Robust Channel Modelling of 2.4 GHz and 5 GHz Indoor Measurements: Empirical, Ray Tracing and Artificial Neural Network Models

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Abstract—Robust channel models for indoor areas are a crucial part of network planning and are immensely valuable for the small cell and indoor 5G network evolution. As the main input for many resource allocation and network planning problems, the accuracy of the path loss model can improve the overall accuracy of these techniques. Previous measurement campaigns exist for outdoor areas and higher frequencies, however extensive indoor measurements at these frequencies is missing from the literature. Both WLAN and LTE networks use 2.4 GHz and 5 GHz bands. For this work, indoor measurements were carried out in two distinct indoor environments, at two frequencies, and various models were compared. The measurements were made at the Deutsches Museum Bonn and the ICT cubes, an office space at RWTH Aachen University. Both empirical and deterministic models are tested on the data, the free space path loss model, the single and dual slope models with line-of-sight and non-line-of-sight, ray tracing models, and artificial neural network models were all tested and evaluated. Overall, the artificial neural network proved to be the most robust model which accurately predicted the propagation in the indoor environments, at both frequencies.

Index Terms—Propagation, 2.4 GHz, 5 GHz, measurements, indoor, artificial neural networks, ray tracing, channel modelling.

I. INTRODUCTION

In order to plan an effective wireless network for an indoor location, such as a museum or an office, a channel model is required to accurately model the path loss behaviour. With the increase in indoor mobile network users, the importance of efficient and accurate indoor channel modelling is of ever growing importance as the path loss model is an input to many resource allocation and network planning problems. Without such indoor modelling the resulting network planning may not result in useful or practical results. Indoor channels are particularly difficult to model due to the overwhelming number of reflections and obstructions which affect the path loss. Modelling the environment perfectly and taking each reflection into consideration would result in a computationally complex deterministic model. For example, to run ray tracing using the imaging method requires computing each reflection in a search space of $A^B$, where $A$ is the number of walls and $B$ is the number of reflections [1]. Simpler, empirical models do not require as much computation, and instead capture the major influences on the path loss. These kind of models can be particularly effective for short, line-of-sight (LOS) paths, but have difficulty with longer, non-line-of-sight (NLOS) paths. Finally, statistic models can offer the best of both worlds, as they are computationally simple and still offer accuracy and robustness based on the statistics of the data.

Other works have undertaken measurement campaigns and analysed their data to ascertain which models most accurately model reality, such as [2] and [3]. In [2], extensive outdoor measurements were done in the mmWave spectrum in New York City and Dallas. The paper analyses the data to find appropriate models, outage probabilities and other characteristics of the data. The work sets out to galvanize the already growing interest in mmWave networks. In [3] outdoor measurements were undertaken and ray tracing simulations were implemented to model this data. The paper finds ray tracing to be a powerful tool in the path loss prediction, with a lower mean error when compared to other models. However, they found the LOS paths were surprisingly hard to predict using these methods, likely due to the building shadowing and objects in the environment which were not accounted for in the model. As these, and many other, measurement campaigns took place outdoors, this work was inspired to do a similar analysis on indoor measurements.

As there is a general lack of indoor measurement data in the literature that researchers can use to test their own models, the majority of indoor propagation methods are assumed to work well either based on results from small measurement campaigns, or based on physics. The main contribution of this work is the following: Extensive indoor measurements at 2.4 and 5 GHz which are made publicly available on GitHub [4] for other researchers to access and test other models on. An analysis and parameterization of the empirical models which highlight the characteristics of the environment which impacted the attenuation most. The testing of deterministic and statistic channel models and the comparison of these, culminating in the development of a robust machine learning based channel model which can accurately predict the signal strength in different indoor environments without the need for new measurements to be made.

In this work, measurements were made in two distinct indoor environments at 2.4 GHz and 5 GHz. One set of
measurements was done in a museum and the other in an office building. All three types of models, empirical, statistic, and deterministic, are investigated and compared. The goal of this work is to find a robust channel model that accurately reproduces the measurements and can be applied to other indoor environments and at different frequencies to aid other researchers in the modelling of indoor networks. Additionally the data is made public so that other models can be applied and investigated. Robustness in this work refers to the applicability of a single model in both environments at both frequencies. In other words, we are looking for a model to perform well in all the test scenarios without requiring any of the measurement data from that scenario except the data required for the training of the initial model. Ideally, someone could use our model in a new indoor environment in the 2.4 GHz - 5.3 GHz range (WLAN and LTE frequencies) without having to make new measurements.

A. Paper Organization

In the following section, some background information on channel modelling and the link budget is presented. This includes an introduction to all the channel models investigated in this work. Following this, the data collection is presented and the two environments are described. The empirical models are parameterized next to demonstrate their efficacy and how the environment parameters affect the model. Next, the implementation of the ray tracing and machine learning based models are discussed in sections V and VI. All the results are compared and discussed in the next section. The paper is concluded in the final section.

II. BACKGROUND

All the models introduced in this work aim to calculate some path loss to predict the relationship between the distance between the transmitter and receiver antenna, the frequency at which the transmission is occurring, and the environment in which the transmission is taking place. Figure 1 shows the block diagram of the measurement system. The received power obtained from the model is then compared to the measurement data. What remains constant, regardless of the model is the transmission power and gain, thus we can define the received power in decibels (dB),

\[ P_{\text{Rx}} = P_{\text{Tx}} - L_{\text{Tx}} + G_{\text{Tx}} - L_{\text{path}} + G_{\text{Rx}} - L_{\text{Rx}}, \]  

(1)

where \( P_{\text{Tx}} \) is the transmitted power, \( G_{\text{Tx}} \) and \( G_{\text{Rx}} \) are the transmitter and receiver antenna gains, respectively, \( L_{\text{Tx}} \) and \( L_{\text{Rx}} \) are the losses at the transmitter and receiver, respectively, and finally, \( L_{\text{path}} \) is the loss due to attenuation. All these values depend on the frequency of transmission and are expressed in dB. The path loss \( L_{\text{path}} \) is the function that we will be attempting to model. It depends on the distance between the transmitter and receiver, the frequency of transmission, and the environment in which the transmission is taking place. The antenna gain at the transmitter is also a function which needs to be appropriately modelled. It depends on the antenna diagrams, which will be discussed further in the next section. In this case the receiver antenna has a 0 dBi gain and the receiver losses are considered noise in the system which is partially contained in the path loss model. In other words, any linear losses caused by the receiver, such as cable losses, are absorbed into the linear loss terms in the path loss model and any random error caused by the receiver, such as jostling of the receiver antenna changing its tilt, contributes to the random noise present in the system. This results in a received power of

\[ P_{\text{Rx}} = P_{\text{Tx}} - L_{\text{Tx}} + G_{\text{Tx}} - L_{\text{path}}. \]  

(2)

A. Empirical Models

1) Free Space Path Loss Model

The free space path loss model (FSPL) is the most widespread and common way to model the path loss \( L_{\text{path}} \) in Equation 1. The path loss \( L_{\text{FSPL}} \), in dB, is a function of frequency \( f \) and distance \( d \),

\[ L_{\text{FSPL}}(d,f) = 20 \log_{10}(d) + 20 \log_{10}(f) + 20 \log_{10}\left(\frac{4\pi}{c}\right), \]

where \( c \) is the speed of light [5]. This becomes,

\[ L_{\text{FSPL}}(d,f) = 20 \log_{10}(d) + 20 \log_{10}(f) - 147.55, \]  

(3)

when \( d \) is in meters and \( f \) in Hz.

2) Dual Slope Model

The dual slope (DS) model is an empirical model that assumes that a breakpoint distance \( d_{BP} \) exists, after which the attenuation increases at a faster rate. The motivation in using a dual slope model is that there are obstacles in the vicinity of the receiver which cause higher attenuation than the free space path loss model. Ray tracing and other deterministic models would be too complex, while an alternative empirical model may be too forgiving. Here, the alpha-beta-gamma (ABG) model is used [6],

\[ L_{\text{DS}}(d,f) = \begin{cases} 10\alpha_{1} \log_{10}(d) - \beta + 10\gamma \log_{10}(f), & 0 < d \leq d_{BP} \\ 10\alpha_{1} \log_{10}(d_{BP}) - \beta + 10\gamma \log_{10}(f) + 10\alpha_{2} \log_{10}\left(\frac{d}{d_{BP}}\right), & d > d_{BP} \end{cases} \]  

(4)

where \( \alpha_{1}, \alpha_{2}, \beta, \text{ and } \gamma \) are parameters which can be determined through the parameterization of the model using measurement data. This models the path loss \( L_{\text{path}} \) in Equation 1.
3) LOS/NLOS Model

In the LOS/NLOS, or multi-wall model [7], the losses due to distance and frequency are simply the loss calculated from the free space path loss model. Additionally, when there is no LOS from the transmitter to the receiver, a constant loss term is added to the path loss for each wall that the ray intersects. The magnitude of this loss is determined by the material through which the ray has passed. The path loss for an environment with \( W \) wall types is thus

\[
L_{\text{LOS/NLOS}} = L_{\text{FSPL}} + \sum_{i=1}^{W} n_i\sigma_i, \tag{5}
\]

where \( n_i \) is the number of walls of type \( i \in W \) that the ray passed through, and \( \sigma_i \) is the associated loss of wall type \( i \).

4) Dual Slope and LOS/ NLOS Model

Instead of using the free space path loss model for the loss due to distance and frequency in the LOS/ NLOS model, one can also use the dual slope model here [6]. The dual slope loss with walls can then be calculated as follows

\[
L_{\text{DSW}} = L_{\text{DS}}(f,d) + \sum_{i=1}^{W} n_i\sigma_i, \tag{6}
\]

B. Ray Tracing

Ray tracing is a deterministic approach to channel modelling which uses Maxwell’s equations. The rays between the transmitter and receiver are traced, thus including the reflections, refractions and diffractions of the rays in the model. Starting at the receiver, all rays are traced back to the transmitter based on image theory. Unlike ray launching, where all point-to-point rays are considered, as ray tracing only considers the rays from the receiver back to the transmitter, there is less computational effort. However, the more complex the environment, the more complex the ray tracing model becomes, making the run time of the model highly dependent on the complexity of the environment.

The rays are assumed to travel in a straight line, as long as the wavelength of the wave is smaller than the materials it reflects on. They follow radio propagation theory when interacting with objects in the environment and are considered to propagate and contain energy. Hence, there are three ways that the rays can interact with their environment, they transmit directly, reflect off or penetrate objects, or diffract and scatter. The direct transmission of rays is also known as LOS and is dealt with as such. When rays reflect off objects, the direction of the resulting ray is determined by the reflection and refraction properties of the material. The Fresnel equations are applied to calculate the magnitude of the resulting ray. Similarly, when rays penetrate through objects, the Fresnel equations, in combination with image theory are used to determine the magnitude and direction of the resulting ray. Finally, the diffraction and scattering of rays occurs at the edge of objects and are more complex to model.

The complexity of modelling diffraction becomes infeasible when there are many objects in the environment, which is the case for our case studies, and thus diffraction is not being modelled in this work.

C. Artificial Neural Networks

In general there are two methods widely used to model wireless channel models, the ones based on measurement data or the mathematical ones which describe the propagation characteristics of electric waves in a radio propagation environment. The first type of model, which is built based on measurement data, might not be robust to different environments, while the second method relies on simplifications and assumptions which may not provide the desired accuracy [8].

Due to these limitations, artificial neural networks (ANN), one of the types of machine learning based methods, can be designed to learn the propagation characteristics of wireless radio channels. The artificial neurons are inspired by biological neurons in the human brain and this technology has been widely applied in fields such as computer vision, voice recognition, data mining and autonomous driving. A database is required to train the ANN and the simulation is completed based on a flexible network architecture.

ANNs are capable of approximating the entire channel model by understanding the relationship between the propagation delay, the path loss, the physical parameters such as the distance between the transmitter and receiver, the operating frequency and the environment-based parameters [9]. ANNs can be generalized allowing them robustness to different frequencies or environments [10]. Nonlinear memoryless channels have also been modeled using ANNs [11], implying that ANNs are a viable solution for fast and accurate modeling of wireless channels.

Since there is measurement data to train the network, the path loss prediction is considered a supervised regression problem where the predicted receiver power is the output and the values of the environment are the input. The relationship between the input and output is considered a black box [12] determined using hidden layers of neurons. Research indicates that the complexity of these hidden layers does not guarantee improvements in the performance of the ANN [13].

The motivation behind using ANNs in this work is to determine whether it is possible to use a smaller training set to build a model that can predict the signal strength in a different environment and at a different frequency. The models investigated here are designed with the purpose of robustness and to show that a smaller measurement route can be sufficient to obtain accurate results in different scenarios. As the measurement data obtained here covers two different environments, with different wall materials and layouts, and different frequencies, it is a suitable data set to investigate this problem.

The important considerations when using ANNs to predict the propagation in these environments is the choice of input used. Section VI will investigate using the ray tracing model as input and predicting the received signal strength using
the environment parameters and FSPL. These sections will describe in more detail the input parameters used and tested.

III. DATA COLLECTION

![Antenna Diagram](image)

Fig. 2: Vertical Antenna Diagram for 5 GHz Antenna. The red patterns correspond to 4.90 - 5.00 GHz, the green and blue patterns correspond to 5.50 - 5.88 GHz.

The data was taken with the same equipment at two locations. The first set of measurements were taken in the Deutsches Museum Bonn (DMB). The museum is made up of a large open gallery, over two floors, with concrete columns and walls and a large space by the entrance that is divided into smaller sections. Before it was a museum, it was intended to be a swimming pool, which explains the open space in the centre. In total six measurement routes were made, summarized in Table I. There are two antenna positions for which measurements were made, ant pos 1 and ant pos 2, positioned at the centre column and on the right side of the balcony, respectively. The museum has two floors, the entrance level, which is also the gallery floor, referred to as UG 1 and the lower level, UG2. The height of the transmitter and receiver are defined from the lower floor.

The visualization of these measurements can be seen in Figure 3.

The second set of measurements were done on the third floor of the ICT cubes, an office building at the RWTH Aachen University. In this building, one extensive route was measured for 4 different scenarios, which are summarized in Table II. Two antenna positions were chosen, one in the corner office, ant pos 1, and one in the hallway in front of the kitchen, ant pos 2. The second antenna position allowed for many LOS data points, while antenna position 1 resulted in mainly NLOS data. The visualization of this data can be seen in Figure 4. Once the received signal strength fell below -100 dBm the measurement equipment could no longer take readings and thus the measurement routes end at different places.

A. Transmission Antenna

For the measurements, there were two transmission antennas used, one per frequency. The horizontal antenna diagrams of both antennas are considered omni-directional, and thus, can be assumed to be negligible. The vertical diagrams however have an impact on the antenna gain term in Equation 1. These diagrams are shown in Figures 5 and 2 for frequencies 2.4 GHz and 5 GHz, respectively. In the 5 GHz antenna pattern we are interested in the red curves as these correspond to the frequency range in which the measurements took place.

There are a number of ways to model the vertical affects on the antenna gains. One method is to directly use the losses from the diagrams. For this method the values were read off of these diagrams every 5° between 0° and 90°, and linear interpolation was used for values between the interval values. These diagrams are obtained under ideal conditions in a test chamber and may not be precise in practical use. For this reason another model was also investigated, the antenna model from the 3GPP Release 14 [14].

In the 3GPP Release 14, the attenuation is given as

\[
A(\theta) = - \min \left[ 12 \left( \frac{\theta}{\theta_{3dB}} \right)^2, A_m \right], \quad \theta \in [-180, 180],
\]

where \(\theta\) is the angle between the direction of interest and the boresight of the antenna, \(\theta_{3dB}\) is the 3 dB beamwidth in degrees, and \(A_m\) is the maximum attenuation. These values can be taken from the antenna diagrams and are \(\theta_{3dB} = 40°\) and \(A_m = 30\) dB for the 2.4 GHz antenna and \(\theta_{3dB} = 25°\) and \(A_m = 30\) dB for the 5 GHz antenna.

The receiver antenna had zero gain and the software responsible for recording the measurements took multiple readings per measurement point and averaged these out in order to reduce the local small scale fading effects.

IV. PARAMETERIZATION OF THE EMPIRICAL MODELS

In order to evaluate the data and determine which aspects of the model are integral to the performance of the resulting path loss model, the simple empirical models, such as the dual slope and LOS/NLOS models, will be tested and parameterized in this section. The goal of the parameterization is to find an appropriate model for the antenna gain as a function of the vertical angle between the transmitter and receiver, and the path loss as a function of distance, the environment, and the frequency.

The museum in which these measurements were taken include two wall types through which we took measurements, metal curtains in the gallery, and concrete walls throughout the space. The losses due to these wall types are defined as \(\sigma_m\) and \(\sigma_c\), respectively. The metal curtains, though curved, are approximated as straight line segments in all the models for consistency. The effect of the columns was also investigated and the attenuation due to the columns is defined...
TABLE I: Measurements Data Sets - DMB

<table>
<thead>
<tr>
<th>Antenna Position</th>
<th>Frequency/ GHz</th>
<th>Route</th>
<th>Height Tx/ m</th>
<th>Height Rx/ m</th>
<th>Gain/ dBi</th>
<th>Power/ dBm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ant Pos 1</td>
<td>2.442</td>
<td>Lower level (UG 2), around display cases and into small rooms</td>
<td>3.08</td>
<td>1.05</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>Ant Pos 1</td>
<td>5.180</td>
<td>Upper level (UG 1), around balcony</td>
<td>3.08</td>
<td>4.05</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>Ant Pos 1</td>
<td>5.180</td>
<td>Lower level (UG 2), around display cases and into small rooms</td>
<td>3.08</td>
<td>1.05</td>
<td>9.27</td>
<td>10</td>
</tr>
<tr>
<td>Ant Pos 1</td>
<td>5.180</td>
<td>Upper level (UG 1), around balcony</td>
<td>3.08</td>
<td>4.05</td>
<td>9.27</td>
<td>10</td>
</tr>
<tr>
<td>Ant Pos 2</td>
<td>2.442</td>
<td>Upper level (UG 1), around balcony and into all upper level rooms</td>
<td>5.30</td>
<td>5.05</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>Ant Pos 2</td>
<td>5.180</td>
<td>Upper level (UG 1), around balcony and into all upper level rooms</td>
<td>5.30</td>
<td>4.05</td>
<td>9.27</td>
<td>10</td>
</tr>
</tbody>
</table>

TABLE II: Measurement Data Sets - ICT cubes

<table>
<thead>
<tr>
<th>Antenna Position</th>
<th>Frequency/ GHz</th>
<th>Height Tx/ m</th>
<th>Height Rx/ m</th>
<th>Gain/ dBi</th>
<th>Power/ dBm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ant Pos 1</td>
<td>2.442</td>
<td>2.40</td>
<td>0.90</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>Ant Pos 1</td>
<td>5.320</td>
<td>2.20</td>
<td>0.90</td>
<td>9.27</td>
<td>10</td>
</tr>
<tr>
<td>Ant Pos 2</td>
<td>2.442</td>
<td>2.40</td>
<td>0.90</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>Ant Pos 2</td>
<td>5.320</td>
<td>2.20</td>
<td>0.90</td>
<td>9.27</td>
<td>10</td>
</tr>
</tbody>
</table>

as \( \sigma_{col} \), these are approximated as small squares instead of circles.

The materials that exist in the office building are: the plaster walls between the offices \( \sigma_p \), the weight bearing, steel enforced concrete walls \( \sigma_w \), the glass walls \( \sigma_g \), and the outer walls, which are predominantly glass as well. When parameterizing the model, a variety of different approaches and parameters were tried, tested and evaluated to choose an appropriate method. To evaluate the different approaches, the root-mean-squared error (RMSE) was used.

Starting with the free space path loss model as a benchmark, Figure 6 shows the FSPL results with a number of antenna loss models for the museum and Figure 7 the FSPL results for the ICT cubes. The models have been mean corrected, so that the trend can be isolated and compared. The LOS data is separated out in order to isolate the antenna gain more precisely, as the NLOS data has many other sources of attenuation which are not considered at this point.

In the museum data sets the mean-corrected FSPL without the antenna pattern considered has the lowest RMSE. In such an open space the reflections, especially off the metal curtains, are going to compensate for antenna losses. At the first data points and around measurement index 900 in the 2.4 GHz data one can see that the received signal strength is not as low as the antenna models predict. This is because when the LOS ray is in the side lobe, which is the case here, the NLOS rays which are reflecting off of surrounding objects are not taken into consideration.

In the ICT cubes, similar trends can be seen. However, here the antenna pattern loss from the diagram was a better fit to the data at 5.3 GHz.

Overall, the FSPL fits the data fairly well when there is LOS and when the data is mean-corrected. Curiously, taking the antenna diagrams into consideration did not consistently result in a better prediction. This is likely due to the strong specular reflections from the metallic surfaces resulting in multipath components that add constructively at the receiver.

Next, the wall attenuation and dual slope models are tested. To test the efficacy of the dual slope model the data was sorted by distance and plotted with respect to the received signal. If a clear breakpoint distance were present, the slope of these plots would increase after this distance. In all plots this phenomenon was not visible. The expectation was that, due to all the display cases and objects in the museum that are unaccounted for in the model, the rate at which the signal decays with respect to distance would increase. The data does not support this claim. This points to the fact that the reflections off of the show cases and metal curtains compensate for the need for a dual slope model. This again could be due to the metallic curtains, however in [15] it was determined that the dual slope model is appropriate for channel modelling in the presence of metallic obstructions. These results are not transferable to our case as the measurements are taken outdoors, however they also could indicate that the metallic curtains are not to blame for the lack of accuracy of the dual slope model in the museum. Instead of the material of the metal curtains causing the discrepancies, it could be a result of approximating the curved objects as straight lines.

Due to the non-linearity of the breakpoint distance variable, it is not optimized concurrently with the other parameters, and is found with all other parameters constant. One would expect the model with the breakpoint to perform better or equal to the model without, as it is the addition of a degree of freedom. Due to the constraints on the other parameters, and the fact that the breakpoint is optimized independently from the other parameters, this is not the case.
Fig. 3: Visualization of Measurement Data in Deutsches Museum Bonn. Blue walls represent metal curtains, black walls represent concrete walls, triangle represents transmitter position.

Table III compares the RMSE for a number of combinations of antenna diagram models and path loss models. For all except the 5.1 GHz NLOS data, the best overall RMSE occurs when the single slope model is used without taking the antenna diagram into consideration. The anomaly for the 5.1 GHz NLOS data set is presumably due to random noise in the data, as the difference between the otherwise optimal models and the 3GPP single slope model is only 0.16 dB.

In Tables IV and V a summary of the RMSE values for the 2.4 GHz and 5.1 GHz data is shown for the museum data. The FSPL model without mean correction is given for reference. Initially the dual slope model was parameterized using the data and at both frequencies handily outperformed the FSPL. The parameterization of the DS was improved upon by investigating the effects of the columns in the space, as the museum has many columns throughout the space. Again, the results at both frequencies improved. Finally, the LOS and NLOS was parameterized separately from one another, and this too resulted in improvements in the RMSE. As already
seen in Table III, the single slope model outperforms the other models. What is interesting is that when the single slope model was parameterized, the columns no longer played an important role and at both frequencies the attenuation due to the columns $\sigma_{col}$ was zero. The attenuation due to the metal curtains also was significantly lower.

The empirical and parameterized models tell us that for the DMB the reflections of the waves in the open space play a large role in the signal strength. The most important variables to determine the signal is the constant, linear term $\beta$ and the NLOS attenuation from the concrete walls. The other terms, such as the antenna losses, and the assumptions that the dual slope model makes were not appropriate in this location.

For the ICT cubes a similar analysis was done, a combination of antenna models and path loss models were compared, these results are in Table VI. Tables VII and VIII summarize the parameters for the ICT cubes for various models, the results are divided by frequency. The outer walls were also considered for NLOS but the linear loss for the outer walls was consistently close to zero, and when removed the RMSE was unchanged. Unlike in the museum, the dual slope model with the antenna diagram considered performs the best in the ICT cubes. There is one anomalous data set, the 2.4 GHz NLOS data has the lowest RMSE for the dual slope with no antenna diagram considered. Here the difference in RMSE is 0.08 dB, which is negligible. Based on these results the rest of the parameterization is done with the dual slope model and the antenna diagram considered. The breakpoint distance $d_{BP}$ was tested for values ranging from 20 m to 2 m and 5 m resulted in the lowest RMSE.

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Dual Slope with $d_{BP} = 5m$</th>
<th>Single Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.4 GHz LOS</td>
<td>5.48 4.57 5.14</td>
<td>3.60 6.12 4.57</td>
</tr>
<tr>
<td>2.4 GHz NLOS</td>
<td>5.70 5.65 5.61</td>
<td>5.36 6.13 5.51</td>
</tr>
<tr>
<td>5.1 GHz LOS</td>
<td>7.53 5.56 6.18</td>
<td>5.09 5.56 5.68</td>
</tr>
<tr>
<td>5.1 GHz NLOS</td>
<td>6.54 5.71 6.01</td>
<td>5.16 5.68 5.00</td>
</tr>
</tbody>
</table>

Table III: RMSE Values for combinations of antenna and path loss models - DMB
Fig. 5: Antenna Diagram for 2.4 GHz Antenna

Fig. 6: FSPL with and without antenna losses considered - DMB

The wall attenuation parameters for the ICT cubes are reasonable, the thicker walls $\sigma_w$ result in a higher attenuation than the thinner, plaster walls $\sigma_p$, while the glass walls $\sigma_g$ are negligible and can be removed from the model. The results demonstrate that the office space is more appropriately modelled by the dual slope model.

The fact that the same model cannot be applied to both scenarios with comparable accuracy indicates that these models are not robust to altering environments. As our goal is to find a more unifying model, the next sections will investigate other applicable models. The empirical models serve as an indication of the importance of different parameters and are overfit to this data.

V. RAY TRACING

In this section we discuss how the ray tracing model is used to predict the received signal strength. These models are evaluated based on their robustness and applicability.
RMSE without antenna pattern loss = 5.18,
RMSE with antenna pattern loss = 5.57,
RMSE with 3GPP antenna loss = 5.67.

Fig. 7: FSPL with and without antenna losses considered - ICT cubes

### TABLE IV: Parameterization Results - Deutsches Museum Bonn, 2.4 GHz Data

<table>
<thead>
<tr>
<th>Model</th>
<th>$\alpha_1$</th>
<th>$\alpha_2$</th>
<th>$\beta$</th>
<th>$\gamma$</th>
<th>$\delta_{BP}$</th>
<th>$\sigma_m$</th>
<th>$\sigma_c$</th>
<th>$\sigma_{col}$</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>FSPL</td>
<td>2</td>
<td>-</td>
<td>147.55</td>
<td>2</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>15.97</td>
</tr>
<tr>
<td>DS</td>
<td>2</td>
<td>4</td>
<td>148.06</td>
<td>2</td>
<td>5</td>
<td>3.56</td>
<td>7.03</td>
<td>-</td>
<td>5.46</td>
</tr>
<tr>
<td>DS cols</td>
<td>2</td>
<td>4</td>
<td>148.52</td>
<td>2</td>
<td>5</td>
<td>3.79</td>
<td>7.24</td>
<td>1.94</td>
<td>5.41</td>
</tr>
<tr>
<td>DS LOS / NLOS</td>
<td>2 / 2</td>
<td>4 / 4</td>
<td>144.79</td>
<td>2 / 2</td>
<td>5</td>
<td>-</td>
<td>- / -5.44</td>
<td>- / 0</td>
<td>4.57</td>
</tr>
<tr>
<td>SS LOS/NLOS</td>
<td>2</td>
<td>-</td>
<td>136.75</td>
<td>2 / 2.04</td>
<td>-</td>
<td>- / -5.69</td>
<td>- / 0</td>
<td>3.60</td>
<td>5.36</td>
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<td></td>
<td>2.62</td>
<td></td>
<td>145.60</td>
<td></td>
<td>0.21</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### TABLE V: Parameterization Results - Deutsches Museum Bonn, 5.1 GHz Data

<table>
<thead>
<tr>
<th>Model</th>
<th>$\alpha_1$</th>
<th>$\alpha_2$</th>
<th>$\beta$</th>
<th>$\gamma$</th>
<th>$\delta_{BP}$</th>
<th>$\sigma_m$</th>
<th>$\sigma_c$</th>
<th>$\sigma_{col}$</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>FSPL</td>
<td>2</td>
<td>-</td>
<td>147.55</td>
<td>2</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>12.17</td>
</tr>
<tr>
<td>DS</td>
<td>2</td>
<td>4</td>
<td>151.52</td>
<td>2</td>
<td>5</td>
<td>1.33</td>
<td>6.27</td>
<td>-</td>
<td>5.98</td>
</tr>
<tr>
<td>DS cols</td>
<td>2</td>
<td>4</td>
<td>152.38</td>
<td>2</td>
<td>5</td>
<td>1.65</td>
<td>6.71</td>
<td>2.95</td>
<td>5.81</td>
</tr>
<tr>
<td>DS LOS / NLOS</td>
<td>2 / 2</td>
<td>4 / 4</td>
<td>149.11</td>
<td>2 / 2</td>
<td>5</td>
<td>- / -4.91</td>
<td>- / 0</td>
<td>-</td>
<td>5.56</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>-</td>
<td>135.85</td>
<td>2 / 2</td>
<td>-</td>
<td>- / -4.09</td>
<td>- / 0</td>
<td>5.09</td>
<td>5.16</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>132.68</td>
<td></td>
<td>0.21</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### TABLE VI: RMSE Values for combinations of antenna and path loss models - ICT cubes

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Dual Slope with $d_{BP} = 5\text{m}$</th>
<th>Single Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dual Slope</td>
<td>Single Slope</td>
</tr>
<tr>
<td></td>
<td>Diagram</td>
<td>3GPP</td>
</tr>
<tr>
<td>2.4 GHz LOS</td>
<td>6.70</td>
<td>4.74</td>
</tr>
<tr>
<td>2.4 GHz NLOS</td>
<td>5.40</td>
<td>4.74</td>
</tr>
<tr>
<td>5.3 GHz LOS</td>
<td>7.29</td>
<td>4.66</td>
</tr>
<tr>
<td>5.3 GHz NLOS</td>
<td>4.93</td>
<td>4.88</td>
</tr>
</tbody>
</table>

1) **Ray Tracing in DMB and ICT cubes**

The implementation of ray tracing used considers three propagation phenomena, the direct transmission (LOS propagation), rays reflecting up to two times, and transmission through blocks. Only two reflections are considered, because the complexity of the environments considered here would cause infeasible run times with more reflections. Additionally, in [16] it was shown that increasing to six reflections only improved the performance by at most 1 dB.

The effects on the propagation due to reflections and transmissions through materials are calculated using the reflection and transmission coefficients [17]. For these calculations the incident angle between the transmitter and receiver and the relative permittivity of the materials is required and will be further discussed in the following section. The FSPL is also required for LOS transmission where the distance between the transmitter and receiver exceeds one meter. The antenna loss is considered using the antenna diagrams, as discussed previously. To evaluate the results from the model and compare the robustness to different environments, the RMSE is used as the performance metric.
TABLE VII: Parameterization Results - ICT cubes - 2.4 GHz data

<table>
<thead>
<tr>
<th>Model</th>
<th>(\alpha_1)</th>
<th>(\alpha_2)</th>
<th>(\beta)</th>
<th>(\gamma)</th>
<th>(d_{\text{BP}})</th>
<th>(\sigma_p)</th>
<th>(\sigma_w)</th>
<th>(\sigma_g)</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>FSPL</td>
<td>2</td>
<td>147.55</td>
<td>2.00</td>
<td>-</td>
<td>2.22</td>
<td>5</td>
<td>1.00</td>
<td>0.33</td>
<td>5.78</td>
</tr>
<tr>
<td>DS</td>
<td>3.60</td>
<td>157.10</td>
<td>2.14</td>
<td>-</td>
<td>2.46</td>
<td>2.79</td>
<td>-</td>
<td>-</td>
<td>4.78</td>
</tr>
<tr>
<td>DS LOS / NLOS</td>
<td>3 / 2</td>
<td>3.00 /</td>
<td>155.93 /</td>
<td>2.02 /</td>
<td>5 - / - / - / -</td>
<td>0.33 /</td>
<td>5.78 /</td>
<td>4.74 /</td>
<td>5.48</td>
</tr>
</tbody>
</table>

TABLE VIII: Parameterization Results - ICT cubes - 5.3 GHz data

<table>
<thead>
<tr>
<th>Model</th>
<th>(\alpha_1)</th>
<th>(\alpha_2)</th>
<th>(\beta)</th>
<th>(\gamma)</th>
<th>(d_{\text{BP}})</th>
<th>(\sigma_p)</th>
<th>(\sigma_w)</th>
<th>(\sigma_g)</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>FSPL</td>
<td>2</td>
<td>147.55</td>
<td>2.00</td>
<td>-</td>
<td>2.01</td>
<td>5</td>
<td>1.86</td>
<td>3.18</td>
<td>4.88</td>
</tr>
<tr>
<td>DS</td>
<td>4.19</td>
<td>158.36</td>
<td>2.01</td>
<td>-</td>
<td>1.86</td>
<td>3.18</td>
<td>-</td>
<td>-</td>
<td>4.66</td>
</tr>
<tr>
<td>DS LOS / NLOS</td>
<td>3.00 / 2</td>
<td>160.28 / 2</td>
<td>2.03 / 5</td>
<td>- / - / - / - / -</td>
<td>0.33 / 5.78</td>
<td>1.86 / 3.18</td>
<td>- / 0</td>
<td>4.66 / 4.88</td>
<td></td>
</tr>
</tbody>
</table>

\(a)\) Environment Parameters

As previously mentioned, the parameters defining the environment play an important role in ray tracing. This includes the layout, which gives information about where all the walls, doors and columns are located, and the information about the materials. First, all walls and objects had to be approximated with straight lines, since curved objects are not permissible. The walls are defined as line segments with Cartesian coordinates defining the start and end points of the walls. Next, the mesh size, or sampling resolution needs to be defined. The number of sampling locations is the length of the boundary divided by the mesh size. The boundary sizes for the two measurements are 80 m \(\times\) 50 m \(\times\) 3 m and 70 m \(\times\) 35 m \(\times\) 6 m for the ICT cubes and DMB, respectively.

The permittivity of the materials in the environments are required in order to calculate the transmission and reflection coefficients. The higher the permittivity of a material, the more difficult it is for the ray to penetrate the material, so for example, concrete, load-bearing walls have a high permittivity. Since the permittivity of the materials was not determined during the measurement campaign, these values need to ascertained from literature and appropriately adjusted when necessary. The materials and permittivities used are summarized in tables IX and X.

Finally, the reflection and transmission rays need to be determined using image theory. The projection from the transmitter on each plane is calculated based on the line-plane intersection rule [18], which takes into consideration the normal of the wall. If we assume a plane with a group of points \(P\) and \(P_0\) is a point on the incident place, and \(n\) is the normal vector to that plane, then the vector equation for a line is

\[
(P - P_0)n = 0,
\]

where \(P\) is the point on the plane, and \(n\) is the normal vector to the plane, then the vector equation for a line is

\[
P = l_0 + dl,
\]

where \(d\) is a real valued scalar, \(l\) is a vector in the direction of the line, and \(l_0\) is a point on the line between the transmitter and receiver. The transmission projection on the plane can thus be found with

\[
d = \frac{(P_0 - l_0) \times n}{l \times n}.
\]

The reflection rays can be found by mirroring the transmission on each plane and calculating the second image of the transmission ray across the wall, based on the first image. This step is computationally expensive and the reason why allowing too many reflections becomes infeasible.

VI. ARTIFICIAL NEURAL NETWORKS

In this section two different applications of ANNs are investigated. First, an ANN ray tracing hybrid (ANN-RT) is designed which uses an error correction algorithm to improve the previous ray tracing results. Second, an end-to-end ANN is designed which predicts the received signal strength based on training on one of the measurement data sets.

A. ANN-RT

With the large amount of available data it is possible to train and test an ANN, specifically the multi-layer perceptron (MLP) to achieve a more robust channel model. The ray tracing model from above is used to produce parameters which can be used as inputs for the ANN.

1) Network Architecture

After testing various network architectures, the resulting architecture was chosen based on its generalization and accuracy, Figure 8.

![Fig. 8: ANN Network Architecture for Ray Tracing input](image-url)
During the learning process the network can adjust the input parameters via the selected number of weights and biases and the goal is the minimization of the RMSE. The data is split into an input, or learning set, which comprises of 80% of the data, and the remaining 20% are used for testing. In addition to testing different network architectures, a number of training algorithms were also tested, the Levenberg-Marquadt algorithm with back-propagation [13] was determined to be the most appropriate algorithm in terms of accuracy. It also has a fast training speed, at less than 20 epochs when implemented in MATLAB 2019b. All the inputs were normalized to within [-1,1].

2) Training Algorithm

In most of the regression problems used for channel modelling, the output of the model is the received signal strength. Intuited by the error-prediction method from [19], [20], the ANN model developed here was trained to minimize the error between the ray tracing model and the measured values. The error from the ray tracing model $E_{RT}$ can be expressed as

$$E_{RT} = \text{RSS}_{RT} - \text{RSS}_{meas},$$

where $\text{RSS}_{RT}$ is the output from the ray tracing model and $\text{RSS}_{meas}$ is the measurement data. In other words, the ANN was designed to compensate for the deficiencies of the existing ray tracing model instead of learning the entire wave propagation mechanism. In the first step the network estimates the error between the data and the ray tracing model $E_{NN}$, this error is added to the ray tracing model, generating a hybrid RSS prediction with ANN,

$$\text{RSS}_{hybrid} = \text{RSS}_{RT} + E_{NN}.$$  

The network compares the RSS from the hybrid model $\text{RSS}_{hybrid}$ with $\text{RSS}_{meas}$ and tunes $E_{NN}$ with the given inputs to minimize this value. Figure 9 illustrates how the ANN model is trained, the input includes the indoor layout with the corresponding material parameters, transmitter positions and characteristics (frequency, power, etc.), and the measurement data. After the ray tracing model has processed this data, the output is fed to the ANN and compared to the measurement data to error correct the model. After the training of the network has taken place, Figure 10 shows how the hybrid ANN model is implemented.

To determine which data sets should be used for training and which input data to use for the training, a number of options were tested and evaluated based on their accuracy, computational speed, and robustness. The following input feature vectors were tested:

- relative permittivity and incident angle in form of Fresnel equation
- distance between transmitter and receiver, and frequency in form of FSPL
- antenna loss
- LOS information, reflections and diffractions
- relative position between transmitter and receiver $(x_{Tx} - x_n, y_{Tx} - y_n)$, where $x_{Tx}, y_{Tx}$ are the coordinates of the transmitter and $x_n, y_n$ are the coordinates of the $n^{th}$ data point.

The final input parameters which had the largest, positive impact on the results were the relative positions, the transmission coefficient and the distance between the transmitter and receiver.

B. Predicting Received Signal Strength with ANN

The results from the simpler, statistic model, the dual-slope multi-wall model, are consistently better than those from the more complex ray tracing model. As was discussed previously however, the model was fine tuned and carefully parameterized to the different frequencies and environments, making it less robust than other models. The idea here is to use an ANN to compensate for this and create a robust and more accurate model that does not require network planners to do extensive measurements in order to get a usable channel model for a new indoor environment.

1) Network Architecture

Unlike the ANN-RT model, this is not an error correction model. Instead, the model directly predicts the receiving signal strength. This is to avoid the added work of parameterizing a model for a new environment, which would always require measurement data. After testing a number of different architectures, the resulting architecture used for this model is shown in Figure 11. In order to solve the linear regression problem, the first hidden layer is activated by a linear function, the second using a sigmoid function, and the output layer is activated by a linear function. These were all extensively tested and this architecture resulted in the most stable output, especially when testing for robustness in different environments.

As before, 80% of the input data was used to train the algorithm and 20% was used for testing. The training process ends when the error between the network output and the
measurement value is minimized. The network learns by adjusting the weights and biases until this goal is achieved. The learning algorithm is based on the Levenberg-Marquardt algorithm with back propagation and was implemented in MATLAB 2019b.

2) Training Algorithm

The network was trained using only data at 2.4 GHz in the ICT cubes. This model was then used on the higher frequency data and the data from the museum to test the robustness of the model.

To find the input features which had the largest, positive effect on the output, many features were tested.

- Distance: the inputs tested were the pure distance values and $10 \log(\text{distance})$
- FSPL
- Antenna loss: the inputs tested were the antenna angle and the antenna loss using the antenna diagrams
- Walls: the inputs tested were the number of walls between the transmitter and receiver, and the total attenuation due to the walls for each data point.

These features were tested separately and in numerous different combinations until the most stable and accurate output was achieved. This output occurred when the input features included all of the above except the antenna loss.

The input values can all be attained through having information about the environment, except the wall attenuation. This is the only value that would either require some measurement work, which we want to avoid, or they need to be taken from literature. Luckily, for most building types and materials these values are available in literature. As we have determined previously however, the environment in which the material exists also makes a difference. The walls in the museum and the walls in the ICT cubes behaved quite differently because the museum was a much more open space where more reflections could dominate the signal strength, while in the office space there were more walls, resulting in a lower attenuation per wall.

The wall attenuation used is shown in Table XI. These attenuation values were found using a similar method as before with the parameterization, except that instead of optimizing over the dual or single slope models, the FSPL model was used, equation 5.

VII. Model Comparisons and Evaluation

In order to compare all the techniques, Table XII and XIII summarize all the results. The ANN models were trained using the 2.4 GHz data from the ICT cubes at both transmitter positions. After the training, the models were applied to the 5.3 GHz data from the ICT cubes and all the data from the museum.

Using ANN for the linear regression resulted in the best overall results in terms of robustness. If an accurate channel model for an indoor is required, this model is the easiest to apply to the environment without requiring any measurements to be made. However some assumptions need to be made about the materials in the environment as the wall attenuation is vital for the model.

The parameterized model provides insight into the effects of different frequencies, materials and spaces and is always a good option when there is a large set of measurements to investigate. These models provided the best results in terms of RMSE, however the parameters ascertained are specific to each environment, and the data we have collected, and are not necessarily transferable to other environments or data sets.
TABLE XI: Wall Attenuation

<table>
<thead>
<tr>
<th>Frequency / GHz</th>
<th>DMB</th>
<th>ICT cubes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\sigma_m$</td>
<td>$\sigma_c$</td>
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<tr>
<td>2.44</td>
<td>4.47</td>
<td>8.59</td>
</tr>
<tr>
<td>5</td>
<td>1.63</td>
<td>5.54</td>
</tr>
</tbody>
</table>

TABLE XII: Model Results for DMB

<table>
<thead>
<tr>
<th>Frequency / GHz</th>
<th>Antenna Position</th>
<th>Floor</th>
<th>RMSE Ray Tracing / dB</th>
<th>RMSE ANN-RT / dB</th>
<th>RMSE ANN / dB</th>
<th>RMSE Parameterization / dB</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.44</td>
<td>Ant Pos 1</td>
<td>UG 2</td>
<td>5.87</td>
<td>5.65</td>
<td>4.77</td>
<td>5.60 (LOS)/ 5.36 (NLOS)</td>
</tr>
<tr>
<td></td>
<td>Ant Pos 2</td>
<td>UG 1</td>
<td>4.82</td>
<td>4.50</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5.18</td>
<td>Ant Pos 1</td>
<td>UG 2</td>
<td>6.38</td>
<td>6.16</td>
<td>5.33</td>
<td>5.09 (LOS)/ 5.16 (NLOS)</td>
</tr>
<tr>
<td></td>
<td>Ant Pos 2</td>
<td>UG 1</td>
<td>5.89</td>
<td>5.62</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

TABLE XIII: Model Results for ICT cubes

<table>
<thead>
<tr>
<th>Frequency / GHz</th>
<th>Antenna Position</th>
<th>RMSE Ray Tracing / dB</th>
<th>RMSE ANN-RT / dB</th>
<th>RMSE ANN / dB</th>
<th>RMSE Parameterization / dB</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.44</td>
<td>Ant Pos 1</td>
<td>7.15</td>
<td>Training Set</td>
<td>Training Set</td>
<td>4.74 (LOS)/ 5.48 (NLOS)</td>
</tr>
<tr>
<td></td>
<td>Ant Pos 2</td>
<td>6.21</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5.32</td>
<td>Ant Pos 1</td>
<td>8.61</td>
<td>5.19</td>
<td>5.10</td>
<td>4.66 (LOS)/ 4.88 (NLOS)</td>
</tr>
<tr>
<td></td>
<td>Ant Pos 2</td>
<td>7.69</td>
<td>5.68</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Overall the ray tracing models that were tested did not perform well. It is a complex model which performs better if the space is empty, or the model defines all the objects in the space. Both of the spaces where the measurements were taken were full of objects and furniture, which were not considered in the model. If these objects had been considered, the complexity of the model would have been too high to achieve realistic run times.

The results of the ANN-RT model show that even when the network is trained on data from a different environment and at a different frequency, it consistently improves the results from the ray tracing model. The most impressive improvement occurs when the environment is the same but the frequency is different. This is not surprising as the transmission coefficient is dependent on the frequency, so the features unique to different frequencies are already determined and differentiated by the ray tracing model. However, despite the indoor layout also being defined, a lot of features that change from one environment to another are more difficult to be explicitly determined as a feature which can be learned by the ANN from one environment and appropriately adjusted for a different environment. The results for the DMB are still improved however, especially the 5.18 GHz RMSE from ant pos 2 on UG1 is significantly improved upon by the ANN.

Especially in regions where the ray tracing was weaker, i.e. where there was NLOS, the benefits from the ANN can be witnessed. The runtime is not largely improved upon as the ray tracing model still needs to be run as a part of the hybrid model. If however the ray tracing model is going to be run anyways, then the hybrid model is a good addition to improve the accuracy.

VIII. Conclusion

In this work two measurement campaigns were undertaken and the resulting data was analysed to ascertain which model could accurately and robustly reproduce the channel characteristics so that future channel models can be accurately made in indoor environments without the need for measurement data. The measurement campaigns took place in an old swimming hall which has been converted to a museum, and a modern office building at 2.4 and 5 GHz. We found that the ANN channel model was able to model the structures present in these environments (columns, thick and thin walls, large open spaces, glass walls, and curved metal objects, to name a few) appropriately. For drastically different indoor structures, such as a tapered theatre or stadium environment, the applicability of these results would need to be ascertained with a new data set.

From the implementation of ray tracing and machine learning algorithms we learned the importance of the materials in the space and the corresponding attenuation losses associated with these materials. The overall most robust model for the indoor measurements was the ANN network that directly predicted the received signal strength. Having been trained only on the office space data at 2.4 GHz, the model out-performed the other two models and came the closest to the parameterization results. To implement this model in a new indoor environment the distance between transmitter and receiver, the number of walls blocking the path, the overall wall attenuation and the FSPL is required. Except for the wall attenuation, these are all values which are known about a space, and the wall attenuation can be found in literature for most materials. Additionally, curved walls or objects can be approximated as straight segments as in the case of the metal curtains and the columns in the museum.

In future research it would be interesting to test the
ANN results from this paper on significantly higher or lower frequency ranges. As robustness in this paper refers to the frequency range and environments studied in this work, it would be valuable to test the robustness on a larger scale.

ACKNOWLEDGMENT

The authors would like to thank Huiting Qin for her help with the implementation of the models, Ms. Niehaus from the Deutsches Museum Bonn and the RWTH Aachen for their cooperation with us to do our measurements and the permission to publish abstractions of their buildings. We are very grateful to brown-iposs for supplying the measurement equipment and specifically, we thank Johannes for setting up the equipment and Eckhard for providing his expertise and experience. Finally, thanks to the funding from the German Federal Ministry of Economic Affairs and Energy through the BIC-iRaptor project (project number 16KN052730) we were able to perform the two measurement campaigns, thank you.

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