WIP: An Open Data Set about Multi-Provider Redundancy in Cellular Networks

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***Abstract*—More and more applications are benefiting from the ever-increasing performance of wireless communication. Certain use cases in the mobility area (e.g. autonomous driving) demand particularly high reliability, which can be achieved through redundant transmission. In practice, however, it can be difficult to measure and study the precise benefit of redundancy for reliability and therefore, appropriate publicly available data sets are desirable. We provide such a data set about multi-provider redundancy in cellular networks: the performance metrics of redundant transmission channels are measured from a driving car, thus taking mobility into account. A statistical evaluation quantifies the effect of correlation on reliability empirically. In the future, this data set can be used for more detailed and elaborate investigations of the influence of redundancy on reliability. The knowledge thus obtained, about the interaction between redundancy and reliability helps to make new safety- and time-critical applications amenable to wireless communication.**

***Index Terms*—Cellular Networks, Mobility, Redundancy, Reliability**

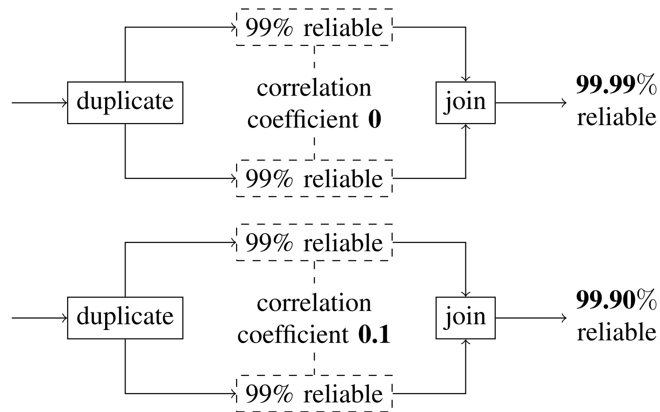

Fig. 1. The effect of correlation on resulting reliability can easily be underestimated. In this case, a correlation coefficient of 0.1 reduces the resulting reliability by an order of magnitude. (Reused figure [4])

I. Introduction

There are many future use cases for wireless and cellular communication that require high reliability. In particular, automotive and industrial applications frequently demand reliability that exceeds the performance of currently available wireless networks. Specifically, such use cases often require a reliability of $99.999\,\%$, which is equivalent to an unavailability of ≈ 5 minutes per year. Here, by reliability we mean the probability of a successfully completed packet transmission, where we consider a packet transmission as successful if the packet arrives at its destination within a specified time limit (e.g. $100\,\mathrm{ms}$). Probably the simplest way to increase reliability in wireless networks is to use an additional, redundant channel over which the same information is transmitted. This means that a packet is duplicated, the duplicates are sent via different channels and, provided both packets arrive, one packet is discarded at the destination. The reliability r of the resulting transmission scheme then depends on the reliabilities r_1 and r_2 of the two underlying channels as well as on the correlation c between them. If the channels are uncorrelated, the resulting reliability r is given by $r_{uc} = r_1 + r_2 - r_1 r_2$. For correlated channels, however, $r = r_{uc} - c\sqrt{r_1 r_2 (1 - r_1)(1 - r_2)}$ (see Section IV for a derivation of these formulas). Hence, for a positive correlation coefficient, the resulting reliability is strictly smaller than for independent channels. In particular, when reliability is considered as "number of nines", this shows that a small correlation can have a large effect on reliability (see Figure 1). Therefore, it is important to take into account when packet losses in different channels are correlated.

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The approach just outlined can be used in theoretical models to determine the reliability of a redundant transmission protocol. However, in practice, the correlation between the channels is unknown and usually not constant. The latter is particularly the case for automotive scenarios. Therefore, it is not clear how to practically quantify the gain in reliability by redundancy. To obtain methods to answer this question, one needs real data sets on redundant transmissions. Such a data set that we collected in an automotive scenario is described in this paper. Additionally, we provide first findings obtained from it. The data set contains key performance metrics (such as data rate and latency) of two different cellular network providers in Austria, which are measured from a car driving on a highway. To make the analyses reproducible we publish our full data set and the tool chains to produce our results. However, we do not publish the full raw data, because this includes personal and sensitive data.

II. Related work

An overview on publicly available wireless communication data sets is provided by [3]. These data sets are grouped into completed one-time experiments (typically performed to build

TABLE I
THIS OVERVIEW OF SELECTED COLUMNS FROM THE DATA SET PROVIDES A (SHORT) DESCRIPTION TOGETHER WITH THE MINIMUM, MEDIAN, AND MAXIMUM VALUE AND THE STANDARD DEVIATION.

	description	min	median	max	std
`time`	time reindexed to whole seconds	2021-06-02 05:14:20	2022-03-31 05:14:24	2022-12-23 15:59:34	
`lat`	latitude from GPS	47.8	47.9	47.9	0.004 19
`long`	longitude from GPS	13.1	13.2	13.3	0.0733
`alt`	altitude from GPS	-471	584	955	60.1
`signal`	signal strength in ”bars”	0	4	5	1.28
`rssi`	received signal strength indicator	-113	-63	-53	7.07
`sinr`	signal-to-interference-and-noise-ratio	-42	13	42	9.72
`rsrp`	reference signal received power	-141	-83	-49	11.9
`rsrq`	reference signals received quality	-20	-10	-3	2.9
`datarateDown`	data rate in bit/s	0	3.52×10^7	2.51×10^8	2.97×10^7
`ping`	round trip latency in ms	0	36.4	9.76×10^3	38.4

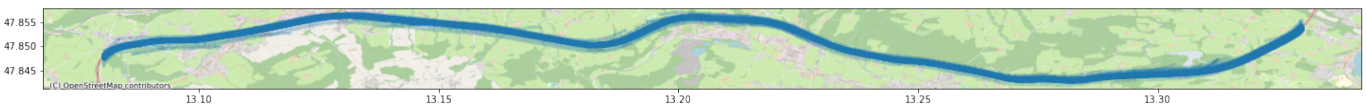

Fig. 2. The measurements were done on a highway that mostly stretches in east-west direction.

physical layer models) and ongoing data collection efforts. The latter are often conducted by federal agencies and mostly collect higher layer application data. A parallel redundancy protocol for railway wireless data communication is proposed by Wang et al. [13]. In this protocol, multiple copies of the same packet are transmitted over different paths. A field test shows that this reduces the packet loss rate by $40\,\%$ at the maximum. The focus of this work is on building a system that uses redundancy. In contrast, we measure the benefits such a system would have. Furthermore, no data set is published in this paper. Two other works [1, 6] on similar topics also do not publish data sets. The former, in particular, reports on improvements in reliability obtained by using multiple mobile networks. The authors find that in most cases, the devices can achieve $99.999\,\%$ connection availability by combining two operators. In addition, no mobility aspects are considered in [1, 6]. Palaios et al. [9] present realistic measurements from vehicles to support robust quality of service (QoS) prediction. They drive cars on highways and measure mobile networks from them. Multiple cars together with dedicated high-precision measurement devices are used and the cell load is known. In contrast to our work, redundancy is not considered. A redundant data transmission system with linear topology is studied by Kozyrev et al. [5]. They calculate the reliability characteristics of the system and investigate the effect of cross-redundancy on the system-level reliability. However, they only consider an analytic approach. Yen et al. [14] propose and study the trade-off of transmitting redundant packets with the low latency configuration in IEEE 802.15.4e to cope with packet loss effects. Shi et al. [12] propose to use scalar redundancy strategies in wireless mesh networks, which increases the fault tolerance capacity and can offer a reliable QoS guarantee. There are some similar publicly available data sets [11, 10, 8, 7], but they do not consider redundancy as their target quantity.

III. DATA SET

In this section, we describe our publicly available data set[1]. As argued in the introduction, it should help to practically analyze the effects of redundancy on reliability. Two measuring devices (each based on a custom-modified Raspberry Pi) are connected to the networks of two different major mobile network providers in Austria. The devices measure either the latency or the data rate on alternating days (where only the type of measurement changes on alternating days, the devices stay the same). For the data rate measurements, the devices constantly exchange data at full load over five TCP flows. More precisely, the measured data rate is the number of bytes transferred in a second by five repeated HTTP downloads from four different servers with sizes of $100\,\mathrm{MB}$ and $1000\,\mathrm{MB}$. The measured latency is the round-trip-time as measured by `ping` to a server in our lab. Additionally, we save the location as determined by GPS, timestamp, and mobile network parameters (such as signal strength). Both measurement devices are installed in the car that drives along a section of the Austrian A1 highway. The data from the devices is collected using the MINER infrastructure [2]. MINER is a programmable measurement infrastructure that integrates existing measurement tools and provides its users higher-level services to define measurement activities, schedule executions and retrieve their results.

In a subsequent preprocessing, the data are cleaned, for example by dropping measurements outside the selected area (see Figure 2). Table I provides an overview of the most important columns of the data. The data set contains measurements on 229 days consisting of 811 trips and 554 004 measurements between 2021-06-02 and 2022-12-23. Most of the trips were

[1] https://github.com/mherlich/redundant-wireless-data-set

daily commutes to and from work (that is, they contain mostly trips during morning and afternoon). The contracts used during the measurements are limited to $150\,\mathrm{Mbit\,s^{-1}}$. We have not immediately removed extreme or implausible values (for example, `alt` $-471\,\mathrm{m}$ and `ping` $0\,\mathrm{ms}$). However, such outliers could be discarded in subsequent evaluations. In particular, we preprocess the data set after creating it and we perform consistency checks before our evaluations.

One of our key concerns while creating the data set was to measure and control the quality of the data set. For this, we implemented certain consistency checks. These checks are implemented in pytest (https://pytest.org) and are tested daily. Thus, we get a notification if there are any problems with new data and can fix problems in the data collection as soon as possible. It turns out that in the beginning of our daily data checking, there occur many failures in the checks. This happens, because we choose most of the boundaries in the checks close to the actual limits that showed up in our data set. Since we build the checks on a limited amount of data, there can appear a variance in the boundary of the parameters if new data is added. These deviations in the checks decrease over time since we adapt the limits and get closer to the real boundaries of the measured values.

IV. Effect of redundancy on reliability

A possible use of redundancy is to increase the reliability of wireless communication, for which we consider two metrics: Packet loss (based on a latency bound) and outage probability (based on a data rate bound). For both metrics we compare how well redundancy is able to increase the performance of the wireless system both for a naive calculation (assuming independence) and the measured value (which includes dependencies). In theory, the correlation between the two channels affects the reliability of the overall transmission as follows: Let X_1 and X_2 denote the results of the two transmissions, where these random variables are equal to 1 if the transmission failed and 0 otherwise. The expectation value $\mathbb{E}[X_i]$ is then given by $1 - r_i$, where r_i is the reliability of the i-th channel. Since the random variable $X_1 X_2$ takes the value 1 if and only if the transmission over both channels fails, the expectation value $\mathbb{E}[X_1 X_2]$ is equal to $1 - r$ with r being the reliability of the redundant transmission scheme. The definition of the (Pearson) correlation coefficient

$$c = \frac{\mathbb{E}[X_1 X_2] - \mathbb{E}(X_1)\mathbb{E}(X_2)}{\sqrt{\mathbb{E}[X_1^2] - (\mathbb{E}[X_1])^2}\sqrt{\mathbb{E}[X_2^2] - (\mathbb{E}[X_2])^2}} \tag{1}$$

thus results in the equation

$$c = \frac{(1-r) - (1-r_1)(1-r_2)}{\sqrt{(1-r_1) - (1-r_1)^2}\sqrt{(1-r_2) - (1-r_2)^2}}. \tag{2}$$

Here, we have used that $X_i^2 = X_i$ since X_i only takes the values 0 and 1. Rearranging and simplifying then yields

$$r = r_1 + r_2 - r_1 r_2 - c\sqrt{r_1 r_2 (1-r_1)(1-r_2)}. \tag{3}$$

This equation shows how the correlation affects the reliability of the overall transmission. In particular, we see that the higher the correlation, the lower the reliability. In the rest of this section we describe how we empirically evaluate this theoretical result. Note that we consider this evaluation preliminary, because its analysis is based on a non-representative convenience data set (see Section V).

TABLE II

The probability that a packet does not arrive during $100\,\mathrm{ms}$ is reduced by using redundant transmission. Confidence intervals (CI) are estimates based on the Clopper-Pearson interval based on the Beta distribution or, in the case of independence, the product of the individual CI bounds.

System	Loss probability	Lower CI	Upper CI
Only network A	0.008 56	0.008 06	0.009 08
Only network B	0.025 62	0.024 76	0.026 51
Assuming independence	0.000 22	0.000 20	0.000 24
True combined value	0.000 77	0.000 62	0.000 94

TABLE III

The outage probability (for $1\,\mathrm{Mbit\,s^{-1}}$) is reduced by using redundant transmission. Confidence intervals (CI) are estimates based on the Clopper-Pearson interval based on the Beta distribution or, in the case of independence, the product of the individual CI bounds.

System	Outage probability	Lower CI	Upper CI
Only network A	0.010 86	0.010 31	0.011 43
Only network B	0.015 99	0.015 32	0.016 68
Assuming independence	0.000 17	0.000 16	0.000 19
True combined value	0.000 71	0.000 57	0.000 86

A. Packet loss

We define a packet as lost when the communication system loses a packet or the round-trip time is greater than $100\,\mathrm{ms}$. Table II shows the packet loss probability in our data set when using (1) only the network of provider A, (2) only the network of provider B, (3) a theoretical combination of both networks under the assumption of independence (i.e. the product of the individual loss probabilities) and (4) the loss probability that does not assume independence (the true combined value, i.e. a packet is considered as lost if it does not arrive over either channel in less than $100\,\mathrm{ms}$). The use of redundancy reduces the loss probability, but not as much as independent transmissions would. For our evaluation, we used the Clopper-Pearson confidence interval (also called the exact interval). This is an alternative for calculating binomial confidence intervals using normal approximation. The Clopper-Pearson interval is based on inverting the equal-tailed binomial tests using the relationship between the binomial distribution and the beta distribution.

B. Outage probability

We arbitrarily define an outage as a state in which the wireless system is not able to transmit $1\,\mathrm{Mbit}$ over $1\,\mathrm{s}$. Table III shows the equivalent to Table II for outage probability. As in the case for reliability based on latency, also based on data rate, the use of redundancy reduces the loss probability, but not as much as independent transmissions would.

V. Conclusion and Future Work

In this paper, we presented a data set on multi-provider redundancy in cellular networks measured in an automotive scenario. This data set is publicly available and should help to practically quantify the gain in reliability obtained by redundant packet transmissions. First findings from the data set are included in this paper. For an easier interpretability, we also deduced the theoretical model underlying redundant transmissions.

In the future, we plan to systematically expand the data set towards a uniformly distributed data set. Collecting data to create a data set depends on different external factors. These factors influence the data, and thus the data are biased. The data collected on a highway, such as the data set in this work, is affected by time and date, as well as the traffic on the highway and the weather. This means, that for example on workdays at rush hour there is more traffic on the highway. This traffic leads to lower speed, which results in more data points for this measurement. Another consequence of high traffic can be a lower data rate or a higher packet loss, as many devices are using the resources of one communication cell. Besides this influenced data, our data set is incomplete. This incompleteness results from relying on convenience sampling for our measurements, because the measurement takes place only when a driver uses the car. We therefore plan to carry out additional measurements with specific properties. Such additional measurements are in this case new measurement drives that should happen at a certain time and date and, if possible, at certain weather and traffic conditions. By dint of these measurements, we hope to reduce the bias of our data set.

After expanding our data set, we will use it to perform a more detailed and elaborate analysis of the influence of redundancy on reliability. For this analysis, we will use both statistical methods and machine learning methods.

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