Fine Tuning an AI-based Indoor Radio Propagation Model with Crowd-sourced Data

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***Abstract*—Recent years have known the development of radio propagation models (RPM) and specially the AI-based ones. These models are interesting for many applications such as radio planing and design, fingerprinting-based localization, radio resources management etc. However most of the proposed AI-based RPMs have been trained on simulated radio data making them not ready or reliable for real condition applications. In this work we tackle the problem of learning and fine-tuning an AI-based RPM from simulated data to real world radio measurements. We raise the inherent problems and limitations and then propose solutions to overcome them. The study has been focused on 5 GHz Wi-Fi and Home network environment.**

***Index Terms*—Wi-Fi, indoor propagation, measurements, AI.**

I. Introduction

The prediction of radio maps using AI-based models has undergone significant developments. AI-based RPMs provide reduced computing time and simplicity of usage : for indoor only a simple floor plan image is required without any need of tedious vectorization. Several models have been already proposed in the literature, some for indoor and others for outdoor [1][2][3][4]. However, almost all these AI-based models have been trained on simulated radio data. The RPMs used to generate such data are mainly ray tracing models. Little attention has been devoted to the use of real world data to train AI-based models, due to the high cost in terms of time, effort and expertise involved in collecting and processing such data. Reference [5] proposes to calibrate the model parameters on real world data for each new environment, using few points to generate the entire radio map. In order to predict realistic radio maps, we have identified 3 strategies.

Strategy 1: Train an AI-based RPM from scratch on huge and reliable radio measurements in different environments. Measurements are made by radio experts in order to obtain reliable data [6] and tailor-made for the radio map prediction task. However, such a process takes an enormous amount of time and effort. It requires not only radio experts, but also dedicated measurement equipment and access to a large sample of environments.

Strategy 2: Fine tune locally an AI-based RPM already trained on simulation data with new data collected on the environment under study [5]. This approach can be applied in 2 ways : train a model with few measurement points to tune part or all its parameters or just center the prediction of the model assuming you know the shift between real and simulated data. This approach is less costly in the short term, but can be limited in term of performance. It requires tuning, and therefore measurement operations for each new environment.

Strategy 3: Fine-tune an AI-based RPM trained on simulated data with crowd-sourced data. In other words, this strategy is based on transfer learning [7]. The purpose is to use knowledge from a related domain (called the source domain) to improve learning performance or reduce the number of samples required in the target domain. We assume that there is a relation between a simulated and a measured radio map. As it is easier to generate simulated radio map than to collect real world radio data, transferring the knowledge learned from simulated data can help reducing the number of real world radio samples to train RPMs. Moreover, using crowd-sourced data spares us the need for measurement campaigns made by experts while ensuring easy access to a diversity of environments. It does, however, present some disadvantages such as the reliability of the collected data and calibration issues due to the diversity of devices used for data collection. In this work, we have experimented with the third approach. Our contributions are as follows:

- Firstly, we expose our measurement campaign dedicated to 5 GHz Wi-Fi in Home environments, based on crowd-sourced radio data collected by several smartphones.
- Then we propose a method for processing and calibrating the collected RSSI data.
- In a previous work [8] we had detailed a new AI-based indoor RPM based on Generative Adversarial Networks (GANs) trained only on simulated data. We propose to tune it by transfer learning on the collected data and compare its accuracy to the initial version not fine tuned.

The remainder of the paper is organized as follows. The radio propagation measurements are described in Section II. The data processing and analysis are detailed in Section III. Our AI-based radio propagation model, its training, its fine tuning and the results analysis are presented in Section IV. Finally, conclusions are drawn in Section V.

II. Propagation measurements

This section focuses on the different data acquisition processes. The first part concerns crowd-sourced data and the second part concerns data for calibration as the collected crowd-sourced data originate from different types of smartphones whose RSSI scales are not necessarily aligned.

A. Crowd-sourced data

Our goal is to collect a large amount of Wi-Fi RSSI data (corresponding to the received Wi-Fi beacon frames) using smartphones with meta data about the context such as floor plan image, physical dimensions, the types of building materials, the type of Wi-Fi gateway and the type of smartphone used. For this purpose, we have organized a FUT (Friendly User Test). We had around 50 volunteers in different French towns. We focused the experiment on large apartments or houses in order to consider the worst cases of Wi-Fi coverage. In all the further analysis transmitter and receiver are always on the same floor. To simplify the data analysis and further calibrations, we selected 3 types of smartphones which were the most common among the testing panel: Samsung S10, S21 and A32. The Wi-Fi measurements have been performed with the Netspot App for android with a 1 m resolution mesh grid after a scaling step of the floor plan. From this grid, physical dimensions in meters can easily be deduced. Below we detail some statistics on the collected data set.

TABLE I
Statistics

	Values
Number of data points	5409
Number of floor plans	58
Number of APs types	5
Number of different building materials	8
Smartphones	S10, A32, S21
Surface	[$65m^2$, $150m^2$]

B. Data for Calibration

1) Measurement environment: Many studies like [9] highlighted the fact that the Wi-Fi RSSI reported by smartphones may present strong deviations between vendors at the same measurement place, up to around 20 dB. RSSI reported depends highly on the device Wi-Fi chipset. Therefore calibration is needed to be closer to true RSSI values, or at least to be able to compare them to a common and reliable reference like an omnidirectional receiving dipole antenna. For this purpose, calibration measurements have been done in a dedicated apartment at Orange Labs Belfort (Fig. 1). The size of the environment is 10.4 x 11.7 x 2.6 m^3. There are different types of building materials and thicknesses (14 to 60 cm). The environment contains several pieces of wooden furniture.

2) Measurement system setup: All the elements of the measurement system are shown in Fig 2. The measurement system is composed of 3 Samsung smartphones (S10, S21, A32) on a rotating plate and 1 dipole antenna[1] as receivers.

[1]https://www.mouser.fr/pdfDocs/linx-ant-w63ws2-ccc-ds1.pdf

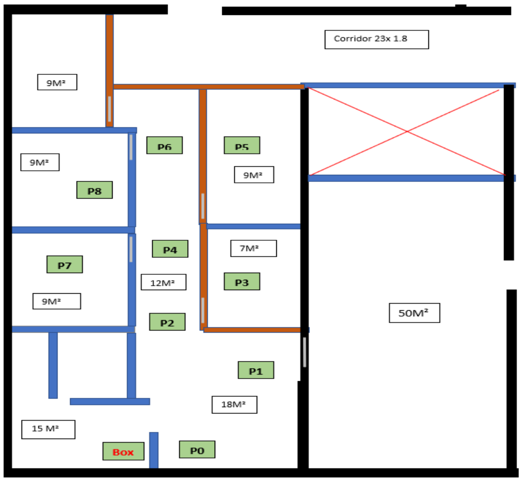

Fig. 1. Measurement apartment in Orange Labs Belfort.

The laptop is connected to the spectrum analyzer to control it and collect the RSSI measurements from the dipole antenna. In term of transmitter, we selected 3 recent models of Orange Wi-Fi gateways for high speed Home Internet, the same as encountered during the FUT. We also developed an android application which allows us to automate measurements and capture RSSI of different Wi-Fi access points. The developed android application is responsible of capturing RSSI measurements at a given sampling rate (typically each 5 s) and storing them in file which is later used for calibration.

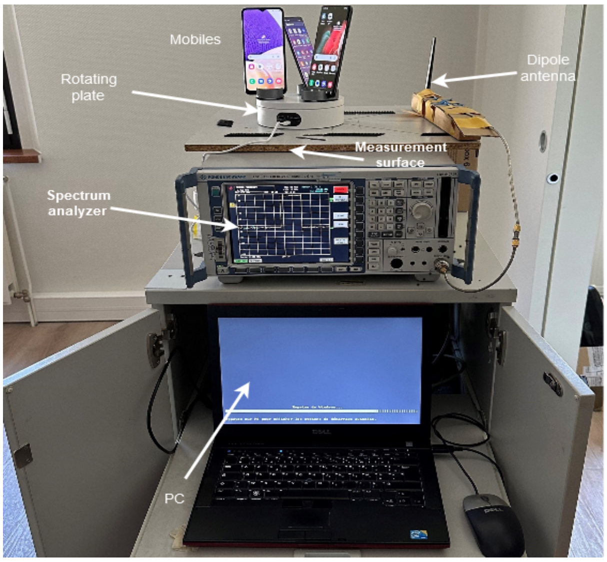

Fig. 2. Measurement setup.

3) Measurement procedure: The RSSI captures have been done on 9 points P_n n=0.. 9, spread across the apartment. For each point, we made measurements for 4 different azimuths of the transmitter (0°, 90°, 180°, 270°).
For the smartphones the measurements have been carried out as follows. For each point P_n and orientation of the transmitter, we made at least 6 min 30 s of captures with a 5 s sampling

rate and the smartphones in continuous rotation (360° in 45 s). This allows us getting the distribution of RSSI according to transmitter and smartphone orientation. Our goal here is to attenuate the effect of smartphones and gateways antenna radiation pattern as we don't have any control on it and any information on their orientation for the crowd-sourced data. By this way we remove also fast fading effects.

For the dipole antenna, the measurements have been carried out on a square wooden plate of size 46.5cmx46.5cm displayed in Fig 3, as if the receiving antenna was on a wooden table. For each points P_n and transmitter orientation, we made 50 acquisitions during around 10 s on the 5 different locations A, B, C, D and E displayed in Fig 3. Note that, the circle around E denotes the location of the rotating plate for the smartphones. The retained RSSI value is the median of each collected series across the A, B, C, D locations and the 4 transmitter azimuths. In term of duration, each point P_n took around 1 hour 20 min of measurement. The measurement process is repeated with the 3 different recent models of Orange Wi-Fi gateways and also Wi-Fi extenders.

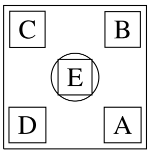

Fig. 3. Dipole antenna measurement surface

III. Data processing and analysis

In this section, we present, and analyze the FUT data and the measurement data from our apartment. We highlight the need to process the data and then detail the methods used for this and particularly for RSSI calibration.

A. *Crowd-sourced data processing*

In Fig. 4 are depicted the raw RSSI measurements from the crowd-sourced data according to the log10 of the distance in meter between transmitter and receiver and the type of smartphone used to collect the data. As studied in [9], we can observe an offset according to the type of smartphone. Fig. 5 shows a filtered version of the crowd-sourced data according to the following processing. Looking at the data, in particular the RSSI, we noticed for each site some outliers generally located near the gateway (d $<$ 1m) or when the signal is lower than -90 dBm. This may be due to a saturation of the RSSI measurement scale. From this observation, we removed all the measurements points at less than 1 meter from the transmitter and those whose RSSI is less than -90 dBm. Then, we did a linear regression of RSSI on the log10 of distance and removed all the measurements out of the confidence interval of 95%. Fig. 6 and 7 shows respectively the calibrated measurements with the S10 and dipole antenna as reference. We observed also that the S21 RSSI presents some high offsets. In fact we have some 20 dB random jumps at a same location measurement in static conditions and so we decided to discard S21 data from the further analysis. Calibration constants corresponding to the RSSI offsets were then deduced from the regression lines for each smartphone. The constant for aligning the A32 to the S10 is -5.302 dB .

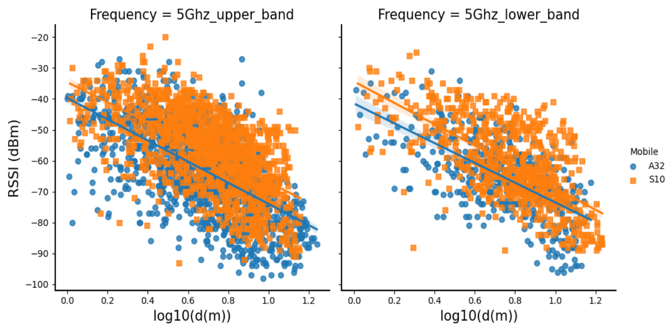

Fig. 4. RSSI distribution according to the distance and type of mobile before processing

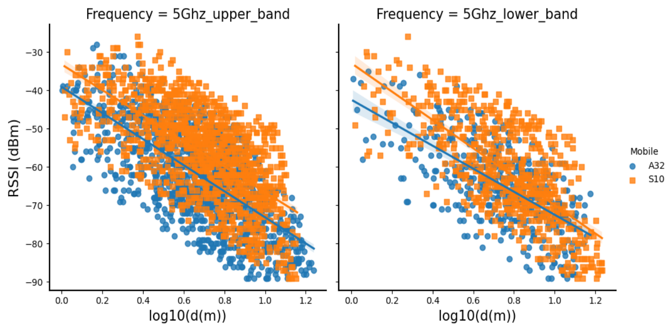

Fig. 5. RSSI distribution according to the distance and type of mobile after filtering

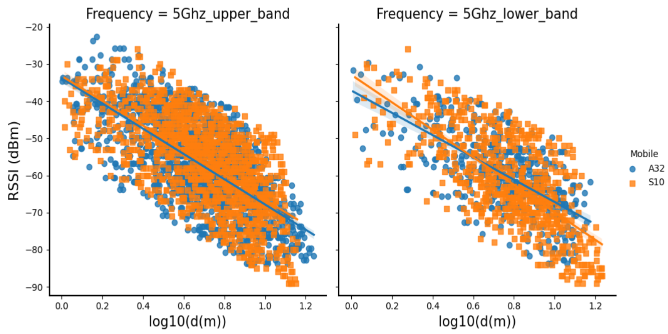

Fig. 6. RSSI distribution according to the distance and type of mobile after filtering and relative calibration on the S10 mobile

B. *RSSI calibration*

Crowd-sourced data allowed making a relative alignment of the distribution coming from the different smartphones on the distribution of a given one. However this is not enough as we can't say which one is close to the ground truth RSSI. For this reason and as described above, we made a measurements campaign with a dipole antenna as reference for the ground

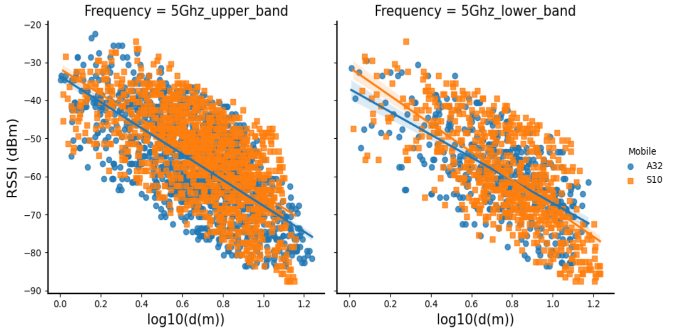

Fig. 7. RSSI distribution according to the distance and type of mobile after filtering and calibration on the dipole antenna

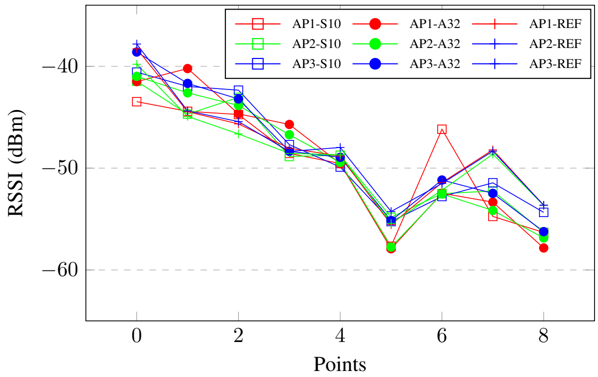

Fig. 9. Data points according to the type of receiver after calibration

truth RSSI. Fig. 8 and 9 shows respectively the average RSSI for the points P_n without and with calibration. Similar trends can clearly be observed, however, with an offset before calibration. The large amount of data from our measurements has enabled us not only to observe the temporal variation of the signal, the behavior of the different mobiles, Wi-Fi gateway, but also to quantify the standard deviations of the measurements at each points over the different orientations of the transmitter and receiver. For example, we observed a standard deviation of 3.14 dB. This value was obtained by averaging the standard deviation of the series of measurements over the nine points. Tab II shows the calibration constants drawn from the measurement campaign.

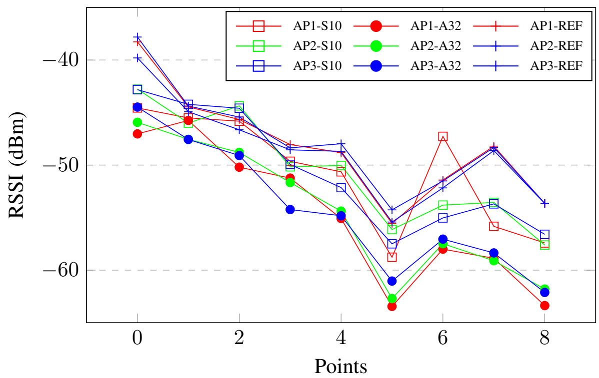

Fig. 8. Data points according to the type of receiver before calibration

TABLE II
CALIBRATION CONSTANT ACCORDING TO THE TYPE OF MOBILE AND ACCESS POINTS

	Mobiles	
Access points	S10	A32
AP1	-1.0 dB	-5.5 dB
AP2	-1.3 dB	-4.9 dB
AP3	-2.2 dB	-5.8 dB
Mean	**-1.5 dB**	**-5.4 dB**

IV. MODELING AND RESULTS

In this section, first we introduce our AI-based RPM and the fine tuning process, then we present and analyze the tuning results.

A. Modeling

In our last works [8], we proposed a cGAN-based indoor radio propagation model called E-IRGAN (Enhanced-Indoor Radio GAN) trained indoors for the 2.4 GHz frequency. Our model has been trained on simulated data based on WinProp models. For the purpose of the actual works, we re-trained our model from scratch on new simulated data for the 5 GHz frequency band. Fig. 10 displays one prediction of the model compared to the ground truth radio map. The model is designed to handle different types of indoor home environments with different building materials (concrete, brick, plasterboard, wood). In order to fine tune our pre-trained radio

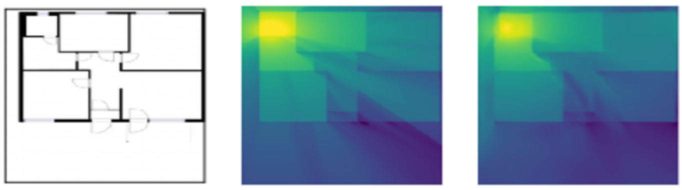

Fig. 10. Prediction from E-IRGAN trained on simulated data. From left to right : Floor plan, Ground truth, Prediction.

map generator G, we split the data set composed of 58 input-output pairs into train and test set. The training set contains 50 samples and the remainder is used for test. We used Adam Optimizer [10] for the learning process. We have noticed that when no layer is frozen, due to the size of the model (39 million parameters) and the amount of data available for fine tuning, the model over-fits, memorizing the training set without being better on test set. After some tests, we decided to set only the 6 last layers as trainable for the fine tuning. The learning rate is set to 10^{-4} and decreases progressively to 10^{-14}. We fixed the number of epochs to 80.
The generator G loss function is the L1 loss given by:

$$L_1 = \mathbb{E}_{x,y\ p_{data}(x,y)}\{||y - G(x)||_1\}. \tag{1}$$

The model implementation is based on TensorFlow [11]. The training of the model is realized on HP Z8 workstation with 2 NVIDIA Quadro P5000 GPUs.

B. Results

Table III shows the performance of our proposed RPM according to the training and testing data set. Firstly we quantify the accuracy of the model trained on simulated data with respect to real world data. Then we explore how to enhance it by using real data for fine tuning and study the importance of data filtering and calibration. The letters F, C means respectively filtering, calibration. Thus "Real w/o FC" means real world data without filtering and without calibration. The first part of Table III exposes the performance of our

TABLE III
E-IRGAN PERFORMANCE ACCORDING TO TRAINING AND TESTING DATASET

Training data	Testing Data	MEAN	STD	RMSE
Simulated	Simulated	-0.9 dB	5.5 dB	6.3 dB
Simulated	Real w/o FC	-16.9 dB	10.2 dB	20.2 dB
Simulated	Real w F	-16.3 dB	8.8 dB	18.9 dB
Simulated	Real w FC	-12.8 dB	8.8 dB	16.1 dB
Real w/o FC	Real w/o FC	-0.8 dB	9.0 dB	10.1 dB
Real w/o FC	Real w F	-0.4 dB	7.8 dB	8.7 dB
Real w/o FC	Real w FC	3.0 dB	7.8 dB	9.1 dB
Real w F	Real w F	-0.9 dB	7.6 dB	8.9 dB
Real w F	Real w FC	2.5 dB	7.6 dB	9.1 dB
Real w FC	Real w FC	-1.1 dB	**7.5 dB**	**8.6 dB**

model trained with simulated data on real data. From a simple observation, we can see that there is a large offset between predicted RSSI and measurements. By assuming, we know its value from sample of measurements, we can mitigate this just by adding a constant to center the model. This can help reducing errors but is not enough. For instance, doing this in our case reduced errors to a minimum of 10.2 dB in term of RMSE and 8.2 dB in term of standard deviation error. Note that the log distance model standard deviation deduced from the same filtered measurements (Fig. 7) is 12.5 dB. As expected, an AI-based radio propagation model trained on high accurate radio propagation model is not necessarily accurate on real world data. The second part of Table III displays the performance of our model fine tuned with real data, processed or not according to F or C. We can see that fine tuning our model on real data centers automatically the model and reduces drastically the error.

As detailed previously crowd-sourced data induces some severe limitations. Transmitter and receiver antenna orientation is not known, which induces a non removable error of at least 3.14 dB standard deviation between any prediction model and measurements. The measurement devices diversity induces also some RSSI calibration errors. The crowd-sourced measurement locations may be also inaccurate, with 1 m meter resolution at the best with the Netspot app. It is also important to note that the home gateways can be placed into or behind some furniture, which also induces some additional errors as well as the other furniture present in the environment but not represented on the floor plan image for sake on simplicity for the end user. A more accurate model with respect to simulated data (3.5 dB of RMSE) led to a RMSE of 5.5 dB with respect to real data w FC which is our best performance.

V. Conclusion

In this paper, we proposed a new way to fine tune an AI-based RPM from crowd-sourced data. We have highlighted the fact that using such data for RPM fine tuning is challenging due to their low reliability (random antenna orientation, positioning errors, diversity of devices, shadowing due to furniture). We have presented our different measurement campaigns for collecting data and for RSSI calibration. We have analyzed the variability of RSSI according to types of devices and proposed a calibration method to deal with it. Finally, we have underlined the gap between a model trained on simulated data and real world data. In future works, we plan to use more data and other frequencies to improve the accuracy and extent the model usage.

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