# Modelling and Evaluation of Uplink and Downlink KPI Variations using Information Bottleneck and Non-parametric Hypothesis

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***Abstract*—The automotive industry framework is being slowly transformed from plain design of conventional vehicle cabin to modified windows with purpose to protect the passengers from infrared (IR) and ultraviolet (UV) radiation. The current design of vehicles is still focused on offering different levels of protections. Commonly, front side windshield offers better protection than rear door windows. Due to current design, the RF propagation is disturbed and thus the cellular communication is substantially affected. To address the aforementioned issue, we perform field measurements at 1800 MHz for timely-synchronized user equipments (UEs) located inside and outside of the conventional vehicle under test (VUT). The proposed measurement setup mimics the quasi-real usage of end users considering data applications. Therefore, in this paper we specifically analyse received and transmitted power of UEs in context of vehicular penetration loss (VPL) on nominal environments. We approach the problem of identifying nominal environments with information bottleneck algorithm. This algorithm enables the assessment of strong changes of statistics of metrics. Furthermore, we propose an approach as a combination of bootstrapping and non-parametric hypothesis, which allows to model deteriorations of the inside against outside of the vehicle UE.**

***Index Terms*—Vehicular penetration loss, benchmarking, information bottleneck algorithm, recursive hypothesis.**

## I. Introduction

The increased rate of active smart phones has drastically increased the demand on resources of cellular networks. Internet usage has become ubiquitous and packet service requirements have been smoothly transformed from a luxurious to a necessity value. Recently, the scenario of cellular users *under mobility* have gained attention from both communities, academia and industry, as an important application of the usage of cellular network services. In the past, this was not addressed at large scale because the achievable data rates were limited, while cellular operators to grow profit were mainly focused on providing qualitative services to high density areas with active users. Nowadays, mobile users continuously use smart machines to acquire different kinds of services such as emergency, navigation, management, billing, information, or infotainment services. To this end, one of the main goals of wireless providers is the realistic designing and effective modelling of wireless networks whith idea to provide acceptable services to end users. Therefore, to focus on such issues we name these particular scenarios as *vehicular use cases*.

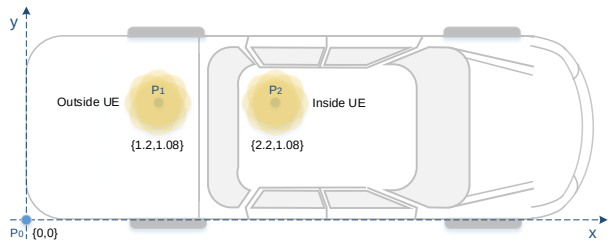


Fig. 1. The VUT with user positions (units are given in [m]) of UEs. Note, the OUE and IUE are located at $P_1$ and $P_2$, respectively, while $P_0$ is the origin.

On framework of energy saving, the automotive industry is working towards newly vehicles designed with metal coated windows. As a results, the solution contributes to the comfort of passengers by protecting them from infrared (IR) and ultraviolet (UV) radiation from the sun. In this context, vehicle windshields, usually made of laminated glass, are often more protective compared to vehicle door windows, which are widely made of tempered glass. In addition, fully or partly metallized structure of the vehicle cabin clearly disturbs RF propagation. Consequently, RF signals are blocked and thus the propagation and connectivity to cellular users are seriously impacted, due to potentially increased level of penetration loss. Intuitively, such an issue becomes more severe for larger transportation vehicles, e.g. trains, since effective surface of metallized structure is significantly higher. To maintain acceptable level of connectivity, it becomes very challenging at service areas with low RF reception, usually rural environments.

Vehicular use cases exhibit similar technical challenges for highways and railways. Particularly on long journeys, passengers in cars, buses or trains spend most of the time passing along gentle curved tracks, while being connected to similar cellular deployment characteristics. On the other hand, the windows of electric cars and current operational trains tend to be designed with metal-coated structure, which leads to similar vehicular penetration loss (VPL) characteristics. To address these issues, in [1] we empirically studied the penetration effect of overall train cabin with Siemens coating windows [2]. Compared to a study performed for cars in [3], it was shown that both types of vehicles are equivalent to each other as they act as *linear operators* in terms of quantiles

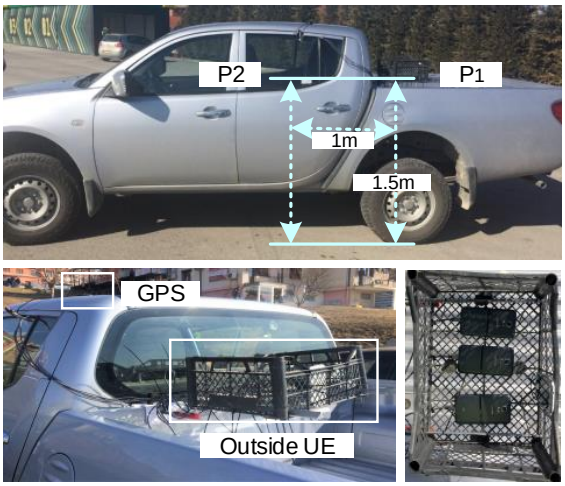


Fig. 2. Measurement setup with IUE ($P_2$) and OUE ($P_1$).

of inside- and outside of the vehicle UEs, and differ only in statistical shift. It was also found that, the modified train cabin showed variation of penetration loss in range 5—11 dB at 800 and 2600 MHz (see [1, Fig.6]), whereas the car cabin 1—5 dB at 1800 MHz (see [3, Fig.4]).

The difference of average received power of outside user equipment (OUE) and inside user equipment (IUE) can be interpreted as marginal link variation. This definition takes into account other propagation effects, such as reflections, shadowing, multipaths, etc. However, this quantity is expected to be comparable to low-multipath measurements. For vehicular use cases, it is common to span various nominal environments during the measurement campaign, which also mean different number of multipaths. Thus, our initial motivation is to deal with identification of nominal environments by using a theoretical framework. To this end, we are interested to find the strong changes of statistics of particular down- and uplink metrics (Section IV-A). This corresponds to modelling nominal environment partitions: urban, sub-urban and rural. We approach this problem with information bottleneck [4], which will be discussed in Section III. Further, based on partitions determined by information bottleneck we apply recursive hypothesis performed on non-parametric resamples, which are produced based on the observations of *one-shot* measurements. We provide the details of this approach in Section IV-B.

## II. Measurement Setup

### A. Placement of UEs and measurement track

One UE is installed outside of the vehicle as denoted by OUE whereas the other UE is located inside of the vehicle as denoted by IUE. The OUE is installed inside a plastic box to ensure it from falling as well as to keep it away from metallized chassis of vehicle. Both UEs are LTE capable smart phones with approximately same antenna height of 1.5 m and inter-distance of 1 m between them as illustrated in Figure 1. The measurement details are summarized in Table I.

The measurement campaign was performed along the route from Prishtina—Vërmica (see Figure 3), with approximately

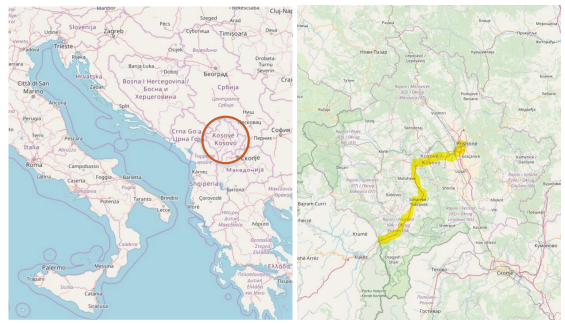

Fig. 3. The highlighted measurement track in Kosovo [5] along the highway "Ibrahim Rugova" (on right). On the left map is shown a part of southeastern Europe.

100 km length and has speed limitation of 120 km/h. It starts from university campus of Faculty of Electrical and Computer Engineering (FECE) in Prishtina (capital city of Kosovo) and then leads south-west along the newly constructed "Ibrahim Rugova" highway toward the Albanian border in Vërmica.

### B. Data outage scenario

We propose a measurement setup which assesses quality of service (QoS) and quality of experience (QoE) from the end user perspective under different RF conditions on-board of the conventional vehicle. The UEs are equipped with dedicated software and chip, and run simultaneously and repeatedly pre-configured scripts with the idea to benchmark among them. The pre-configured scripts perform sequential tasks such as browsing tests, file transferring and video-streaming. This configuration is based on data application but it still ensures to mimic the *quasi-real* usage of end users.

In this work, we focus on received and transmitted power, however other key performance indicators (KPIs) such as signal-to-interference-and-noise ratio (SINR) and physical throughput are analysed as well but the results are not shown here due to limited space. Nevertheless, among nominal environments, particular KPIs may vary quickly with time. For this reason, we initially want to group such variations by first identifying nominal environments. In this context, the marginal link variation is not constant, which stems from the fact that e.g., rural environments have lower number of multipaths.

## III. Identifying nominal environment partitions

Since our main interest to identify nominal environments is based on strong changes of statistics of metric under investigation $c$, we formulate this as problem of partitioning *original time* $t$ into $N$ intervals, while such partitions correspond to strong changes of statistics of $c$. Thus, our measurements data are represented as pair $o = (t_i, c_i)$, where $t_i$ is the time variable and $c_i$ is our metric under investigation or KPI, e.g., received power, transmitted power, SINR, or physical throughput. Importantly to mention, variable $t$ preserves the information of location $g$, provided that we consider mobility scenarios as vehicular use case.

We approach this with information bottleneck algorithm [4] which finds a quantization $\tilde{t}$ of the time variable $t$ which is

Tab. I. Measurement parameters.

| Parameter | Value |
|---|---|
| Location | Kosovo |
| Measurement track | Prishtina—Vërmica |
| Date | 22.02.2017 |
| Center frequency | 1800 MHz LTE |
| MIMO | 2x2 |
| Frequency band | 15, 20 MHz |
| Tx antenna height | 24, 30 m |
| Rx antenna height | 1.5 m |
| Vehicle model, type | Mitsubishi KAOT L200, pickup truck |
| Average speed | 63 km/h |
| UE type | Rohde and Schwarz Swiss QualiPoc Freerider [7] |
| Smart phone model | Samsung S5 |
| GPS antenna | NaviLOCK, Model No:NL-402U |

equivalent in finding quantization $\tilde{g}$ of the location variable $g$. The idea of this algorithm is to find such $\tilde{t}$ that minimizes the mutual information with the original time variable $I(t;\tilde{t})$ as well as maximizing the mutual information with metric under investigation (from now on called *relevance variable* to be in compliance with [4]) $c$, $I(c;\tilde{t})$.

First, we perform a fine-grained quantization with 1 s interval which produces a discrete time variable $\hat{t}$. The UEs provide granulation of 2 pps, which corresponds to the number of samples assigned to the relevance variable $c$. Now it is possible to find the joint probability mass function (pmf) $p(c,t)$ which further allows to calculate the empirical conditional pmf $p(c|t)$. As we are interested to find $\tilde{t}$ with $N$ intervals that minimizes the expected Kullback-Leibler divergence [6] between $p(c|\hat{t})$ and $p(c|\tilde{t})$

$$D\Big(p(c|\hat{t})||p(c|\tilde{t})\Big) = \sum_{\hat{t}_i} p(c|\hat{t}) \log \frac{p(c|\hat{t})}{p(c|\tilde{t})} \tag{1}$$

we specifically use the *agglomerative* information bottleneck [8]. Thus, two adjacent time intervals that have the most similar empirical pmfs $p(c|\hat{t}_i)$ and $p(c|\hat{t}_k)$ are merged together based on the smallest merging cost. To find the best possible merge, the reduction of information of relevance variable $c$,

$$\delta I(\hat{t}_i, \hat{t}_k) = I(\hat{T}_M; c) - I(\hat{T}_{M-1}; c) \tag{2}$$

should be evaluated based on

$$\delta I(\hat{t}_i, \hat{t}_k) = (p(\hat{t}_i) + p(\hat{t}_k)) JS\Big(p(c|\hat{t}_i), p(c|\hat{t}_k)\Big) \tag{3}$$

where $JS(x,y)$ is Jensen-Shannon divergence which is a generalized version of Kullback-Leibler divergence, $\hat{T}_M = \{\hat{t}_1, ..., \hat{t}_M\}$ is the $M$-partition of $\hat{t}$ and $M-1$ is the newly created partition.

On each iteration, the cost of merging the new adjacent time intervals is recalculated for $N$ intervals from $|\tilde{t}| = |\hat{t}_N|, |\hat{t}_{N-1}|, ..., 1$, where $|\cdot|$ is the order of the set. In this way, on each iteration, the number of intervals is reduced by 1, and then, one can pick the most fitting number of intervals.

### A. Measurement results and discussion

In Figure 4 we show the measurement results of reference signal received power (RSRP) [9, 10] and transmit power denoted with $P_{Tx}$ for OUE and IUE. Our discussion focuses on the following aspects: First, we investigate the partitions determined by information bottleneck. Second, we discuss the possible matches of such partitions between OUE and IUE.

Tab. II. The subsets $\mathcal{M}_N$ are partitioned based on agglomerative information bottleneck for $N = 4$. The values of parameters are given in 95% confidence intervals. The indexes in relevance variables $o$ and $i$ stand for *OUE* and *IUE*, respectively.

| Relevance variable | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_3$ | $\mathcal{M}_4$ |
|---|---|---|---|---|
| $r_i$ (dBm) | $[-82.3, -82.1]$ | $[-88.8, -87.9]$ | $[-112.8, -112.3]$ | $[-104.5, -103.7]$ |
| $r_o$ (dBm) | $[-80, -79.9]$ | $[-88.6, -87.7]$ | $[-110.7, -109.9]$ | $[-103.5, -102.6]$ |
| $P_{Tx,i}$ (dBm) | $[9.6, 10]$ | $[21.9, 22]$ | $[14.3, 15]$ | $[22.1, 22.2]$ |
| $P_{Tx,o}$ (dBm) | $[6.6, 7]$ | $[18.1, 18.6]$ | $[13.2, 14.1]$ | $[22, 22.1]$ |

We set $N = 4$ since we tend to group nominal environments that show similar statistics. Such $N$ is chosen for RSRP to correspond to urban, sub-urban, rural and sub-urban environments as denoted with $\mathcal{M} = \{\mathcal{M}_1, ..., \mathcal{M}_4\}$.

Figure 4a represents *OUE*, where the level of RSRP shows stable stationarity over time till it reaches the first first partition $\mathcal{M}_1 - \mathcal{M}_2$ (urban–sub-urban). Similarly occurs in Figure 4b, but with a difference of statistical shift (see Table II). Next follows $\mathcal{M}_2 - \mathcal{M}_3$ (sub-urban–rural), and so forth. As expected the level of marginal link variation is not constant among $\mathcal{M}_N$.

On the other hand, as expected the transmit power of *IUE* is higher than *OUE*. Interestingly, for $\mathcal{M}_4$ both UEs transmit at maximum power of 22 dBm. This stems from the fact that RSRP level is relatively low. Thus, in order to maintain the connectivity, UEs are imposed to reach the maximum transmit power.

## IV. Modelling and Evaluation

### A. Marginal link variation

Since the vehicle cabin is made of metallized and glass structures, in case of relative high distance between transmitter and receiver, the azimuth of arrival (AoA) dominates the statistics along a trace. Particularly under low-multipath environment, due to total higher effective surface of windows, they become the main contributor of RF penetration loss, whereas equivalently the impact of vehicle roof becomes lower. The variation of marginal link between IUE and OUE imposes difference in RSRP as determined in [3], which can be writen as in the following

$$\Delta\text{RSRP} = r_o - r_i. \tag{4}$$

where $r_o$ and $r_i$ are RSRP of OUE and IUE, respectively. This quantity is expected to be comparable to low-multipath measurements and can be denoted by $\Delta$VPL as defined in [11, 12]

$$\Delta\text{VPL} = 10 \log\left(\frac{P_o}{P_i}\right) = L_o - L_i \tag{5}$$

where $P_o$ and $P_i$ are the downlink measured power levels of outside and inside of the vehicle UEs, respectively. The variation $L_o - L_i$ can be interpreted as marginal link variation between differently located UEs. In this context, in [3] we found that the penetration loss changes from 2—4 dB when measured on *simultaneous serving cells*.

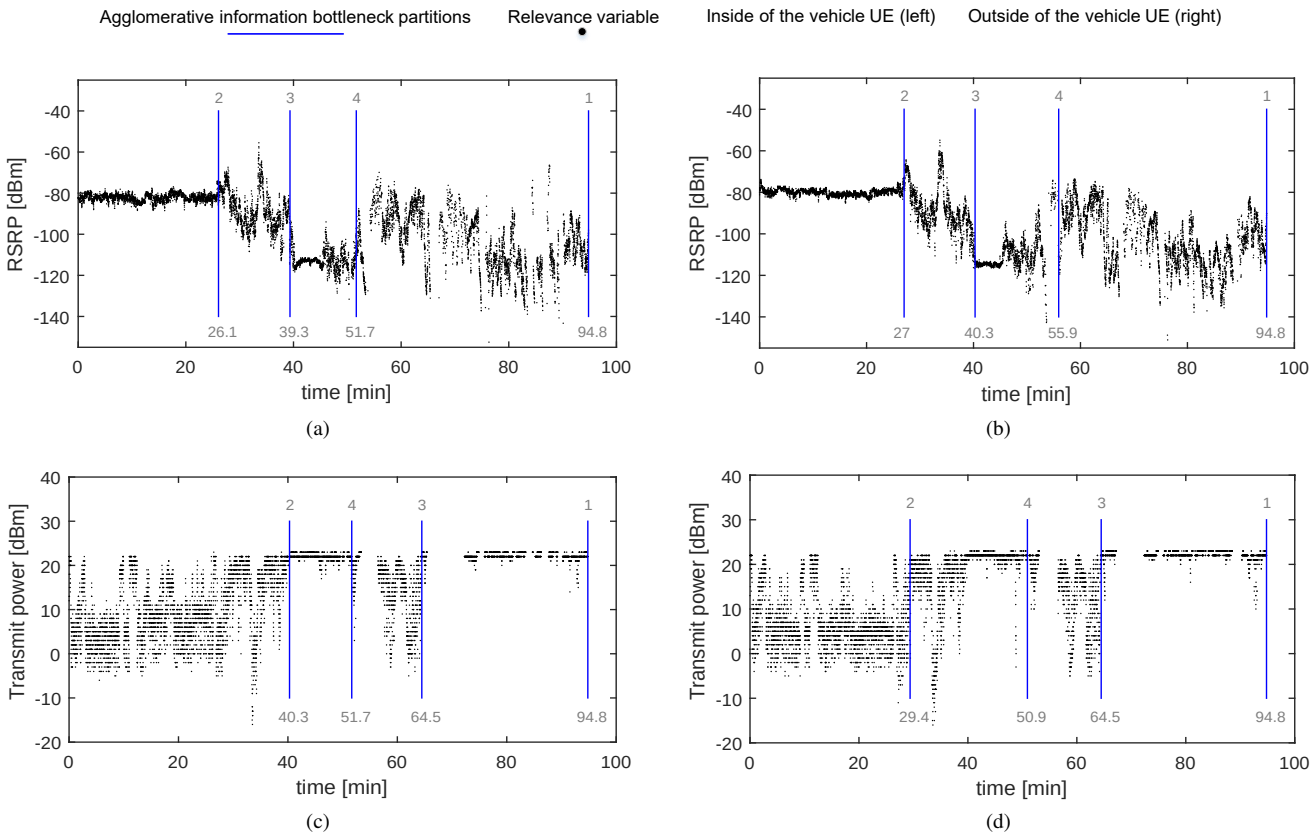


Fig. 4. The produced partitions of RSRP $[\mathrm{dBm}]$ and transmit power, $\mathrm{P}_{Tx}$ $[\mathrm{dBm}]$. (a) IUE. (b) OUE. (c) IUE. (d) OUE.

Similarly, the quantity $\Delta$VPL impacts other KPIs such as physical throughput, SINR, transmit power, and so forth. For instance, in [13] we addressed this issue and considered the effect of $\Delta$RSSI in throughput based on the measurements conducted on urban environment (city). Herein, we found a significant deterioration of $1.4\,\mathrm{Mbit/s}$ at IUE compared to OUE [13, Tab. II] based on 3—$4\,\mathrm{dB}$ on non-line of sight (NLOS) and line of sight (LOS) conditions, respectively.

Thereby, under quasi-isotropic assumption of the behaviour of the overall vehicle cabin, the quantity $\Delta$RSRP directly imposes a quantity $\Delta\mathrm{P}_{Tx}$, which can be defined as

$$\Delta\mathrm{P}_{Tx} = P_{Tx,i} - P_{Tx,o} \tag{6}$$

where $\mathrm{P}_{Tx,i}$ and $\mathrm{P}_{Tx,o}$ are the transmit power of IUE and OUE, respectively. In other words, a higher received power at OUE triggers UE to transmit at lower $\mathrm{P}_{Tx}$, while the opposite is expected to occur for IUE.

### B. Modelling of KPI variations

Let us denote with $X_i$ and $X_o$ the *original* sample distributions for inside and outside of the vehicle UEs, respectively. In order to avoid taking of new sample distributions, we estimate the population distribution based on the observed sample distribution (original sample). In other words, we utilize the observations gathered during only one campaign, as previously called one-shot measurements. Thus, we first resample the original respective samples, $X_i$ and $X_o$, based on replacement of original elements of sample in order to obtain $K$ number of bootstrap resamples which form respective *empirical bootstrap* distributions

$$\hat{X}_{i,1}, \hat{X}_{i,2}, ..., \hat{X}_{i,K} \tag{7a}$$

$$\hat{X}_{o,1}, \hat{X}_{o,2}, ..., \hat{X}_{o,K} \tag{7b}$$

Now, the non-parametric recursive hypothesis is established based on *Mann-Wilcoxon-Whitney* test [14]. Herein, the unpaired non-parametric tests of null $\mathrm{H}_{0,j}$ against alternative hypothesis $\mathrm{H}_{1,j}$ can be defined as below,

$$\begin{aligned} H_{0,j} &: F_{\hat{X}_{i,j}}(x) = F_{\hat{X}_{o,j}}(x), \\ H_{1,j} &: F_{\hat{X}_{i,j}}(x) \neq F_{\hat{X}_{o,j}}(x) \\ &\forall j = 1, 2, ..., K \end{aligned} \tag{8}$$

where $F_{\hat{X}_{i,j}}(x)$ and $F_{\hat{X}_{o,j}}(x)$ are empirical cumulative distribution functions (ECDFs) of inside and outside of the vehicle UEs, respectively. Then, the hypothesis imposes a refined model

$$F_{\hat{X}_{i,j}}(x) = F_{\hat{X}_{o,j}}(x - \Delta\mathrm{RSRP}) \tag{9}$$

under the assumption that the distributions differ only in statistical location shift. Thus, we test the null hypothesis for which $\Delta\mathrm{RSRP} = 0$ against the alternative $\Delta\mathrm{RSRP} \neq 0$ for two-sided test. Assuming $\Delta\mathrm{VPL} > 0$, the hypothesis is equivalent to testing the null hypothesis $\Delta\mathrm{RSRP} = 0$ against one-sided alternative $\Delta\mathrm{RSRP} > 0$. Similarly, we arrive at a refined model for the case of $\Delta\mathrm{P}_{Tx}$ under assumption that the distributions

Tab. III. Rejection rates for p-values with adjustment at $\alpha = 0.05$ and $K = 1000$.

| **Relevance variable** | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_3$ | $\mathcal{M}_4$ |
|---|---|---|---|---|
| RSRP (dBm) | 1 | 0 | 0.99 | 0.89 |
| $P_{Tx}$ (dBm) | 1 | 1 | 0.83 | 0.005 |

differ only in statistical location shift

$$F_{\tilde{X}_{o,j}}(x) = F_{\tilde{X}_{i,j}}(x - \Delta P_{Tx}) \tag{10}$$

where $\tilde{X}_{o,j}$ and $\tilde{X}_{i,j}$ are the corresponding samples of outside and inside of the vehicle UE.

Then, we need to compensate for inflation of type I error. In this manner, *original* statistical significance p-values are adjusted by controlling false discovery rate (FDR) through the usage of Benjamini-Hochberg procedure [15]. This procedure rejects the null hypotheses if (11) is strictly satisfied,

$$p_{(j)} \leq \frac{j\alpha}{K} \tag{11}$$

with $\alpha = 0.05$. For the sake of notation, we denote with $j$ the rank number which is derived by arranging in ascending order the original p-values, as defined in (8). Thus, the newly *arranged* statistical significance quantities are produced, denoted by $p_{(j)}$. The procedure is also applied in [16], while instead of empirical bootstrap we used nested models.

In Table III we summarize the rejection rates of adjusted $p_{(j)}$ with $K = 1000$ resamples. The rejection rates are given for all datasets $\mathcal{M} = \{\mathcal{M}_1, ..., \mathcal{M}_4\}$ that are determined by information bottleneck. The rejection rate of $\mathcal{M}_1$ fully supports the alternative hypothesis for both relevance variables. This indicates that statistical change in RSRP impacts $P_{Tx}$ similarly. Next, note that $\mathcal{M}_3$ of RSRP is equivalent to $\mathcal{M}_2$ of $P_{Tx}$ (see Table III and Figure 4). The rejection rate of dataset $\mathcal{M}_4$ at RSRP strongly suggests rejection of null hypothesis, whereas at $P_{Tx}$ strongly suggests failure to reject the null hypothesis. Independent from positions, this comes due to the fact that transmit power reaches the maximum output power. As a consequence, both UEs tend to preserve desirable quality of connectivity.

## V. Conclusion

In this paper we showed the necessity of identifying nominal environment partitions based on strong changes on statistics of KPIs. This problem was approached with information bottleneck algorithm. The KPIs were collected during one-shot measurement campaign performed along real cellular network 1800 MHz for vehicular use cases. Based on nominal environment partitions, we then established recursive hypothesis with purpose to model deteriorations of inside- against outside the vehicle cellular users. The modelling of deteriorations was approached by using a combination of recursive non-parametric hypothesis applied on bootstraped resamples. We found that downlink marginal link variations of up to 2.4 dB imposed uplink marginal variations of up to 3.8 dB, when power is used as KPI. In rural environments, due to poor RF reception, the transmitted power level attained upper bound at roughly 22 dBm.


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