Tracking and Predicting Link Quality in Wireless Community Networks

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Abstract: Community networks have emerged under the mottos of "*break the strings that are limiting you*", "*don't buy the network, be the network*" or "*a free net for everyone is possible*". Such networks create a measurable social impact as they provide to the community the right and opportunity of communication. As any other network that mixes wired and wireless links, the routing protocol must face several challenges that arise from the unreliable nature of the wireless medium. Link quality tracking helps the routing layer to select links that maximize the delivery rate and minimize traffic congestion. Moreover, link quality prediction has proved to be a technique that surpasses link quality tracking by foreseeing which links are more likely to change its quality. In this work, we focus on link quality prediction by means of a time series analysis. We apply this prediction technique in the routing layer of large-scale, distributed and decentralized networks. We demonstrate that this type of prediction achieves about a 98% of success in both the short and long term.

Keywords: Community Networks, Link Quality Tracking, Link Quality Prediction, Time Series Analysis

I. Introduction

Community networks are distributed, large-scale and decentralized networking infrastructures composed of several nodes, links and services where the resources are made available to a group of people living in the same locality. Networks of this kind are extremely diverse and dynamic because they are composed of decentralized nodes and mix wired and wireless links, several routing schemes and diverse services and applications. The network is managed using an open peering agreement, which avoids barriers for the participation in the network. Governance, knowledge and ownership of the network are open. These networks are therefore not just decentralized but also owned and managed by community members, growing dynamically in links, capacity and services. Some relevant examples of community networks are Guifi.net [1] and Funkfeuer [2].

These large, decentralized, dynamic and heterogeneous structures raise challenges that can be of interest to researchers, both as a source of inspiration and as a field to apply their research findings. One of the most important challenges is the effect of the unreliability and asymmetrical characteristics of wireless communications on routing protocols and network performance. Many metric-based routing protocols for mesh networks that track link quality and select higher-quality links have been proposed to maximize delivery rate and minimize traffic congestion [3], [4], [5] and [6]. Hence, link quality tracking is definitely a key method to apply when routing packets through an unreliable network. Moreover, it has been shown that routing algorithms should avoid weak links whenever possible [7], and as soon as possible [8].

Link quality estimation (or prediction) [9], [10] and [11] is an approach that increases the improvements in routing performance achieved through link quality tracking. Typically, real-time metrics do not provide enough information to detect the degradation or activation of a link at the right moment. Therefore, prediction techniques are needed to foresee link quality changes in advance and take the appropriate measures.

In this work, we present a link quality analysis and prediction of the Funkfeuer wireless mesh community network [2]. For the evaluation and comparison of results, we use the Weka framework [12], which incorporates some well-known time series analysis algorithms. To the best of our knowledge, no previous works explore link quality prediction in the routing layer of large-scale, distributed and decentralized systems, composed of many nodes, links and services.

The main contributions of this work are the following:

- The use of time series analysis to estimate link quality in the routing layer for real-world wireless mesh community networks.
- A detailed evaluation of the results obtained from several learning algorithms, showing the potential of time series to estimate link quality.
- Clear evidence that link quality values computed through time series algorithms can make accurate predictions in wireless mesh community networks.

This paper is structured as follows. Section 2 gives an overview of prediction and its application to computer networks. In Section 3, we describe our proposal to use link quality prediction in community networks. Section 4 presents the experimental methodology used followed by the analysis of results presented in Section 5. Finally, in Section 6 we provide some concluding remarks and indications for further work.

II. PREDICTION IN NETWORKS

Prediction methods have been applied in computer networks to achieve diverse goals, such as energy efficient routing, routing traffic reduction, network reliability and link quality estimation.

A. *Energy Efficient Routing*

Lifetime Prediction Routing (LPR) [13] is a routing protocol for Mobile Ad Hoc Networks (MANETs) where each node tries to estimate its battery lifetime taking into account of its past activity level. The Minimum Drain Rate (MDR) mechanism [14] is also applied to MANETs and uses the "drain rate" metric to estimate the energy dissipation of a given node. Another approach for energy efficient routing in MANETs is the E-DSR routing protocol [15] that combines route selection mechanisms and mobility prediction to improve data delivery ratio and energy consumption.

B. *Routing Traffic Reduction*

OLSRp [16] uses prediction methods to estimate the topology control messages. By doing so, OLSRp avoids resending some routing messages. It reduces the messages transmitted through the network, the computational processing and energy consumption. This approach was proved to be effective in MANETs [16] and also in Human Centric Wireless Sensor Networks [17]. The Kinetic Multipoint Relaying (KMPR) protocol [18] also focuses on reducing the amount of redundant retransmissions. However, it applies mobility prediction to detect when a change in the neighborhood is about to happen and to adapt accordingly.

C. *Network Reliability*

The Mobile Gambler's Ruin (MGR) algorithm [19] deals with global mobility prediction in MANETs by identifying nodes that are more likely to be disconnected in the near future and, therefore, maintaining continuous connections among devices. Mobile prediction is also applied to estimate the link expiration time between adjacent mobile nodes [20], and to determine if a node moves from its current location to the next location within a certain period of time [21]. In the former case, prediction helps to reconstruct routes before they expire whereas in the latter, it facilitates resource reservation and route maintenance.

III. LINK QUALITY PREDICTION IN WIRELESS NETWORKS

Link quality tracking has been previously applied in several scenarios and in several ways [3], [4], [5] and [6] to select higher quality links that maximize delivery rate and minimize traffic congestion. Link quality prediction is used in addition to link quality tracking to determine beforehand which links are more likely to change their behavior. As a result, the routing layer can make better decisions at the appropriate moment.

LQE (Link Quality Estimators) are in charge of measuring the quality of the links between nodes based on logical or physical metrics. Physichal metrics focus on the received signal quality and logical metrics focus on the percentage of lost packets. Link Quality Estimators with metrics like LQI (Link Quality Indication) [22], SNR (Signal-to-Noise Ratio) [23] or RSSI (Received Signal Strength Indication) [24] fit in the former category, whereas metrics like RNP (Required Number of Packets) [25], ETX (Expected Transmission Count) [26] or PSR (Packet Success Rate) [3] fit in the latter. All these metrics can be used by LQE in isolation or even, as a combination of some of them [9], [10] and [11] to select the more suitable neighbor nodes when making routing decisions.

MetricMap [27] is a routing protocol for wireless sensor networks that uses a learning-enabled method for link quality assessment. Based on the observation that high traffic rates make tracking link qualities more difficult, this protocol uses prediction methods to estimate them in advance. In a first stage, a machine-learning algorithm is applied to classify link qualities. Two types of classifiers are evaluated: a decision tree and a rule-based classifier. The data used to train both classifiers was preclassified offline based on a link quality indicator and other metrics that represent some features of the nodes. In a second stage, the MetricMap routing protocol estimates the link quality at runtime by replacing the current traffic information with the rules collected offline from the classifiers. Results show that MetricMap can achieve a significant improvement on the data delivery rate in high traffic rate applications. This work is the most similar to this paper as both use time series analysis to improve the routing protocol, but there are some significant differences:

- They evaluate a small wireless sensor network whereas we evaluate a large wireless mesh community network.
- They give only a flavor of the potential of time series analysis to predict link quality. In contrast, we perform a detailed and deep analysis of this potential.
- They apply a time series analysis to predict current link quality values while we use a time series to predict future link quality values.
- They use a cross-validation method, which uses a subset of the sample data to validate the link quality estimation. We, on the other hand, use new data to validate the link quality estimation.

IV. EXPERIMENTAL METHODOLOGY

A. *Funkfeuer Network and Open Data Set*

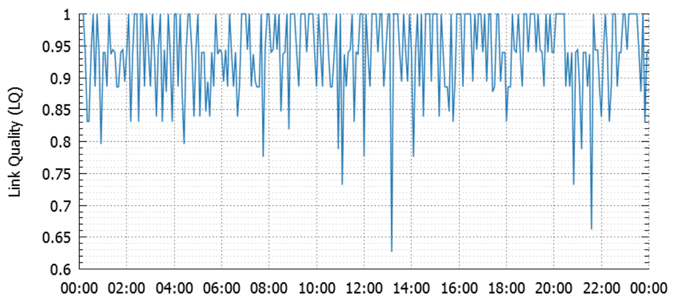
Funkfeuer [2] is a free experimental Wireless Mesh Community Network deployed in several locations in Austria (Vienna, Graz, Weinviertel and Bad Ischl). This network is a non-commercial project maintained by computer enthusiasts that install Wi-Fi antennas across rooftops. Currently, there are around 2000 wired and wireless links but every week new antennas are added to the network. Funkfeuer uses the OLSR-NG routing protocol, which expands the capabilities of OLSR protocol and makes it highly scalable. In fact, some members of the Funkfeuer network are actively involved in the olsr.org open source project as developers and also test it in this network.

We used open data set from the Funkfeuer network, available through the Confine Project platform [28]. This data set is composed of OLSR information such as routing tables and network topology data of 404 nodes that were collecting information during 7 days (from April 28th to May 4th, 2014). Notice that the total number of nodes is high. Also, every node has about 3.5 neighbors on average (degree) and the highest of the shortest paths in the network (diameter) is 16. This means that there are several paths where packets have to go through a relatively high number of hops in order to reach their destination. The routing protocol must, therefore, react quickly to any change in the network topology since it will be critical to achieve high performance.

B. Link Quality

ETX [26] is a link metric that measures the expected number of data transmissions required to send a packet over that link and widely used in several mesh network protocols. The ETX of a particular link is calculated as: ETX = 1 / (LQ × NLQ), where LQ and NLQ stand for "Link quality`` and the "neighbor link quality`` of that link. The Optimized Link State Routing (OLSR) protocol uses the EXT to choose, for each device and packet, the next hop. The LQ assumed by OLSR is defined as the fraction of successful packets (HELLO) that were received by a node from a given neighbor within a certain time window, while the NLQ is the fraction of successful packets that were received by the neighbor within a time period. We focus on predicting the LQ as the NLQ is implicit and the EXT can easily calculated using both predictions.

Fig. 1. A sample of variation of LQ values of a link over a day



In the open data set used there are 2095 links and approximately half of them (1068) experienced some variations in the link quality, as illustrated in Figure 1. From this latter group, we discarded those links that do not have enough samples to perform the time series analysis. Therefore, our study only considers 1032 links. Notice that the prediction results will only be given for those links that present variations in the link quality. Considering all the nodes would result in higher prediction accuracy but predicting the behavior of nodes with unaltered link quality is trivial.

C. Time Series Analysis

Time series analysis is the process of using statistical techniques to model and explain a time-dependent series of data points. Time series forecasting is the process of using a model to generate predictions (forecasts) for future events based on known past events. Time series data has a natural temporal ordering that differs from typical data mining or machine learning applications, where each data point is an independent example of the concept to be learned, and the ordering of data points within a data set is not important.

We applied a training and test sets validation approach to evaluate the predictive accuracy of the models. After a model is processed using the training set, it is tested making predictions against the test set. For this purpose, we used the Weka workbench system [12], a framework that incorporates a variety of learning algorithms and some tools for the evaluation and comparison of the results. Weka has a dedicated environment for time series analysis that allows forecasting models to be developed and evaluated. The Weka's time series framework takes a machine learning or data mining approach to model time series by transforming the data into a form that can be processed by standard propositional learning algorithms. To do so, it removes the temporal ordering of individual inputs by encoding the time dependency via additional input fields. These fields are sometimes referred to as "lagged" variables.

Particularly, we used more than one classification algorithm so that we do not rely on a specific learning technique. We applied four well-known approaches: Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Regression Trees (RT) and Gaussian Processes for Regression (GPR).

D. Metrics and Plots

Typically, classification studies assess the predictive power of their model using Mean Absolute Error (MAE). This is a common method to evaluate the performance of prediction approaches and is widely used in related work. Therefore, we also use this metric, which is calculated through the formula: MAE = sum(abs(predicted - actual)) / N

Boxplots are classic representations of a statistical distribution of values. A box is drawn around the region between the first and third quartile, and a horizontal line at the median value. Whiskers extend from the box to the lowest and highest value within the 1.5 interquartile range of the lower and upper quartile respectively. Points that lie outside these limits are independently drawn.

V. Analysis of Results

A. Comparison of learning algorithms based in time series

The main aim of this work is to explore if time series analysis and prediction can be used to predict the next link quality value. For this reason, we compared the results obtained using four different learning algorithms: Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Regression Trees (RT) and Gaussian Processes for Regression (GPR).

Figure 2 shows the average Mean Absolute Error (MAE) per link using a training data set of 1728 instances (6 days), a test data set of 288 instances (1 day) and a lag window composed of the last 12 instances. This test was performed to verify if time series learning algorithms could predict the next value of link qualities. The results show that we achieved the best result for the Regression Tree (RT) and the worst for Gaussian Processes for Regression (GPR). Notice that the maximum link quality value is 1 and the MAE per link is 2.7% for RT and 4.5% for GPR.

We analyzed the error variability from each algorithm using boxplots. The four algorithms achieved a similar performance for most of the links, as shown in Figure 3. Although the median, first quartile and third quartile values are similar for all of them, there are some outliers with high errors. These outliers increase the average values and change the overall evaluation of the algorithms.

Fig. 2. Mean of Mean absolute error (MAE) of links

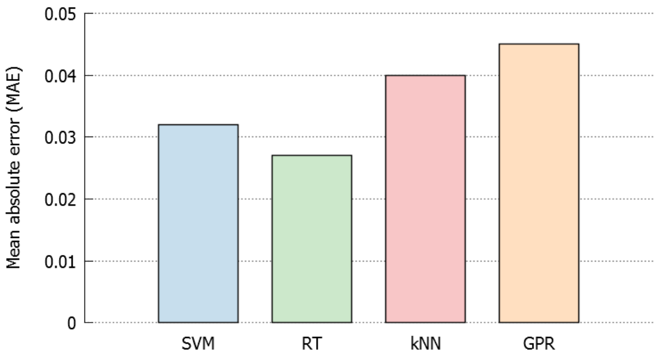
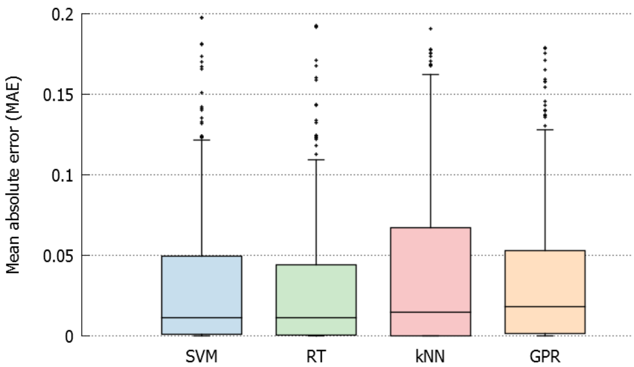


Fig. 3. Mean absolute error (MAE) of links as a boxplot



We applied a T-test to mean values for independent samples (at 95% confidence level) in order to compare the classification algorithms using the MAE. After this analysis, p-values smaller than 0.05 indicate that the means are significantly different, and therefore, we would reject the null hypothesis of no difference between the means. Consequently, we can claim that the RT is a good candidate to predict link quality.

B. Analysis of impact of lag window size

This analysis was performed to check the impact of the lag window in the prediction of the next link quality value. Figure 4 shows the average MAE per link of the RT algorithm using the same experimental setup as in the previous test (1728 and 288 instances for training and testing respectively) but now we used a lag window size ranging from 1 to 24 instances.

Lagged variables are the main mechanism by which we can capture relationships between past and current values of a series using propositional learning algorithms. They create a "window" or "snapshot" over a time period. Basically, the number of lagged variables determines the size of the window.

We obtained good results using window sizes ranging from 3 to 18 (Figure 4). The worst results were obtained for window sizes of 1 and 24. Nevertheless, these results are similar or even better than the best results obtained by the other algorithms. Thus, we can sustain the claim that RT is the best candidate.

Once more, we analyzed the variability of errors for each window size using a boxplot. All window sizes achieved a similar performance for most of the links, as shown in Figure 5. Although the values for the median and the first quartile are similar for all window sizes, the values of third quartile and outliers are a bit different. These differences in the variability of errors lead to the differences in the average MAE. Most of these results are better than those obtained using the other algorithms, as depicted in Figure 2.

Fig. 4. Mean of Mean absolute error (MAE) of links

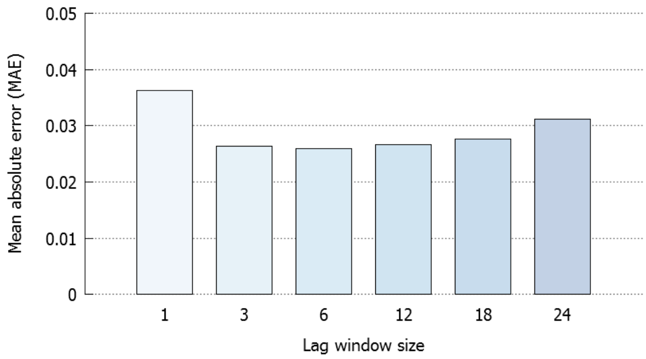
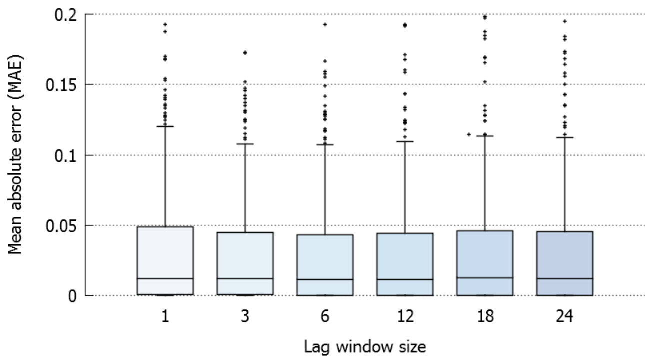


Fig. 5. Mean absolute error (MAE) of links as a boxplot



Once again, we tried to find the best lag window size for mean values by means of the T-test for independent samples (at 95% confidence level). After this analysis, we could not reject the null hypothesis at 95% of significance. Consequently, our results do not provide clear evidence of the best window size.

C. Prediction of some steps ahead

This analysis was performed to explore if time series analysis and prediction can be used to predict the value of link quality some time steps ahead into the future.

Figure 6 shows the average MAE of links. It shows the results of the RT algorithm using the same setup as the baseline experiment (a lag window size of 12 instances, a training data set of 1728 instances and a test data set of 288 instances) but predicting from 1 to 8 time steps into de future. We obtained good results for all values of steps ahead. The average MAE grows slower than linear. In the absence of a more detailed study, analyzing these exploratory results, it seems be able to predict the link quality some steps ahead. Once more, we analyzed the variability of errors for each value of steps ahead using boxplot, shown in Figure 7. Although the values for the median and the first quartile are similar for all steps ahead values, the values of third quartile and outliers grows with steps ahead values. These differences in the variability of errors lead to the differences in the average MAE.

Fig. 6. Mean of Mean absolute error (MAE) of links

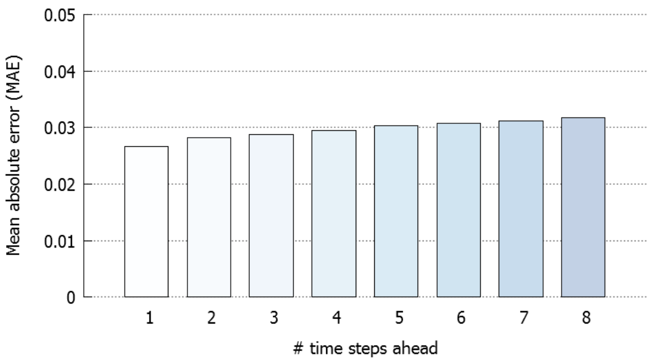
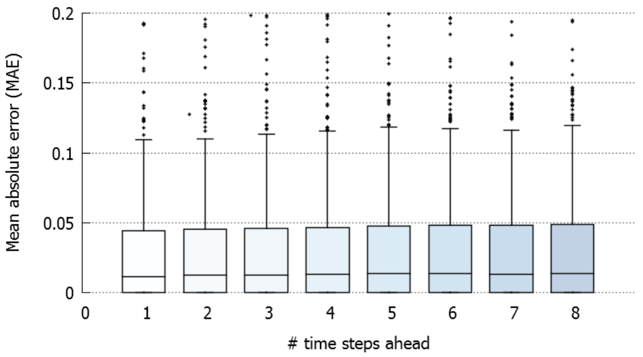


Fig. 7. Mean absolute error (MAE) of links as a boxplot



D. Degradation of the Regression Tree model over time

This experiment was performed to evaluate the accuracy of the prediction models over time. Figure 8 shows the average MAE of the overall network and its approximation to a linear function. It shows the results of the RT algorithm using the same setup as the baseline experiment (a lag window size of 12 instances and a training data set of 288 instances) but using a test data set ranging from 144 (½ day) to 1728 (6 days) instances. We used standard techniques to compute the parameters and estimate the goodness-of-fit, obtaining a linear function with these parameters: slope = 0.0212 and b = 0.0132 (line in Figure 8). Thus, we can affirm that a linear function can be used to model the degradation of the RT over time.

Figure 9 depicts the variability of errors. We can observe that the variability of errors increases linearly with the number of instances of the test data set. For this reason, it is important to train the model again after a certain period of time. Due to the fact that both the MAE and the error variability follow a linear function we could easily determine a trade-off between error and the frequency of updates to the model.

Fig. 8. Mean absolute error of network for different test data set size (number of instances).

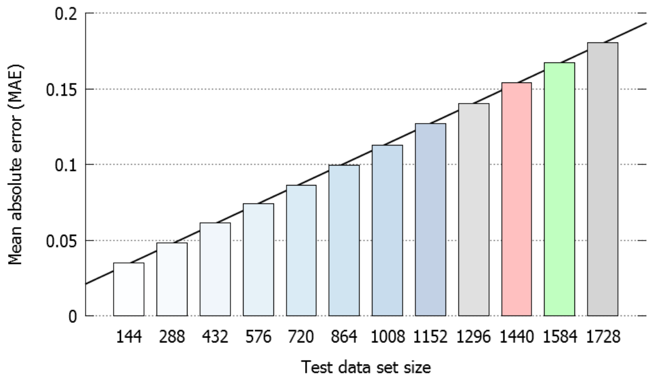


Fig. 9. Error of different test data set size (# instances) plot as a boxplot.

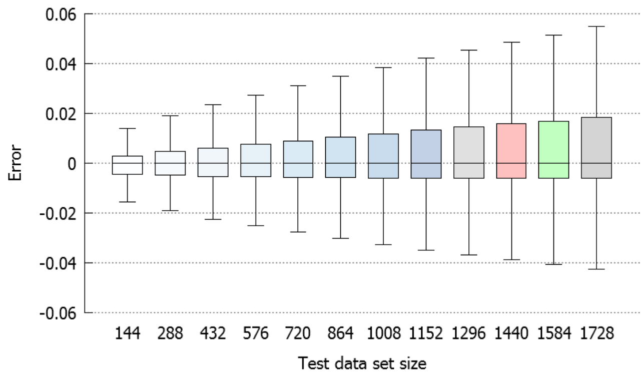


Fig. 10. Prediction error with training data set sizes of 1728 and 228 instances.

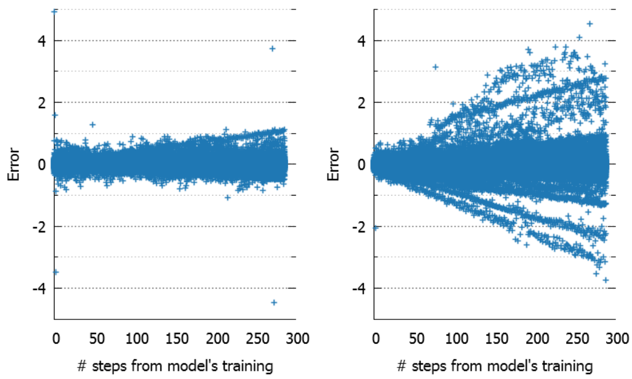


Figure 10 depicts the evolution of the prediction error over time. In both figures, the RT model was trained at time 0. The figure at the left shows 288 values predicted after having used 1728 instances for training. The figure at the right also shows 288 values predicted but after having used only 288 instances for training. Both figures show the impact of the size of the training data set in the prediction error. We observe that the higher the size of the training data set, the smaller the error. However, further analysis would be necessary to be able to determine an ideal size for the training data.

VI. CONCLUSIONS

This study demonstrates that time series analysis is a promising approach to accurately predict link qualities in community networks. This technique can be used to improve the performance of the routing protocol by providing information to make, at the right time, appropriate decisions to maximize delivery rate and minimize traffic congestion.

We analyzed results from four learning algorithms (Support Vector Machine, k-Nearest Neighbors, Regression Tree and Gaussian Processes for Regression) that model time series. All algorithms achieved percentages of success between 95% and 98% when predicting the next value of the link quality, being the Regression Tree the best one. Moreover, these results were obtained only considering those links that experienced variations. Therefore, the prediction accuracy could have been even better including all the network links. In addition, we showed that the prediction of values that are more than one step ahead (and not only the next value) also achieves high success ratio, between 97% and 98%. Finally, we observed that the size of the training data set is a key factor to achieve high accuracy of predictions. The bigger the size of the data set the smaller the degradation of the error over time.

Regarding future work, on the one hand, we plan to identify which links contribute the most to the error of the link quality prediction. We will also try to understand what factors make difficult to predict the behavior of these links. On the other hand, we also want to extend the analysis presented in this research work to other community networks, such as Guifi.net [1], to see if the observed behavior could be generalized.

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