Analysis of Machine Learning for Link Quality Estimation

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Abstract—Since the emergence of wireless communication networks, quality aspects of wireless links have been among the main focus of many studies. The analysis of the rich body of existing literature on link quality estimation that uses models built from data traces indicates that the techniques used for modeling are becoming increasingly complex. Several recent estimators use machine learning techniques that require a complex design and development process, and each step of this process has the potential to significantly impact the final performance.

The aim of this paper is to provide an in-depth study of how each step in the process of designing and developing a link quality estimator based on machine learning techniques affects its overall performance. Based on the analysis of the state-of-the-art, we selected a representative subset of machine learning models used in the literature and a representative publicly available dataset. We then performed a systematic study on the influence of the design decisions taken in each step of the machine learning process on the performance of machine learning-based link quality estimators. The results indicate that measurement data preprocessing and feature engineering have a higher influence on the performance of the model than the choice of the algorithm, calling for cautious use and parameterization of the algorithm.

Index Terms—link quality estimation, machine learning, data-driven wireless networking, data-driven optimization, data preprocessing, feature selection, model building, analysis

I. INTRODUCTION

In wireless networks, the propagation conditions for radio signals may vary significantly with time and space, affecting the quality of radio links. To ensure reliable network performance, an effective estimation of link quality is needed, so that the radio link parameters can be adapted or an alternative, more reliable channel or route can be selected for wireless data transmission. Research on data-driven Link Quality Estimators (LQEs) using real measurement data started in the late 90s [1], but related papers are currently still being published [2]. Early papers on the topic used recorded traces and manually developed models [1]–[11]. In recent years, works concerned with developing LQE are increasingly using machine learning (ML) algorithms [12]–[14]. The use of ML techniques in LQE can significantly impact the performance of wireless networks due to the ability of the technology to process and learn from large amounts of data traces that can be collected across various technologies, topologies and mobility scenarios, allowing them to be much more agile and adaptive.

Ideally, using machine learning, a more generic and high-level understanding of wireless links could also be attainable. A generic, automated mechanism to study links for any transceiver and any technology could help researchers better understand current operational aspects of increasingly heterogeneous wireless networks and open new horizons into wireless network design and optimization [15], [16]. Such mechanisms are currently being proposed, for instance, for studying radio frequency (RF) spectrum usage [17], [18].

With the recently proposed LQEs that use ML techniques, it is often difficult to understand the relation between the design choices and the reported results, because each model that relies on machine learning assumes a complex building process [19], [20]. Each step of this process has the potential to significantly impact the overall performance of the model and needs to be well understood and carefully selected. Additionally, to support a better understanding of the design process, as well as fair comparison with alternative new approaches, it is of critical importance to be able to reproduce the process and results [21]–[23], which requires open sharing of data traces.

The problem of different and sometimes contradictory observations arising from the large amount of research work on LQE based on different platforms, approaches, measurement sets, etc., has already been identified and addressed in [24].

The authors provided a comprehensive survey on empirical studies on low-power links in wireless sensor networks but did not address procedures using ML techniques. In this paper, we complement that survey by analyzing the rich body of existing literature on link quality estimation with a focus on models built from data traces. We also analyze publicly available data traces that are suitable for LQE research.

Our analysis, confirms the increasing complexity of techniques used for LQE modeling and the lack of deeper investigation of the design and configuration choices with respect to the implementation of these techniques. Motivated by this finding, we provide an in-depth study of how each step in the process of designing and developing an LQE using ML techniques affects the performance of the final model. For this investigation, we selected a representative subset of machine learning models used in the literature and a representative publicly available dataset.

The two major contributions of this paper can be summarized as follows.

• The first major contribution is a comprehensive analysis of existing literature on link quality estimation based on models built from data traces and sources of measurement data for such data traces. The analysis showed that LQEs not only exhibit an increasing complexity, but their performance is becoming more difficult to understand, reproduce and compare due to the complex design and
Section VIII concludes the paper.

The second major contribution is the extensive investigation of the impact of various steps of the machine learning modeling process on the overall LQE model performance, indicating that the domain knowledge-based data preprocessing, feature engineering and sampling all have a higher influence on the performance of the model than the choice of the algorithm.

This paper is structured as follows. Section II summarizes and analyzes related work. Section III summarizes and discusses freely available tracesets suitable for link quality estimation. Section IV discusses the standard process used when designing a machine learning model. Section V analyzes the design choices of the data preparation on the performance of the model. More specifically, Sections V-A, V-B, V-C and V-D consider the contributions of cleaning and interpolation, feature selection, window size and sampling strategy, respectively. Section VI then analyzes the contribution of the algorithm selection to the performance of the model, while Section VII identifies challenges yet to be addressed. Finally, Section VIII concludes the paper.

II. OVERVIEW OF DATA-DRIVEN LINK QUALITY ESTIMATION

With the emergence and spread of wireless technologies in the early 90s [25], it became clear that packet delivery in these networks was inferior to that of wired networks [1]. The wireless transmission medium is characterized by significantly larger losses than wired transmission mediums. As a result, various techniques for estimating the quality of links based on actual data traces, in addition to, or instead of simulated models emerged; some of them are summarized in Table I.

The work in [1] aimed to characterize the loss behavior of proprietary AT&T WaveLAN. It used packet traces with various configurations for the transmission rate, packet size, distance and the corresponding packet error rate. Then, they built a two-state Markov model of the link behavior. The same model was used in [3] but with a different goal. In [3], they attempted to estimate the quality of the wireless links to improve congestion performance of the Transmission Control Protocol (TCP). They used two Cumulative Distribution Functions (CDFs) computed from the collected traces, to model the transition probabilities in the two-state Markov model.

In [4], the authors aimed to improve the reactivity of routing tables in constrained devices such as sensor networks. They collected traces of transmissions for nodes located at various distances from each other. Then, they computed reception probabilities as functions of distances and evaluated a number of existing link estimation metrics such as moving average. They also proposed a new estimation metric called window mean with an exponentially weighted moving average (WMEMWMA) and showed an improvement in network performance as a result of more appropriate routing table updates. The improvements were shown both in simulations and in experimentation. This work was among the early works introducing the three different regions of wireless links, i.e., good, intermediate and bad.

The authors of [6] noticed that by considering additional metrics, also from higher levels of the protocol stack, the link estimation could be better coupled with data traffic. Therefore, they introduced a new estimator referred to as Four-Bit (4B) where they combined information from the physical (Packet Reception Ratio (PRR), Link Quality Indicator (LQI)), link (ACK count) and network layers (routing) and showed that it performs better than the baseline they chose for evaluation.

The same research group then proposed another link quality estimator [7]. They used PRR and the Gilbert-Elliot model of a channel. The Gilbert-Elliot model is a 2-state Markov process with good and bad states with 4 transition probabilities. The output of the model was the channel memory parameter that describes the “burstiness” of a link. They evaluated the proposed channel memory parameter on 4 different traces both for IEEE 802.15.4 and IEEE 802.11 technologies. They concluded that the model starts to converge at approximately 40,000 packets.

Another new link quality metric was proposed in [8]. The new TRIANGLE metric used the Pythagorean equation and computed the distance between the instant SNR and LQI vectors in a 2D space where the origin corresponds to the worst SNR and the worst LQI (0,0). Then, the authors used three empirically set thresholds to identify four different link types: very good, good, average or bad. The metric required approximately 10 packets to provide the estimation in either a static or mobile scenario.

In [9], the authors developed a new LQE based on fuzzy logic. WMEMWA, averaged PRR value, stability factor (SF), asymmetry level (ASL) and average SNR (ASNR) are used as inputs to the model. As output, the model classifies links as high-quality (HQ) or low-quality (LQ). In a later paper [26], the same authors compared Fuzzy logic LQE (F-LQE) against PRR, expected transmission count (ETX) [28] Required Number of Packets (RNP) [29] and 4B [6] on the RadiaLE [26] testbed. The comparison of the metrics was performed using different scenarios including various data burst lengths, transmission powers, sudden link degradation and short bursts. Among their findings, they showed that PRR, WMEMWA, and ETX, which are PRR-based LQEs, overestimate the link quality, while RNP and 4B underestimate the link quality. F-LQE performed better estimation than other compared estimators.

While several of the metrics surveyed in this section use
TABLE I
EXISTING WORK ON LINK QUALITY ESTIMATION USING REAL NETWORK DATA TRACES

| Title | Tech. | Goal | Input | Model | Output | Data | Reproduce |
|-------|-------|------|-------|-------|--------|------|-----------|
| A trace-based approach for modeling wireless channel behavior | WaveLAN, BARWAN testbed, BSD 2.1 | Maximize throughput, channel error model | SNR, signal quality, throughput[PRR] | improved two-state Markov model | probability of error to occur and persist | Not specified (<1500 bytes/packet, 1000 s/trace) | No* |
| Explicit loss notification and wireless web performance | WaveLAN, University of California testbed | Improve TCP Reno on wireless links, maximize throughput | bitrate, packet size, no. bits, throughput, bit error rate (BER) | CDF of error and error-free durations | probability of error to occur and persist | 800 000 packets (100 000 packets/execution, 8 experiments) | No* |
| Taming the underlying challenges of reliable multihop routing in sensor networks | proprietary, MICA mote, TinyOS | Improve routing table management | WMEWMA[PRR] | Shortest path, minimum transmission, broadcast, destination sequenced distance vector | Decision on keep/remove routing table entry | ≈600 000 packets (8 packets/s, 200 packets/Pkt) | No* |
| (4B) Four-bit wireless link estimation | Intel Mirage: 85x MicaZ; USC TutorNet: 94x TelosB; IEEE 802.15.4, TinyOS | improve routing table management | LQI, PRR, broadcast, ACK count | Construct 4-bit score of link state | Estimated link quality | Mirage: N.A., 40-69 min/experiment; TutorNet: N.A., 3-12h/experiment; | No* |
| A Kalman filter-based link quality estimation scheme for mobile wireless sensor networks | probably TelosB, IEEE 802.15.4 | PRR estimation | SNR(RSSI, noise floor) | Kalman filter + SNR to PRR mapping | estimated PRR | 25 200 000 (500 samples/s, 14 h) | No |
| PRR is not enough | IEEE 802.11, IEEE 802.15.4 | Link state estimation | PRR | Gilbert-Elliott Model (2-state Markov process), good and bad state | link quality transition probability | Rutgers and Mirage tracesets | Yes |
| The triangle metric: fast link quality estimation for mobile wireless sensor networks | Tmote Sky, Sentilla JCreate, IEEE 802.15.4, Contiki OS | new LQE | SNR(RSSI, noise floor), LQI | Pythagorean equation maps to distance from the origin (hypotenuse) | Estimated link quality as very good, good, average or bad | 30 000 + N.A., (64 packets/s, all channels, unicast) | No |
| F-LQE: A fuzzy link quality estimator for wireless sensor networks | RadiaLE testbed, 49x TelosB, IEEE 802.15.4, TinyOS | link quality estimation, improve routing | WMEWMA[PRR], SF[PRR], ASL[PRR], ASNR(SNR) | Fuzzy logic maps current to estimated link quality | binary high/low-quality (HQ/LQ) link estimation | N.A. (bursts, packet sizes, 20-26 channel) | No* |
| Foresee (4C): Wireless link prediction using link features | 54x Tmote testbed | Improve routing | WMEWMA[PRR], RSSI, SNR, LQI | Logistic regression model | Probability of receiving next packet | 80 000 + 80 000 noise floor (≥10 packets/s) | No* |
| Temporal adaptive link quality prediction with online learning | Motelab, Indriya and (local) 54x Tmote testbed, IEEE 802.15.4 | link quality estimation, improve Routing | WMEWMA[PRR], RSSI, SNR, LQI | Logistic regression with SGD and s-ALAP adaptive learning rate | binary, estimates if link quality above desired threshold | 480 000, (30 bytes size, 6 000 per exp., 10 sec.), Rutgers and Colorado tracesets | No |
| Fuzzy logic-based multidimensional link quality estimation for multihop wireless sensor networks | (local) 15x TelosB, TinyOS, IEEE 802.15.4 | improve routing, minimize topology changes | D_r(PRr), CV(PRr) | Fuzzy logic link quality estimator | binary high/low-quality link estimation | N.A., (20 min/ experiment, 12h) | No |
| Low-Power link quality estimation in smart grid environments | IEEE 802.15.4 | Improve routing, LQE reactivity | RNP, SNR, ASL[PRR] | optimized F-LQE with better reactivity | binary high/low-quality link estimation | N.A., 500kV substation env. data, TOSSIM 2 | No |
| WNN-LQE: Wavelet-neural-network-based link quality estimation for smart grid WSNs | 10x, CC2530 WSNs, IEEE 802.15.4 | Improve routing, estimate PRR range | SNR | Wavelet-neural-network-based link quality estimator | Upper and lower bound of confidence interval for PRR | 2 500 (20 bytes size, 3.33 per second) | No |
| Quick and efficient link quality estimation in wireless sensor networks | Grenoble testbed FIT-IoT; 28x AT86RF231, IEEE 802.15.4 | Analysis of LQI, fast decisions, improve routing | LQI | classification based on arbitrary values | Classify link as good, uncertain or weak | N.A. (2 000 per link, 16 channels) | No* |
statistics to estimate the quality of the links. Foresee (4C) [12] is the first one to introduce statistical ML techniques. Such techniques can approximate the underlying distribution from the input data. Therefore, the authors used a Received Signal Strength Indicator (RSSI), SNR, LQI, WMEMONA and smoothed PRR as input features into the models. They trained three ML models based on naïve Bayes, neural networks and logistic regression. In their experiments, the three models were very close in performance. Because of its simplicity, they chose logistic regression for empirical implementation and validation in their testbed. The authors claimed 20% to 30% improvement in end-to-end delivery using this approach compared to TinyOS’s vanilla ETX. The authors suggested that data gathered from 4-7 nodes for approximately 10 minutes should be sufficient to train their models offline.

The same research group then proposed a new ML-based LQE called TALENT [27]. The first difference with respect to 4C is that it uses an online ML approach, where the model built on each device adapts with each new data point as opposed to being precomputed on a server. The second difference is that TALENT has a binary output (i.e., whether PRR is above the predefined threshold) while 4C has a multiclass output. The third difference is that TALENT uses new models for LQE: stochastic gradient descent (SGD) [30], smoothed AlmeidaLangloisAmaralPlakhov algorithm [31] for the adaptive learning rate and logistic regression. The experiment ran on 18 intermediate quality links (0.45 < PRR < 0.89) on which TALENT was able to predict short, high-quality link intervals.

Similar to F-LQE, the authors of [10] used fuzzy logic and proposed a Fuzzy-logic Link Indicator (FLI) for link quality estimation. While both share the goal of being used for link quality estimation in routing, they take into account different input features. The FLI model uses PRR, the coefficient of variance of PRR and the quantitative description of packet loss burst, which are gathered independently, while F-LQE requires sharing PRR stats/information. FLI was evaluated in a testbed for 12 hours worth of simulation time against 4B [6], and it was reported to perform better. Additionally, it reduced the frequency of topology changes while maintaining a higher end-to-end success rate.

The authors of [11] proposed an optimized FLI that is suitable for a specialized environment of smart grids. Such environments have higher than normal values for electromagnetic radiation, 50 Hz noise and acoustic noise. The performance of the optimized FLI was evaluated against ETX, 4B and the baseline FLI by focusing on their stability, reliability and reactivity. The authors concluded that ETX often overestimates link quality, 4B is more reliable than ETX, and the baseline FLI is even more reliable than 4B. Furthermore, they reported that the baseline FLI is computationally expensive and not sufficiently reactive and that 4B as a sender-side estimator is more reactive than the baseline FLI. The proposed optimized FLI omits the link stability factor at the cost of accuracy and replaces it with a smoothed required number of packets metric. In their simulations, the optimized FLI showed better reactivity.

Another proposal for estimating link quality in smart grid environments uses a wavelet neural network based LQE (WNN-LQE) [14]. WNN-LQE is designed to provide confidence intervals for the predicted SNR. The proposed solution is compared against several other approaches: a backpropagation neural network, a Kalman filter, an ARIMA-based estimator and XCoPred. In their evaluation, the authors showed that WNN-LQE could capture the link quality within the confidence intervals. They also showed a relative comparison of the algorithms for stable and unstable links.

The most recent work [2] takes a step back from complex algorithms and reevaluates LQI as a prospective LQE. The goal was to make fast decisions as to whether a wireless link should be established or maintained. The authors proposed an estimator that categorized links as good, uncertain or weak, based on LQI. However, it was not clear from the paper how they defined the quality intervals (i.e., good: LQI = 255; uncertain:165 ≤ LQI < 255; weak: LQI ≤ 165). Using data collected from the IoT-LAB testbed, they drew two conclusions. First, they reported that below −85 dBm, RSSI becomes irrelevant and LQI becomes a valuable asset. Second, they reported that good directed links have a 95.6% probability of maintaining the quality in the opposite direction and 0% probability of degrading to bad in the opposite direction. Uncertain and weak directed links are slightly above 50% likely to keep the quality in the opposite direction.

A. Discussion

Our investigation focuses on data-driven link quality estimation. In Table I we summarized the most related publications that used real network data traces recorded from actual devices. As a result, a large part of the proposed models and metrics are data-driven - developed from raw data and then possibly fitted to a well-known or a newly proposed model. Considerable effort in the related work went into modeling, evaluation and quantifying the quality of wireless links.

The first column in Table I contains the title, reference and the year of publication. The second column provides the testbed, the hardware and the technology used in each of the papers. The third column lists the goals of the papers with respect to LQE. Columns four, five and six focus on the aspects of the estimators, particularly on their corresponding input(s), model and output. The last two columns give numbers about the size of the data used and whether the data are publicly available for reproducibility of results.

Table I indicates that contributions span from the emergence of wireless communication technologies until now. The majority of publications related to LQE are focused on sensor networks (IEEE 802.15.4) and only some target other types of wireless networks such as WiFi (IEEE 802.11) or Bluetooth (IEEE 802.15.1). This can be explained by the fact that IEEE 802.15.4-based wireless sensor networks have become relatively cheap to deploy and maintain. Sensor nodes have been open for implementing proprietary solutions. This has resulted in a large wave of research focusing on ad hoc, mesh and multihop communications, all of which rely on the estimation of link quality. The nodes implementing the selected technologies have been deployed and are maintained in various university testbeds.
With respect to the research goal, the surveyed papers can be categorized into two groups. The goal of the first group was to improve the performance of a protocol. Authors of [1], [3] investigated TCP performance improvement while others focused on routing protocol performance. This group of papers proposed new LQEs as an intermediate step towards achieving their goal. The goal of the second group of papers was to propose a new or improve an existing link quality estimator. For this class of papers, any protocol improvement in the evaluation process was secondary.

With respect to the metrics used for estimating the quality of a link, we distinguish between the single metric approaches used in [2], [4], [7], [14] and the multiple metric approaches considered in [1], [3], [5], [6], [8], [12], [27]. The most widely used metric, either directly or indirectly, is PRR. PRR values are used as model input in [1], [4]–[7], [9]–[12], [27], while categories derived from PRR values are used as model input in [5], [8]. Looking at the frequency of use, PRR is followed by hardware metrics i.e., RSSI, LQI and SNR in [2], [5], [6], [8], [12], [14], [27]. Other features are less common and tend to appear in single papers.

Considering the model used for developing LQE, the surveyed approaches can be distinguished as those using statistical models [1], [3]–[5], [7], rule-based models [2], [6], [8], [10], [11], [26] and statistical ML models [12]–[14].

Regarding the output of LQEs, we identified binary estimators [4], [10], [11], [13], [26], multiclass estimators [2], [7], [8] and continuous-valued estimators [1], [3], [5], [6], [12], [14].

Finally, with respect to the reproducibility of the results in the analyzed papers, our investigation shows that only [7], [13] are easily reproducible, because they rely on publicly available traces. Studies reported in [1]–[4], [6], [12], [26] use open testbeds that, in principle, could be used to collect data and reproduce the results. However, it is not clear whether some of the testbeds are still operational 10-20 years after the publication of the research. We did not find any evidence that the results in [5], [8], [10], [11], [14] could be reproduced as they relied on an internal one-time deployment and data collection.

As seen, the state-of-the-art analyzed in Table I shows that the link quality estimators vary in the input signals from a single input to multiple inputs, and from instant values to values derived by various computational approaches. The algorithms used for model selection vary from averaging and smoothing to logistic regression, decision trees, fuzzy logic and neural networks. The output of the models also vary from values to classes. In general, the above observation renders direct comparison of the performance of different estimators very difficult, and in most cases, the observation is additionally aggravated by the unavailable testing dataset or ill-defined validation setup, calling for the systematic approach and investigation proposed in this article.

III. OVERVIEW OF MEASUREMENT DATA SOURCES

To enable a better understanding of each of the steps involved in link quality estimation using real measurement data and ML models, we identified the most suitable publicly available sets of measurement data that can be used for a systematic study of each step. Measurement data comes in different shapes and forms, and in most cases, it cannot be directly used by ML algorithms. Measurements are mostly taken for a given period of time on a given radio link; we refer to such measurements as traces. When we have a set of such traces for a number of links and/or periods of time in a given testbed we talk about a trace-set. Traces and trace-sets, in general, can have missing values or some other irregularities and need to be preprocessed for the use by machine learning algorithms; we refer to such preprocessed trace-sets as datasets.

In Table II we summarize the publicly available trace-sets that, given the contained metrics, are suitable for investigating link quality estimation. Other datasets that could be suitable, but are not publicly available, are not considered. The first column lists the source of the trace-set and the estimated year of creation. The second column lists the hardware and technology used for the trace-set collection. The third column lists the type of communication used in the measurement campaign, and the last column contains notes about particularities of the trace-sets.

As shown in Table II we identified nine candidate trace-sets for performing link quality estimation. These trace-sets were collected by teams at various universities worldwide using their testbeds ( [32], [34], [38]) or one time deployments ( [35]–[37], [39], [41]). Four of the traces use IEEE 802.11, three use IEEE 802.15.4, one is based on IEEE 802.15.1, and one uses proprietary radio technology. The number of entries (i.e., measurement points) range from 6 thousand to 21 million, while the number of features per entry range from one to more than fifteen.

Two of the trace-sets, Rutgers [34] and Colorado [36], were used in two surveyed papers in Table I. In particular, [13] used both Rutgers and Colorado, while [7] used only Rutgers.

The Roofnet [32] is a well known WiFi-based trace-set from MIT. It is the biggest (in number of entries) of all listed trace-sets. However, it is hard to find the exact Roofnet setup/configuration used for collecting the measurement data, since it evolves over time, and it is not clear whether links are multihop. One particular drawback of Roofnet is that PRR can only be computed as an aggregate value per link and not in temporal sequence within a link.

The Rutgers trace-set [34] was gathered in the ORBIT testbed, and it is large enough, requires only moderate preprocessing and is properly formed for data-driven LQE. It exhibits the overall packet loss of 36.5%. However, RSSI is the only meaningful feature for LQE.

The “packet-metadata” [35] is a large dataset and comes with plenty of features useful for LQE. In addition to the typical LQI and RSSI, it provides information about the noise floor, transmission power, energy consumed and several network stack and buffer related parameters.

The Colorado trace-set [36] contains information from all network stack layers; therefore, it is the most complete trace-
TABLE II
PUBLICLY AVAILABLE TRACE-SETS FOR LQE INVESTIGATION

| Source and year | HW & Tech. | Data | Size | Type | Notes |
|-----------------|------------|------|------|------|-------|
| MIT, Roofnet, 2005 | Cisco Aironet 350, IEEE 802.11b, mesh, custom Roofnet protocol | source, destination, sequence, time, signal, noise, ... | 21 258 359 (1725 links, 4 bitrates) | 1-to-1, multishop? | not clear which packets were lost on a link |
| Rutgers University, ORBIT testbed, 2007 | 29x PC + Atheros 5212, IEEE 802.11abg | seq. number, RSSI | 611 632 (406 links, 300 packets/link, 1 packet/100 ms, 5 levels of noise) | 1-to-N | minor preprocessing |
| “packet-metadata” 2015 | 2x TelosB, IEEE 802.15.4 | RSSI, LQI, noise floor, packet size, no. retries, energy, Tx power, ACK, queue size, ... | 14 515 200 (300 packets per 80646 runs per 6 distances) | 1-to-1 | requires minor preprocessing |
| Colorado, 2009 | 5x listeners, IEEE 802.11 | signal strength, data rate, channel, timestamp, ... | 29 000 (500 packets per 58 locations, ) | 1-to-1 | Wireshark PCAP format, require preprocessing |
| University of Michigan, 2006 | 14x Mica2, proprietary protocol, sub-GHz ISM | RSSI | 580 762 (1 packet/0.5s, 30 min/device, 3191 records/link) | 1-to-N | MATLAB binary format, dirty data (leading zeros, no units), can only assume link relations |
| EVARILOS, UGent, 2015-03-11 | 6 nodes, Bluetooth | RSSI, timestamp | 5 938 (<2000 records/link) | N-to-1 | Hospital environment, No interference |
| EVARILOS, UGent, 2015-03-11 | 5 nodes, IEEE 802.15.4 | RSSI, Time-of-Arrival, timestamp | 110 126 (<35000 records/link) | 1-to-N | Hospital environment, No interference |
| University of Colorado, 2009 | 6x PC with omni antenna, 1 directional antenna, IEEE 802.11 | seq. number, coordinates, direction, TX power, 5x RSSI values per log | 5x 623 207 (500 packets per 180 positions per 4 directions per 11 Tx levels per 5 nodes) | 1-to-N | 3 types of antenna variable, Tx power, 4 directions, extensive documentation |
| Brussels University, 2007 | 19x Tmote Sky, IEEE 802.15.4 | seq. number, RSSI, LQI, timestamp | 112 793 (<1 600 packet/link) | 1-to-N | requires preprocessing, seq. number gaps; 3 other trace sets available |

set from the list.

Upon closer analysis, the last five trace-sets listed in Table II proved unsuitable for data-driven LQE. The trace-set from the University of Michigan [37] is incomplete and suffers from an inconsistent format, lack of units, missing sequence numbers and lack of context and documentation. The two EVARILOS trace-sets are in good shape; however, they have fewer than 2,000 entries each and are thus too poor for the LQE evaluation study. In the Colorado trace-set, all links seem to be in a good state as it has less than 1% packet loss, making it not representative for a general wireless network. Finally, the Brussels University trace-set is too small and suffers from an inconsistent structure and incomplete documentation.

IV. DATA-DRIVEN LINK QUALITY ESTIMATION THROUGH CLASSIFICATION

To classify the quality of the link, we chose the 3-class distinction model (good, bad and intermediate) based on PRR. This distinction was extensively used by [24]; however, it also appeared in [9], [29], [42]. Some articles [43]-[45] also used the terminology of regions, i.e., connected, transitional and disconnected regions.

To perform a systematic study of the influence of the various processing steps in classifying the quality of the links, we start from the well-established Knowledge Discovery Process (KDP) illustrated in Figure 1. We study the influence of data preprocessing steps such as data cleaning, data interpolation, feature generation and resampling on the performance of the learned model. There is no fixed, predetermined order of executing these steps, and when searching for the best settings of the process, some of the steps may need to be iteratively repeated. We use one possible ordering of steps; however, this should not affect the outcome of the study. We also investigate the relative performance of a selected set of various linear and nonlinear learning models. The aspects subject to the investigation are depicted in Figure 1 under the respective steps of the KDP.

The influence of each step on the results of the learned model is discussed in the following sections. After analyzing the existing publicly available trace-sets in Section III, the Rutgers trace-set was the most appropriate for further consideration in this study. This trace-set includes 4,060 separate link traces, collected on 812 unique links with 5 different noise levels (i.e., 0, -5, -10, -15 and -20 dBm). The directly available trace-set features include raw RSSI and sequence numbers, source node ID, destination node ID and artificial noise level. From the experiment description, we know that packets were sent every 100 milliseconds for a period of 30 seconds. Therefore, every trace consists of 300 packets. An example of a trace with an overall intermediate quality of the link from the Rutgers trace-set is depicted in Figure 2. Based on the specifications of the used radio, each RSSI value is defined between 0 and 128, where the value of 128 indicates an error and is therefore invalid.

A statistical analysis of the Rutgers trace-set reveals that 960 link traces out of 4,060 (23.65%) are completely empty (no packet received) and that, out of a total of 1,218,000 packets sent, only 773,568 (63.51%) were correctly received. Figure 3 illustrates the distribution of the Rutgers trace-set. The analysis shows the correlation between the average RSSI and the overall PRR for all links. The bar chart on top shows the distribution of the RSSI values. The vertically oriented bar chart on the right shows the distribution of PRR values. The central plot illustrates the correlation between RSSI and PRR, where a darker color indicates more data-points in the corresponding hexagonal area (the number of data-points is in log-scale). These three plots indicate that the majority of links...
Data Preprocessing

As discussed in Section III, a close look at publicly available trace-sets reveals missing values, inappropriate formatting, unaligned samples, unnecessary or missing features, etc. Thus, before being fed to machine learning algorithms or used to build a link quality model, these trace-sets need to be preprocessed. Typical preprocessing steps are depicted in Figure 1 and their impact on the performance of a data-driven link quality estimator are explained in the following subsections on the example of the Rutgers trace-set. It is worth noting that many of the design choices in the preprocessing steps depend on the purpose for using the data; however, the steps are general and applicable to any use of the obtained dataset.

A. Cleaning & interpolation step

Before building a data-driven model for link quality estimation, the selected Rutgers trace-set has to be examined...
and prepared for model building. First, a valid time series describing each link has to be extracted. By a valid time series, we refer to a series of ordered tuples where each tuple contains a packet sequence number and corresponding measured or calculated link metrics. The values in the tuples have to be within valid ranges. For instance, sequence numbers have to correspond with the packets sent during the trace collection, and the link metrics values have to be in the valid ranges specified by the transceiver datasheets or other corresponding documentation. In general, link metrics related to received radio signals, i.e., signal-level link metrics such as RSSI, LQI, can be obtained directly from the hardware registers of the corresponding transceivers, whereas link metrics related to packet data transmission, i.e., packet-level link metrics such as PRR, PSR, are calculated with suitable software procedures.

As described in Section IV the Rutgers trace-set has some invalid values and a considerable number of missing sequence numbers due to lost packets. Models created automatically using machine learning algorithms can be significantly biased by invalid and missing data. Many out-of-the-box data mining algorithms cannot handle invalid values (e.g., NaN and ±∞ from IEEE 754 specs), or they ignore them. After analyzing the link quality estimators from Table 1 that use machine learning models, it is unclear what strategy, if any, was used for handling invalid and missing data, nor their effect on the final model. Therefore, in this section, we investigate the effects of missing data on model performance. With respect to other influencing parameters evaluated and discussed in Sections V-B, V-C, and V-D, we assumed the use of a nonlinear decision tree algorithm trained with a trio of instant RSSI, averaged RSSI and standard deviation RSSI values, standard normalization and the random oversampling approach.

In the ML community, there are many approaches to handling missing data [48], [49]. To analyze the impact of the approach to missing values on link quality classification, we trained the same model (i.e., decision trees), with the same feature set, once without handling the missing values, once using a simple time series specific approach where we interpolated the missing samples with 0 indirectly preserves the information about those invalid values and a considerable number of missing sequence numbers effectively. In the case of interpolation with Gaussian noise, converges toward a normal distribution and starts losing information about the intermediate class. The results of the worst performing model, where invalid data points are dropped, is shown in Figure 4a. This model is unable to recognize bad quality link cases as the information about those cases was discarded from the trace.

B. Feature selection step

Feature selection is the process of selecting relevant raw features and/or creating synthetic features to be used for training of ML algorithms. It is a fundamental process in the Knowledge Discovery Process (KDP) and can be performed manually or, in some cases, can be built by existing algorithms. The Rutgers trace-set has only one feature useful for LQE, the instant (raw) RSSI value and the sequence number that is used to compute the label for training according to the following:

\[
y = f(PRR) = \begin{cases} 
good, & \text{if } PRR \geq 0.9 
bad, & \text{if } PRR \leq 0.1 
\text{intermediate}, & \text{otherwise}
\end{cases}
\]

\[
y = [y_1, y_2, \ldots, y_n], \quad \forall y \in \{\text{good, intermediate, bad}\}
\]

A typical approach in machine learning for such trace-sets is to investigate whether synthetic features, such as average RSSI over a time window or polynomial interactions [50], can help in training more accurate models than with only instant RSSI values. For the analysis, the correlation was investigated in terms of the coefficient of determination (R^2) statistics and Mean Squared Error (MSE). Note that the R^2 statistic can be negative if the model is not appropriate for the data.
### TABLE III
REGRESSION ANALYSIS ($R^2$) OF THE PREDICTED VALUE OF SYNTHETIC FEATURES

| Feature                     | $R^2$ | MSE  |
|-----------------------------|-------|------|
| $PRR^{-3}$                  | 1.000 | 0.000|
| $PRR$                       | 0.988 | 0.012|
| $RSSI_{avg}$                | 0.483 | 0.517|
| $RSSI$                      | 0.476 | 0.524|
| $RSSI_{avg} \cdot RSSI_{std}$ | 0.355 | 0.645|
| $RSSI_{std}$                | 0.327 | 0.673|
| $RSSI + RSSI_{std}$         | 0.321 | 0.679|
| $RSSI_{avg}^2$              | 0.030 | 0.970|
| $RSSI + RSSI_{avg}^2$       | 0.029 | 0.971|
| $RSSI_{avg}$                | 0.028 | 0.972|
| $RSSI_{std}^3$              | -0.000| 1.000|
| $RSSI_{avg} \cdot RSSI_{std}$ | -0.057| 1.057|
| $RSSI + RSSI_{avg} \cdot RSSI_{std}$ | -0.066| 1.066|
| $RSSI_{std}^2$             | -0.085| 1.085|
| $RSSI_{avg}^2$             | -0.243| 1.243|
| $RSSI_{std}^3$             | -0.243| 1.243|
| $RSSI + RSSI_{avg}^2$        | -0.244| 1.244|
| $RSSI + RSSI_{avg}^2$        | -0.244| 1.244|
| $RSSI_{avg} + RSSI_{std}$  | -0.317| 1.317|
| $RSSI + RSSI_{avg}^2 + RSSI_{std}$ | -0.322| 1.322|

By looking at $R^2$ and MSE for the predicted PRR (indicated as $PRR^{-3}$) assuming different combinations of features in Table III, it can be anticipated that the average RSSI will be slightly more valuable in the model performance than the instant RSSI. Due to space limitations, we only show a subset of combinations of synthetic features, some with positive and some with negative predicted values. The table also shows that in the case of the Rutgers trace-set, polynomial interactions are unlikely to improve the model performance.

For evaluating the influence of various feature combinations on the performance of the ML-based LQE, including polynomial interactions, we selected logistic regression as a representative of linear models and decision trees as a representative of nonlinear models. Figures 5 and 6 show the influence of the best-performing feature combinations on the classification performance. For these results, we assumed interpolation based on domain knowledge (i.e., replacing missing values with zeroes as discussed in Section V-A), synthetic feature creation with the window sizes $W_{PRR}$ and $W_{history}$ set to 10, standard normalization and the random oversampling approach (see Section V-D and Section V-C). The goal was to predict the link quality as per Eq. 1 for the next prediction window $W_{PRR}$.

The best performing feature combination for the linear model is $RSSI^{-3}$ and $RSSI^{-3}$ with an accuracy of 94.6% (see Figures 5i and 5j). This is followed by the feature combinations ($RSSI, RSSI_{avg}, RSSI_{std}$), ($RSSI, RSSI_{avg}$) and ($RSSI_{avg}$) shown in Figures 5b, 5c and 5d, respectively, with only 0.1 to 0.2 percentage points lower accuracy. However, it can be seen in Figures 5j and 5k that the best performing model in terms of accuracy is poor at correctly discriminating intermediate and bad classes, yielding only 26% and 31% correct answers, respectively. The high accuracy, in this case, can be explained by the heavily unbalanced data where good links are the majority and dominate the accuracy value. While only 0.1 percentage point inferior in accuracy, the model with the feature combination (RSSI, RSSI$_{avg}$, RSSI$_{std}$) depicted in Figure 5d correctly discriminates all three classes in 94%, 86% and 97% of instances.

For the linear model, it can also be seen in Figure 5a that an instant (interpolated) RSSI feature vector offers a good classification result for good and bad classes (above 93%), but the model is unable to identify the intermediate class, where it yields only approximately 31% correct answers. The performance further degrades when experimenting with $RSSI^2$, $RSSI^3$ and $RSSI^4$, where with an increasing exponent the discrimination capabilities of the model between bad and intermediate classes decrease. Linear models trained with synthetic data that uses a negative exponent for RSSI (i.e., $RSSI^{-1}$, $RSSI^{-2}$, $RSSI^{-3}$, $RSSI^{-4}$) (Figures 5l, 5i, 5k and 5l) offer a high classification rate for the good class (above 91%); however, they largely confuse the intermediate and bad link quality classes.

Other feature combinations such as ($RSSI, RSSI_{std}$), ($RSSI_{avg}$, RSSI$_{std}$) do not show good results and are therefore omitted from Figure 5.

A general observation for the linear model is that RSSI$_{avg}$, followed by RSSI and RSSI$_{std}$ are the most relevant features for training a well-performant model. The best model (RSSI, RSSI$_{avg}$, RSSI$_{std}$) in Figure 5d is followed by the (RSSI, RSSI$_{avg}$) in Figure 5c. Comparing the results of these two models, it can be seen that they perform comparably for the good and bad links; however, the addition of RSSI$_{std}$ to the already existing (RSSI, RSSI$_{avg}$) improves the recognition of the intermediate class by 8 percentage points. These conclusions also confirm the analysis from Table III where it can be seen that individual features explain the predicted PRR window because they have the highest $R^2$ values and small MSE.

For the nonlinear model represented by the decision trees, similar conclusions can be drawn for the linear model. The best performing model shown in Figure 6d with an accuracy of 95.2% uses the feature combination (RSSI, RSSI$_{avg}$, RSSI$_{std}$). The second best model using the feature combination (RSSI, RSSI$_{avg}$) has an accuracy of 94.2% as shown in Figure 6c. By comparing these two best performing feature combinations for nonlinear models, it can also be seen that adding RSSI$_{std}$ to the already existing (RSSI, RSSI$_{avg}$) has only a minor advantage of 0.2 percentage points for the class of good links while the performance on the other classes remains the same.

Figure 6 also shows that RSSI$_{avg}$ alone with the nonlinear model yields quite good results (87% for intermediate). Applying polynomials to RSSI or RSSI$_{avg}$ degrades the performance when compared to RSSI or RSSI$_{avg}$. For instance, as seen in Figure 6e, RSSI$_{avg}$ drops the recognition of the intermediate class by 13% while the other two classes are unaffected.

The performance comparison of the same best performing
feature vectors in the linear model in Figure 5 and the nonlinear model in Figure 6 shows that the nonlinear model slightly outperforms the linear model.

C. Window selection step

For studying the influence of the window selection on the performance of the model, we need to distinguish between two types of windows. The first is the historical window \( W_{\text{history}} \) that is used for computing the features such as \( \text{RSSI}_{\text{avg}} \). The second is the prediction window \( W_{\text{PRR}} \) that is used for computing the link quality labels. Given that the investigated trace-set consists of 300 packets per link, the size limits for the two windows are within \([0, 300]\) packets. However, choosing the value 0 implies no windowing, while choosing the value 300 implies per link labeling. Thus, we limited the range for the size of the windows to \([2, 100]\) packets, within which we investigated the performance with a discrete set of nine values \(\{2, 5, 10, 15, 20, 30, 50, 80, 100\}\). In this experiment, we were predicting the link quality for the next prediction window \( \text{PRR}(W_{\text{PRR}}) \) considering the Rutgers trace-set with domain knowledge interpolation, the nonlinear decision tree algorithm with the feature vector \((\text{RSSI}, \text{RSSI}_{\text{avg}}(W_{\text{history}}), \text{RSSI}_{\text{avg}}(W_{\text{history}}))\), standard normalization and the random oversampling approach.
As graphically depicted in Figure 7, the best performing model uses $W_{PRR} = 100$ and outperforms the models using other settings most of the time. Figure 8 shows a more in-depth look at the per class performance of the models in the form of a confusion matrix for various window sizes. The accuracy for $W_{PRR} = 100$ and $W_{history} = 100$ increases to 98.9% and the per class classification becomes 100% for good links, 96% for intermediate links and 98% for bad links. The results, in general, show that (i) a longer historical window improves prediction because there is more information about how the link performed in the past, and (ii) increasing the prediction window (looking into the future) also increases the accuracy. Both observations, however, can also be a side-effect of “smoothing”/averaging data from a relatively static trace-set. In particular, larger prediction windows are unable to inform on short-term effects, although they better describe the overall link behavior. It needs to be noted that the optimal combination of values for historical and prediction windows is data specific; however, the tradeoffs discussed in this section are general. While the Rutgers trace-set is relatively static, for a more dynamic trace-set the optimal window sizes are likely smaller.

For engineering a suitable link quality predictor, the agility of the estimator has to be specified by its user (e.g., the routing
algorithm) but also the practical memory limitations of the devices have to be taken into account. More agile predictors use smaller window sizes, and thus, they tend to consume less memory; however, they also yield lower accuracy. For large window sizes, the cold start period during which the historical window is initialized tends to be longer.

D. Resampling strategy

By analyzing the actual values in the considered trace-set, it can be seen that there are 61% good, 34% bad and only 5% intermediate class entries. This distribution of data is largely due to the artifact of the experiment, where the nodes were relatively close to each other, and the interference level was relatively low. Therefore, the majority of the links were actually good, and this was not due to missing values within one class category of link quality. Additionally, it has been acknowledged in the literature [24], that the intermediate region of the receivers tends to be relatively narrow compared to the good and bad regions, and therefore, naturally forming a minority class in most such trace-sets.

Unbalanced trace-sets are often encountered in the machine learning and data mining communities, and they are typically solved by an appropriate resampling strategy. For studying the influence of the resampling strategy on the performance of the model for link quality classification, we employed the Random Over-Sample (ROS) and the Random Under-Sample (RUS) approaches. The ROS [51], [52] approach equalizes all class sizes to the size of the majority class by reusing the dataset entries of the minority classes; therefore, the resulting resampled trace-set is larger. The RUS [51], [52] approach, on the other hand, equalizes all class sizes to the size of the minority class by taking the smallest minority class and random samples from other larger classes. The new resampled dataset is therefore smaller. With both approaches (ROS and RUS), however, a training dataset is obtained with balanced classes.

Figure 9 shows that resampling strategies on the Rutgers trace-set decrease the overall accuracy of the classification model from 97.2% to slightly above 95%. However, when no resampling is performed, the minority class (i.e., intermediate) is only correctly detected in 61% of the instances, meaning that the model is overfitted to the majority of the classes. In the case of resampling, the minority class is correctly detected in over 87% of the instances, yielding a 20 percentage points increase in performance. This improvement comes at a relatively small cost for the majority of the classes, a 3-4 percentage points decrease for the good links and a 2 percentage points decrease for the bad links.

The results for the selected trace-set show that there is no significant difference between the two resampling strategies, RUS and ROS. This is probably due to the relatively large size of the intermediate class. Although the intermediate class only represents 5% of the population, it still contains more than 52,000 samples. However, looking beyond this particular trace-set, the RUS approach may suffer from excluding a certain number of majority class instances and may affect the representativeness of the remaining data points, especially for more dynamic datasets. However, due to the enlarged number of data points, the ROS approach requires more computing resources for building a model.

The results in this section are based on interpolation and cleaning using domain knowledge, instant RSSI, RSSI\textsubscript{avg} and RSSI\textsubscript{std} as features and W\textsubscript{PRR} and W\textsubscript{history} of size 10.

VI. BUILDING THE MODEL

The final step of this study concerns the influence of model selection on the performance of a link quality estimator. For this, we selected logistic regression and linear SVM as representatives of linear models and decision trees, random forests and a multilayer perceptron, that is a class of feed-forward neural networks, as representatives of nonlinear models. As a
baseline reference model, we assumed the majority classifier which in our case classifies all links in the good class.

The results in this section use the Rutgers trace-set with domain knowledge interpolation, the feature vector consisting of instant RSSI, RSSIavg and RSSIstd, windowing with $W_{PRR} = 10$, $W_{history} = 10$, and a random oversampling approach. The models were evaluated using 10-times stratified K-fold cross-validation [47], [53].

Figure 10 shows that all the selected models except for the reference majority classifier have comparable performance. The difference in performance between algorithms is less than 3 percentage points for any class. The model with the highest accuracy of 95.3% is the random forest in Figure 10d, closely followed by decision trees in Figure 10c and a multilayer perceptron in Figure 10f. The fact that linear models perform slightly worse is consistent with the findings in Section V-B.

Looking at the ability of models to recognize the minority class, it can be seen that the multilayer perceptron performs the best.

**VII. DISCUSSION ON OPEN CHALLENGES**

During the examination of the related LQE work summarized in Table I and our systematic study of data-driven LQEs, we identified two distinct sets of challenges, one concerned
A. Data source related challenges

Challenges concerning data sources that need to be appropriately accounted for when building LQE models are dealing with the collection and/or generation of representative trace-sets.

1) Trace-set collection: For data-driven research using trace-sets collected from real networks, the understanding of the experimental setup and its influence on the obtained data is important. The related work analyzed in this paper (see Table I) is mostly restricted to trace-sets collected from static networks with relatively well-connected nodes and low levels of interference present. It seems that only [11] considered industrial environments; however, they mostly model the data. Moreover, in the analyzed works, they collected data using short bursts of packets. It is unclear how representative these traces are for real wireless (sensor) network deployments in real-world environments including factory floors and industrial robots. As such, we see an opportunity for defining representative classes of operating scenarios and types of network loads. These should then lead to suitable experiment descriptions that enable collecting representative trace-sets that consist of both static and dynamic (mobile) links with various types of traffic. Such trace-sets would enable the community to carry out more systematic and representative studies about the quality of the links, and thus, be able to better answer some of the existing contradictions identified in [24].

2) Trace-set generation: An alternative to the experimental collection of trace-sets is the generation of synthetic trace-sets. Producing highly representative synthetic data, which is usually obtained through a simulation based on real data or a well-known model, is a challenging task. While synthetic training data can be useful for designing and developing an ML-based system to solve a problem; such a system will likely need to be redesigned or re-engineered for a production-grade problem. Additionally, mistakes or biases in synthetically generated data due to oversimplified or even incorrect assumptions may lead to questionable results as was the case with the synthetic network intrusion data-set generated for the Knowledge Discovery and Data mining (KDD) cup [54].

B. LQE related challenges

LQE related open challenges mostly concern the generalized applicability of LQEs in heterogeneous networks and their use for deeper understanding of the quality of the links in various operating environments.

1) Generalized applicability of LQEs: Traditionally, LQEs are designed for a particular wireless technology, usually considering a network consisting of links based on homogeneous technology. Heterogeneous wireless networks with a multitude of overlapping technologies operating in the same frequency bands, often used in devices with multiple modes, would benefit from a more generic approach for estimating the quality of links. However, insufficient work has been performed on LQEs for heterogeneous technologies. In fact, only some research has been performed on LQEs within heterogeneous environments, where other than primary technology were treated as noise, whereas we could not find any link quality estimation work considering heterogeneous technologies on a single node or multiple technologies in a single LQE model.

ML-based LQEs are not dependent on the technology underneath but rather on the available training dataset. The challenge here is thus to develop a data-driven LQE based on a representative multiple technology dataset and investigate its generalized applicability for heterogeneous wireless networks. This comes down to the selection and/or synthetization of such features for training the ML algorithm that can imply information about multiple overlapping technologies, which could, for instance, be exploited in multimode devices for best technology selection or in flexible software-defined radio modules for adapting their transceiver characteristics.

An important part of the challenge here is also obtaining a representative multiple technology dataset. Most of the publicly available datasets were obtained in homogeneous testbeds with data sources used for building LQE models and the other with designing more generally applicable LQEs, suitable for heterogeneous networks with multitechnology nodes.

---

| Algorithm          | Accuracy | Good | Intermediate | Bad |
|--------------------|----------|------|--------------|-----|
| No resample        | 0.972    | 697,938 | 52,498 | 697,938 |
| Undersampling      | 0.952    | 52,498 | 697,938 | 52,498 |
| Oversampling       | 0.951    | 52,498 | 697,938 | 52,498 |

![Fig. 9. Different resampling strategies on the pipeline with a standard normalization and nonlinear decision tree algorithm using (RSSI, RSSI<sub>avg</sub> and RSSI<sub>bad</sub> features](image-url)

| Algorithm          | Accuracy | Good | Intermediate | Bad |
|--------------------|----------|------|--------------|-----|
| Majority classifier| 0.953    | 697,938 | 52,498 | 697,938 |
| Logistic regression| 0.944    | 52,498 | 697,938 | 52,498 |
| Decision Trees     | 0.951    | 52,498 | 697,938 | 52,498 |
| Random Forest      | 0.954    | 52,498 | 697,938 | 52,498 |
| SVM classifier      | 0.944    | 52,498 | 697,938 | 52,498 |
| Multilayer perceptron| 0.951    | 697,938 | 52,498 | 697,938 |

---

With the collection and/or generation of representative trace-sets, appropriately accounted for when building LQE models are dealing with the collection and/or generation of representative trace-sets. Producing highly representative synthetic data, which is usually obtained through a simulation based on real data, is a challenging task. While synthetic training data can be useful for designing and developing an ML-based system to solve a problem; such a system will likely need to be redesigned or re-engineered for a production-grade problem. Additionally, mistakes or biases in synthetically generated data due to oversimplified or even incorrect assumptions may lead to questionable results as was the case with the synthetic network intrusion data-set generated for the Knowledge Discovery and Data mining (KDD) cup [54].
or laboratory environments considering the same hardware on all nodes, with no inter or intratechnology interference, and typically using one-to-one communication. The model based on such dataset may be overfitted to a given hardware configuration, and may not be able to estimate short-period changes of link quality caused by the same or another technology operating in the same environment. Even if multiple technologies dataset is considered, the resulting LQEs based on data from a laboratory environment will likely miss several aspects of the real-world heterogeneous deployment and will lack generality. For instance, they will not be aware of the extent of the influence among interfering technologies, such as when Bluetooth interferes with Wi-Fi and causes Wi-Fi back-off and retransmit.

2) Understanding of the quality of the links in various environments: Under this open challenge we envision that a data-driven approach has the potential for designing not only multitechnology link quality model but also a further generalized tool for link quality monitoring and assessment by chaining several independent models of radio chips or modules, channel, operating environment, protocol stack, etc. Such a generalized model would provide a deeper understanding of the quality of the links under changing conditions and in various environments, i.e., static vs. dynamic, characterized by intertechnology vs. intratechnology interference, with changed radio modules, etc. In fact, based on existing LQE models we have a rather limited understanding of a quality of the links in various environments. Another step toward the real-world environment would be taking into account the intratechnology and intertechnology interference. The latter has not yet received considerable attention in the context of LQEs. There are trace-sets, such as EVAARILOS [38], which explicitly consider noisy environments. However, they provide no information about intertechnology interference nor noise statistical properties, other than what is embedded in radio features.

VIII. Conclusions

The data-driven approach has long since been adopted in the area of link quality estimation. However, with the adoption and adaptation of ML algorithms, it has recently gained new momentum, promising more generalized applicability and a deeper understanding of various influences on overall link quality.

In this paper, we first provided an in-depth analysis of existing literature on link quality estimation models built from data traces. The analysis showed that with the increasing use of ML techniques in LQEs the models are becoming increasingly complex and that the influence of different design and configuration choices on the overall performance are not well studied and understood. Thus, we selected a representative subset of ML models used in the literature and a representative publicly available dataset and carried out a systematic study on the influence of the design decisions taken in each step of the ML process on the performance of ML-based LQEs. We experimented with data cleaning and interpolation, feature selection, various window sizes, data-set sampling strategies and different algorithms to build a model.

The investigation indicates that trace-set preprocessing and feature engineering have a higher influence on the overall performance of the model than the choice of the algorithm. For the selected ML models and Rutgers trace-sets, we also show that:

- Interpolation with domain knowledge improves the accuracy of the ML-based LQEs by 7 percentage point compared to not using any interpolation.
- Feature selection improves the classification of intermediate links for up to 50 percentage point compared to using only raw data, with overall model improvement by 6 percentage point.
- A sampling approach boosts the classification of intermediate links by 26 percentage point compared to no sampling used at the penalty for an overall model accuracy below 2 percentage point.
- Nonlinear algorithms performed only slightly better at classifying link quality for the selected representative dataset than linear algorithms.

Finally, we concluded the paper with a discussion of the open challenges with respect to (i) data sources used for building LQE models; more precisely on trace-set dynamics, generation and collection, and (ii) generalized applicability of LQEs to heterogeneous networks with multitechnology nodes and deeper understanding of the quality of the links in various environments.

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REFERENCES

[1] G. T. Nguyen, R. H. Katz, B. Noble, and M. Satyanarayan, “A trace-based approach for modeling wireless channel behavior,” in Proceedings of the 28th conference on Winter simulation. IEEE Computer Society, 1996, pp. 597–604.
[2] H.-J. Audéoud and M. Heusse, “Quick and efficient link quality estimation in wireless sensors networks,” in Wireless On-demand Network Systems and Services (WONS), 2018 14th Annual Conference on. IEEE, 2018, pp. 87–90.
[3] H. Balakrishnan, R. H. Katz et al., “Explicit loss notification and wireless web performance,” in IEEE Globecom Mini-Conference, IEEE, 1998, pp. 1–5.
[4] A. Woo, T. Tong, and D. Culler, “Taming the underlying challenges of reliable multihop routing in sensor networks,” in Proceedings of the 1st international conference on Embedded networked sensor systems. ACM, 2003, pp. 14–27.
[5] M. Senel, K. Chintalapudi, D. Lal, A. Keshavarzian, and E. J. Coyle, “A kalman filter based link quality estimation scheme for wireless sensor networks,” in Global Telecommunications Conference. 2007. GLOBECOM’07. IEEE, IEEE, 2007, pp. 875–880.
[6] R. Fonseca, O. Gnawali, K. Jamieson, and P. Levis, “Four-bit wireless link estimation,” in HotNets, 2007.
[7] K. Srinivasan, M. A. Karandjieva, M. Jain, and P. Levis, “Prp is not enough,” 2008.
[8] C. A. Boano, M. Zuniga, T. Voigt, A. Willig, and K. Römer, “The triangle metric: Fast link quality estimation for mobile wireless sensor networks,” in International Conference on Computer Communication Networks, 2010, Zürich, Switzerland, 2010.
[9] N. Baccour, A. Koubâa, H. Youssef, M. B. Jamâa, D. Do Rosario, M. Alves, and L. B. Becker, “Flq-e: A fuzzy link quality estimator for wireless sensor networks,” in European Conference on Wireless Sensor Networks. Springer, 2010, pp. 240–255.
