RSRP Prediction on LTE Network Testbed Using a Software Defined Radio (SDR) Platform

Wilker de O. Feitosa, Ruan A. da Silva, Victor F. Monteiro and Fco. Rodrigo P. Cavalcanti

***Abstract*— As processing cost became more affordable, the telecommunications market started to replace one-purpose hardwares, e.g., modulators and amplifiers, by their software implementation version creating Software Defined Radio (SDR) systems. Some of the advantages of SDR systems are the low cost to develop new functionalities and the short time to market by quickly making new software available to be downloaded. In this context, the present work used an SDR platform to deploy a Long Term Evolution (LTE) network testbed and evaluate an algorithm to predict the signal quality of a link between an User Equipment (UE) and an Evolved Node B (eNB). A performance evaluation showed that low error of prediction can be achieved based on the choice of the algorithm parameters, which can be configured according to the environment conditions.**

***Keywords*— Software-defined radio (SDR), Channel prediction, Mobile Communications.**

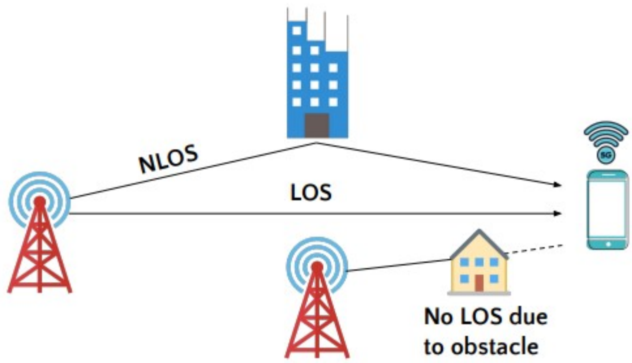


Fig. 1. Representation of LOS and NLOS components arriving at the receptor.

I. Introduction

The next generations of wireless cellular communications, the Fifth Generation (5G) and soon the Sixth Generation (6G), are coming to revolutionize the connectivity-based services with new features and capabilities. For example, 5G New Radio (NR) is expected to focus on the performance enhancement of at least three main use cases: Ultra-Reliable Low-Latency Communications (URLLC), Enhanced Mobile Broadband (eMBB) and Massive Machine-Type Communications (mMTC) [1]. Concerning 6G, topics like Artificial Intelligence (AI) and ultra-broadband services are already being studied [1].

In order to allow 5G and 6G to properly satisfy their demands, one envisioned solution is the use of higher frequencies: millimeter Waves (mmWaves) and Terahertz bands for 5G and 6G, respectively. In both cases, due to the propagation properties at these bands, the signals will have more difficulties to trespass obstacles [2].

As illustrated in Fig. 1, a signal between a transmitter and a receiver may have two types of components: LOS and NLOS. The LOS component has a direct path between transmitter and receiver and the NLOS component is formed by the sum of all paths that are reflected/refracted.

Due to the mobility of the User Equipments (UEs) and the high propagation loss of the 5G and 6G frequencies, the signal may have its LOS component blocked while the UEs try to communicate. Hence, it is important to monitor the signal that arrives on the receiver, in order to react as fast as possible to sudden changes that may harm the communication. Even better would be to be able to predict when signal quality of the serving Evolved Node B (eNB) is predicted to decrease, and then initiate in advance a handover procedure to connected to a better eNB.

Real wireless channels are space-time correlated. Taking advantage of this property, works from the literature [3] model a received signal as a Time Series (TS) and then try to forecast its behavior. The Prediction of TS has been the subject of studies for years with many approaches and techniques like statistical models [4] and Machine Learning (ML) based models [5]. However, many of the already proposed solutions were not tested in a real environment or even with real data, making uncertain how they perform in real-time networks.

To overcome this issue, real wireless networks can be emulated by Software Defined Radio (SDR) transceivers, which are programmable Radio Frequency (RF) frontend devices. There are many hardware platforms and softwares that can be assembled together as SDRs. One of them is the srsRAN[1], an open-source software enabling the deployment of a fully functional Fourth Generation (4G)/Long Term Evolution (LTE) wireless network testbed with open code and available metrics allowing analyses and audit.

In this context, the present paper aims at deploying a LTE network testbed with a SDR platform to evaluate the performance of a proposed signal predictor on real data. Different from other solutions from the literature, the proposed solution is a low complexity RSRP predictor that can be deployed in real wireless networks.

The paper is organized as follows. Section II presents the considered SDR testbed. Furthermore, Section III presents the

The authors are with the Wireless Telecommunications Research Group (GTEL), Federal University of Ceará (UFC), Fortaleza, Ceará, Brazil. Wilker de O. Feitosa and Ruan A. da Silva were supported by CNPQ.

[1]For more information: https://www.srsran.com/

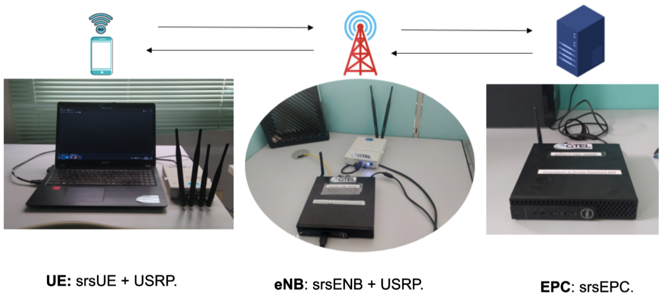


Fig. 2. Components of the deployed SDR network.

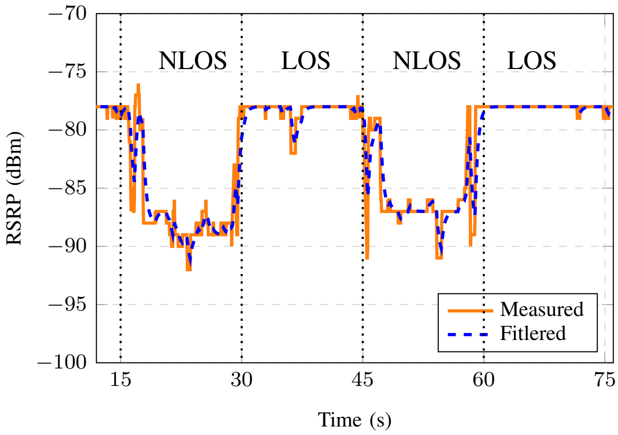


Fig. 3. Measured and filtered RSRP.

proposed predictor. Its performance is evaluated in Section IV. Finally, in Section V, the main conclusions of this work are summarized and future perspectives are presented.

II. System Model: SrsRAN

The srsRAN is an open-source 4G and 5G software radio suite built to be used with SDR devices for deployment, analysis, research and prototyping in real wireless networks. The srsRAN together with SDR transceivers create an open-source fully-functional LTE network testbed. One of the advantages of using this setup is that everything is open to be captured, analyzed and reprogrammed. Due to these caracteristics, the srsRAN suite has been used in a large range of research areas, from cross-technology interference detection [6] to cyber security testing [7] and even 5G broadcast testbeds [8].

Fig. 2 presents the setup adopted in the present work. There were three main components:

- **UE:** it consisted of an Universal Software Radio Peripheral (USRP) b210 (for the radio interface) and a notebook running the srsUE. The srsUE is the UE component of the srsRAN. It can be configured as either a LTE or a 5G-Non-Stand-Alone (NSA) UE. In our case we used the LTE configuration.
- **gNode B (gNB):** it consisted of an USRP b210 (for the radio interface) and a miniPC running the srsENB. The srsENB is the srsRAN implementation of an eNB, i.e., LTE-Base Station (BS). The srsRAN has also an implementation of a gNB, i.e., a NR-BS.
- **Evolved Packet Core (EPC):** it consisted of a miniPC with Internet connection running the srsEPC. The srsEPC is the srsRAN implementation of the EPC, i.e., the 4G-Core Network (CN).

The UE was wireless connected to the gNB by the RF interface, while the miniPCs running the srsENB and the srsEPC were connected via a network cable type CAT6.

Some of the LTE configured features in this setup were mobility management, paging procedure, UE authentication and Internet access through the srsEPC. Regarding the Radio Access Network (RAN), besides other functionalities, we set Medium Access Control (MAC) layer packet capture, command-line trace metrics, user plane encryption with the srsENB and Single Input Single Output (SISO) transmission mode, even though Multiple Input Multiple Output (MIMO) was also supported. Some of the noteworthy UE capabilities configured in the present work were Universal Subscriber Identity Module (USIM) authentication, MAC and Non-Access Stratum (NAS) layer packet capture, detailed log systems, real-time network metrics and SISO transmission mode, even though MIMO was also supported.

The Reference Signal Received Power (RSRP) values measured by the UE were used as data input by the TS predictor, where the RSRP is defined for LTE, in [9], as the linear average over the power contributions (in Watts) of the resource elements that carry cell-specific reference signals within the considered measurement frequency bandwidth. In the next section, the predictor, as well as, the data treatment will be presented.

III. Adopted Solution: Trend Prediction

Considering a real communication scenario with multiple LOS/NLOS transitions and the abrupt change in the RSRP value when the channel transits between LOS and NLOS states (as illustrated in Fig. 3), the present paper proposes a low complexity RSRP predictor that can be deployed in real wireless networks. For this, we have modeled the signal as a TS and proposed a predictor based on the RSRP trend.

In summary, the algorithm of the trend prediction (described in Alg. 1) tries to predict, at time t, the next S samples, i.e., samples y_t^{t+k} of $\mathbf{y}$ $\forall k \in \{1, 2, \cdots, S\}$, where $S \in \mathbb{N}$ and y_i^j is the value of the RSRP at instant j predicted at time i.

Algorithm 1 RSRP predictor

$\mathbf{x}_{\text{input}} \leftarrow [RSRP[t-w], \cdots, RSRP[t-1]]$
$x_{mean} \leftarrow mean\left(\mathbf{x}_{input}\right)$
$x_{std\_dev} \leftarrow std\_dev\left(\mathbf{x}_{input}\right)$
$x_{trend} \leftarrow trend\_lin\left(\mathbf{x}_{input}\right)$
if $x_{std\_dev} \neq 0$ **then**
  $\mathbf{x}_{scaled} \leftarrow \left(\mathbf{x}_{input} - x_{mean}\right)/x_{std\_dev}$
  $\mathbf{x}_{extrap} \leftarrow extrap\left(\mathbf{x}_{scaled}, x_{trend}, S\right)$
  $\mathbf{y} \leftarrow x_{std\_dev} . \mathbf{x}_{extrap} + x_{mean}$
else
  $\mathbf{y} \leftarrow \mathbf{x}_{input}$

For this, we first calculate the mean, the standard deviation and the trend of the vector $\mathbf{x}_{input}$ formed by the w most recent RSRP values measured previous to instant t (lines 1-4 of Alg. 1), where the linear trend represents the straight line passing through the two most recent samples in $\mathbf{x}_{input}$, i.e., RSRP$[t-2]$ and RSRP$[t-1]$. Then, the calculated mean value is subtracted from the samples of $\mathbf{x}_{input}$, and we divide the result by the standard deviation, resulting in vector $\mathbf{x}_{scaled}$ (line 6 of Alg. 1). After, $\mathbf{x}_{scaled}$ is extrapolated to S instants ahead based on the calculated trend (line 7 of Alg. 1). Finally, the inverse process is done, i.e., $\mathbf{x}_{extrap}$ is multiplied by the standard deviation and added the mean of $\mathbf{x}_{input}$ (line 8 of Alg. 1).

Two of the main characteristics of this predictor are its low complexity and its statistical assumption. Due to its low computational cost, it is possible to deploy it in real-time wireless networks. However, since its predictions are based on the assumption that the next values of the TS will follow the trend of previous samples and therefore have similar statistical properties, this algorithm should not be used to predict values far in the future, it must take into account the channel coherence time.

In order to improve the performance of the predictor, the use of techniques related to data enhancement [10] and statistical treatment of TSs were used. In terms of data enhancement, it was used the LTE standard L3 filtering model [11], defined as:

$$F_n = (1-a).F_{n-1} + a.M_n, \quad (1)$$

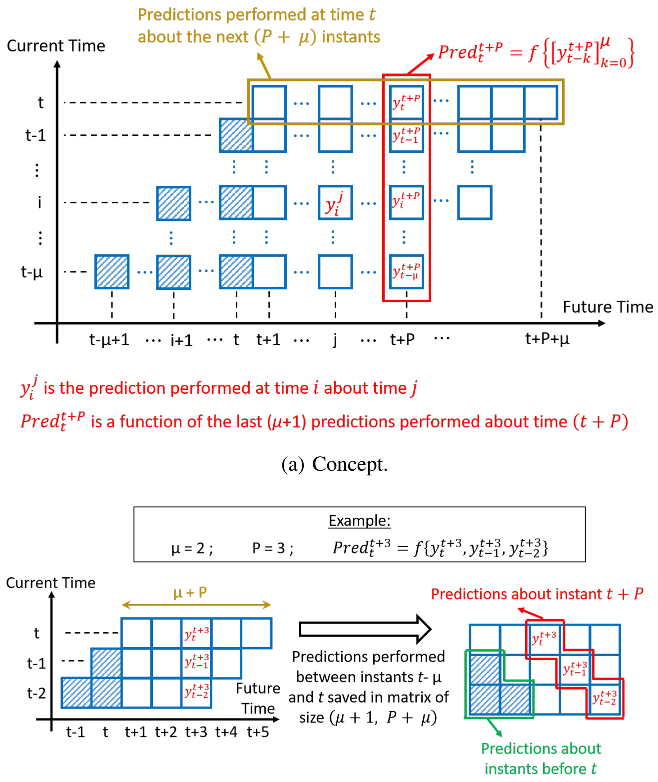
where M_n is the measurement performed at instant n, F_n is the updated filtered measurement, F_{n-1} is the previous filtered measurement, $a = (1/2)^{k/4}$ and k is the filter coefficient. Fig. 3 illustrates a measured RSRP curve and its corresponding filtered curve obtained with Eq. (1).

To a more statistical approach, the result of our prediction was not only based on the most recent predicted value. Actually, it was a function of consecutive predicted values, as illustrated in Fig. 4a. More specifically, in a given time t (vetical axis of Fig. 4a), we predicted the RSRP for the next $S = (P+\mu)$ instants of time, i.e., y_t^{t+k}, $\forall$ k in $\{1, 2, \cdots, P+\mu\}$ (predictions in Fig. 4a inside the yellow rectangular). Then, at instant t, instead of directly considering the predicted value of the RSRP for instant $t+P$, i.e., y_t^{t+P}, we considered a function of the predicted values in the μ previous instants of time, i.e.,

$$Pred_t^{t+P} = f\left\{\left[y_{t-k}^{t+P}\right]_{k=0}^{\mu}\right\}, \quad (2)$$

predictions in Fig. 4a inside the red rectangular. Fig. 4b presents ans example considering μ and P equal to 2 and 3, respectively.

We have tested different possibilities for the function f, e.g., simple mean, mean with linear weights and mean with exponential weights. Since as long as the time passes more decorrelated the samples are, we have selected f as a weighted averaged of $\left[y_{t-k}^{t+P}\right]_{k=0}^{\mu}$, where the weights followed an exponential distribution with the most recent predictions having the highest weights.



(a) Concept.

(b) Example.

Fig. 4. Temporal weighted function.

Next section presents a performance evaluation taking into account the concepts presented until now.

IV. Performance Evaluation

Before presenting the experiment results, we present how it was performed.

A. Experiment Setup

The experiment was performed in an office with similar characteristics to the typical office indoor scenario described in [12]. The srsRAN platform presented in Section II was used. We performed 100 realizations of the experiment with duration of 75 s each.

In each realization, UE and eNB were placed in front of each other. After the first 15 s of the experiment, a metallic surface was slowly placed between them, staying there for a while blocking the LOS component between the UE and the eNB. This part took another 15 s. Then, after 30 s of the start of the experiment the metallic surface was removed, unblocking the LOS component between the UE and the eNB. This process was repeated for another 30 s, i.e., 15 s with unblocked LOS and 15 s with blocked LOS. Finally, during the final 15 s of the experiment, the LOS was left unblocked. Table I presents other information about the experiment setup.

RSRP measurements were performed at each 50 ms. They were filtered using the L3 filter, i.e., Eq. (1), with $k = 13$. The RSRP measurements were used as input of the predictor described in Section III. More precisely, for each time instant

TABLE I

NETWORK PARAMETERS.

Parameter	**Value**
Mini-PCs model	DELL OptiPLex 3070
SDR device	NI USRP-2901
Antenna model	VERT2450
Carrier Frequency	2.4 GHz
Measurement Sampling Time	50 ms
eNB number of PRB	50
Transmission Mode (TM)	Single antenna
UE LTE 3GPP release alignment	10 with features up to release 15

t, the previous w samples of measured RSRP were used by Alg. 1 to predict y_t^{t+k} $\forall k \in \mathbb{N}$ subject to $1 \leq k \leq (P + \mu)$. Finally, Eq. (2) was used to estimate the value of $Pred_t^{t+P}$.

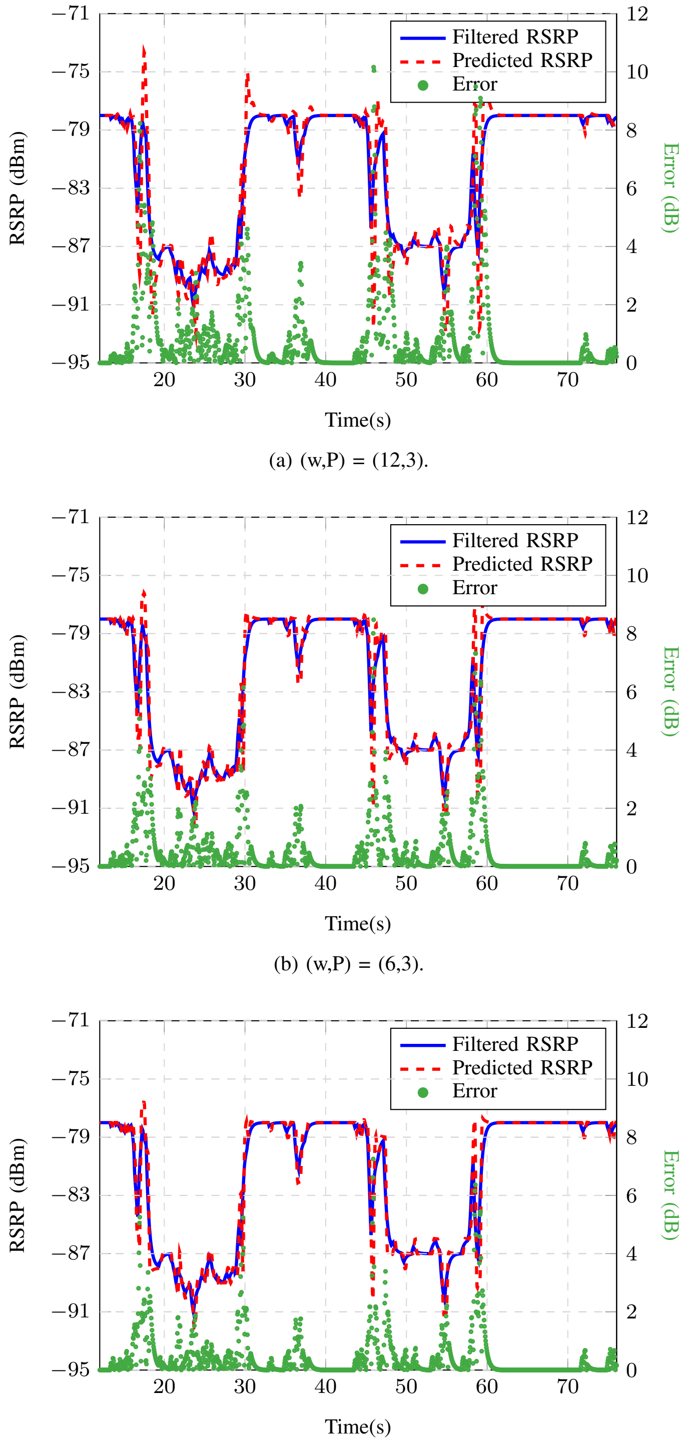
Regarding the predictor, due to its low complexity and fast execution, for each realization of the experiment, it was possible to make a grid search on the parameters w and P to understand how the error is impacted by the value these parameters. However, we only tested values satisfying $P \leq w$, i.e., we considered that the number of samples being predicted should be lower or equal to the number of samples being used as input.

B. Experiment Results

In order to firstly get insights about the behavior of the error in the predictions, we randomly selected one of the realizations to analyze. Fig. 5 shows the result of this selected realization. It presents the filtered RSRP (blue solid curves), the predicted RSRP (red dashed curves) and the error of prediction (green dots), where the error of prediction was the absolute value of the difference between the predicted and the filtered RSRP. The x-axis of the three subfigures in Fig. 5 is the time, the y-axis on the left side is the value of filtered and predicted RSRP and the y-axis on the right side is the value of the error. The difference between these three subfigures is the value of (w, P) that was used by the predictor. Specifically, Fig. 5a, Fig. 5b and Fig. 5c considered (w, P) equal to $(12, 3)$, $(6, 3)$ and $(6, 2)$, respectively. Remind that the RSRP was measured at each 50 ms, thus the configuration (w, P) means taking a window of $(w*50)ms$ as input and predicting the RSRP value in the next $(P*50)ms$. For examples, $(w, P) = (6, 3)$ means an input of 300 ms and an output of 150 ms.

First of all, notice in these three figures that the error is impacted by the presence or not of the LOS component. More specifically, in the presence of the LOS component, the RSRP is almost constant, thus the error of prediction is very low, since the samples being predicted are very correlated with previous samples being used by the predictor. On the other hand, in the transition from LOS to NLOS and vice-versa, the correlation between future and previous samples is low, thus the error of prediction achives its maximum value. Finally, in the absence of LOS component, the RSRP is very noisy, which makes the error also noisy.

Fig. 5a, Fig. 5b and Fig. 5c had 50, 23 and 16, respectively, measures of error with value higher than 3 dB. As expected, we can conclude that reducing either the number of instants



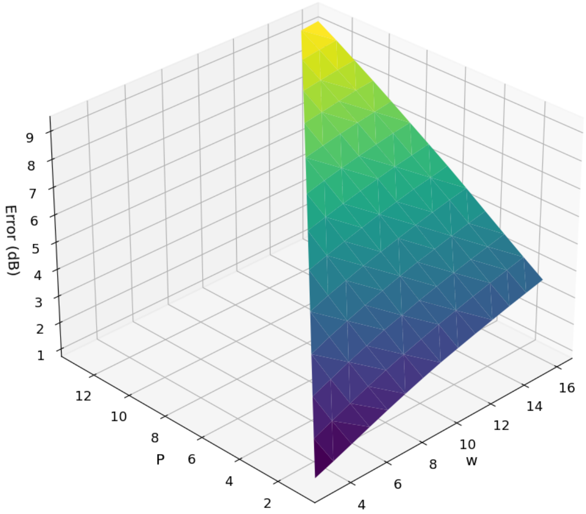
(a) (w,P) = (12,3).

(b) (w,P) = (6,3).

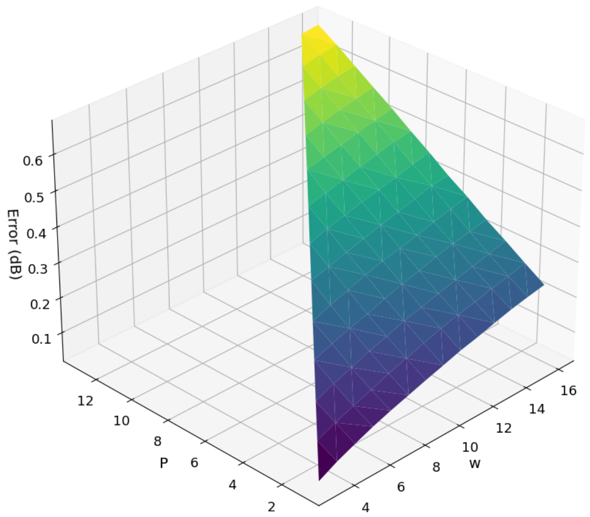
(c) (w,P) = (6,2).

Fig. 5. Error of RSRP prediction for different values of (w, p) in a given realization.

ahead that we want to predict, i.e., reduncing the value of P, or the number of previous measurements that we take into account to perform predictions, i.e., reducing the value of w, can reduce the error of predictions. This is explained by the fact that the considered predictor assumes statistical correlation between input and output samples. However, since the channel coherence time reduces during the transition from one state to another, the error of prediction increases when either trying to prediction a value far in the future or taking into account as input old samples.



(a) $95-ile$ surface.



(b) $50-ile$ surface.

Fig. 6. CDF percentiles of error of prediction for different values of (w, P).

To validate the conclusions drawn in the analysis from one random realization, for each considered pair of values (w, P), we evaluated the Cumulative Distribution Function (CDF) of the error of prediction considering the 100 realizations. Fig. 6a and Fig. 6b present surfaces of the $95-ile$ and $50-ile$, respectively, of these CDFs. For example, a given point (w, P, e) in Fig. 6a means that, when the predictor was configured with (w, P), the error of prediction was not higher than e in 95% of the samples.

As expected, increasing the value of w and P increases the error of prediction. Moreover, the value of P, i.e., how far in the future we want to perform predictions, seems to impact more the error than the value of w, i.e., how many previous samples are taking as input by the predictor. Finally, an important conclusion is that with suitable choices of (w, P) one can get low value of error.

V. Conclusion and Future Perspectives

In this work, we have used a SDR platform to deploy a LTE network and to test RSRP prediction on real data. A low complexity predictor was proposed and evaluated. Based on the results, we concluded that the environment characteristics , e.g., presence or not of LOS, and the choice of the predictor's parameters impact the error of prediction. Then, as a continuation of this work, we will implement an adaptive version of the proposed predictor in which the parameters can dynamically change based on the current value of error, e.g., if the error is higher than a given threshold the algorithm will reduce the number of previous samples taken as input of the predictor, i.e., the value of w, or reduce how far in the future predictions are performed, i.e., reduce the value of P. Similarly, if the error is below a given threshold, the values of P and w can be increased.

Another perspective of this work is to include another eNBs in the setup and to use the output of the predictor to perform mobility management re-configuring the LTE network when needed. For example, when the signal quality of the serving eNB is predicted to decrease, a handover procedure can be initiated to connected the UE to a better eNB.

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