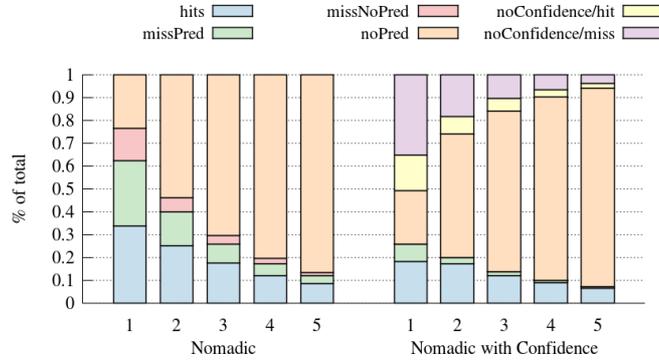


Fig. 6. History-based prediction using a 2-bit confidence-mechanism

4.5 Dynamic History-Depth

With the aim of improving the total number of hits, we relaxed the condition of fixed history-depth patterns, in order to have more opportunities to correctly predict the next TCI packet. When a pattern has no previous history and/or not enough confidence, we decrease in 1 the history depth and we check again if a prediction can be made (with the same selection policy), as a way to minimize *noPred* cases. We call this method *Dynamic History-Depth* (or *Tree*).

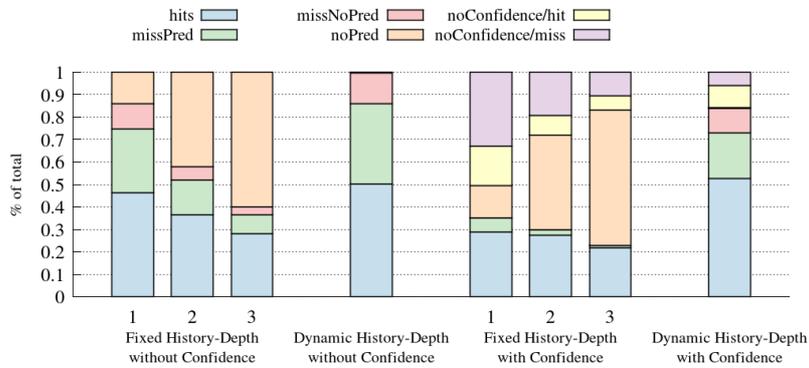


Fig. 7. Fixed History-Depth versus Dynamic History-Depth (Tree)

Figure 7 shows the results of using *Fixed* versus *Dynamic History-Depth* with and without confidence (using SLAW mobility, 10 nodes, 5 as maximum HD, maximum speed 1 m/s and the last-value policy). We can see that the *Tree* method minimizes *noPred*. Therefore, for the same percentage of hits, the total number of hits increases significantly. When we include a confidence mechanism (right side of Figure 7), *Fixed History-Depth* shows a decrease in number of hits and misses. However, *Tree* with Confidence achieves better results, maximizing hits and minimizing misses.

5. Conclusions and Future Work

In this work, we have analyzed the performance of a history-based strategy for predicting the topology control information generated by routing protocols for mobile ad hoc and opportunistic networks. This analysis was done simulating several mobile collaboration scenarios. The obtained results indicate that the history-based prediction (HBP) strategy contributes to reduce the traffic on these networks and saves energy in the mobile devices supporting mobile collaborative activities.

First, we have observed that around 80% of the times, for low densities of nodes, a packet has already appeared in the past. This percentage falls to 50% when considering a network with a higher node density. This demonstrates that the upper bound limits of the HBP strategy remain high for an ample variety of interaction scenarios, which make us expecting important benefits for mobile collaborative applications that use these networks as communication support. Second, the results also show that few packets contribute significantly to the total percentage of packets delivered through the network. This means that there is a high opportunity for predicting the TCI, and this prediction can be just focused on a small subset of packets. Finally, we have identified the role played by different history-depth patterns, prediction policies, confidence mechanism, and the combination of several approaches at the same time after analyzing the behavior of history-based prediction mechanisms under several scenarios. Considering all these issues and a worst-case scenario (with high density of nodes), we can correctly predict at least 30% of the control packets, minimizing the percentage of errors and getting an upper-bound limit of predictions that is close to 50% in such an scenario.

As a future work, we plan to analyze in detail all combinations of work scenarios, considering node density, speed and mobility patterns. We also want to develop more complex confidence mechanisms and combine the prediction approaches to see if their benefits can be accumulated. Moreover, it would also be interesting to analyze in a next step the prediction performance in opportunistic networks involving heterogeneous environments, like those presented by Li et al. [22]. Addressing these scenarios will allow developers to address IoT-based solutions.

Acknowledgments

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