

Applying and Comparing Two Measurement Approaches for the Estimation of Indoor WiFi Coverage

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Abstract—Radio coverage is a crucial component in any radio network design and deployment. In order to develop a design and deployment tool, we studied and utilized two different measurement approaches suitable for estimating indoor WiFi coverage. One of the tested approaches uses a handheld spectrum analyzer, while the other is a protocol-dependent method using standard Windows API calls. The applicability of these approaches is shown and the pros and cons of both measurement approaches are discussed based on visualization of the examples and comparison of the results. An analysis of the degree of dynamic radio channel effects for the observed differences between the two methods is also presented.

Keywords—data analysis and visualization, indoor coverage, indoor propagation models, industrial Internet-of-Things, WiFi

I. INTRODUCTION

In recent years, the Internet-of-Things (IoT) and Industrial IoT (IIoT) have become a focus of both academia and industry all over the world and are currently widely considered one of the most important technologies of the twenty-first century. A description of these phenomena and their major challenges, including design and deployment issues, are reported in, e.g., [1] and [2].

The major technical challenges for developing industrial wireless applications can be found in, e.g., [3] and [4]. Because of the unique characteristics and technical challenges, developing wireless industrial applications requires a combination of expertise from several different disciplines, including RF design and propagation environment expertise, which is necessary to address communication challenges and RF interference problems in industrial environments [3]. The harsh radio wave propagation conditions in industrial environments is often characterized by the presence of multi-path propagation, interferences from other devices, and noise generated by equipment or heavy machinery [4]. Also, link condition in industrial environments is subject to change over time due to industrial processes and activities (e.g., cars or workers moving, goods replacement).

Our study is performed as part of the industrial IoT in a research project entitled Industrial Internet as a Business Enabler

(IIBE). One of the objectives of the project is industrial process monitoring and control using reliable wireless networks. More information about the IIBE project and other demonstrations within the project are reported by [5] and [6].

II. RELATED WORK

The indoor WiFi coverage, as any radio coverage, is mainly affected by radio wave propagation. A recent study surveyed indoor propagation models [7]. These models include ray-tracing-based models, e.g., [8], [9], and [10]. The problem of ray-tracing-based models is that they require vector-based information about the surroundings in order to identify and predict reflected and diffracted rays. Another class of models is statistical (or site-specific) models. This class includes classical models [11], [12], and [13], and many followers also take into account floor and wall losses with recent empirical models such as those in [14] and [15]. The statistical models are easy and fast to use and the site-specific adjustments require only the linear regression to be used. The third type of prediction model is a heuristic model; a good representative is the model by Plets et al. [7], where heuristic predictions are based on one or more rules of thumb in order to make accurate yet fast predictions. Other WiFi related research includes coverage and performance comparisons by Sendra et al. [16], wherein several WiFi variants (i.e., IEEE 802.11) were compared with each other. The results of our earlier evaluations of coverage and performance using 2.4 GHz and other industrial, scientific, and medical (ISM) band radios in industrial outdoor and indoor environments are reported in [17].

III. COVERAGE ESTIMATION USING DIFFERENTS MEASUREMENTS METHODS

A. Measurements Based on WiFi Protocol-Dependent Tool

A WiFi Protocol-Dependent Tool called CENTRIA tool is a software application for Windows-based operating systems that can measure and record WiFi received signal strength indicator (RSSI) using standard Windows API calls. Measured RSSI value can be placed on a map and a heat map overly of the signal strength can be generated by interpolating between measured

data points. The current version of the tool measures only RSSI value, which is provided by the Windows networking interface. Thus, the measured RSSI value is affected by the wireless setup of the system.

Measurements were performed on a laptop (Lenovo X201) using its internal wireless network adapter and a built-in internal antenna. The wireless adapter used in this laptop is Intel's N-6300 wireless networking module, supporting 802.11a/g/n with 3x3 MIMO. Adapter settings were left to default. All measurements were done using the same laptop to keep measured values comparable.

In practice, the measurement was carried out by walking through selected measurement points in the factory hall and in each point WiFi RSSI, MAC, and SSID values from different networks were recorded using the CENTRIA tool and placed on the floor plan by clicking the nearest position on the map.

B. Measurements with Spectrum Analyzer

The measurements with the spectrum analyzer were made with a handheld spectrum analyzer (Rohde & Schwarz, model FSH8) that includes a software option called Indoor Mapping Measurement Application. With the indoor mapping function, we were able to measure indoor radio coverage by recording the signal strength in the environment where a GPS signal is not available, while keeping the information on measurement locations.

The antenna used in the measurements was an omnidirectional antenna at 2.4 GHz. Before the measurements, the indoor floor plan was imported into the application. Three GPS coordinates were given to the floor plan. Based on the given coordinates, it was possible to locate the measurement positions indoors.

WiFi channels used in the industrial environment included 1 (2412 MHz), 7 (2442 MHz), and 13 (2472 MHz). In the measurements, only one channel was measured. Channel 13, which was most strongly heard at the beginning position, was chosen as the channel to be measured.

The analyzer was kept in hand during the measurements. At each measuring point, we moved the pointer manually in the analyzer floor plan to get the right location and measure the signal strength. The measuring locations (i.e., sites) of the CENTRIA tool and the analyzer were kept at nearly the same positions and the measurements were approximately simultaneously performed. Table I summarizes the spectrum analyzer measurement settings.

C. Measurement Campaign and Site

The measurements analyzed in this paper were performed at the factory of one of Finland's biggest manufacturers of kitchen cabinets and fixtures. Fixtures consist of different types of storage space like wardrobes, upper and lower cupboards, and

drawers. Some process phases need to be separated, e.g., for fire safety reasons. Five WiFi access points were located in the industrial site as shown in Fig. 1 and Fig. 2.

IV. DATA ANALYSIS AND VISUALIZATION OF THE MEASUREMENT RESULTS

A. Pre-processing of Measurements

The measurement campaign was performed during the normal working day at the industrial site described above. Obtaining comparable results from both measurement approaches required some pre-processing of the measurement results. Two issues had to be considered in the pre-processing: summing of radio signals from different sources and differences in measurement devices and antenna configurations and gains.

The CENTRIA tool is a protocol-dependent tool which by nature produces at each measurement location separate outputs for every detected base station with separate channels or MAC addresses. A more generic estimation of received power levels of the selected channel is achievable using only a spectrum analyzer, i.e., the spectrum analyzer results in the sum of all radio signals at the chosen frequency window. Because we did not manipulate the established base station positions during the measurement phase, the most practical solution was to emulate spectrum analyzer behavior with the CENTRIA tool, i.e., to add up all signals from different base stations on the selected channel, channel 13. The signals were constructively summed assuming that all received signals are in-phase. This naturally causes some errors as it is extremely improbable that all signals are in-phase. Therefore, the sum of the measurements from the protocol-dependent CENTRIA tool overestimates the received signal strength compared with the spectrum analyzer. The other practical option would be to compare each different base station and MAC address combinations from the CENTRIA tool and select only those spectrum measurement sites at some threshold distance from the CENTRIA tool measurements sites.

The RSSI levels of the two measurement approaches must be adjusted because of their different sensitivity levels and antenna gains. To minimize the abovementioned differences, 23.11 dB was added during pre-processing to the raw results of the spectrum analyzer. This value was derived by setting the sum of the five strongest signals (i.e., with low probability of multi-path fading) of both approaches as equal.

B. Comparison Using Extrapolated Heat Maps

A way to analyze and visualize coverage areas is to draw 'heat maps'. In our examples, we have used a 0.25-meter grid and interpolation and extrapolation to produce coverage area maps. The analysis was carried out using Matlab, which has several options for two-dimensional interpolation or both interpolation and extrapolation. In the results shown here, we have used the bi-harmonic spline interpolation (MATLAB® griddata method 'v4'). The resulting heat maps of both measurement approaches are shown in Fig. 1. The color bars on the right side of the pictures relate the used color scheme to the pre-processed RSSI levels. The measurement points of approach being used are shown with black dots while back circles represent the other approach not used in the analysis in question.

TABLE I. SPECTRUM ANALYZER MEASUREMENT SETTINGS

Ref. Level	RBW (Resolution Bandwidth)	SWT (Sweep Time)	Attenuation	Preamp	Detect
-40 dBm	3 MHz	100 ms	0	On	RMS

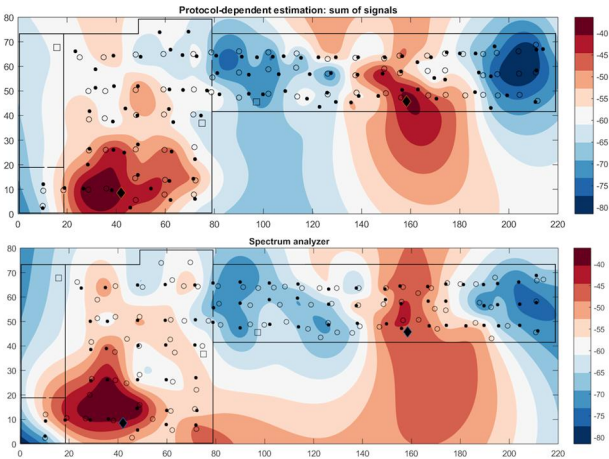


Fig.1. Comparison of measurement approaches with extrapolated heat maps with base stations at channel 13 shown with black diamonds and base stations at channels 1 or 7 shown with black open squares.

Interpolation also allows quantitative comparison at each grid point. This quantitative difference between the used approaches is presented in Fig. 2 showing that there are areas where the difference of the estimated RSSI values of the used approaches is above ± 10 dB. As expected the two measurement approaches give quite similar results, although some differences can be found in Figs. 1 and 2. The discrepancies between the approaches are not unexpected, because measurements were not simultaneous in exactly the same places, combined with the well-known incoherent characteristics of the radio channel.

C. Analysis of Differences Between Measurement Approaches Against Radio Channel Characterization

In order to better analyze the statistical differences between the coverage measurements and the deviation of the distributions and to compare the results with the prediction models, we used path loss instead of the signal power levels. The basic parameter of suitable statistical attenuation models is distance between the transmitter and receiver. As there were two base stations, the measurement sites (i.e., the receiving-end stations) were separated into two sets for each approach. The separation criterion was chosen with the aid of the heat maps. The measurement sites with x-coordinates below 85 meters are in the vicinity of and presumably being served by the left base station.

We have compared the measured attenuation values with two simple statistical attenuation prediction models: a log-normal shadowing path model [11] and a simplified dual slope model [12], [13]. In the log-normal shadow model, the attenuation, or path loss, is expressed as

$$PL(d) = PL(d_0) + 10n \log_{10} \left(\frac{d}{d_0} \right) \quad (1)$$

where n is variable path loss depending on the environment, and $PL(d_0)$ is loss at reference distance d_0 . The dual slope model (DSM) can be expressed as

$$PL_{DS1}(d) = 10 n_1 \log_{10} \left(\frac{d}{d_0} \right) + PL(d_0) \quad \text{for } d \leq d_{BR} \quad (2)$$

$$PL_{DS2}(d) = PL_{DS1}(d_{BR}) + 10 n_2 \log_{10} \left(\frac{d}{d_{BR}} \right) \quad \text{for } d > d_{BR}$$

where n_1 and n_2 are path loss exponents before and after d_{BR} , which is the breaking distance, and λ is the wavelength. In the

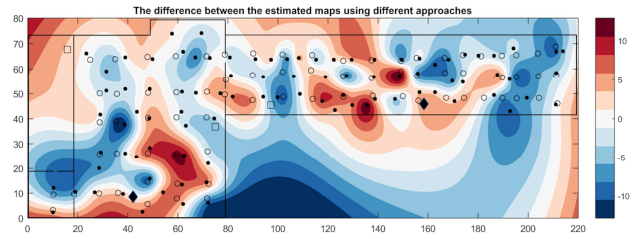


Fig. 2. Difference between the extrapolated heat maps.

simplified dual slope model, $n_1 = 2$, i.e., corresponding to free-space propagation loss.

We used a reference distance of $d_0 = 1$ and direct and piecewise linear regression to fit the measured attenuation with the log-normal shadowing path model and the simplified dual slope model, respectively. The results and parameters of these fits are summarized in Table II. As can be seen, in this industrial environment the simplified dual slope model gives slightly better fit than the log-normal shadowing path model. The adjusted R-squared value of 0.667 means that 66.7% of the variation in the attenuation can be explained by the linear regression model. RMSE is the root mean squared error value. The measured attenuation values and the simplified dual slope model fit are shown in Fig. 3. Summary of used data sets is given in Table III.

V. DISCUSSION

The protocol-dependent CENTRIA tool is best suited to verifying existing base station deployment and to providing suggestions on deployment changes to fill any detected gaps in the overall WiFi coverage area. One should note that the presented coverage area maps show only the signal powers received for the two base stations using WiFi channel 13. The factory actually uses three other WiFi base stations, which are used for different channels. Because this approach records all the base station transmissions above the sensitivity level of the receiver, it can be used to estimate the co-channel interference possibility and interference from the adjacent channels. As it is well-known that both fading of the wanted signal and the high interference level from other radio signals are the cause of the outages, the interference analysis capability is an important option, especially in interference rich dense network deployments. Another possibility for further developing the CENTRIA tool and the associated data analysis is to include the capture of the link level and the application level throughput values. This is indeed the direction of our future studies. The cons of this approach are poorer sensitivity, weaker generalization, and transferability of the results to other radio

TABLE II. SUMMARY OF LINEAR REGRESSION MODEL FITS

Parameters and goodness of fit results	Propagation models	
	Log-normal shadowing	Simplified dual slope
$PL(d_0 = 1)$	34.43 dB	40.37 dB
n or n_2	2.58	3.01
d_{BR}	not used in this model	18.45 m
Adjusted R-squared	0.667	0.683
RMSE	4.991	4.865
Correlation	0.82	0.82

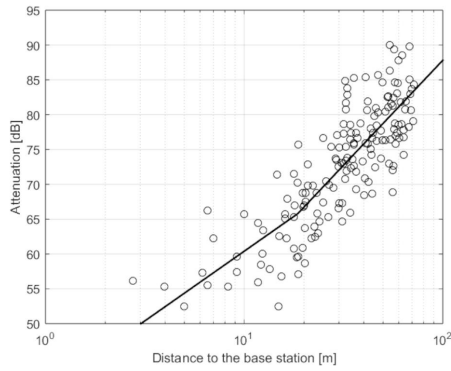


Fig. 3. Attenuation vs. distance to the serving base station and the associated simplified dual slope model with regression line fit.

protocols using the same frequency allocations compared with the spectrum analyzer method.

The handheld spectrum analyzer allows fast and easy implementation of the radio coverage measurements, which is a feature very well suited as a method for analyzing new deployments of radio networks. As the user can choose the measurement center frequency and bandwidth, this method is a generic one that can be adjusted to apply to any radio protocol of interest. At 2.4 GHz frequency band, for example, there are several other radio protocols beyond WiFi such as Bluetooth and Bluetooth low energy, 6lowpan, and ZigBee, which are commonly considered alternatives for wireless sensor network-based IoT applications.

VI. CONCLUSION

In radio network deployment, the radio coverage determined primarily by range of radio links is an important design parameter. We have demonstrated the use of two different measurement approaches for the purpose of estimating indoor WiFi coverage. Both methods are applicable to coverage estimation with the consideration that the features of the radio-dependent method such as the CENTRIA tool are at their best in the profound analysis of an existing network deployment rather than in green-field deployment planning.

Although the use of wireless communication provides many benefits for the industry and there are many various potential application areas for industrial wireless automation, the problem of implementing reliable wireless communication in real-life industrial environments is still very complicated and requires further on-site research. While utilizing radio coverage measurements, it is always good to keep in mind the uncertainties caused by the dynamic radio channel, especially in high multi-path environments such as indoor or industrial environments.

TABLE III. SUMMARY OF DATA SETS

Parameters	Coverage		Radio Channel Characteristics				
	RS ^a	PD ^b	RS	PD	RS	PD	Sum
Base stations	2	2	1	1	1	1	2
Measurement sites	75	91	(41)	(47)	(34)	(44)	166
Parameter	RSSI [dB]		Path loss [dB]				
Auxiliary parameter	Location		Distance to serving base station [m]				

^a. Spectrum analyzer: Rohde & Schwarz (RS)

^b. Protocol-Dependent (PD) method, i.e. CENTRIA tool

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