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EXECUTIVE SUMMARY

The hi-STAR project addresses one of the most critical challenges for the next generation wireless networks, which is integration of non-terrestrial networks with terrestrial 5G network. The general objective of the WP4 is to develop a intelligent traffic control unit (ITCU) that will benefit from multiple RANs (Radio Access Networks) and increase the reliability of users' communication. In order to develop the TCU and verify its performance, it is necessary to create a simulation environment and propose the handover procedure that will improve the user experience.

This deliverable is a result of the work done in the context of WP4 Subtasks T4.2 (Design of traffic control module placed in HUT) and T4.3 (HUT integration into RF-SoC platform). The proposed artificial intelligence (AI) – based solution incorporates neural networks (NN) to predict channel state information and subsequently to increase overall spectral efficiency of the network. Various NN architectures are tested to see which ones can provide signal-to-noise ratio (SNR) prediction that can improve spectral efficiency in simulated channels with channel parameters (shadowing levels, Doppler frequency shifts, and expected SNRs). Finally, it is explained how the HUT module equipped with ITCU will be integrated into the framework implemented on the RF-SoC platform.

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ABBREVIATIONS

AI	**Artificial intelligence**
CSI	**Channel State Information**
GCS	**GUI, Control and Channel Switching Logic**
HUT	**Hybrid User Terminal**
ITCU	**Intelligent Traffic Control Unit**
LEO	**Low-Earth-Orbit**
LSTM	**Long-Short-Term Memory**
LR	**Linear regression**
NN	**Neural network**
MSE	**Mean square error**
MSE	**Mean squared error**
ML	**Machine learning**
MODCOD	**Modulation and Coding**
OI	**Outdated Information**
RAN	**Radio access network**
SNR	**Signal-to-Noise Ratio**
SVM	**Support vector machine**
WP	**Work Package**

SECTION 1 - INTRODUCTION

Ensuring stable, efficient, and reliable communication is paramount in today's technological landscape. Low Earth Orbit (LEO) satellite networks have emerged as a promising solution, particularly for extending connectivity to remote and underserved regions. Their proximity to Earth allows for reduced latency and enhanced data transmission speeds, making them suitable for real-time applications and bridging the digital divide. However, optimizing the deployment and operation of LEO satellite systems presents challenges, including managing complex constellations, ensuring seamless coverage, and addressing regulatory considerations. Despite these hurdles, the potential of LEO satellites to revolutionize global connectivity continues to drive innovation and investment in this sector.

The work presented in this deliverable focuses on the use of machine learning for SNR prediction in LEO satellite communications. The proposed approach relies on a simulator that generates channels with varying SNR values, Doppler shifts, and shadowing conditions. The simulator generates data from 90 distinct channels, which include variations in six SNR levels, five Doppler shift conditions, and three shadowing levels. This setup aims to explore the relationship between different channel conditions and the performance improvements that machine learning algorithms can offer for single-channel communication, compared to a baseline approach. The evaluation of the proposed methods goes beyond SNR prediction, also assessing spectral efficiency and transmission error rate using the DVB-S2X protocol, with a focus on real-world applications. Additionally, the algorithms are tested on channels from two separate satellites, analyzing each channel pair under identical shadowing conditions.

We introduce a systematic approach that examines the relationship between various channel conditions and the improvement in spectral efficiency for LEO satellites following the DVB-S2X protocol. In addition to exploring multiple scenarios, we propose a neural network algorithm with a modified loss function, which outperforms the traditional outdated information approach as well as a neural network with a standard loss function, both for single-satellite and two-satellite channel observations. This novel method, which consistently achieves low transmission error rates while enhancing spectral efficiency, paves the way for future research focused on adjusting neural network loss functions to meet specific system optimization goals. The improvements in prediction accuracy and spectral efficiency also enable user-centric handover procedures. Furthermore, the study evaluates the potential for reducing outage probabilities when utilizing two satellites instead of one.

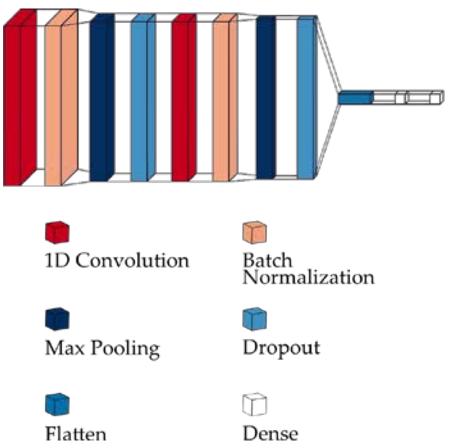
This deliverable is structured as follows: In Section 2 the expert system that is used for the channel state prediction is explained, including various ML algorithms and corresponding performances. In Section 3, multiple neural network architectures were evaluated to see which one would be the optimal solution in various simulated LEO satellite communication channels. Section 4 discusses the implementation issues, and Section 5 concludes the document.

SECTION 2 – A NOVEL CHANNEL STATE PREDICTION IN AI MODULE

2.1. SNR PREDICTION ALGORITHMS

For SNR prediction, the outdated information (OI) approach was used as a baseline, alongside two neural network-based approaches and two other machine learning (ML) models: support vector machine (SVM) and linear regression (LR). The OI approach assumes that the future SNR value will be the same as the most recently estimated value. This method works well in scenarios with low Doppler frequency shift and minimal shadowing, but is not useful for channel estimation in scenarios where the channel state is changes more quickly and more often. In contrast to the OI, the machine learning models use the last 10 estimated SNR values to predict the next true SNR value. This fixed input sequence length of 10 was chosen as it provides enough data for the ML algorithms to recognize channel characteristics without introducing excessive input features or requiring long data buffering.

The two simpler ML models were implemented with default parameters used in the scikit-learn library. The focus of the research was to evaluate the performance of basic ML algorithms across different scenarios, rather than explore complex model architectures. For the neural network-based prediction, convolutional neural networks (CNNs) were used, all with the same architecture but different loss functions. The architecture of the neural networks is illustrated in Figure 1.



Type of layer	Parameters
Input layer	size = 10
1D Convolution	filters = 32, kernel size = 5, strides = 1, padding = same, activation = ReLU
Batch Normalization	
1D Max Pooling	pool size = 2, strides = 2
Dropout	rate = 0.5
1D Convolution	filters = 32, kernel size = 5, strides = 1, padding = same, activation = ReLU
Batch Normalization	
1D Max Pooling	pool size = 2, strides = 2
Dropout	rate = 0.5
Dense	10 neurons, activation = ReLU
Dense	1 neuron, no activation

Figure 1. The architecture of the implemented neural networks.

The proposed architecture is a simple convolutional neural network with a fully connected layer at the end. Given the prediction tasks, small neural networks were chosen, considering that for the number of inputs the benefits of more weights would be limited in terms of spectral efficiency, and the practical applications of larger networks would pose more barriers as well. The neural networks have a possibility for modifying the loss function which can greatly influence the way the network “learns”, and the goal was to analyze this, comparing the two implemented neural network algorithms.

The difference between the regular neural network implementation (NN) and the modified one (NN2) was that the NN had a standard mean square error loss function, while the NN2 had a mean absolute error loss function with an added factor of $0.5 \times (\hat{y} - y)$, where $\hat{y}$ represents the prediction of the network, and y represents the true value. The motivation behind the implementation of the modified loss function of NN2 is that predicting higher SNR values than the true ones often result in unsuccessful data transmission, while a lower SNR prediction is suboptimal but communication exists. In terms of simple SNR prediction, NN2 is expected to perform worse than a regular NN, but when performing further evaluations using various MODCODs, its intentionally lower predictions could be beneficial for both a lower error rate and a higher spectral efficiency. Both neural networks were trained using an Adam optimizer, batch size of 256, validation split of 0.2, and patience of 20 epochs.

The implementation of the ML models, neural networks, signal processing, evaluation and visualization was done in the Python programming language [1], using the numpy [2], scikit-learn [3], keras [4], and matplotlib [5] libraries. Any parameters of the implemented NN and ML models that are not stated are left as default in the keras version 2.13.1 and scikit version 1.0.2 libraries. The initial evaluation of the proposed algorithms (OI, LR, SVM, NN, NN2) was done using the mean square error (MSE) between the predictions $\hat{y}$ and labels y (with n samples)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2. \tag{1}$$

The training of the algorithms was done on the first 75% of the signal and the evaluation was performed on the last 25% of the SNR signal, generated based on the method proposedin [6]. The inputs to the algorithm were estimated SNR values, while the labels were the true SNR values, as generated by the simulation. On training and test set input-output pairs were created by sliding a window of 10 samples for creating inputs based on the estimated SNR values, and taking the next consecutive sample of the actual SNR as the label that should be predicted.

2.2. MODCOD SELECTION EVALUATION

After the initial evaluation that shows the ability of the algorithms to perform SNR predictions, the next step was to evaluate the algorithms in terms of spectral efficiency. For spectral efficiency evaluation, all operation points of the DVB-S2X protocol [7] (short frame communication) are used. For the considered MODCODs, the spectral efficiencies (M_i) and the SNR thresholds ($T(M_i)$), minimal SNR value needed to operate with the efficiency, are listed in Table 1. Based on the algorithms' predicted SNR, the system takes the highest possible MODCOD that could be successfully used with that predicted SNR.

The first level of evaluation was done for each channel separately. So, the evaluation for each ML algorithm was done for 90 different channels. To ensure the evaluations relate to practical use cases, margins were determined on the training set so that the transmission error on the training set is lower than 0.01 where possible, or lower than 0.001+unavoidable error, with the unavoidable error being the percentage of samples where the SNR is lower than the lowest operation threshold, i.e. the samples where the transmission error is unavoidable.

Table 1. MODCODs, the spectral efficiencies (M_i) and the SNR thresholds ($T(M_i)$).

MODCOD	M_i[b/s/Hz]	$T(M_i)$[dB]
BPSK-S 1/5	0.1	-9.9
BPSK-S 11/45	0.12	-8.3
BPSK 1/5	0.2	-6.1
BPSK 4/15	0.27	-4.9
BPSK 1/3	0.33	-3.72
QPSK 11/45	0.49	-2.5
QPSK 4/15	0.53	-2.24
QPSK 14/45	0.62	-1.46
QPSK 7/15	0.93	0.6
QPSK 8/15	1.07	1.45
QPSK 32/45	1.42	3.66
8PSK 8/15	1.60	4.71
8PSK 26/45	1.73	5.52
16APSK 7/15	1.87	5.99
16APSK 8/15	2.13	6.93
16APSK 26/45	2.31	7.66
16APSK 3/5	2.40	8.1
16APSK 32/45	2.84	9.81
32APSK 2/3	3.33	11.41
32APSK 32/45	3.56	12.18

This margin was extracted for each algorithm and scenario separately (simple search with a resolution of 0.5 dB) and was then applied to the predictions on the appropriate test set. In this way, all algorithms would have a comparatively fixed error rate, and the performance in terms of spectral efficiency could be adequately compared between different cases. The determined error rate threshold of 0.01 was selected as the highest possible error rate that might be considered usable for transmission, and further evaluation was done on two channels as it is considered that combining two channels would create a scenario where, at least in theory, a lower error rate could be obtained.

The final step of the evaluation was performed using two channels, where each combination of channels within the same level of shadowing is considered. This was done for OI and NN2 to provide easier comparison, since NN2 has shown to have better performance in terms of spectral efficiency than all other algorithms. For this evaluation, a greedy selection was performed by the algorithms, i.e. for each point in time the channel with the higher predicted SNR was selected. This creates a single array of SNR prediction values for the final algorithm predictions. The true labels were selected based on the labels for the channel that was selected for that corresponding point in time. The same principle for margin estimation was performed, extracting the margin on the training set, and then applying it on the test set for OI and NN2 separately. The resolution for the search was 0.5 dB as well, but the goal transmission error was 0.001, since two channels would often allow for a lower transmission error. If the transmission error of 0.001 was unattainable, the margin would be determined to reach the unavoidable error+0.0001 on the training set. For the sake of the interpretation of such high-dimensional data, the comparison between the NN2 and OI is done by using relative improvement in spectral efficiency gained by using the NN2, calculated as $(M_i^{NN2} - M_i^{OI})/M_i^{OI}$.

2.3. PERFORMANCE OF AI MODULE

2.3.1. SNR prediction

The initial testing results present the MSE between the predictions and labels on the test set, for various channels and for the five observed algorithms. The OI is considered a baseline algorithm as it is simple to implement and is often used in literature, while the ML models were expected to offer improvement. In terms of MSE performance (as well as spectral efficiency) the implemented LR and SVM performed the same or worse that the regular NN, so for an easier comparison, only the results of the NN will be presented in this and further sections as it will be a good representative of the best performing simple ML algorithms. The MSE values for all observed scenarios are shown in Table 2, while Figures 2, 3. and 4. show the same metric visually for light shadowing, average shadowing and heavy shadowing, respectively.

Table 2. The MSE [dB^2] achieved on the test set for various scenarios, OI/NN/NN2.

			MSE [dB^2]		
SNR [dB]	**f_{Dm} = 5 Hz**	**f_{Dm} = 25 Hz**	**f_{Dm} = 50 Hz**	**f_{Dm} = 75 Hz**	**f_{Dm} = 100 Hz**
			Light shadowing		
0	1.0/0.5/0.6	2.2/1.4/2.1	4.5/2.9/3.9	7.4/4.8/6.4	11.7/7.2/9.1
3	0.7/0.3/0.5	1.8/1.3/1.7	3.6/2.4/3.5	6.8/4.4/5.7	10.5/6.8/8.8
6	0.5/0.3/0.4	1.5/1.0/1.4	3.6/2.2/2.9	7.3/4.6/5.7	10.2/6.8/8.5
9	0.4/0.3/0.3	1.2/0.9/1.2	3.2/1.9/2.5	6.3/3.9/5.4	9.8/6.5/8.3
12	0.3/0.3/0.3	1.3/0.9/1.1	3.3/1.9/2.8	7.0/4.2/5.2	9.5/6.3/8.2
15	0.2/0.2/0.2	1.0/0.7/0.9	3.5/2.0/2.7	6.7/4.1/5.2	10.2/6.8/8.8
			Average shadowing		
0	1.5/0.8/1.1	7.4/3.8/4.7	17.2/7.3/9.5	31.4/11.9/14.5	38.2/13.8/17.0
3	1.5/0.8/0.9	6.8/3.3/4.1	17.0/7.2/9.2	27.8/10.8/13.7	35.5/13.2/16.2
6	0.7/0.6/0.6	7.1/3.0/4.1	17.7/7.2/9.1	30.1/11.5/13.9	35.9/13.6/16.3
9	0.7/0.5/0.6	6.1/2.6/3.4	17.2/7.1/9.1	27.5/11.2/13.5	33.5/13.2/16.3
12	0.4/0.4/0.4	5.4/2.3/3.3	16.9/6.8/8.3	26.7/10.8/13.2	35.4/13.6/16.6
15	0.6/0.5/0.6	6.2/2.6/3.2	16.8/6.8/8.3	29.4/11.1/13.9	34.3/13.3/16.8
			Heavy shadowing		
0	3.4/1.2/1.8	7.9/3.9/5.4	15.7/7.8/10.3	26.2/13.5/17.1	34.0/18.5/23.2
3	2.3/1.1/1.6	6.2/2.9/4.1	14.9/7.2/9.4	24.7/12.5/16.1	34.2/18.0/23.3
6	1.1/0.6/1.3	5.7/2.7/3.5	13.9/6.4/8.0	22.8/11.4/14.8	32.5/17.6/23.1
9	0.8/0.5/0.6	5.0/2.3/2.9	12.7/5.7/7.6	22.2/11.1/15.0	31.8/17.3/22.1
12	0.8/0.5/0.8	5.2/2.0/3.3	12.6/5.7/7.5	22.8/11.0/14.0	30.5/17.6/21.3
15	0.6/0.4/0.5	4.6/1.8/2.5	12.7/5.4/6.8	22.9/11.5/15.0	30.4/17.3/22.1

When observing the values from Table 1, it can be concluded that based on different scenarios, the MSE can have quite a large range of values, from 0.2 dB^2 to 38.2 dB^2 for the outdated information. The vast range of these values shows that based on different channel characteristics, different expectations for SNR prediction quality should be present. The ranges of MSE for NN and NN2 have the same minimum value as the OI, and this value is so low that it can be concluded that the implementation of additional algorithms outside of OI can be completely redundant in certain scenarios, e.g. f_{Dm} = 5 and higher expected SNR values. On the other hand, The maximum MSE for NN is quite lower than the maximum value for outdated information, amounting to 18.5 dB^2 which is less than half of the maximum value of the OI, an almost half of the OI MSE value for that respective scenario. Notably, the NN2 has a consistently higher MSE than the NN, but also provides an improvement when compared to the OI. This is to be expected as the loss function of the NN2 is not made to optimize for the MSE or exact prediction, rather, it is created to force the network to rarely overestimate the SNR value. For pure SNR prediction this is impractical, but it will later be shown that this has its benefits when observing practical applications and spectral efficiency.

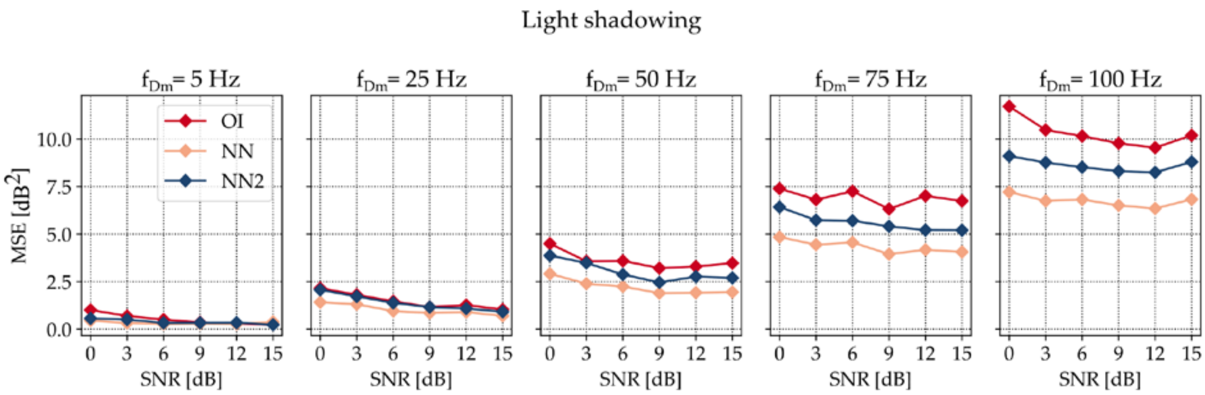


Figure 2. The achieved MSE for SNR prediction on the test set for various scenarios under light shadowing conditions.

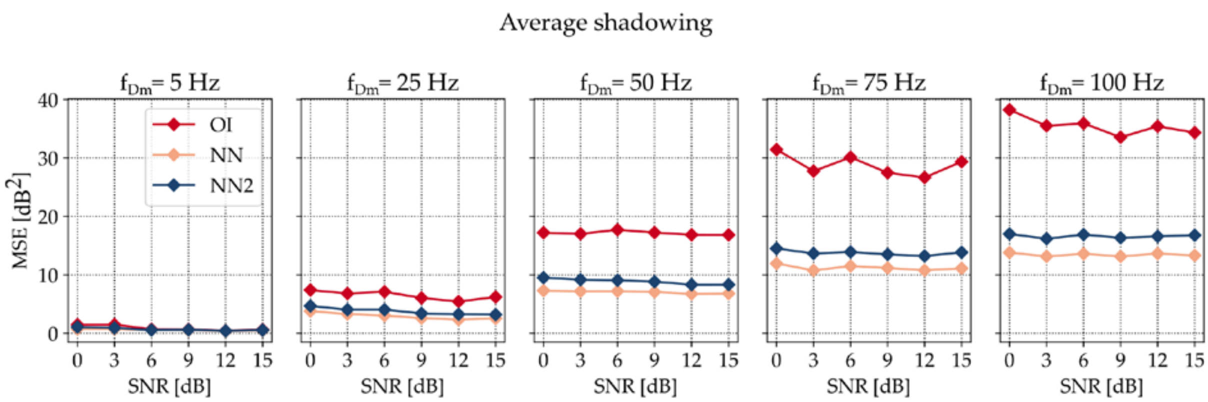


Figure 3. The achieved MSE for SNR prediction on the test set for various scenarios under average shadowing conditions.

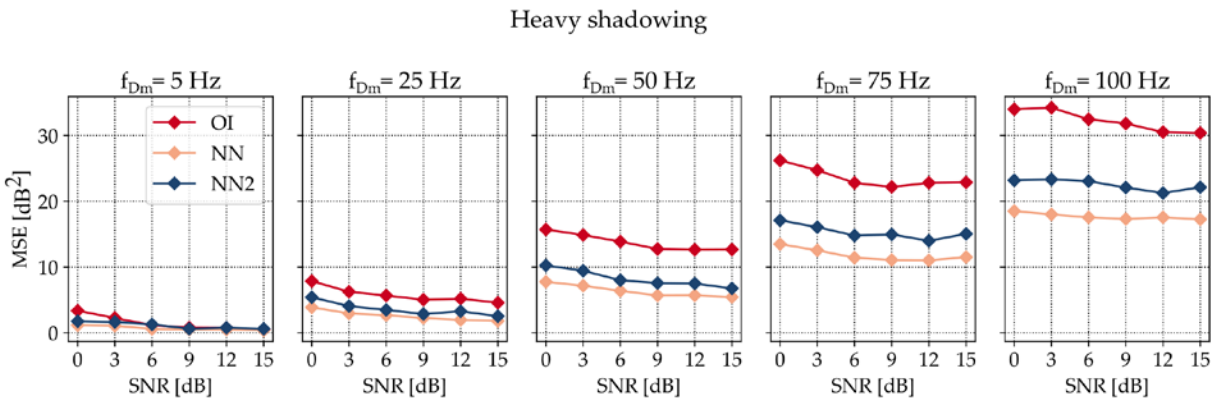


Figure 4. The achieved MSE for SNR prediction on the test set for various scenarios under heavy shadowing conditions.

The results shown in Figures 2, 3. and 4 intuitively show the overall trends of the MSE in terms of various algorithms and channel scenarios. Notably, it can be observed that for all algorithms the MSE is higher when the f_{Dm} parameter rises. This is expected as the higher values of f_{Dm} correspond to channels that have less predictable changes and both OI and neural networks have difficulties performing when more rapid SNR changes are present. It is also evident that for a very low f_{Dm}, regardless of SNR, at the algorithm perform quite similar. As presented in Table 4, improvements do exist in most scenarios, but they are so minor that the development of special algorithms for prediction of SNR can be considered redundant. On the other, hand, for high f_{Dm} values, the improvements that the neural networks provide become more evident. It is interesting to note, that the discrepancy between the performance of NN and NN2 also increases with the increase of f_{Dm}, regardless of shadowing conditions. This is most likely because a higher f_{Dm} creates a more unpredictable channel, and since the NN2 is penalized for overestimating the SNR, it starts to consistently predict much lower values in order to avoid overestimating. This results in a higher MSE, and therefore worse performance when compared to the NN approach.

Another interesting characteristic that is worth noting is that the OI has a higher MSE for heavy shadowing as opposed to average shadowing for f_{Dm}s of 50 Hz and above (75 Hz and 100 Hz), for all SNR values. This is an interesting find as the heavy shadowing is considered a worse scenario than average shadowing. On the other hand, for unpredictable channels, such as those with high f_{Dm} values, heavy shadowing actually creates a more predictable pattern, although the SNR values are lower, more frequent shadowing occurrences create more regularity in the pattern and create a correlation between previous samples and future ones. The neural networks, however, compensate for these characteristics and the same aspect is not prominent in neural networks' performance.

2.3.2. Single channel spectral efficiency

Considering the achieved results, it is clear that the neural networks can provide clear improvement in terms of SNR prediction when compared to the baseline OI approach, and the next step represents the evaluation of spectral efficiencies for all observed channels. The initial step is to analyze the outage probabilities if perfect SNR predictions would have been performed for the test channels, presented in Table 3. These outage probabilities present the unavoidable error on the test set and are relevant for the interpretation of further results.

Table 3. The outage probability on the test set for each observed scenario. The probabilities higher than or equal to 0.01 are presented in red.

			Outage probability		
SNR [dB]	**f_{Dm} = 5 Hz**	**f_{Dm} = 25 Hz**	**f_{Dm} = 50 Hz**	**f_{Dm} = 75 Hz**	**f_{Dm} = 100 Hz**
			Light shadowing		
0	0.016	0.022	0.019	0.02	0.021
3	0.01	0.009	0.007	0.008	0.009
6	0.003	0.004	0.004	0.004	0.004
9	0.001	0.001	0.001	0.002	0.002
12	0	0.001	0.001	0.001	0.001
15	0	0	0	0	0
			Average shadowing		
0	0.03	0.035	0.031	0.037	0.037
3	0.016	0.015	0.014	0.014	0.015
6	0.005	0.009	0.007	0.008	0.007
9	0.002	0.003	0.004	0.003	0.004
12	0.001	0.001	0.001	0.002	0.002
15	0	0.001	0.001	0.002	0.001
			Heavy shadowing		
0	0.091	0.095	0.096	0.098	0.094
3	0.048	0.048	0.05	0.052	0.051
6	0.021	0.026	0.026	0.026	0.025
9	0.009	0.012	0.012	0.012	0.012
12	0.007	0.007	0.007	0.007	0.007
15	0.002	0.003	0.003	0.004	0.003

The results show that for the set threshold of 0.01 for single channel evaluation, outage probability is too high in some scenarios, making the set threshold unobtainable. These outage probabilities, however, should not impair the improvements of spectral efficiency that the neural networks should offer. The outage probabilities are more prominent for higher levels of shadowing, which is expected as 1 percent of the test set corresponds to 250 samples, and more frequent, heavier shadowing can easily make more than 250 samples have values lower than the minimum operational threshold.

Table 4. shows the results in terms of spectral efficiency and achieved error transmission rate for all considered conditions and algorithms. Figures 5, 6 and 7 show the relationship between the SNR and the achieved spectral efficiency for light, average and heavy shadowing, respectively, while Figures 8, 9, and 10. show the results visually in terms of improvement percentage compared to the OI spectral efficiency, for light, average and heavy shadowing, respectively.

The results in Table 4. show the wide range of performances that can be achieved for various scenarios and again point out that different channel characteristics can quite heavily influence the performance of the algorithms. Expectedly, as opposed to the MSE results, the expected SNR plays a significant role in achieving higher spectral efficiency. More specifically, the higher the expected SNR, the higher the achieved spectral efficiency. This stands regardless of the implemented algorithm or f_{Dm} value.

Table 4. The achieved spectral efficiency [b/s/Hz] achieved on the test set for a single channel for various scenarios, OI/NN/NN2. The spectral efficiencies in bold represent the ones for which the transmission error rate was lower than 0.01.

	$\boldsymbol{M_i[b/s/Hz]}$				
SNR [dB]	**f_{Dm} = 5 Hz**	**f_{Dm} = 25 Hz**	**f_{Dm} = 50 Hz**	**f_{Dm} = 75 Hz**	**f_{Dm} = 100 Hz**
			Light shadowing		
0	0.33/0.4/0.41	0.27/0.29/0.28	0.19/0.19/0.2	0.14/0.14/0.14	0.11/0.11/0.12
3	0.73/0.77/0.79	**0.55/0.54/0.59**	**0.37/0.39/0.41**	**0.24/0.24/0.27**	**0.17**/0.18/**0.17**
6	**1.25/1.24/1.27**	**1.0/1.06/1.06**	**0.73/0.85/0.89**	**0.54/0.57/0.63**	**0.4/0.4/0.42**
9	**1.84/1.82/1.96**	**1.63/1.63/1.65**	**1.28/1.45/1.41**	**0.92/1.05/1.12**	**0.77/0.75/0.79**
12	**2.62/2.53/2.66**	**2.26/2.36/2.36**	**1.86/2.05/2.1**	**1.44/1.62/1.62**	**1.18/1.19/1.25**
15	**3.16/3.06/3.2**	**2.94/3.04/3.04**	**2.51/2.74/2.77**	**2.05/2.25/2.25**	**1.73/1.79/1.82**
			Average shadowing		
0	0.33/0.35/0.36	0.15/0.2/0.19	0.1/0.12/0.13	0.1/0.1/0.1	0.1/0.1/0.1
3	0.6/0.66/0.67	0.24/0.35/0.37	0.11/0.15/0.16	0.1/0.12/0.12	0.1/0.1/0.1
6	**1.15/1.07/1.25**	**0.5/0.69/0.79**	**0.19**/0.33/**0.31**	**0.12/0.18/0.19**	**0.11/0.13/0.14**
9	**1.7/1.68/1.71**	**0.98/1.2/1.24**	**0.44/0.66/0.7**	**0.23/0.37/0.38**	**0.17/0.28/0.27**
12	**2.49/2.37/2.52**	**1.46/1.83/1.98**	**0.78/1.12/1.17**	**0.49/0.76/0.77**	**0.32/0.57/0.54**
15	**2.99/3.01/3.02**	**2.13/2.45/2.62**	**1.24/1.56/1.74**	**0.78/1.25/1.24**	**0.6/0.96/1.0**
			Heavy shadowing		
0	0.34/0.42/0.39	0.22/0.26/0.27	0.14/0.18/0.19	0.11/0.13/0.14	0.1/0.11/0.11
3	0.6/0.67/0.71	0.36/0.42/0.5	0.2/0.26/0.3	0.14/0.19/0.19	0.11/0.14/0.14
6	0.94/1.0/1.04	0.52/0.7/0.83	0.25/0.49/0.51	0.17/0.26/0.27	0.13/0.16/0.17
9	**1.4/1.46/1.51**	0.74/1.03/1.2	0.36/0.62/0.71	0.2/0.36/0.41	0.14/0.2/0.23
12	**2.05/2.22/2.14**	**1.21/1.73/1.78**	**0.67/1.09/1.26**	**0.36/0.61/0.68**	**0.3/0.35/0.44**
15	**2.73/2.67/2.77**	**1.94/2.41/2.47**	**1.2/1.7/1.94**	**0.78/0.97/1.21**	**0.51/0.62/0.7**

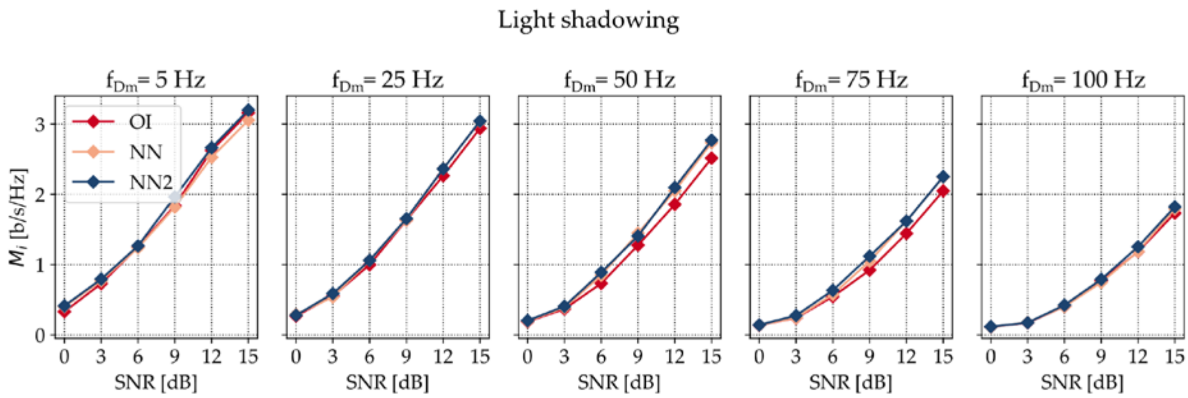


Figure 5. The achieved spectral efficiency on the test set for various scenarios under light shadowing conditions using a single channel.

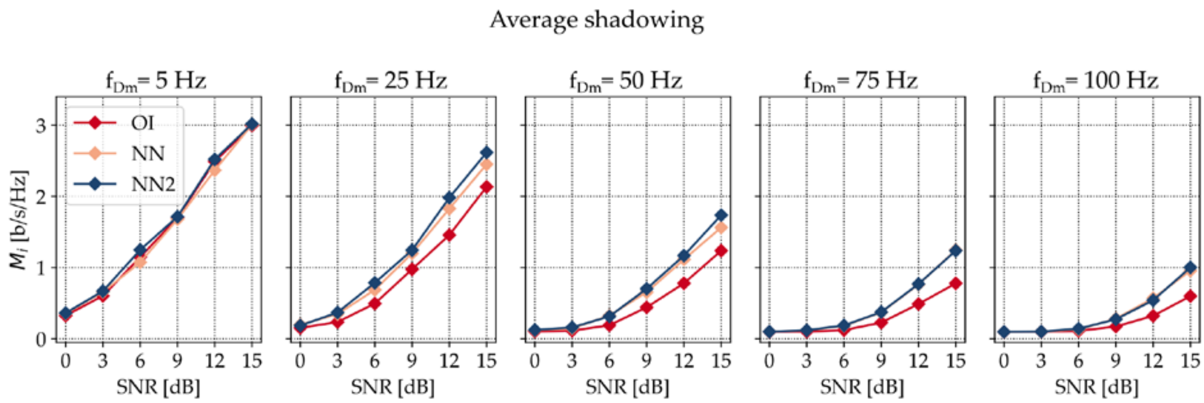


Figure 6. The achieved spectral efficiency on the test set for various scenarios under average shadowing conditions using a single channel.

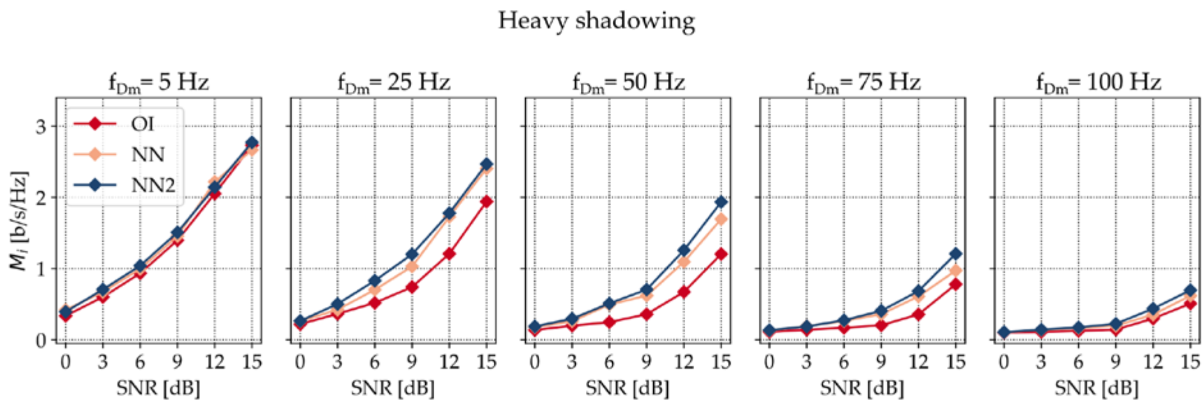


Figure 7. The achieved spectral efficiency on the test set for various scenarios under heavy shadowing conditions using a single channel.

It is also important to note that there are many scenarios for which the transmission error rate is higher than 0.01, essentially making reliable communication impossible, regardless of the spectral efficiency that can be achieved. As can be seen in Table 3, all of the scenarios for which the desired error rate of 0.01 is not achieved have an unavoidable transmission error higher than 0.01. The implemented approach for margin determination does not make achieving an error of less than 0.01 on the test set certain, as the margin is determined on the training set, and only then applied on the test set. However, the results indicate that this approach works quite well as all the scenarios in which the error is larger than 0.01 correspond to the ones where the unavoidable outage probability is above 0.01.

The visual representations of the obtained spectral efficiencies shown in Figures 5, 6. and 7. indicate clearly how the trends of spectral efficiencies behave for different shadowing, f_{Dm} and SNR conditions. NN2 is consistently better than the OI with NN also being better in most cases. For an SNR of 0 dB, the improvement seems negligible, but as the SNR increases the difference between spectral efficiency becomes more prominent. The shapes of the presented curves also change based on the amount of shadowing. It can be seen in Figure 5, that the spectral efficiency rises mostly linearly with the SNR for most of the light shadowing conditions, regardless of the algorithm, but the trends do become more curved as the f_{Dm} increases. For average shadowing the trends seem more curved, and for heavy shadowing, almost no curve looks linear. This conclusion also stands for all algorithms, meaning that regardless of the achieved improvement, the relationship between SNR and spectral efficiency has a different trend based on the type of channel that is observed.

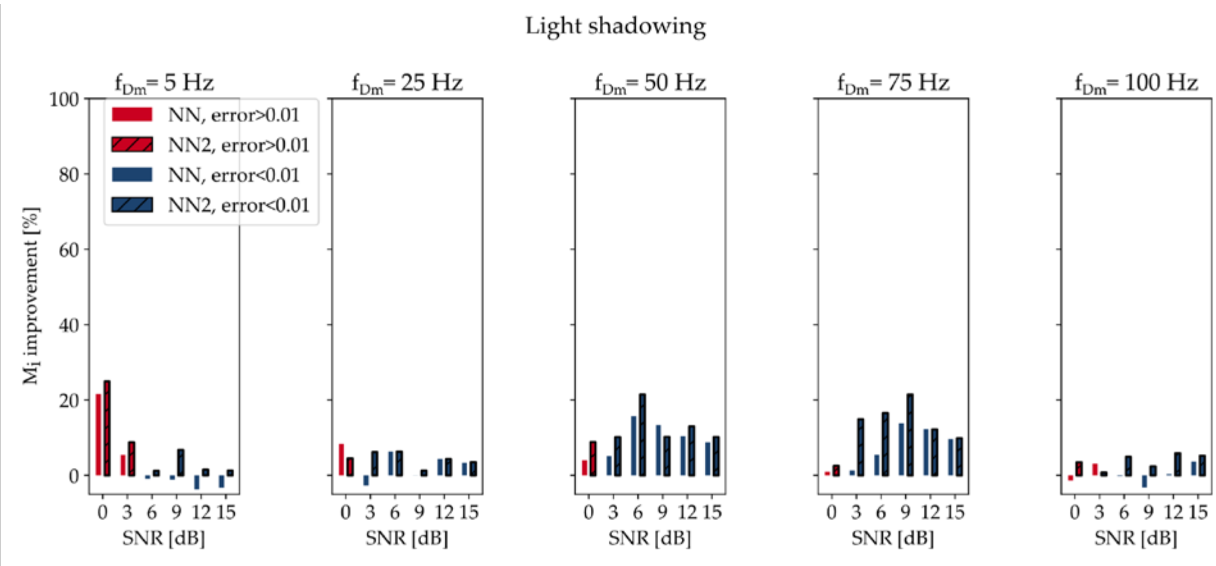


Figure 8. The achieved spectral efficiency improvement in % compared to the OI, on the test set for various scenarios under light shadowing conditions using a single channel. Scenarios where the transmission error is <0.01 are shown in blue, and scenarios where the transmission error is >0.01 are shown in red.

Observing the results from Figure 8, it can be seen more clearly that the NN2 has a consistently better performance than OI, and almost always a better performance than NN. The improvement in spectral efficiency that the NN2 provides is not drastic in comparison to OI or NN, as can be seen, but it is consistent. This clearly indicates the importance of considering different scenarios, as in certain ones developing complex algorithms can provide limited improvement. The consistency shows that the proposed method is conceptually good, but for practical applications it is important to weigh the benefits of the spectral efficiency improvement against the complexity of integrating complex models into a system.

When comparing NN2 and NN, it is important to note that, as opposed to the simple SNR prediction, NN2 has better performance. This is due to the introduced margin and the need for a transmission error rate no greater than 0.01. Since there are many MODCODs considered for communication, their operations thresholds are not that far apart. Hence, if the neural networks predict an SNR value that is much higher than the operation point of the best possible MODCOD, no data will be transmitted, and a transmission error will occur. This is why the NN2 approach of underestimating values is useful because it is less likely to make such mistakes, so the determined margin ensuring a low error rate will not be as high, and will not bring down the spectral efficiency improvements as much as it will for NN.

In terms of achieving a transmission error rate no greater than 0.01 for light shadowing specifically, Figure 8. recapitulates that for an expected SNR of 0 dB it is not possible, and no approach achieves this, but it is also shown that for the SNR od 3 dB and an f_{Dm} of 5 Hz, none of the algorithms could obtain a transmission error rate lower than 0.01. This channel does not fall under the category of difficult or unpredictable, as there is light shadowing, and the f_{Dm} is quite small. However, since the SNR is not high, it is always possible that the SNR values so happen to be distributed in such a way that the outage probability is higher than 0.01 which is exactly what happened in this case. This stands in line with the results that are obtained for average and heavy shadowing, as for both, there was an error rate higher than 0.01 for all scenarios where the expected SNR was equal to 3 dB. One more interesting occurrence is that for and f_{Dm} of 100 Hz and an expected SNR of 3 dB, the NN did not achieve an error rate lower than 0.01 while NN2 and OI did. This simply shows that the errors that NN makes can be such that the SNR prediction itself is better, but the overestimating of values that sometimes occurs can have a negative impact on reaching certain goals, such as low rates of transmission error. In terms of obtainable improvement for light shadowing, for a frequency range of 40 MHz, if the best relative improvement scenario is considered for NN2 (f_{Dm} = 75 Hz, SNR = 9 dB), the contribution of NN2 would be (1.12-0.92)b/s/Hz × 40 MHz = 8 Mb/s.

Observing average shadowing, similar patterns can be observed as for light shadowing, with some changes. Firstly, for average shadowing, for an expected SNR of 3 dB, the transmission error rate was always higher than 0.01. This is because more frequent or heavier shadowing increases the intervals in which no communication can occur, thus raising the unavoidable error, which exceeds 0.01 in these scenarios.

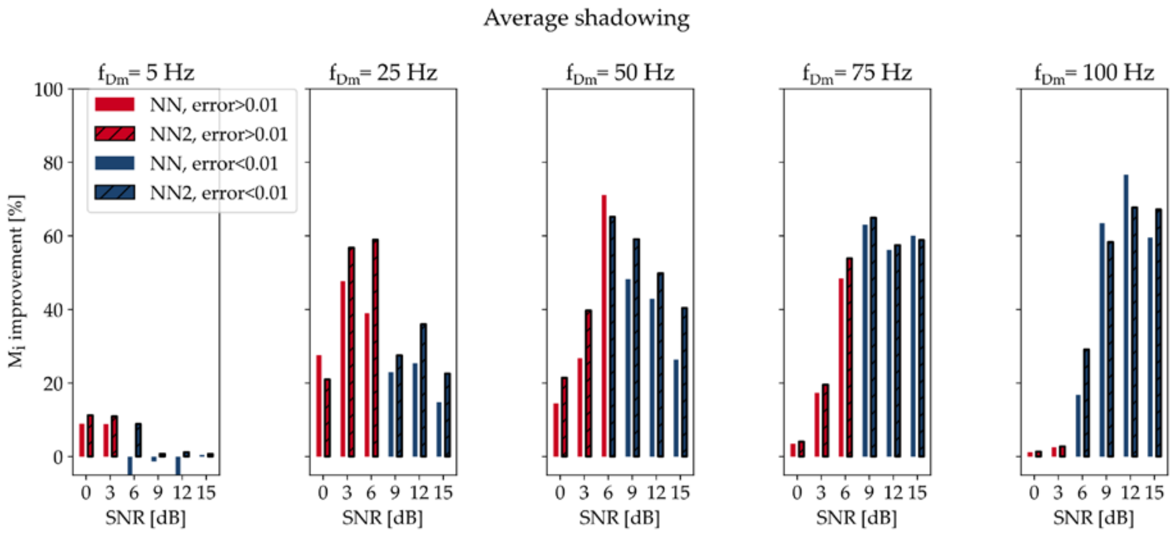


Figure 9. The achieved spectral efficiency improvement in % compared to the OI, on the test set for various scenarios under average shadowing conditions using a single channel. Scenarios where the transmission error is <0.01 are shown in blue, and scenarios where the transmission error is >0.01 are shown in red.

It can also be seen, in comparison to the low shadowing conditions, for higher f_{Dm} values, the achieved spectral efficiencies are overall quite lower, while for the lower f_{Dm} values this is not as prominent. This is to be expected as the combination of quicker changes in SNR in combination with more frequent shadowing makes predictions significantly more difficult, whereas if more shadowing but for slower changing SNR channels (lower f_{Dm}), the SNR pattern during shadowing can be more easily predicted and therefore not hinder the performance as severely. One more important observation is that although the absolute values are overall lower for higher f_{Dm} when compared to the light shadowing, the relative improvement between OI and NN2 is more pronounced. This would indicate that for less favorable scenarios, such as average shadowing and a high f_{Dm}, although the absolute spectral efficiency cannot be high, introducing more complex algorithms for SNR prediction could provide a significant benefit. Another occurrence that has happened for light shadowing as well, was that in certain scenarios NN has a transmission error rate higher than 0.01 while OI and NN2 do not. This has now happened for f_{Dm} of 50 Hz, and an expected SNR of 6 dB, for the same reason described in the light shadowing scenario. Once again, in the results obtain for heavy shadowing, it can be seen that the expected SNR of 6 dB does not allow for communication under any f_{Dm} conditions. For the average shadowing, in terms of obtainable absolute improvement (for a frequency range of 40 MHz), the best relative improvement scenario for NN2 (f_{Dm} = 100 Hz, SNR = 12 dB), the contribution of NN2 would be (0.54-0.32)b/s/Hz × 40 MHz = 8.8 Mb/s.

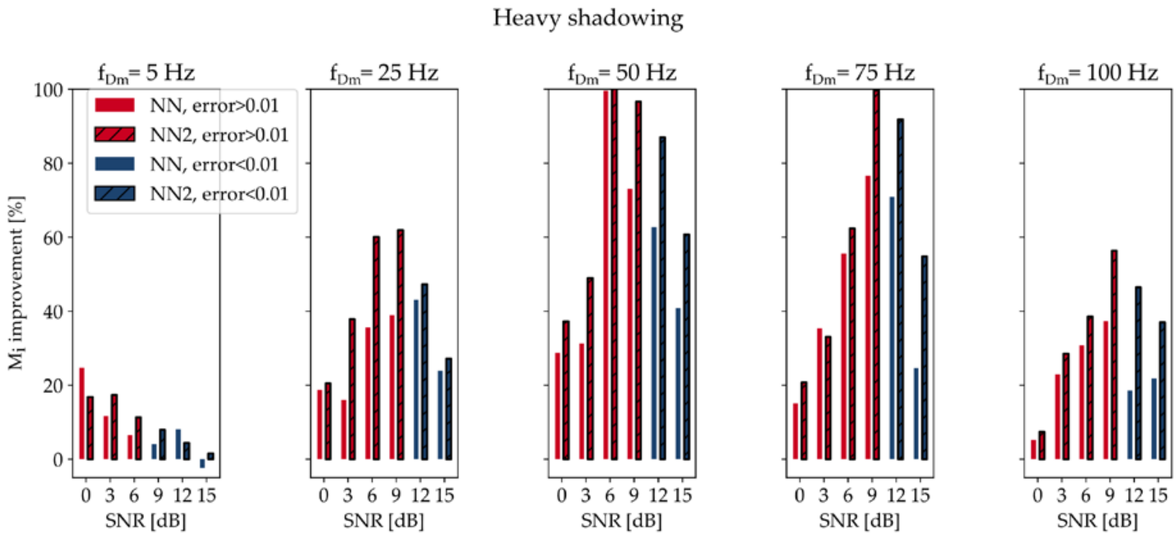


Figure 10. The achieved spectral efficiency improvement in % compared to the OI, on the test set for various scenarios under heavy shadowing conditions using a single channel. Scenarios where the transmission error is <0.01 are shown in blue, and scenarios where the transmission error is >0.01 are shown in red.

The analysis of the results obtained for heavy shadowing is quite similar as the one for previous scenarios. The transmission error rate was higher than 0.01 for almost all f_{Dm}s, for the expected SNR up to 9, with the only exception being SNR of 9 dB and f_{Dm} of 5 Hz. This just shows that channel SNR values can play out in such a way that they allow for communication to be established in a way that is not possible for similar scenarios. One more important observation that stands for all shadowing conditions, but can best be seen for heavy shadowing, is that even in the scenarios where the transmission error rate is higher than 0.01, the improvements of spectral efficiency exist between OI and NN2 and that the absolute value of spectral efficiency rises with the rise of the expected SNR. This is extremely important, because even if a desired error rate is unattainable, this approach will still provide the improvement in spectral efficiency, which is crucial when considering multiple channels with different characteristics and the usability of the provided method. The relative improvement provided in certain scenarios for heavy shadowing is the highest among the observed scenarios and exceeds 100% in some cases. For the best relative improvement scenario for NN2 (f_{Dm} = 75 Hz, SNR = 12 dB), considering a frequency range of 40 MHz, the NN2 contribution amounts to 12.8 Mb/s.

4.3.3. Double channel spectral efficicency

The final evaluation step is the one where the performance of the proposed method is evaluated for two communication channels. Here, only the NN2 and OI are compared for an easier overview of the results, especially considering that the NN2 approach has provided better results for the single channel spectral efficiency improvement. Figure 11. shows the results for light shadowing, Figure 12. for average shadowing and Figure 13. for heavy shadowing.

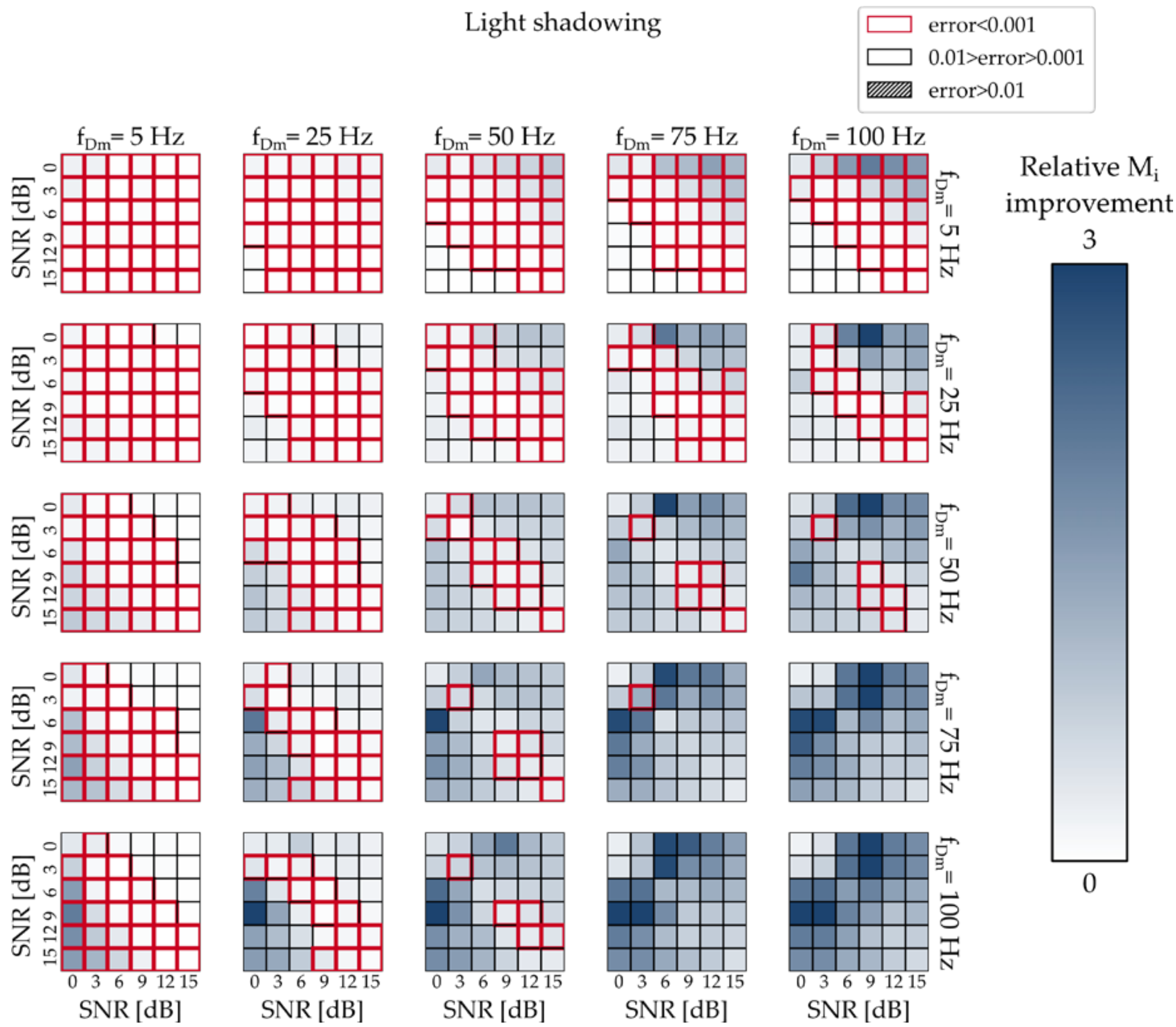


Figure 11. The achieved spectral efficiencies on the test set for various scenarios under light shadowing conditions using two channels, comparing OI and NN2. The color of each square represents a relative improvement of the achieved spectral efficiency calculated as $(M_i^{NN2} - M_i^{OI})/M_i^{OI}$.

Figure 11. shows how the combination of 2 channels can influence the performance of the proposed system. Each larger square represents a scenario where the channels f_{Dm}s are fixed (e.g. second row, third column, $f_{Dm}1$ = 25 Hz, $f_{Dm}2$ = 50 Hz), while the smaller squares correspond to various combinations of expected SNR. The type of square, red outline, regular outline, hatched, correspond to the range of transmission errors for that scenario, and the color scale corresponds to the relative improvement in spectral efficiency. The relative improvement is above 0 for all scenarios, i.e. there are no scenarios where the OI outperformed the NN2. Secondly, the red squares outline the scenarios in which the desired transmission error rate was achieved, i.e. it was under 0.001. It can be seen that for a low f_{Dm} it is always achievable, but as the f_{Dm} rises, this becomes more difficult, and for the f_{Dm} = 100 Hz, regardless of SNR, the proposed method achieved a transmission error rate lower than 0.01 but not lower than 0.001.

On the other hand, it can be seen that the relative improvement of spectral efficiency provided by the NN2 is much more prominent for the scenarios with a higher f_{Dm} (as seen in dark blue) as opposed to the ones for lower f_{Dm} (seen in white or light blue). This just shows that depending on the scenario, different goals can be achieved, and that the final goal has to be considered through the design of the algorithm, since the most straight forward solution (such as NN) might not provide the best results. Overall, scenarios where lower errors are obtainable present ones where SNR is easier to predict, hence OI has initially good performance, which is why the relative improvement offered by the NN2 is not as high as for some other scenarios.

Figure 12. shows how the increase in shadowing effects the performance of the system. When compared to the light shadowing conditions, a lot of the results are in darker blue, showing a greater relative improvement than the one achieved for light shadowing. Secondly, it can be seen that aside from a couple of scenarios of both channels having and f_{Dm} of 25 Hz, an error rate lower than 0.001 could not be achieved if one of the channels does not have an f_{Dm} of 5 Hz. Thirdly, it can be seen, that for some scenarios of higher f_{Dm}s and lower expected SNRs not even an error rate of 0.01 could be achieved. This is due to the unavoidable error rate, in the same manner as it was present for single-channel evaluation.

The results shown in Figure 13. have several outcomes that could be considered expected, and several ones that provide new information. Firstly, the scenarios where the unavoidable error is above 0.01 are more prominent. As can be seen for lower expected SNR scenarios where multiple field are hatched. Secondly, there are more scenarios where the transmission error could be lower than 0.001 for higher f_{Dm}s when compared to the average shadowing. This might seem unexpected as more frequent and heavier shadowing is not a favorable condition. However, it is possible that for higher f_{Dm}s, more frequent shadowing ads a level of order into the noisy signal, making the NN2 better at predicting what future SNR values will be. The "shadowed" parts of the signal provide very low SNR values, and if the NN2 can predict these values to be quite low, than the margin that is introduced might not need to be as high, and the overall performance could be better. The shadowed intervals have accurately low predicted SNRs, but regular parts of the signal could have adequate predictions as well, that will not be hindered by an extremely high margin. When observing the error transmission ranges and the obtained results, it is important to note that the next order of magnitude, i.e. having a transmission error rate of 0.0001 or lower was only unobtainable since the current test set has 25 000 samples and such an error rate would imply no more than 2 samples could be allowed to be incorrectly transmitted.

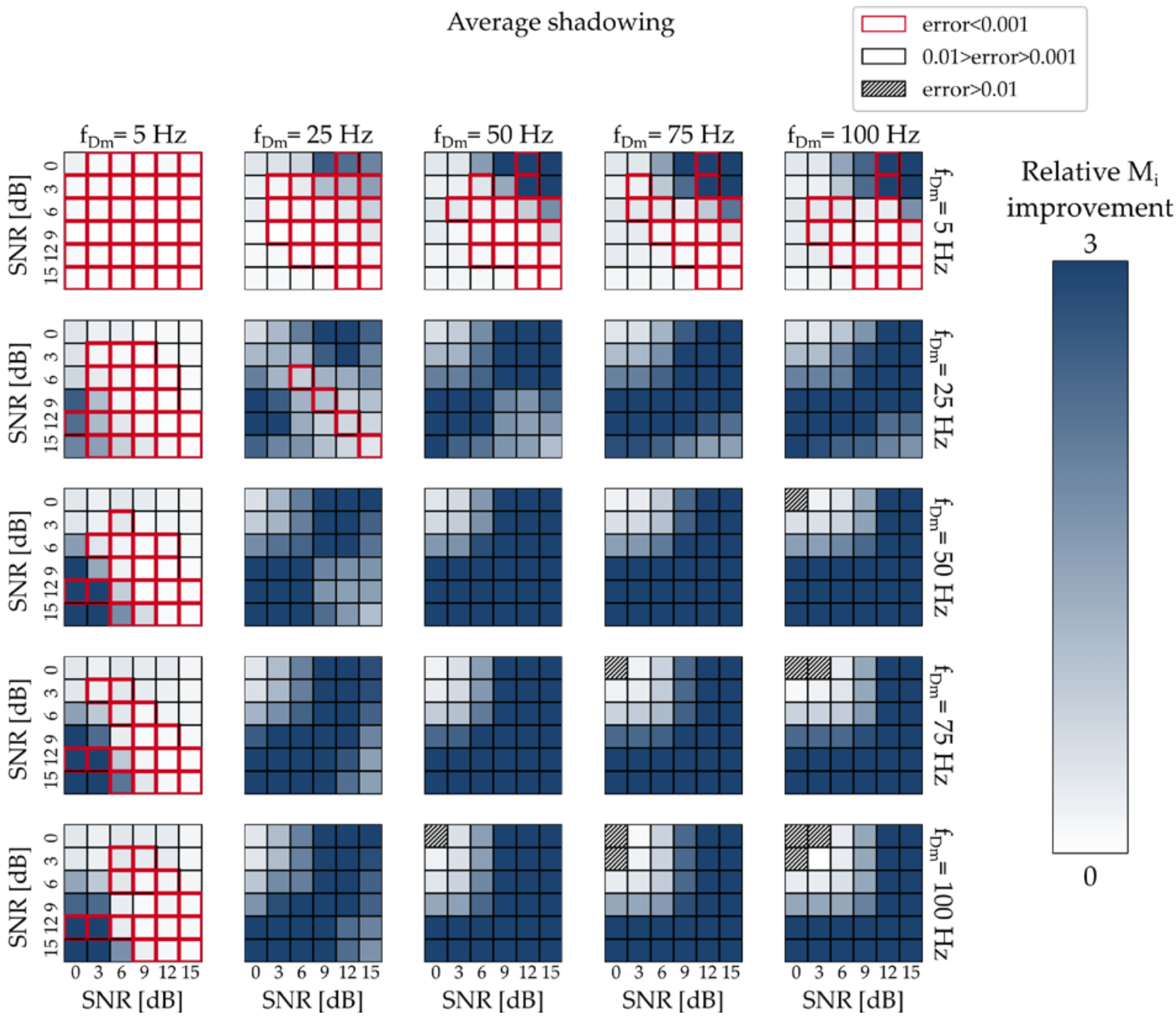


Figure 12. The achieved spectral efficiencies on the test set for various scenarios under average shadowing conditions using two channels, comparing OI and NN2. The color of each square represents a relative improvement of the achieved spectral efficiency calculated as $(M_i^{NN2} - M_i^{OI})/M_i^{OI}$.

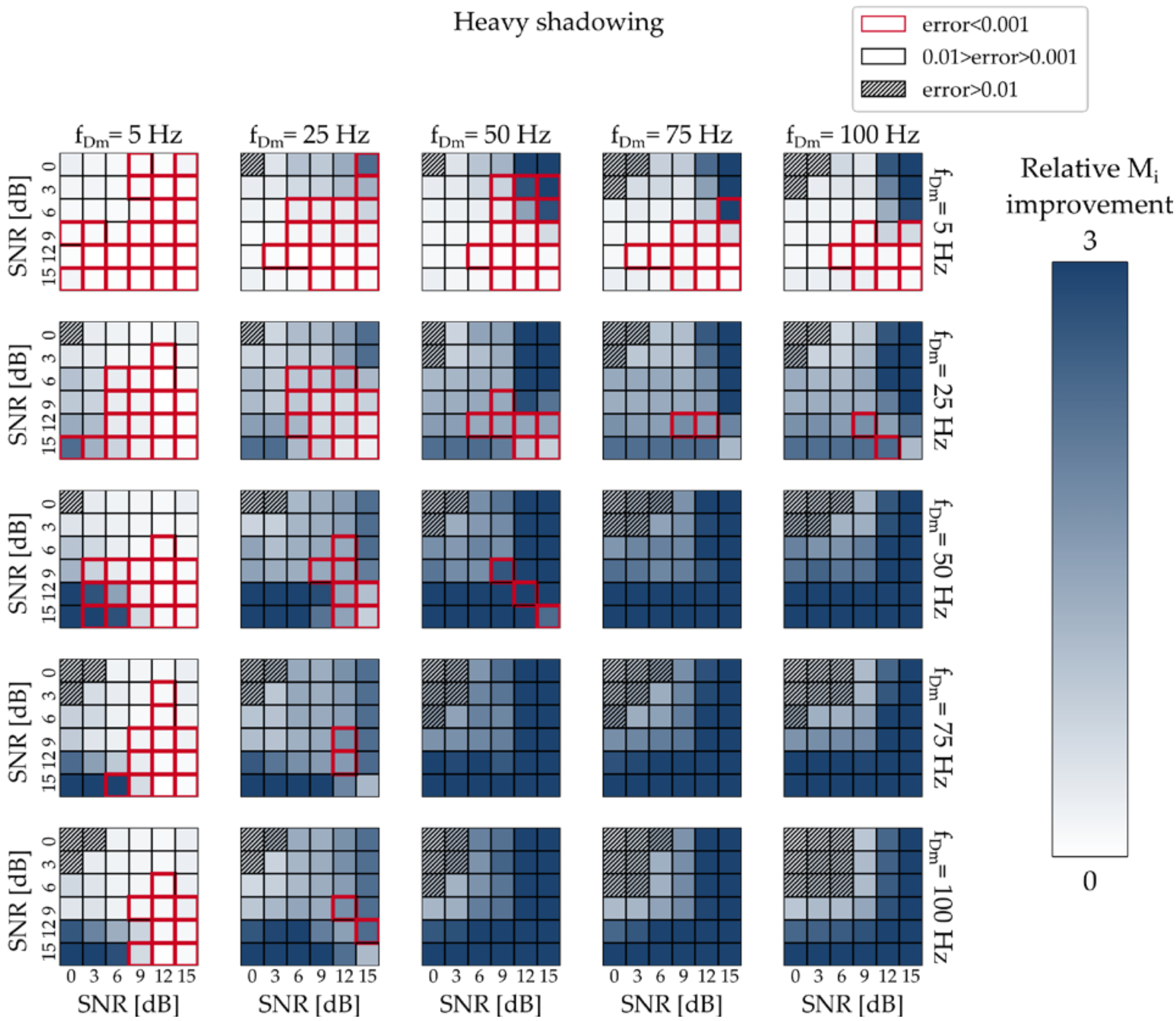


Figure 13. The achieved spectral efficiencies on the test set for various scenarios under heavy shadowing conditions using two channels, comparing OI and NN2. The color of each square represents a relative improvement of the achieved spectral efficiency calculated as $(M_i^{NN2} - M_i^{OI})/M_i^{OI}$.

Furthermore, even with a larger test set, two channels and the considered shadowing conditions would probably not allow for such a low error to be theoretically obtainable anywhere where there is average or heavy shadowing. This could direct future work towards analyzing 3 or more channels, or simply analyzing the performance obtainable when two channels of different shadowing levels are combined. These scenarios are understandably of interest but would simply be out of scope for this paper as the goal was to perform a sort of grid analysis in terms of ML algorithm performance for various channels, and to evaluate whether a neural network that purposefully underestimates values could be of interest considering fixed transmission error rates.

3. COMPARING VARIOUS NEURAL NETWORK ARCHITECTURES

In this section, various NN architectures are tested to see which ones can provide SNR prediction that can improve spectral efficiency in simulated channels with various shadowing levels, Doppler frequency shifts, and expected SNRs.

The SNR prediction proposed in this analysis is done on each of the 90 channels separately, focusing on the improvements that can be provided in the spectral efficiency. For this purpose, four different NN architectures were used in the study; two convolutional neural networks, and two long-short-term memory (LSTM) networks. The NNs used a sequence of 10 samples of estimated SNR to predict the true value of the SNR of the following sample and to aid in selecting the optimal modulation and coding (MODCOD) for communication. All the proposed networks had a modified loss function as described in the previous section (originally presented in our paper [8]) which would make the NNs underestimate the SNR predictions, as to avoid causing errors in communication.

We consider the following architectures:

1. NN1 was the same as the architecture proposed in [8] and is a simple convolutional NN that has 2 identical blocks consisting of a 32 filter 1D convolution layer with a kernel size of 5, a batch normalization layer, a max pooling layer with a kernel size of 2, and a dropout layer with a probability of 0.5. After these two blocks, a flatten layer was introduced, after which one fully connected layer with 10 neurons, and finally an output layer with a single neuron. All the layers had the rectified linear activation function, except for the output layer which had no activation.
2. The NN2 model is also a convolutional NN, with everything the same as in NN1 but with an increased filter size of 64 in both layers. The kernel size was kept fixed as the sequence length is only 10, but the goal was to analyze whether the added layer of depth could contribute to a better prediction.
3. NN3 was a simple LSTM network with a size of 32, followed by a batch normalization layer, flattens layer, a fully connected layer with 10 neurons, and an output layer with a single neuron.
4. The same logic as for the convolutional models was used to select the NN4, and it has 64 units in its LSTM layer.

All the Networks were optimized with the Adam optimizer, and any parameters that are not listed are kept as are default in the Keras Python library which was used for their implementation [4]. The training of the network was done on the first 75% of the generated channel and evaluated on the 25%, and repeated 4 times to show the average results. As a baseline for performance comparison, the outdated information approach is used which outputs the last obtained measured value as a prediction for the subsequent one. The spectral efficiency evaluation was done following the method from [8], choosing the highest possible MODCOD that satisfies the threshold of the predicted SNR.

To ensure that the error rate for the communication process is sufficiently low, a margin search was implemented on the train set, so that the error is below 0.01 (where possible) and this margin was applied to the predictions of the test set.

When comparing the overall performance of the NN architectures for all scenarios, the results are presented in Figure 1, where for each channel condition only the best-performing algorithm is shown. The results shown also do not present absolute values, rather the improvement compared to the outdated information is shown so that the differences can be seen more clearly. Overall, the NN1 is the least frequent architecture, being present in 13 out of the 90 scenarios. The second last is NN3 with 19 occurrences, than NN4 with 28 occurrences, and the most frequent NN2 with 29 occurrences. The absolute differences between the best performing and second best performing NN might not be significant, but still, the results show a clear bias towards LSTM networks (NN2 and NN4) in comparison to the convolutional NNs (NN1 and NN3). This indicated that perhaps focusing more on a different type of architecture rather than on the size of the network might be more beneficial. Still, in some cases, it is important to calculate the benefit of a more complex architecture such as an LSTM and whether the difference in performance is worth the extra computations.

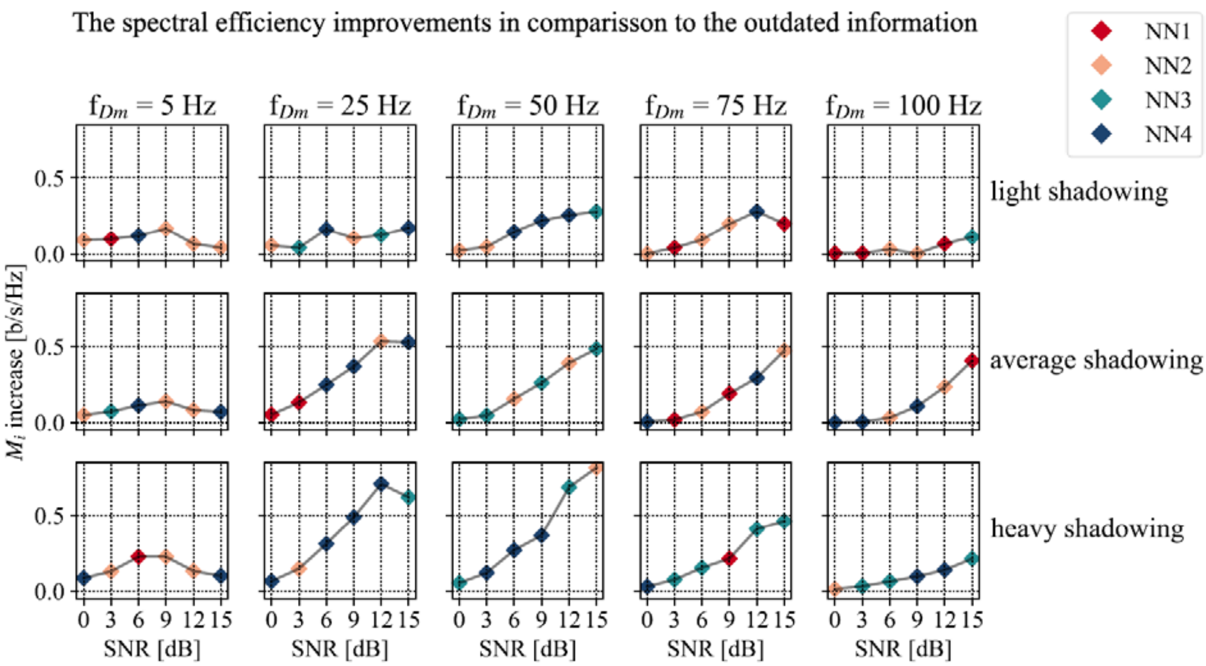


Figure 14. The representation of the improvements in spectral efficiency obtained by the proposed NNs in comparison to the outdated information approach, with each scenario showing the spectral efficiency of the best performing NN.

4. IMPLEMENTATION OF AI MODULE IN HUT

The Hybrid User Terminal (HUT) is implemented as a Graphical User Interface (GUI) application written in C++ language, which ensures portability across different operating systems. Overall, the HUT architecture is proposed in our paper [9] and it is presented in Figure 15.

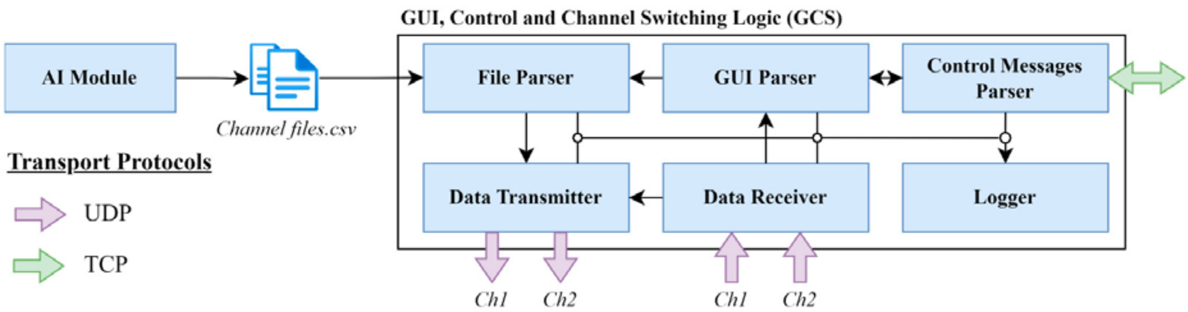


Figure 15. The architecture of the HUT module.

The HUT consists of two basic components:

- An AI module;
- GUI, Control and Channel Switching Logic (GCS).

The AI module's functionalities are centered on enhancing adaptive communication in LEO satellite systems. Specifically, the module processes sequences of measured SNR values to predict the optimal modulation and coding scheme (MODCOD) for upcoming transmission intervals. This predictive approach aims to maximize spectral efficiency while ensuring the transmission error rate remains below a predefined threshold, thereby facilitating high-speed data transmission with minimal errors under varying channel conditions.

Upon determining the optimal MODCOD, the system calculates the maximum number of frames that can be transmitted over each channel in the subsequent timeslot. This information is utilized by the GCS part on the HUT side to select the most suitable channel for frame transmission, optimizing overall communication performance.

The integration of machine learning techniques, such as neural networks, into adaptive modulation and coding schemes has been shown to enhance system capacity and reliability in satellite communications. As explained in the previous sections, by leveraging historical SNR data, these models can effectively predict future channel conditions, enabling more informed and efficient MODCOD selection.

Further details about the implementation of the HUT can be found in Deliverable 6.2.

SECTION 5 – CONCLUSIONS

This Deliverable presents the chosen expert system implemented in ITCU module, that incorporates an ML model to predict future SNR values. Various NN architectures are analysed to identify ones can provide signal-to-noise ratio (SNR) prediction that can improve spectral efficiency in simulated channels with channel parameters. Also, the implementation of AI module as a part of HUT has been considered.

The study demonstrates that neural networks can effectively predict SNR values across various channel conditions, corroborating findings from prior research where different neural network architectures successfully predicted CSI in LEO satellite systems. Utilizing a comprehensive simulator, this paper evaluates performance across 90 distinct channels, introducing a novel method that enhances spectral efficiency while maintaining transmission error rates below specified thresholds. Although the targeted error rates (0.01 and 0.001) may not suit all applications, the approach lays a foundation for future enhancements and serves as a proof of concept. This foundation can be integrated with other optimization strategies, such as accounting for weather influences and improving energy efficiency.

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