# A Mobile App for Real-Time Testing of Path-Loss Models and Optimization of Network Planning

David Plets, Roel Mangelschots, Kris Vanhecke, Luc Martens, Wout Joseph
WiCa - Dept. of Information Technology - iMinds - Ghent University
G. Crommenlaan 8 box 201, B-9050 Ghent, Belgium
Email: david.plets@intec.ugent.be

***Abstract*---A mobile application is presented for real-time testing and optimization of path-loss models and network planning, based on the execution of validation measurements in the considered environment. The application is tested in three indoor scenarios and for three path-loss models. Without optimization, average absolute prediction errors of about 5 dB are obtained, with a simple free-space model performing best. Executing a limited set of ten additional measurements suffices to improve predictions by up to more than 40%. The application is particularly useful for very quick path-loss model tests in a certain environment or for easily obtaining more accurate network deployments, as a single measurement only takes a few seconds and optimization of the path-loss model is fully automated.**

## I. Introduction

During recent years, more and more electronics have become wirelessly connected to the internet. As these devices are most often used indoors, a reliable wireless connection has to be provided. Indoor environments easily allow the use of Wireless Local Area Networks (WLANs) for indoor mobile internet access and as a reliable offloading mechanism for macrocell connections. Reliability is indispensable for applications such as video conferencing, which require a continuous transmission of data with a low delay. The reliability of a WLAN link is for a large part determined by the wireless channel between the access point (AP) and the receiving mobile device, in particular by the path loss between the transmit and receive antennas. Therefore, it is of major importance to perform a reliable wireless network planning in the environment where user devices require a wireless internet connection.

In recent and in less recent years, different indoor path loss [1], [2] and penetration loss [3] models have been proposed, sometimes claiming a high accuracy for a specific environment type (e.g., conference [4], industrial, office,...), sometimes claiming a more general applicability. Time-consuming ray tracing tools [5] have tried to fully characterize the channel by accounting for reflections, diffractions, wall absorptions,... that occur in indoor environments [6]. However, the physical complexity of the indoor environment often still significantly impairs the quality of the wireless network prediction. A possible workaround to obtain a reliable network planning is to perform a site survey on the spot [7]. Many site survey tools do not incorporate any intelligence and just measure and plot the WiFi signal strength without an automated planning, urging the user to measure at all locations. Moreover, indicating the measurement locations is not always user-friendly when using e.g., a measurement laptop and specialized WLAN sniffer software (e.g., AirMagnet [8], Ekahau [7], Acrylic WiFi [9],...).

In this paper, a mobile application for real-time testing and optimization of path loss models using Android smartphone or tablet is presented. It allows combining the intelligence of a network planner with the measurement and optimization possibilities of state-of-the-art site survey tools. After a calibration of the Android tablet, the testing method is applied to three different environments and three different path-loss models. The user-friendliness of the touchscreen is exploited to allow quickly performing an extensive set of measurements and optimizing network planning in real-time, which is illustrated in an application example. In Section II, a system overview is given. Section III discusses the scenarios that will be investigated, and describes the tested path-loss models and environments. A full discussion of the results of the testing and optimization scenarios is presented in Section IV, and finally, the paper's main findings are summarized in Section V.

## II. System overview

The proposed system is based on a mobile Android application connecting with a backend server that exhibits network planning functionalities. The entire system is based on the WiCa Heuristic Indoor Propagation Prediction (WHIPP) tool [5]. After discussing this existing WHIPP system, we will describe the mobile application system.

### A. WHIPP tool

The WHIPP tool is a wireless indoor network planning toolbox developed within the Wireless & Cable group [5]. It allows predicting network coverage for WiFi, Zigbee, or Universal Mobile Telecommunication Systems (UMTS) and Long Term Evolution (LTE) femtocells. Another feature is an automatic network design algorithm, which optimally places APs on a floor plan, based on user-defined throughput requirements in the different rooms [5]. The WHIPP tool allows the user to choose from different path loss models for the simulation, e.g., the IEEE 802.11 TGn model [10], a user-defined one-slope log-distance model, a multiwall model [11], or the free-space model.

The original tool is constructed as a webservice connecting to a backend server. This server accepts input (e.g., floor plan, simulation parameters,...) from the webservice, performs all simulations on the backend and returns the output data to the webservice for visualisation. Input is provided by, and output is received by a classical desktop pc or laptop, communicating with the web service via an ethernet connection or a WiFi connection. The following section will describe the development of the mobile version of the tool. Fig. 1 (top) shows the main screen of the tool, where the user draws a ground plan.

## B. Mobile application

Given the limited processing power on mobile devices and the nature of the original architecture, it is a straightforward choice to use a similar architecture for the mobile application: the Android device communicates with the backend server via the same web service, over a WiFi, 3G, or 4G connection. In order to maximize the number of devices that are compatible with the application, the lowest possible Android version was chosen (Android 2.2 Froyo). With respect to the graphical aspects of the mobile application, usage is mainly expected on tablets, to allow visualisation of a floor plan and functionalities on the screen. All functionalities of the original tool were reprogrammed for Android, with the mobile application allowing importing existing floor plans (that have been created on a desktop computer) or drawing a plan, by clicking and/or dragging the touched location on the screen. Horizontal/vertical scrolling and zooming functionalities are also implemented, leading to a completely mimicked version with respect to the functionalities and usage of the original tool. Fig. 1 (bottom) shows the same screen as in the computer version, redesigned for Android. Using this mobile application, it is now possible to perform measurements in the building. This is done by tapping the location at which the user is located. The location's coordinates and the recorded Received Signal Strength Information (RSSI) value are stored on the device and can be exchanged with the backend server for testing and/or optimization purposes.

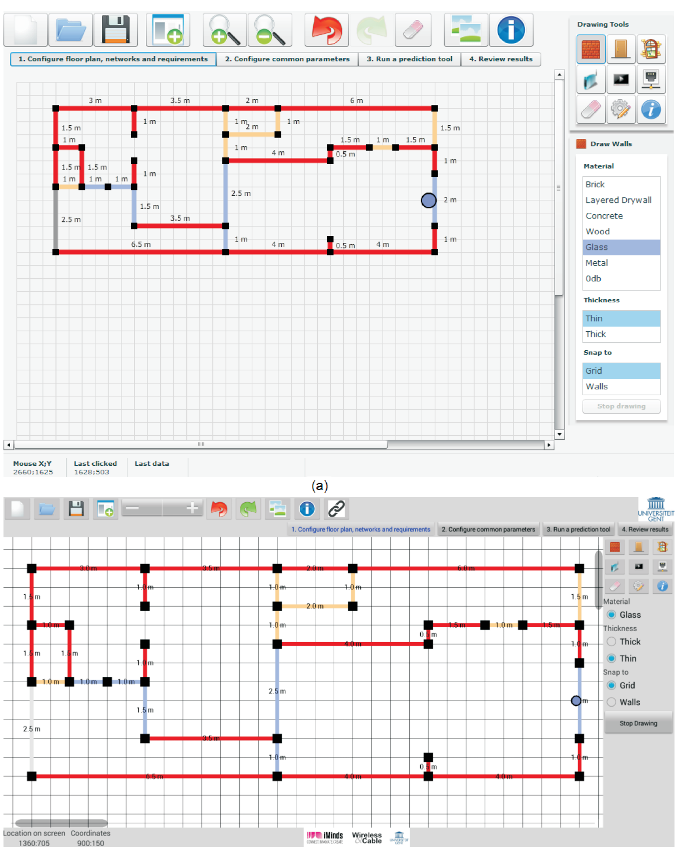


Fig. 1. WHIPP tool's main screen for computer (a) and Android app (b)

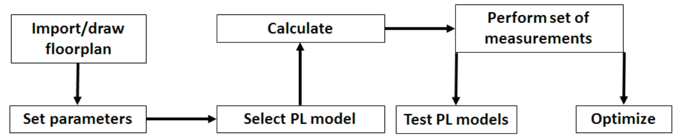


Fig. 2. Flow graph of test scenario.

# III. Scenarios

As explained earlier, using an Android device allows adding additional functionalities to the original WHIPP tool: (1) the mobile nature of the device with its integrated antenna allows an easy and quick execution of RSSI measurements and (2) the touchscreen allows a very user-friendly way of indicating the location of the measurements. In this paper, two scenarios will be investigated. First, a set of three path-loss models will be tested against a large set of additional measurements in three different indoor environments. Second, it will be investigated to what extent these measurements allow improvement of the accuracy of the models (and the wireless network planning). Fig. 2 shows a flow graph of these test scenarios. First a ground plan is obtained by importing existing files or by drawing it with the mobile app. After setting parameters (receiver type, fading margin,...) and selecting a path loss model, the network deployment is calculated for the given AP location(s). Then, the user performs measurements at different locations. These measurements not only allow comparison of the accuracy of the different available PL models (scenario 1), but also allow optimization of these models for an improved accuracy and network planning (scenario 2).

## A. Path loss models

Three different path loss models are considered in the tests:

**Free-space**: The free-space loss (FSL) [dB] is the path loss between two antennas in idealized conditions, meaning that the antennas are in each others far-field, the environment is unobstructed free space, the antenna polarizations are perfectly matched, ... The free-space loss is sometimes used as an estimate for path losses and is calculated as follows:

$$FSL \;= 20 \cdot log_{10}(d) + 20 \cdot log_{10}(f) + 32.45, \qquad (1)$$

with d [km] the distance between transmit and receiving antenna, and f [MHz] the operating frequency. At 2.4 GHz, eq. (1) can be rewritten as

$$FSL \;= PL_0 + 10 \cdot n \cdot log_{10}(d), \qquad (2)$$

with $PL_0$ = 40.05 dB and n = 2.

**IEEE 802.11 TGn model** [10]: The IEEE 802.11 TGn model (TGN) is a two-slope path loss model, which is suitable for path-loss predictions in office environments. The median TGN loss TGNL [dB] is calculated as:

$$\begin{aligned} TGNL &= PL_0 + 10 \cdot n_1 \cdot log_{10}(d) & (d < d_{br}) \\ TGNL &= PL_0 + 10 \cdot n_2 \cdot log_{10}(d) - 32 & (d > d_{br})\,, \end{aligned} \qquad (3)$$

with $d_{br}$ = 10 $m$, $PL_0$ = 40.05 dB, $n_1$ = 2, and $n_2$ = 5.2. For $\mathrm{d} < \mathrm{d_{br}}$, the TGn model equals the free-space model.

Fig. 3. Test environments: Turnhout (left), Bruges (middle), Ghent (right).

**Multiwall model**: The multiwall model (MWM) is a model consisting of a distance-dependent part and a wall-dependent part that adds a wall-specific loss for each wall that is crossed by the direct ray between transmitter and receiver. The median path loss MWL [dB] according to the MWM is calculated as:

$$MWL \; = PL_0 + 10 \cdot n \cdot log_{10}(d) + \sum_i L_{W_i}, \qquad (4)$$

with $PL_0$ [dB] the path loss at a reference distance of 1 m (under the absence of walls), n [-] the path-loss exponent, $L_{W_i}$ [dB] the loss of wall $W_i$ that is crossed, with a summation over all walls $W_i$ crossed by the transmitter-receiver line. Here, $PL_0$ and n will be chosen so as to match FSL ($PL_0$ = 40 dB, n = 2). The wall loss values are chosen as described in [5], metal walls (e.g., elevators) are modeled with a loss of 100 dB.

### B. Environments

Three different indoor environments will be tested. A picture of the environments is shown in Fig. 3. A ground plan with the measurement locations is shown in Fig. 4. The location of the APs is indicated with a red dot with a black edge.

**Turnhout**: a residential house with wooden walls and doors. The considered AP was a DLink dir-615 (hardware version H2, firmware version 8.02) with two antennas and a transmit power of 13 dBm, installed at a height of 1 m. The total considered surface equals 89.25 $\mathrm{m}^2$, consisting of 112 possible measurement locations (1.255 possible measurements per $\mathrm{m}^2$).

**Bruges**: an old townhouse with brick walls and wooden or glass doors. The considered AP was a DLink dir-600 (firmware version DD-WRT v24-sp2) with one antenna and a transmit power of 8 dBm, installed at a height of 1 m. The total considered surface equals 77.75 $\mathrm{m}^2$, consisting of 96 possible measurement locations (1.235 possible measurements per $\mathrm{m}^2$). Compared to the 'Turnhout' environment, the Bruges environment is more cluttered (cupboards with books, piano,...).

**Ghent**: office building with layered drywalls around a core of concrete walls. The same AP type as in Bruges was used. The total considered surface equals 243.5 $\mathrm{m}^2$, consisting of 272 possible measurement locations (1.117 possible measurements per $\mathrm{m}^2$). The environment contains less objects than the other two environments.

### C. Experiment equipment

The tablet is a Sony Xperia Tablet Z (Model SGP311E4/8) with 802.11n capabilities. Just like many other measurement devices, this tablet measures RSSI instead of the actual Radio Frequency (RF) power. Therefore, a calibration measurement of the Android Tablet was performed.

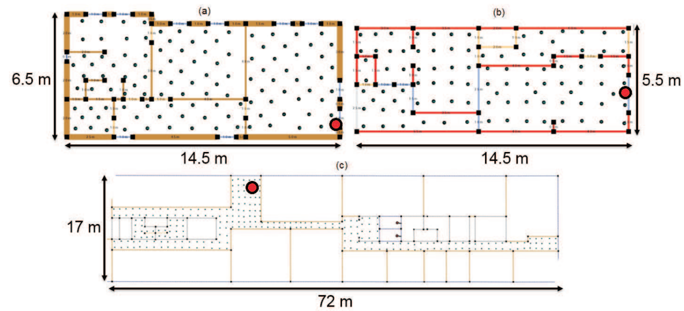


Fig. 4. Ground plan of Turnhout (a), Bruges (b), and Ghent (c) with indication of measurement locations and AP.

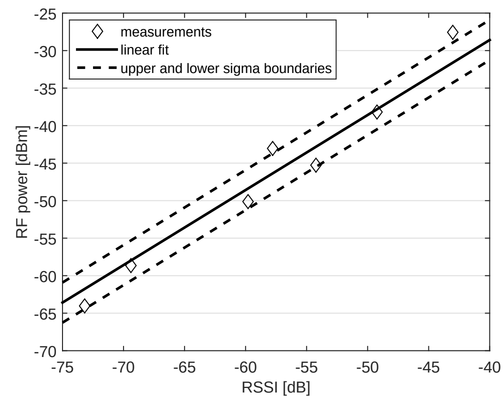


Fig. 5. Relation between measured RSSI and measured RF power with linear fit and one-sigma deviation boundaries.

*1) Tablet RSSI calibration:* For the calibration tests, 7 locations in an office building were selected. An access point was installed and the RSSI was measured with the tablet computer (5 instantaneous measurements per location). At the same time, the actually received power was recorded with a spectrum analyser. The difference between the recorded RSSI value and the recorded RF power equals 11.4 dB with a standard deviation of 2.67 dB. Fig. 5 shows a plot of the measured RSSI and RF powers and the linear fit with a difference of 11.4 dB. The plot shows that most measurements lie within a one-sigma deviation from the fit. However, it should be noted that RSSI measurements with an internal antenna of a mobile device will always be less accurate than actual RF measurements, e.g., due to the proximity of the body.

## IV. Results

In this section, results for the two described scenarios (path-loss model *testing* and *optimization*) will be presented.

### A. Scenario 1: path loss model testing

Here, it will be tested which of the three proposed path-loss models shows the best prediction performance. Fig. 6 shows the predicted power as a function of the tablet-measured power for the three considered environments and the three considered path loss models. The solid line indicates a perfect prediction of the received power. Table I shows the average prediction errors $\overline{\delta}$, the average absolute prediction errors $\overline{|\delta|}$, and the standard deviation $\sigma_{\overline{|\delta|}}$ on the average absolute

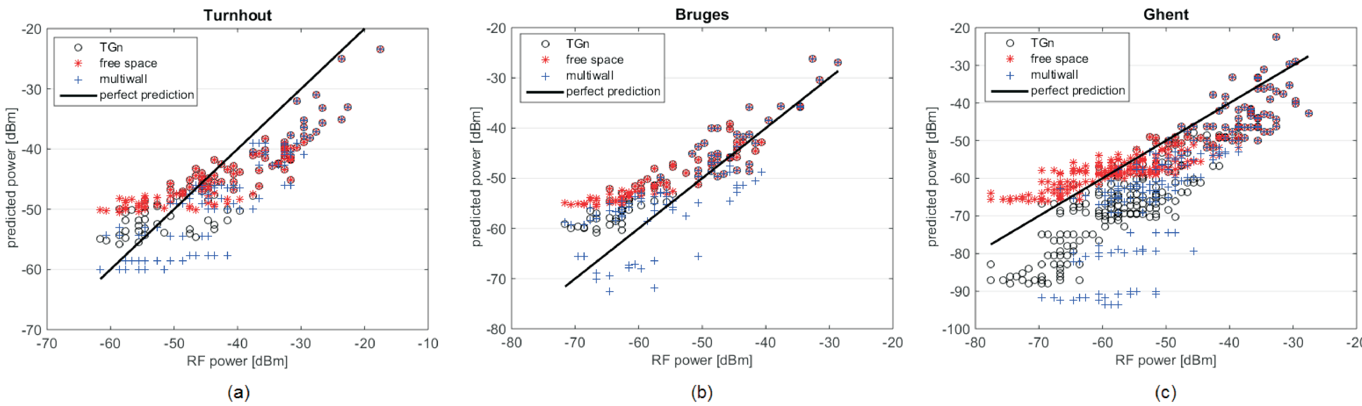


Fig. 6. Predicted power vs. measured RF power for (a) Turnhout, (b) Bruges, and (c) Ghent

prediction errors, over all measurement locations (see Fig. 4). Fig. 6 shows that for all environments, the three models predict the same received power in unobstructed line-of-sight (LoS) situations (higher received powers in the figure), since they all use the free-space approximation for unobstructed LoS (see Section III-A). Unlike for the Bruges and Ghent environments, the received powers in LoS (highest powers) in the Turnhout environment are somewhat underestimated. For the Turnhout environment, the TGn and free-space models pretty accurately predict the received powers (average errors below 3 dB, average absolute errors around 5 dB, see Table I), while the multiwall model mostly underestimates the received power (or overestimates the path loss). This phenomenon often occurs in environments with many walls (or with smaller rooms), such as in office buildings (Ghent). This is indeed observed in the Ghent environments, where due to the high losses by the metal elevator (modeled as 100 dB loss per wall), powers as low as -300 dBm are predicted (Y-range cut off in Fig. 6 (c) for reasons of clarity). This leads to the average prediction errors of 55 dB shown in Table I. Overall, the free-space loss model appears to be the best prediction model with average absolute errors of about 5 dB. However, the quite horizontal left tail of the free-space markers in Fig. 6 (c) also shows that, as expected, path losses are underestimated and measured powers are overestimated by the free-space model at higher distances from the AP (i.e., for lower RF powers). This is compensated for by the second slope $n_2$ in eq. (3) of the TGn model: the TGn markers are indeed closer to the perfect prediction for lower RF powers and hence, also lower absolute errors are observed for Turnhout and Bruges. However, in the office building in Ghent, this phenomenon is overcompensated: the TGn markers now lie below the perfect prediction line for lower powers, i.e., the path loss is overestimated or the predicted received powers are underestimated. This is mainly due to the fact that the Ghent environment consists of light walls (layered drywalls) with small penetration losses, where path losses are lower than in typical office environments. Finally, Table I shows that on average, all models underestimate the received power ($\overline{\delta} > 0$), except for the Bruges environment, where all models overestimate the received power ($\overline{\delta} < 0$). This indicates that performing additional environment-specific measurements would allow improvement of the models by only performing a simple linear shift. The application of such optimization will be investigated in the next section. Although an advantage of our system is that no additional hardware is required to use it, it could be argued that the lack of an external antenna will cause the measurement accuracies to probably be lower than those of classical systems that use an external antenna connected to a laptop via Universal Serial Bus (USB). Technically, however, it would be possible to improve our system by connecting a better (external) measurement antenna to the Android device.

TABLE I. AVERAGE PREDICTION ERRORS $\overline{\delta}$, AVERAGE ABSOLUTE PREDICTION ERRORS $\overline{|\delta|}$, AND STANDARD DEVIATION $\sigma_{\overline{|\delta|}}$ ON $\overline{|\delta|}$, OVER ALL MEASUREMENT LOCATIONS (IN dB).

| | TGn | | | Free space | | | Multiwall | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\overline{\delta}$ | $\overline{\lvert\delta\rvert}$ | $\sigma_{\overline{\lvert\delta\rvert}}$ | $\overline{\delta}$ | $\overline{\lvert\delta\rvert}$ | $\sigma_{\overline{\lvert\delta\rvert}}$ | $\overline{\delta}$ | $\overline{\lvert\delta\rvert}$ | $\sigma_{\overline{\lvert\delta\rvert}}$ |
| | [dB] | | | | | | | | |
| Turnhout | 2.8 | 5.0 | 3.4 | 1.8 | 5.3 | 3.3 | 5.4 | 5.9 | 3.9 |
| Bruges | -4.3 | 4.9 | 3.2 | -5.3 | 5.9 | 4.2 | -1.2 | 4.9 | 3.4 |
| Ghent | 8.7 | 9.1 | 5.3 | 1.4 | 4.9 | 3.4 | 55.7 | 55.9 | 95.1 |

### *B. Scenario 2a: path loss model optimization*

Here, each of the path loss models will be optimized for each of the environment, based on the total set of measurements executed in each of the environments (see Section III-B). Each set of measurements yields a value of the average prediction error for the considered model in the considered environment (values of $\overline{\delta}$ in Table I). This value will then be used to linearly shift the path loss models (adjustment of parameter $PL_0$ in eqs. (2,3,4)), so that the average prediction error becomes zero. Since this shift accounts for all measured points, it is assumed to deliver the best possible linear shift. Table II shows the same metrics as Table I, but now after adjustment of the path loss model. For the TGn model, especially the Bruges and Ghent environments benefit from the optimization, since the original predictions deviated more from the measurements than the Turnhout environment and thus had more room for improvement. Similarly, for the free-space model, the small original average errors $\overline{\delta}$ in the Turnhout and Ghent environment leave less room for improvement compared to the Bruges environment (absolute error reduction of 30% vs. 6% or 2%). The multiwall model's improvement is mainly in the Turnhout environment (37%). In the Ghent environment, however, no performance improvement is possible with a simple linear shift. In this case, adjustment of the wall losses would be required to obtain better models. Analogously, for

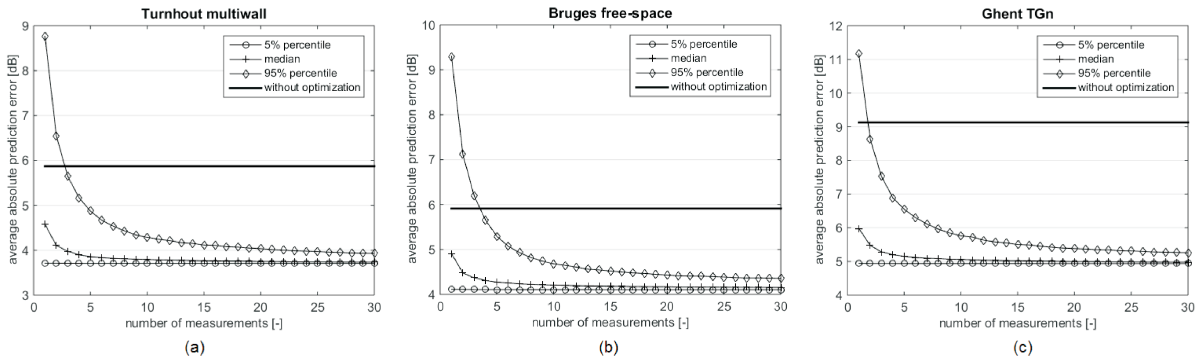


Fig. 7. Average absolute prediction error as a function of the number of random measurements, for (a) Turnhout, (b) Bruges, and (c) Ghent

the other models, an additional adjustment of the slope of the free-space loss (making it a classical one-slope model) or the slopes of the TGn two-slope model would allow a further improvement of the performance. In general, it can be observed from Table II that not only the average absolute error decreases after the optimization (up to 46%), but also the standard deviations on the error (up to 36%).

### *C. Scenario 2b: path loss model optimization with a limited number of additional measurements*

As mentioned earlier, the presented linear shifts from the previous section are the most accurate ones, since they account for all measurements. Executing measurements at all locations is time-consuming and might be not necessary. In this subsection, it will be investigated how fast the average error of a subset of measurements converges to the average error of the total set of measurements. A quick convergence would indicate that with already a few measurements, the path loss models and the network planning can be improved in at most a few minutes. To investigate this, random RSSI measurements were taken from the total measurement set for each environment, with the subset size varying between 1 and 30. For each subset size, 10,000 random subsets were created. From the average prediction error at the subset locations, the linear shift was again derived and then applied to the path loss model. For environments in which there is room for improvement when predicting according to a certain path loss model, performing additional measurements will likely improve the prediction performance. Therefore, we will first investigate three environment-model combinations where $|\overline{\delta}| > 5$ dB in Table I (remark the difference between $|\overline{\delta}|$ and $\overline{|\delta|}$). Then, we will investigate the probability of a deteriorating prediction performance when the original prediction was good already. Since the optimization calculation time itself is negligible, only the time to conduct measurements is relevant. However, this time is very limited as each measurement only involves tapping the current location of the tablet.

*Degree of performance improvement* - Fig. 7 shows the resulting average error over all measurement locations. All three path loss models were applied, each to a different environment. Fig. 7 indicates the 5%, 50%, and 95% percentiles over the 10,000 subsets, as well as the original average absolute errors without applying any linear shift (original situation). It shows that with very limited additional measurements, there is a chance of more than 95% to improve the path loss model: two measurements for Ghent TGn, three for Turnhout multiwall, and four for Bruges free-space. On average, five additional measurements already lead to predictions where the error is approaching the minimal error with a linear-shift optimization, which is equal to $\overline{|\delta|}$ in Table. II.

*Degree of possible performance deterioration* - When the original prediction is already good (e.g., free-space model in Ghent, where the maximal improvement is only 2%, see Table II), there is a reasonable probability that tuning the model based on a limited set of measurements will actually worsen the prediction. Therefore, Fig. 8 shows the resulting average error over all measurement locations as a function of the subset size of the additional measurements. It shows that the prediction could indeed deteriorate (see 95%-percentile line). When only 5 measurements are added, there is a chance of 5% that the resulting average absolute error is more than 6.4 dB, compared to an original error of 4.94 dB. On average, this error will be 5.1 dB. With a chance of 5% for a maximal error increase of less than 1.5 dB, it is fair to state that the possible worst-case impact is limited when using only 5 measurements. For 10 measurements, this maximal error further reduces to 0.7 dB. It can be concluded that performing 10 additional measurements will in almost all cases result in an improvement of the prediction performance.

### *D. Network planning application*

In this section, the optimization method for the path loss model will be applied to a network planning problem for the Ghent environment with the TGn model. An 802.11b/g network with 16-dBm APs is to be designed for a physical-layer coverage of 54 Mbps over the entire building floor. Fig. 9 (a) shows the received power according to the network design using the original non-optimized TGn model (APs are located in the centres of the circles). Five APs are required to provide the required throughput. For this application, we assume an additional (random) measurement set of 10 samples with its median deviation (overestimation of the path loss) of 8.7 dB. After decreasing $PL_0$ in eq. (3) with 8.7 dB, the resulting designed network of Fig. 9 (b) consists of 3 APs instead of 5, indicating the value of the application. As the cost of the AP itself is only around one third of the total installation cost [12], an accurate network planning could -in this case-save a significant amount of money for the company or person installing the network. Moreover, using less APs also reduces

TABLE II. AVERAGE ABSOLUTE PREDICTION ERRORS $\overline{|\delta|}$ AND STANDARD DEVIATION $\sigma_{\overline{|\delta|}}$ ON $\overline{|\delta|}$, OVER ALL MEASUREMENT LOCATIONS AFTER OPTIMIZATION OF THE PATH LOSS MODEL (IN DB). REDUCTIONS COMPARED TO ORIGINAL SITUATION ARE INDICATED BETWEEN BRACKETS.

| | **TGn** | | **Free space** | | **Multiwall** | |
|---|---|---|---|---|---|---|
| | $\overline{\|\delta\|}$ | $\sigma_{\overline{\|\delta\|}}$ | $\overline{\|\delta\|}$ | $\sigma_{\overline{\|\delta\|}}$ | $\overline{\|\delta\|}$ | $\sigma_{\overline{\|\delta\|}}$ |
| | **[dB]** | | | | | |
| Turnhout | 4.6 (-8%) | 2.6 (-23%) | 5.0 (-6%) | 3.3 (-0.3%) | 3.7 (-37%) | 2.6 (-34%) |
| Bruges | 3.4 (-31%) | 2.1 (-34%) | 4.2 (-30%) | 2.6 (-36%) | 4.7 (-5%) | 3.5 (+4%) |
| Ghent | 5.0 (-46%) | 3.4 (-36%) | 4.8 (-2%) | 3.3 (-4%) | 68.6 (+22%) | 65.9 (-31%) |

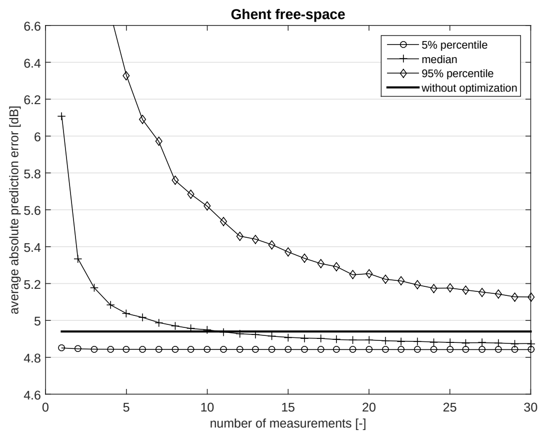


Fig. 8. Average absolute prediction error as a function of the number of random measurements

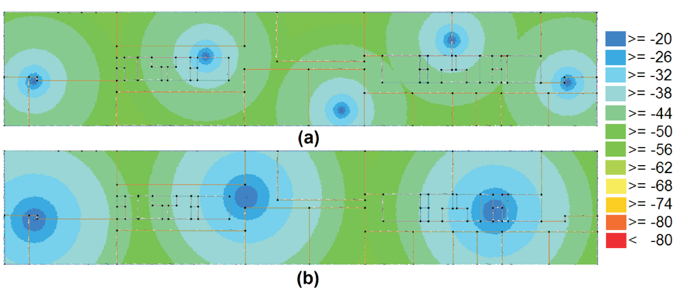


Fig. 9. Network design for Ghent environment (90 m x 17 m) according to (a) original TGn model and (b) TGn model tuned with 10 measurements. Legend indicates predicted received power in dBm. APs are located in the centre of the circles.

interference. If, on the other hand, the original network appears to be underdimensioned, the application will redimension the network to fill coverage holes, avoiding an extensive and expensive site survey later. All network planning calculations are executed within a negligible time duration.

## V. CONCLUSIONS

In this paper, a mobile Android application is presented for testing path-loss models and for optimization of the wireless network planning by tuning the used models based on a set of measurements with the app. The application is extremely easy to use thanks to the built-in antenna of mobile devices and the possibility to indicate the measurement locations on a tablet. Three different indoor environments (two houses and one office building) were considered, as well as three different path-loss models. It was shown that overall, the free-space model delivered slightly better results than the IEEE TGn model and the multiwall model (average absolute errors around 5 dB), although no really harsh environments were considered. Deriving a linear shift from a set of additional measurements with the mobile app, and applying it to the path-loss models, allowed for reductions of the prediction error of up to 46% for the considered environments and models. Further, it is shown that only a few additional mobile measurements often already suffice for a drastic improvement of the path loss model in the considered environment. Executing only 10 random measurements in the environment, a task which can be done in at most a few minutes, is already sufficient to obtain a path-loss model that is close to the optimal model that can be obtained through a linear shift. Even in the worst considered scenario, where the original model is performing very well already, there is a chance of less than 5% that the error increases by 0.7 dB when performing 10 additional measurements.
In the future, the performance of more advanced path-loss models (e.g., accounting for the physical properties of the environment [5]) and more advanced optimization techniques will be investigated (e.g., changing the slope of the models, wall penetration losses in advanced models). Further, the application will be able to differentiate between the RSSI from different APs, yielding more optimization data in the same time. Finally, thanks to the user-friendly indication of measurement locations on a map, the application is also well-suited for quickly building an RSSI fingerprint database for localization purposes.

## REFERENCES


[1] A. Turkmani and A. de Toledo, ''Modelling of radio transmissions into, and within, multistorey buildings at 900, 1800 and 2300 MHz,'' *IEE Proceedings-I*, vol. 140, no. 6, pp. 462--470, Dec. 1993.

[2] R.S. de Souza and R.D. Lins, ''A new propagation model for 2.4 GHz wireless LAN,'' in *Communications, 2008. APCC 2008. 14th Asia-Pacific Conference on*, Tokyo, Japan, 14-16 October 2008, pp. 1--5.

[3] W. Joseph, L. Verloock, D. Plets, E. Tanghe, and L. Martens, ''Characterization of coverage and indoor penetration loss of DVB-H signal of indoor gap filler in UHF band,'' *IEEE Transactions on Broadcasting*, vol. 55, no. 3, pp. 589--597, 2009.

[4] F. Heereman and W. Joseph and E. Tanghe and D. Plets and L. Verloock and L. Martens, ''Path loss model and prediction of range, power and throughput for 802.11n in large conference rooms,'' *AEU - International Journal of Electronics and Communications*, vol. 66, no. 7, pp. 561--568, July 2012.

[5] D. Plets, W. Joseph, K. Vanhecke, E. Tanghe, and L. Martens, ''Coverage Prediction and Optimization Algorithms for Indoor Environments,'' *EURASIP Journal on Wireless Communications and Networking, Special Issue on Radio Propagation, Channel Modeling, and Wireless, Channel Simulation Tools for Heterogeneous Networking Evaluation*, vol. 1, 2012. [Online]. Available: http://jwcn.eurasipjournals.com/content/2012/1/123

[6] J. Moreno Delgado, M. Domingo Gracia, J. Basterrechea Verdeja, J.R. Perez Lopez and L. Valle Lopez, ''Automatic Channel and Aps Allocation in WiFi Networks Using Ray Tracing Techniques and Particle Swarm Optimization,'' in *3rd European Conference on Antennas and Propagation*, Barcelona, Spain, 12-16 April 2010.

[7] Ekahau, ‘‘Ekahau site survey,’’ Website, http://www.ekahau.com/wifidesign/ekahau-site-survey.

[8] Fluke networks, ‘‘Airmagnet survey,’’ Website, http://fr.flukenetworks.com/products/airmagnet-survey.

[9] Acrylic WiFi, ‘‘Acrylic wlan scanner,’’ Website, https://www.acrylicwifi.com/en/wlan-software/wlan-scanner-acrylic-wifi-free/.

[10] Q. Li, M. Ho, V. Erceg, A. Janganntham, and N. Tal, ‘‘802.11n channel model validation,” IEEE 802.11-03/894r1, 11-03-0894-01-000n-802-11n-channel-model-validation.pdf,’’ Tech. Rep., 2003.

[11] J.M. Keenan and A.J. Motley, ‘‘Radio Coverage in Buildings,’’ *BTSJ*, vol. 8, no. 1, pp. 19--24, January 1990.

[12] N. Liu and D. Plets and K. Vanhecke and L. Martens and W. Joseph, ‘‘Wireless Indoor Network Planning for Advanced Exposure and Installation Cost Minimization,’’ *Eurasip Journal on Wireless Communication and Networking*, 2015, accepted.