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# Application of Machine Learning Algorithms in Wireless Connections at Higher Frequency Bands

Thesis Booklet

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# 1 Introduction

My research focuses on the theoretical background necessary to address certain current challenges in radio communication, as well as the exploration of potential solutions through the application of machine learning. In modern technology, wireless connectivity is being increasingly employed across various domains, often necessitating the utilization of additional frequency bands. This necessity arises from the fundamental fact that the characteristics of radio links can typically be optimized along two strategic directions. One approach involves improving channel transmission by selecting more advanced modulation and coding schemes or enhancing interference protection between individual antennas. The alternative strategy entails employing additional frequency bands, which, in many cases, are still novel in their respective applications—often at the expense of limiting or blocking other potential uses of the spectrum.

In the millimeter-wave frequency range, two major applications stand out: the deployment of next-generation mobile communication networks to support a higher number of users and achieve higher data transmission rates, as well as satellite communications, where the key challenge remains maximizing the volume of transmitted data.

However, the utilization of higher frequency bands, such as those in the millimeter-wave range, presents a variety of challenges due to the fact that the wavelengths of the electromagnetic waves become comparable to the dimensions of environmental structures. Consequently, communication links are significantly affected by reflections, severe attenuation, and fading effects. Moreover, path loss increases proportionally with distance, necessitating the use of highly directional antennas for efficient communication. In outdoor scenarios, weather conditions—particularly precipitation—can induce substantial variations in signal attenuation. Meanwhile, reflections and antenna directivity in indoor environments introduce additional complexities for practical deployment.

In my research so far, I have addressed two key theoretical problems. In indoor applications, I have investigated methods for mitigating the challenges posed by moving users while striving to maximize data throughput. In outdoor applications, my focus has been on predicting and mitigating the adverse effects of atmospheric variations on channel attenuation, which can significantly impact communication reliability.

# 2 Thesis Group 1: Models Related to Signal Propagation

Machine learning algorithms require large amounts of data; the number of required training samples can easily reach millions. If this amount of data cannot be obtained through measurements within an acceptable time frame, simulation must be used.

I also encountered this problem during my research on indoor wave propagation. In order to solve it, I developed procedures that each constitute a separate thesis.

## 2.1 Thesis 1: Improved Model for Indoor Propagation Loss for mmWave

I aimed to understand how signal levels evolve in indoor environments and to develop a model suitable for machine learning applications.

Based on my observations, I constructed a model that:

- includes only measurable parameters,
- accounts for antenna directivity,
- can describe the propagation environment even when antennas are not directly facing each other.

By analyzing and improving existing models, I developed my enhanced model [1]. The following model was found to be the most suitable for the previously stated goals in terms of use:

$$P_L = 63.76 + 20.3 \cdot \log_{10}(d) + F(\vec{r}) + G(\alpha, \beta) + C, \tag{1}$$

where

- $P_L$ is the loss,
- $d$ is the distance in meters,
- $F$ is the relative environment function, which is a function of location ($\vec{r}$ is the location vector),
- $G$ is the attenuation due to the directivity of the two antennas and
- $C$ is the specification of the constant in the ITU recommendation (ITU-R P1238 2019).

Several other functions (non-linear, etc.) were tested to obtain the result; however, only the best-performing result was presented due to lack of space. Most of the variations involved using nonlinear function variables with the same components. At 38.72 GHz, I got the following:

$$P_L = 63.76 + 20.3 \cdot \log_{10}(d) + 15 \cdot \hat{F}_{adv}(\vec{r}) + 20 \cdot \sqrt{(\alpha + \beta)} + C, \tag{2}$$

where

$$\hat{F}_{adv}(\vec{r}) = \frac{\sum_{n=1}^{N} t(n,k)}{N}, \tag{3}$$

where the auxiliary function takes the following form:

$$t(n,k) = \begin{cases} 1, & \text{if } |(f(n,k))| > |k| \ , \\ 0, & \text{otherwise,} \end{cases} \tag{4}$$

where

- $||$ is the absolute value symbol,

- $f()$ is the power at the given receiving point,
- $k$ is the chosen power limit,
- $n$ is the number of discrete directions,
- and $N$ is the last index.

The effectiveness of my model should be compared with the baseline ITU model(ITU-R P1238 2019, which was the best model at that time), shown in Figure 1. I have successfully created a highly accurate model. Compared to the best existing model, the following differences can be observed:

- The values correctly estimated by the original model did not change meaningfully.
- The absolute deviation from the measured values has decreased by approximately 10 dB, down from the previous 40 dB.
- The error of the obtained results decreased by 70%–80% compared to the baseline case, depending on the specific test scenario.
- Correct results are obtained even at points close to reflective surfaces.
- The most significant improvement is observed at points near the antenna plane with a large angular deviation from the central axis. However, in these cases, the error remains relatively higher compared to other points.

If we exclude these interpolated values from the simulated results, the minimum accuracy increases to approximately 84%.

**Thesis 1**

I developed an indoor signal propagation model for the gigahertz range, which takes into account the distance between devices, the angle between antennas, and the reflective properties of the environment.

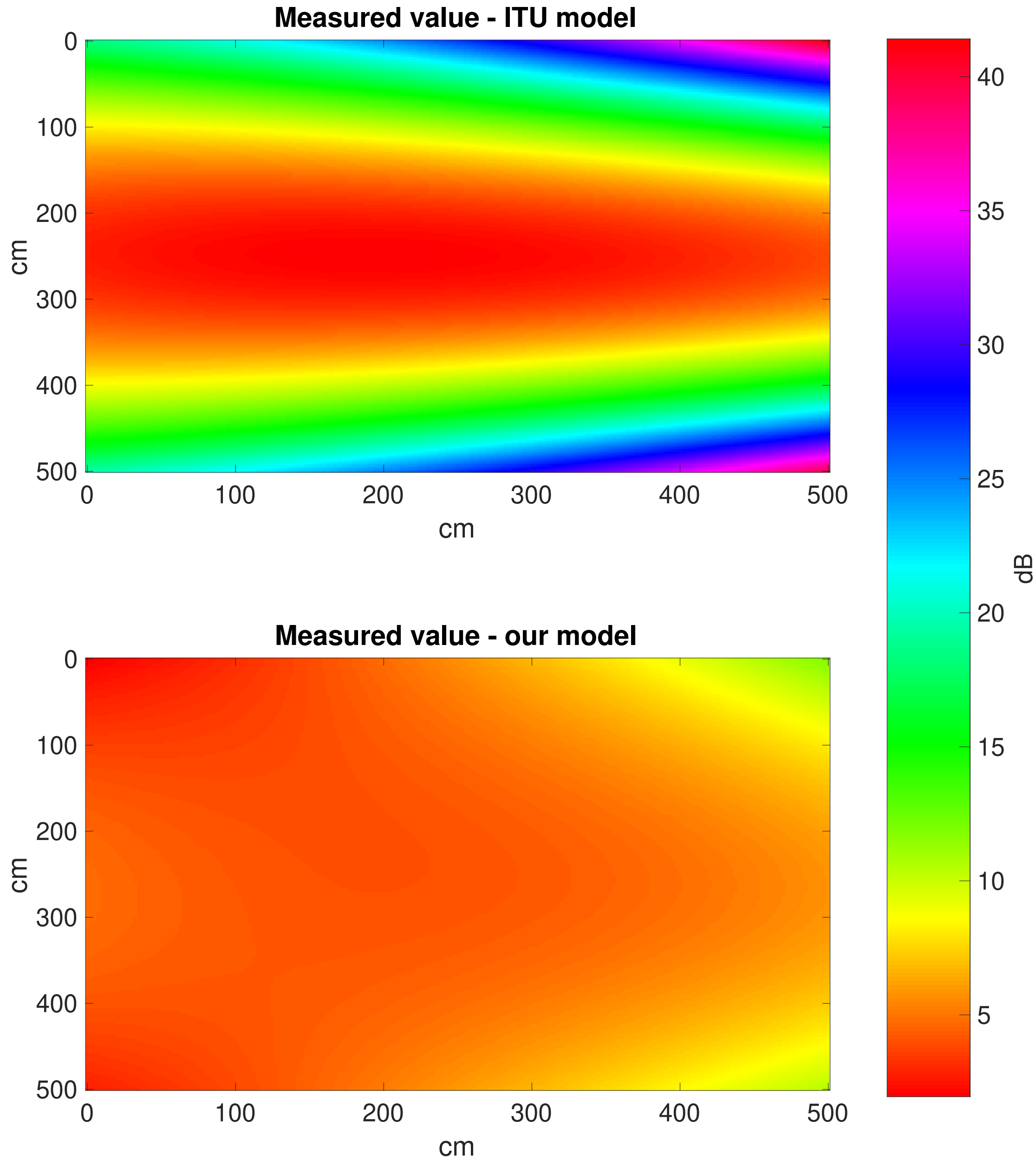


Figure 1: Difference between the measured and modeled values in dB. Linear interpolation between two measurement points was applied. The dimensions of the room are expressed in centimeters. The transmitting antenna is located on the right side of the room/figure, in the middle (at the boundary), which represents the edge of the calculation domain, although the wall behind it was approximately 30 cm away. The depicted plane was located approximately 140 cm above the ground level. 3 walls of the room are heavily glassed. The furnishings were appropriate for a small university classroom. On the wall opposite the antenna, most of the wall was just a traditional classroom blackboard.

# My Publications Related to This Thesis

[1] Á. L. Makara and L. Csurgai-Horváth, 'Improved Model for Indoor Propagation Loss in the 5G FR2 Frequency Band,' *Infocommunications Journal*, vol. 13, no. 1, pp. 2–

10, 2021, ISSN: 20612079. DOI: 10.36244/ICJ.2021.1.1. Accessed: 27th Dec. 2022. [Online]. Available: https://www.infocommunications.hu/2021_1_1.

## 2.2 Thesis 2: Modeling of a Moving User

Originally, my plan was to develop a user movement modeling approach for indoor signal propagation problems. The underlying idea was that if users do not significantly influence the electromagnetic field, then simulating a static field should be sufficient. In this case, the dynamic behavior would be introduced by individual users moving within this precomputed field. As long as user movement does not alter the field more than the inherent noise level, the model remains valid. This approach ultimately allows for a faster simulation, facilitating the generation of large datasets.

I have examined various approaches to generating random progress, each based on well-established mathematical and physical principles, to develop my own model. Some of the most widely used methods include Brownian motion, Monte Carlo simulations, random walks, Markov chains, and the Langevin equation, among others.

The developed method has surpassed its original objective and now enables the modeling of arbitrary users in arbitrary environments [2]. This is achieved by decomposing all movement into two components: one proportional to the static field and another corresponding to the user's individual behavior.

The main steps of my procedure:

1. Map the simulated space onto a two-dimensional graph. The points of the graphs are a discretised representation of the area to be covered.

2. Construct the environment-generated Markov chain as shown in Figure2. Several considerations are used to calculate the environmentally proportional tag. In general, we can calculate the ratio of the available space to the displacement possibilities. The rationale behind this is that a user will tend to spend more time in general where there is more space, i.e., move more in that direction.

3. Generate a user movement profile for each user, as illustrated in Figure3. Incorporate memory by tracking the user's direction in relation to their current direction.

4. Using the user movement behavior profile (MBP), generate a Markov chain for each arrival direction.

The prepared Markov chains can be used to model motion as follows:

1. Select a user and the corresponding Markov chains. Start from every possible point.

2. Depending on the direction from which the user arrived at the new state according to the MBP, choose the appropriate Markov chain, along with the necessary elements for transition determination.

3. Repeat the process until the simulation concludes.

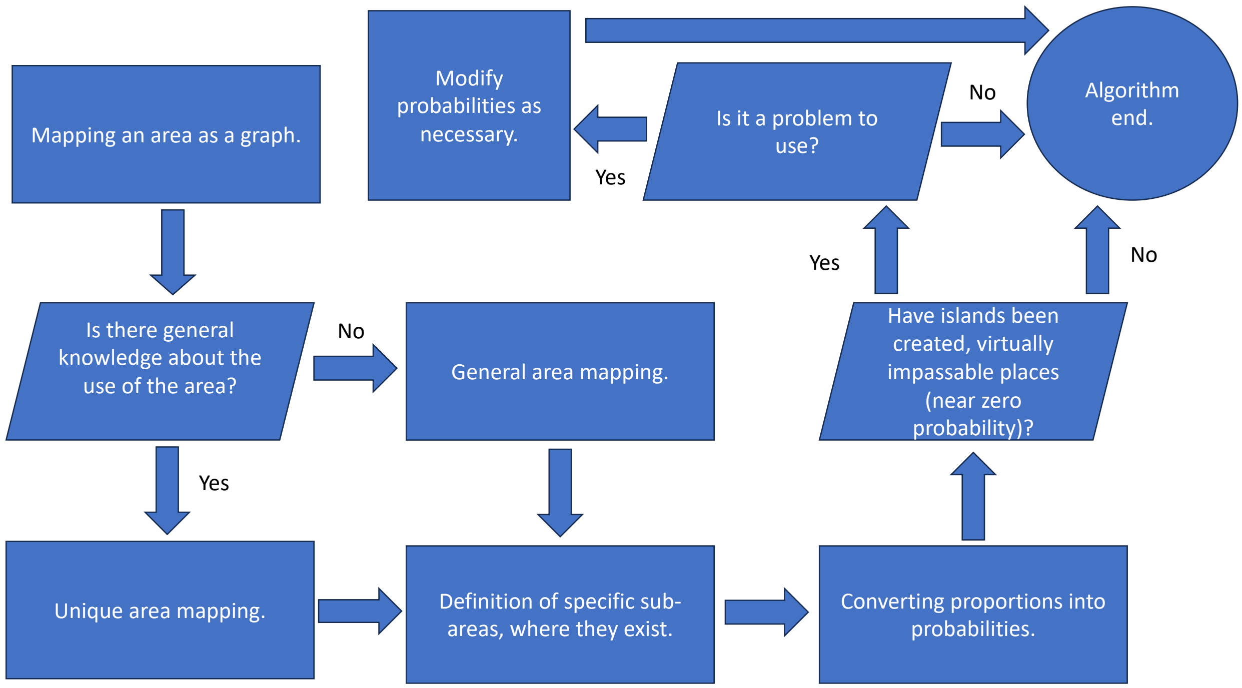


Figure 2: The main steps in mapping an arbitrary space. The process can be used both indoors and outdoors.

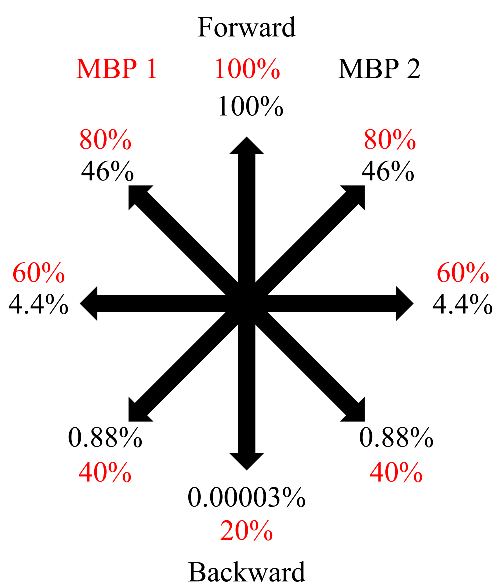


Figure 3: Two MBP examples.Top view diagram. Staying in place is not indicated in the figure. The selection of each value depends on the movement to be simulated. It is not necessary to choose the individual values symmetrically.

The algorithm can be used to represent a huge variety of upward movements. An extracted example is shown in Figure4. Each step of the algorithm can be executed in constant time. Therefore, the algorithm's runtime complexity is $O(n)$, with a lower memory requirement than would be needed for a more complex Markov chain:

- It is well parameterizable, with enough variation to generate data.
- It can be used for both static and dynamically changing spaces.
- Its computing capacity is acceptable for generating large amounts of data.

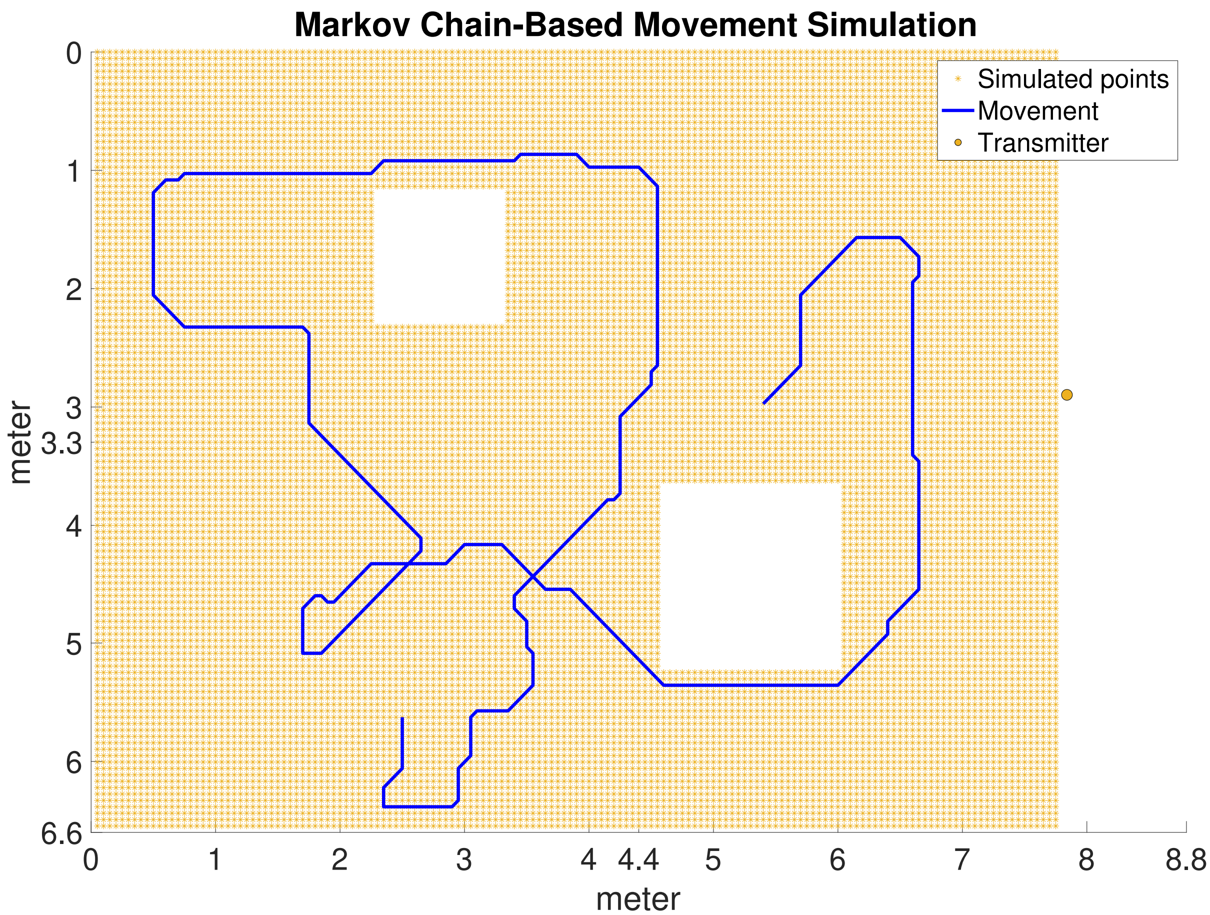


Figure 4: Movement modeling. The white color indicates columns made of a similar material to the walls of the room. Used MBP: [40 4.6 0.044 0.00088 0.0000003 0.00088 0.044 4.6] (displayed without normalization, as this makes it easier to interpret), where the values correspond to the following directions: forward, forward left, left, backward left, backward, backward right, right, and forward right. Standing still was not allowed, with forward movement occurring in every discrete time step. Room identifier: A1.

**Thesis 2**

I created a Markov chain-based motion modeling algorithm that can be used to generate freely parameterizable random user movements in any given environment.

## My Publications Related to This Thesis

[2] Á. L. Makara and L. Csurgai-Horváth, 'Indoor User Movement Simulation with Markov Chain for Deep Learning Controlled Antenna Beam Alignment,' in *2021 International Conference on Electrical, Computer and Energy Technologies (ICECET)*, Cape Town, South Africa: IEEE, Dec. 2021, pp. 1–6, ISBN: 9781665442312. DOI: 10.1109/ICECET52533.2021.9698600. Accessed: 27th Dec. 2022. [Online]. Available: https://ieeexplore.ieee.org/document/9698600/.

# 3 Thesis group 2: DNN-Based Antenna Direction Estimation for Mobile Users

The thesis group is organized around a central idea: how to predict where a moving user will require data transmission in the next time instance. In other words, how should the transmitter be directed to achieve this effectively?

The primary objective of my research was to accomplish this prediction purely based on the received signal strength at a theoretical level, which I successfully achieved. This means that no additional signal-based tracking methods were employed, and the user did not provide any extra information to assist in the process.

## 3.1 Thesis 3: DNN-based Antenna Direction Predictor

I have developed a method to predict how a user should direct their own antenna for optimal reception in the next time slot [3][4]. This prediction is based solely on the measured signal strengths, as illustrated in Figure 5.

At a given point, the user performs measurements from multiple directions, selecting from a set of discrete possible directions. The number of possible directions is also finite and discrete. Typically, the user collects measurements from 4 incoming directions and can choose from 18 possible transmission directions.

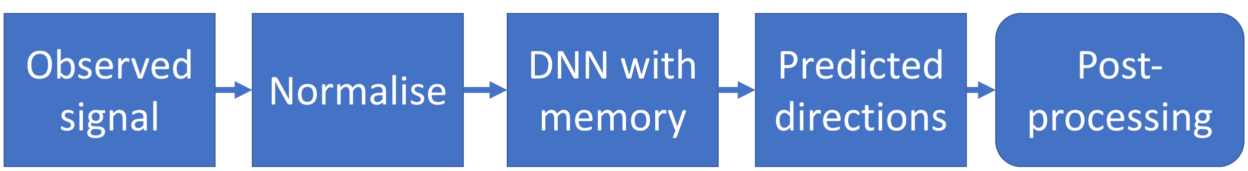


Figure 5: Schematic structure of the procedure..

I applied a deep neural network based on a Long Short-Term Memory (LSTM) architecture to solve the problem, which has an internal memory mechanism. Therefore, it was crucial to minimize the structure to ensure it runs as efficiently as possible on any user device. The number of parameters of the smallest, best performing model that can learn: 62218.

I applied three different accuracy metrics to evaluate the results and based on these, the obtained outcome is satisfactory (one example is shown in Figure6). Naturally, the results can be further improved by expanding the network structure and retraining.

If we evaluate the estimated signal level rather than the classification, we get a more favorable picture. For example, if we accept a signal level that is up to 6 dB lower than the

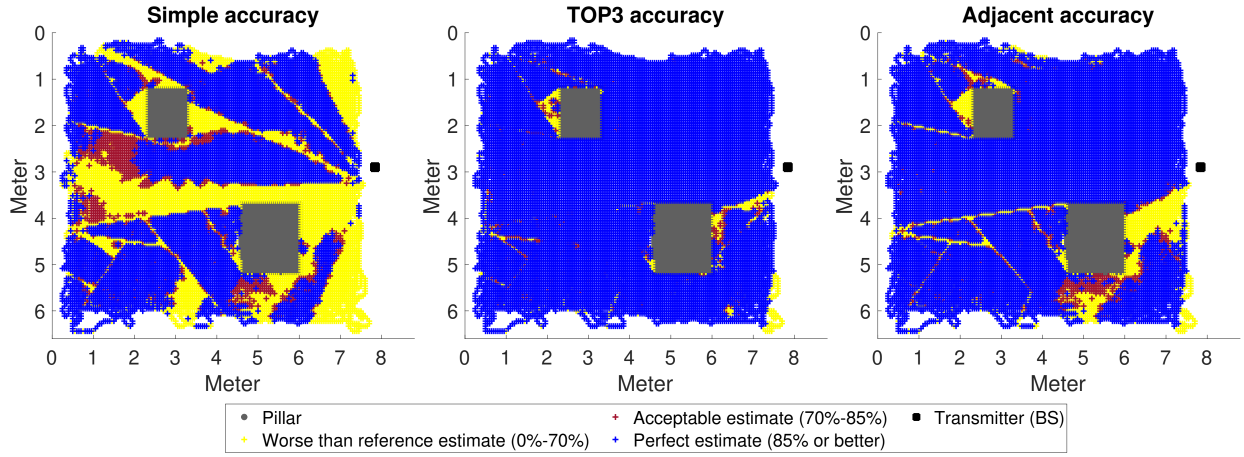


Figure 6: A movement of 5 000 000 steps in Room A1, the accuracy interpreted according to the metrics is presented. The areas marked in white were not visited during the test. The neural network used to generate the figure was trained with the dataset generated by our own Markov chain-based motion modeling (see Section 2.2).

current maximum available signal level as a correct estimate, then in all tested rooms, the algorithm estimated correctly in 99% of cases and in at least 85

The main findings of of my work are as follows:

1. A procedure can be developed that does not rely on classic tracking information, such as relative displacement or location data, to estimate direction.
2. Direction estimation can be achieved by selecting the highest signal level, providing an effective method for determining movement orientation.
3. The algorithms used in this study can be easily enhanced (through retraining or online retraining) or extended (by adding additional layers or restructuring the architecture). The research was not aimed at producing production-ready deep neural networks (DNNs) for immediate application. However, based on the current results, further development could lead to algorithms that are ready for practical use.

**Thesis 3**

I developed a method to implement antenna control for a moving user. The procedure is theoretical and free of physical constraints.

# My Publications Related to This Thesis

[3] Á. L. Makara, B. T. Csathó, L. Csurgai-Horváth and B. P. Horváth, 'Measurement-based Indoor Beam Alignment Utilizing Deep Learning,' in *2021 International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME)*, Mauritius, Mauritius: IEEE, Oct. 2021, pp. 1–6, ISBN: 9781665412629. DOI: `10.1109/ICECCME52200.2021.9590951`. Accessed: 27th Dec. 2022. [Online]. Available: `https://ieeexplore.ieee.org/document/9590951/`.

[4] Á. L. Makara, B. T. Csathó, A. Rácz, T. Borsos, L. Csurgai-Horváth and B. P. Horváth, 'Deep-Learning-Based Antenna Alignment Prediction for Mobile Indoor Communication,' *Sensors*, vol. 23, no. 7, 2023, ISSN: 1424-8220. DOI: `10.3390/s23073375`. [Online]. Available: `https://www.mdpi.com/1424-8220/23/7/3375`.

## 3.2 Thesis 4: Possibility of Comparing Indoor Environment by Attenuation Distribution

During my research, it was necessary to compare different rooms to determine how much they differ in terms of signal propagation. I developed a metric based on the distribution of possible directions [5]. I analyzed the distributions of transitions (primarily memoryless) based on their direction (see Figure x) and examined their correlation with different accuracy levels in various rooms.

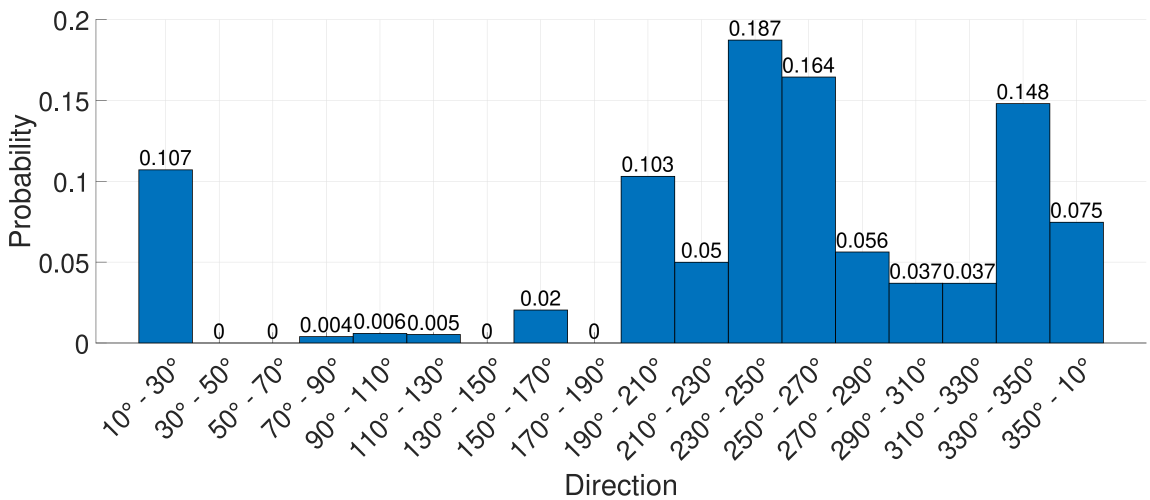


Figure 7: Movement S, training data distribution (the distribution of the best directions taken during movement ), from room A1.

I observed that using Total Variation Distance provides the most reliable method to determine how similar two rooms, training datasets, etc., are in terms of signal propagation. The total variation distance has several names: statistical distance (this name may be misleading), statistical difference, or variational distance. In the general case:

$$\delta(A, B) = D_T = \sup |A(v) - B(v)|, \tag{5}$$

where || is the absolute value. Discrete probability variables can be calculated as follows:

$$D_T(A, B) = \sum_v |A(v) - B(v)| \cdot \frac{1}{2}. \tag{6}$$

Based on the results obtained, it may be useful to use additional memory distributions for a more precise description.

**Thesis 4**

I have created a procedure for comparing the similarity of a training data set from a signal propagation point of view.

# My Publications Related to This Thesis

[5] Á. L. Makara and L. Csurgai-Horvath, 'Classification of Indoor Environment in Neural Network Controlled FR2-band Communication,' in *2022 International Conference on Electrical, Computer and Energy Technologies (ICECET)*, Prague, Czech Republic: IEEE, Jul. 2022, pp. 1–6, ISBN: 9781665470872. DOI: 10.1109/ICECET55527.2022.9873040. Accessed: 27th Dec. 2022. [Online]. Available: https://ieeexplore.ieee.org/document/9873040/.

# 4 Thesis group 3: Investigation of Satellite Channel Attenuation

In my final thesis group, I focused on how to adaptively modify the settings of wireless connections to maximize the amount of useful transmitted data. To achieve this, I conducted studies on Earth-satellite links, as they present significant challenges and are diverse enough to encompass a wide range of different phenomena.

## 4.1 Thesis 5: Fading Prediction for Satellite Channels

I developed a method that uses binary classification to predict whether a fading event will occur in the next reception period [6][7]. This provides additional information during decision-making about whether a drastic signal level drop or even a transmission outage is expected. A schematic diagram of the method is shown in Figure 8.

I chose the algorithm to be as small as possible, as it was important to minimize both the latency and computational capacity. The number of parameters of the smallest, best performing model that can learn: 203,002. The accuracy of the presented model is 93%. Table1 shows the performance of the pair of DNNs, indicating the number of LSTM elements. My method works even if the frequency of the channel used for the control is not too different from the channel used as the input for the estimation.

**Thesis 5**

I created a procedure to predict the occurrence of fading in real time.

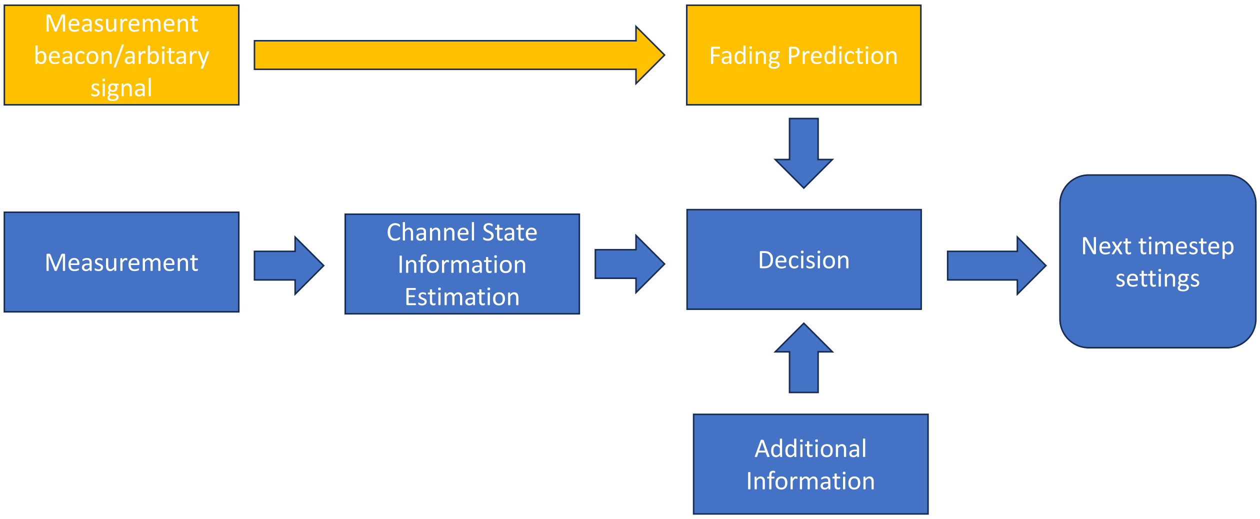


Figure 8: The structure is equipped with my proposed fading prediction method, which can be seamlessly integrated into any existing solution. My own research contributions are highlighted in orange. Any input signal that exhibits behavior similar to the channel can be utilized for control.

Table 1: **Balanced accuracy across LSTM sizes** (binary classification.

| **LSTM units** | **Recall (%)** | **Specificity (%)** | **Balanced Accuracy (%)** |
|---|---|---|---|
| 10 | 95.0 | 73.3 | 84.15 |
| 25 | 95.1 | 76.2 | 85.65 |
| **50** | **94.9** | **81.2** | **88.05** |
| 75 | 95.3 | 74.6 | 84.95 |
| 100 | 96.0 | 64.5 | 80.25 |
| 150 | 95.4 | 71.8 | 83.60 |
| 200 | 95.4 | 69.6 | 82.50 |
| 500 | 96.5 | 58.4 | 77.45 |

**Balanced Accuracy (BA)** is $\text{BA} = \frac{1}{2}(\text{Recall} + \text{Specificity})$; it counters class imbalance by weighting the positive and negative classes equally.
This is useful here because non-fading dominates the dataset, and **"positive" is defined as non-fading**. The best BA is achieved by the 50-unit LSTM (88.05%), indicating the strongest trade-off between detecting usable (non-fading) intervals and correctly identifying fading.

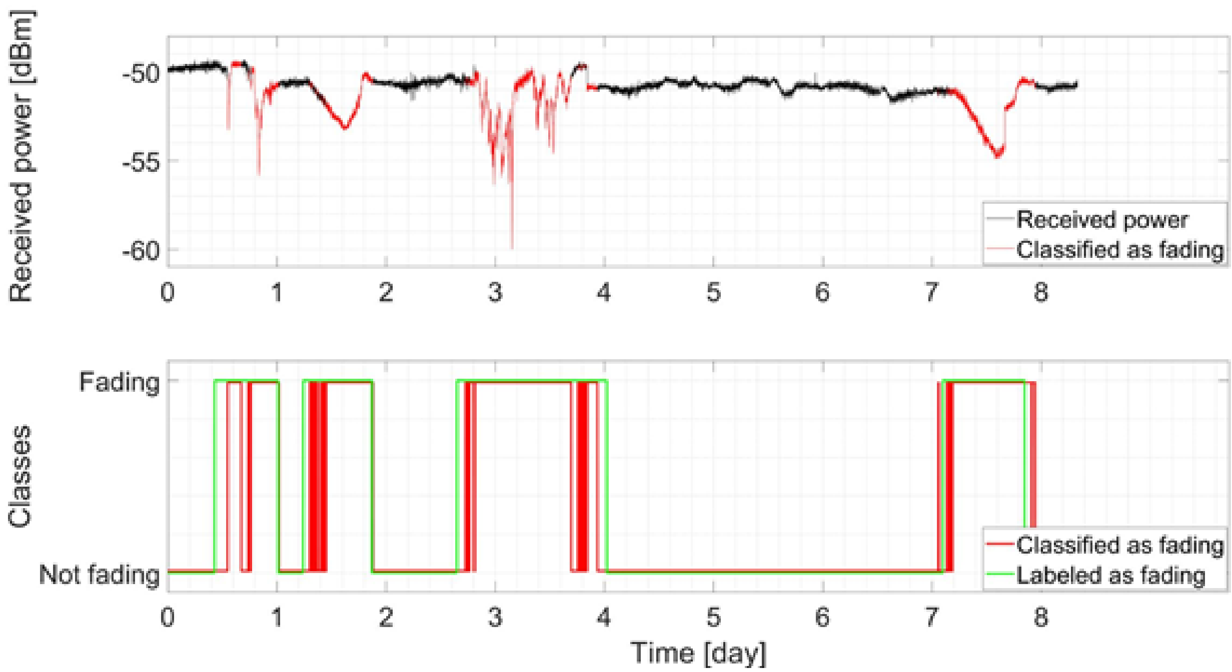


Figure 9: Top figure shows fading labeling on a few days of data series. The bottom figure shows the prediction result of DNN.

# My Publications Related to This Thesis

[6] Á. L. Makara, T. Deli and L. Csurgai-Horváth, ‘AI-Supported Fading Prediction,’ English, in *26th Ka Band Communications Conference 2021 Propagation*, ser. Propagation 4: ISSN-2573-6124, Washington DC: Ka, Broadband Communications, Navigation and Earth Observation Conference, Sep. 2021, pp. 1–5. Accessed: 14th Oct. 2021. [Online]. Available: https://proceedings.kaconf.com/papers/2021/ka4_2.pdf.

[7] Á. L. Makara and L. Csurgai-Horváth, ‘Application of Artificial Intelligence in Satellite Communications,’ in *Selected papers of the 7th International Conference on Research, Technology and Education of Space (H-SPACE2022)*, 2022, pp. 1–5. [Online]. Available: https://space.bme.hu/wp-content/uploads/2022/09/Proceedings_Papers_HSPACE-2022.pdf.

## 4.2 Thesis 6: Deep-Learning-Based ModCod Predictor for Satellite Channels

During my research on fading prediction, I came up with the idea that a full link adaptation could be implemented using a deep neural network. This would minimize errors. In this case, the structure is shown in Figure 10.

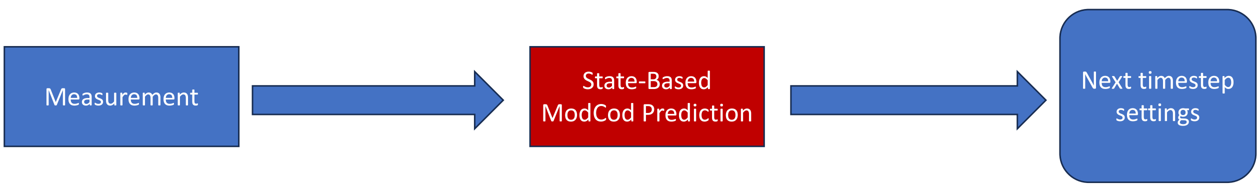


Figure 10: My new structure. I have assigned each task to a DNN, reducing the number of modules needed. Given the right parameters, it can be even faster than more complex systems.

I have developed a deep neural network based method that can solve this problem[8][9]. By creating a category from a finite combination of coding and modulation options (see Figure 11). In this way, in effect, the adaptive problem becomes a simple classification (with supervised machine learning).

My method can work with a much smaller neural network than expected. The number of parameters of the smallest, best performing model that can learn: 2748. Thus, it can work well in almost any application because of its low computational power. The limitation of the method is that retraining is required for each different link.

Based on my analysis, it is even able to learn the optimal frequency of switches. Thus it can even achieve cost efficiency. Considering the length of the messages sent over the communication channel, the accuracy of the algorithm is a little over 95%. My method works even if the frequency of the channel used for the control is not too different from the channel used as the input for the estimation.

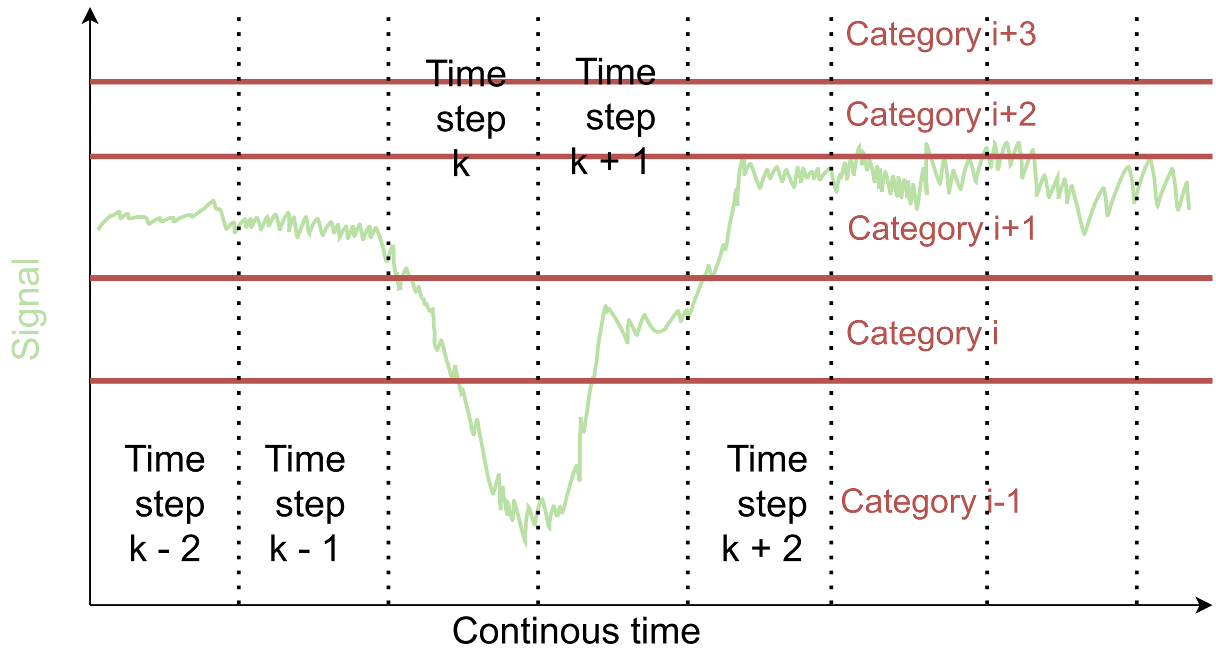


Figure 11: The measured – for simplicity, scalar – signal is marked in green (arbitrary dimension). We can assign a category to it at any moment, which is, in fact, the ACM setting. I have marked the discretization of an arbitrary discretization with vertical dotted lines; this is, in fact, the discrete-time of the example system.

**Thesis 6**

I have developed a method to estimate modulation and coding state on a radio channel, using nearly 95% of the overall channel capacity.

## My Publications Related to This Thesis


[8] Á. L. Makara and L. Csurgai-Horváth, 'Supporting adaptive coding and modulation techniques for satellite radio channel,' in *Proceedings of the 1st Workshop on Intelligent Infocommunication Networks, Systems and Services (WI2NS2)*, 2023, pp. 31–36. DOI: `10.3311/WINS2023-006`. [Online]. Available: `https://m2.mtmt.hu/api/publication/33707827`.

[9] Á. L. Makara and L. Csurgai-Horváth, 'Deep-Learning-Based ModCod Predictor for Satellite Channels,' *Radioengineering*, vol. 33, pp. 182–194, 2024, ISSN: 1805-9600. DOI: `10.13164/re.2024.0182`.